3rd AFRICAN CONFERENCE ON PRECISION AGRICULTURE

3-5 | December | 2024

AfCPA 2024

www.PAafrica.org | #AfCPA2024

PRECISION AGRICULTURE *in* ACTION *for* AFRICA

PROCEEDINGS

PROCEEDINGS OF THE

3rd African Conference on Precision Agriculture (AfCPA)

AfCPA 2024

www.PAafrica.org | #AfCPA2024

3-5 | December | 2024

PUBLISHED BY:

African Plant Nutrition Institute

Benguérir, Morocco

www.apni.net

CONFERENCE WEBSITE:

www.paafrica.org

This publication contains the full paper submissions from the AfCPA. These papers, along with all other accepted abstract submissions are available at the conference website.

3rd African Conference on Precision Agriculture (AfCPA)

ORGANIZED BY:

AFRICAN PLANT NUTRITION INSTITUTE

UM6P University Mohammed VI Polytechnic

ISPA International Society of Precision Agriculture
www.ispag.org

AAPA AFRICAN ASSOCIATION for PRECISION AGRICULTURE

SPONSORED BY:

OCP NUTRICROPS

TABLE OF CONTENTS

ADOPTION OF PRECISION AGRICULTURE

A CALL FOR ACTION: IMPLEMENTING THE AFRICAN CERTIFIED AGRONOMY ADVISORY PROGRAM

#10939

*Canon Engoke Norris Savala, Ivan Adolwa, Esther Mugi, Samuel Njoroge, Kwame Frimpong, James Mutegi, Kaushik Majumdar, Shamie Zingore
African Plant Nutrition Institute (APNI), ICIPE Compound, P.O. Box 30772-00100, Nairobi, Kenya
*e-mail: c.engoke@apni.net

ABSTRACT

Agriculture remains the backbone of many African economies, providing livelihood for millions of people while addressing food security concerns. However, productivity often lags other world regions due to various challenges, including limited access to modern agronomic practices and advisory services. In response to the pressing need for enhancing agricultural productivity and sustainability in African countries, it is imperative to establish a standardized extension training program at the continental level. The African Certified Agronomy Advisory Program (CAAP) aims to enhance agricultural productivity, sustainability, and resilience by providing farmers with access to high quality agronomy advisory services. The CAAP initiative addresses the critical gaps in access to relevant agronomic knowledge and guidance among smallholder farmers, thereby promoting sustainable farming practices and improving livelihoods. The CAAP framework encompasses a multi-faceted approach, including the training and certification of agronomy professionals, development of strategic partnerships with private, governmental and non-governmental entities, and the utilization of innovative communication technologies for information dissemination and sharing. Through country or regional tailored advisory services, CAAP will provide farmers with practical insights into soil and crop management, pest and disease control, and climate-resilient farming techniques. Central to the success of CAAP is its emphasis on local capacity building and community engagement. By empowering agronomic advisors and farmers with the necessary skills and knowledge, the program seeks to foster a culture of self-reliance and entrepreneurship within rural communities. Furthermore, monitoring and evaluation mechanisms will ensure the effectiveness and impact of CAAP interventions, allowing for continuous refinement and improvement. By collaborative promotion of precision nutrient management such as 4R practices and empowering smallholder farmers, CAAP has the potential to enhance food security, mitigate environmental degradation, and contribute to overall economic development in the region.

Keywords: Adoption, Capacity Development, Climate Change, Communication, Extension, Partnership, Technology, Training

INTRODUCTION

Agriculture plays a crucial role in the economies of many African nations, serving as a primary source of livelihood for a significant portion of the population. It contributes substantially to GDP and employment, particularly in rural regions where subsistence farming predominates. Agriculture is also vital for export earnings, with commodities such as cocoa, coffee, and tea forming the cornerstone of international trade (Jayne et al., 2023). However, despite its importance, the sector faces a multitude of challenges that limit its full potential. One major challenge is the limited access to modern agronomic practices and advisory services, which deprives farmers off essential resources such as knowledge and utilization of high-quality seeds, fertilizers, and machinery necessary for enhancing productivity and yields (Masangano & Mthinda, 2017). Furthermore, African agriculture is highly vulnerable to climate change and variability, with extreme weather events posing significant threats to crop production and livestock rearing. Strengthened advisory services will improve mitigation technics of smallholder farmers, who rely heavily on rain-fed agriculture and particularly susceptible to climatic shocks that lead to food insecurity and economic losses (Alston et al., 2022).

Strengthening of agronomic advisories should accompany financial services to farmers and policy amendments. Access to financial services and markets is another significant barrier, impeding farmers' ability to invest in modern inputs and technologies. Policy and regulatory constraints, bureaucratic inefficiencies, and land tenure issues further hinder agricultural development across Africa (Bambio et al., 2022). Despite these challenges, there are emerging initiatives aimed at improving agricultural productivity through sustainable farming practices, enhanced agricultural extension services, and better access to markets and finance (Camillone et al., 2020). This paper explores the potential of, and need for the African Certified Agronomy Advisory Program (CAAP) to address these challenges by building capacity among agronomy professionals, promoting sustainable agricultural practices, and improving food security and economic resilience in Africa.

Problem Statement and Objectives

Smallholder farmers are the backbone of agricultural production in Africa, yet they often lack access to the knowledge and resources needed to improve their farming practices. This results in sub-optimal yields, increased vulnerability to pests and diseases, and heightened susceptibility to climate variability, all of which negatively impact food security and livelihoods (Alston et al., 2022). Therefore, CAAP seeks to enhance agricultural productivity, sustainability, and resilience in Africa by providing farmers with access to high-quality agronomy advisory services. The program aims to fill critical gaps in agronomic knowledge and guidance, promote the adoption of sustainable farming practices matching transforming food systems and ultimately improve the livelihoods of smallholder farmers.

Framework Overview

CAAP is to be built on a comprehensive framework that includes the training and certification of agronomy professionals, the development of strategic partnerships, the use of innovative communication technologies, and the provision of tailored advisory services to farmers. A cornerstone of CAAP is the rigorous training and certification of agronomy professionals. These individuals will be equipped with the skills and knowledge necessary to provide high-quality advisory services that help farmers improve their food systems productivity and adopt sustainable practices (Jayne et al., 2023). CAAP seeks to collaborate with a diverse array of partners, including private companies, government agencies, research institutions (national and international) and non-governmental organizations, to leverage resources and expertise. These partnerships are crucial for knowledge development, policy alignment and effective delivery of agronomy advisory services and for ensuring the sustainability of CAAP interventions (Masangano & Mthinda, 2017). The program will utilize innovative communication technologies, such as mobile phones and the internet, to train agronomists and disseminate agronomic information to farmers. These technologies facilitate real-time communication and information sharing, allowing agronomy advisors and farmers to access timely knowledge, guidance and inturn share feedback for improvement (Camillone et al., 2020). CAAP will provide tailored advisory services based on the specific needs and contexts of farmers. These services will include practical insights into soil and crop management, pest and disease control strategies, and climate-resilient farming techniques (Bambio et al., 2022).

Case Studies from Africa

In Kenya, extension has worked with smallholder farmers to enhance soil fertility through the adoption of sustainable soil and crop management practices. By promoting practices such as conservation agriculture and organic farming, the program helped farmers increase yields while preserving soil health (Jayne et al., 2023). In Ghana, extension has implemented integrated pest and disease management strategies to combat common agricultural pests and diseases. Using biological control methods, crop rotation, and resistant crop varieties, extension reduced reliance on chemical pesticides while effectively managing pest and disease outbreaks (Masangano & Mthinda, 2017). In Ethiopia, extension has introduced climate-resilient farming techniques to help farmers adapt to the challenges posed by climate change. These techniques include the use of drought-tolerant crop varieties, water harvesting and conservation practices, and agroforestry systems, enabling farmers to maintain productivity despite changing climatic conditions (Alston et al., 2022).

Empowerment of Farmers

CAAP emphasizes the empowerment of farmers by providing them with the skills and knowledge needed to improve their farming practices. By fostering a culture of self-reliance and entrepreneurship within rural communities, the program aims to enhance agricultural sustainability and food systems productivity (Bambio et al., 2022). Implementation of the program will also promote entrepreneurship among farmers by supporting the development of agribusinesses and value-added enterprises through supply of raw materials. By diversifying income streams and creating market linkages, CAAP will help farmers improve their economic resilience and livelihoods (Camillone et al., 2020). CAAP will actively involve local communities in the design and implementation of its interventions, ensuring that they are culturally appropriate and contextually relevant. Through activities such as farmer field schools, ‘living labs initiative’ and participatory research initiatives, CAAP will strengthen social cohesion and ownership of agricultural development initiatives (Jayne et al., 2023).

Potential Impact of CAAP

Through continuous monitoring and evaluation, CAAP will ensure the effectiveness and impact of technology and strengthened advisory interventions. These mechanisms allow for the assessment of progress towards program objectives, identification of challenges and bottlenecks, and adjustment of strategies as needed (Alston et al., 2022). This strategy will allow CAAP to refine and improve its approaches over time. With an iterative process approach of learning and adaptation, CAAP will remain responsive to the evolving needs and priorities of smallholder farmers in Africa (Masangano & Mthinda, 2017). CAAP will promote sustainable farming practices and improve agricultural productivity thereby enhancing food security in Africa. Increased yields and diversified crop production can help ensure a stable and nutritious food supply for rural communities (Bambio et al., 2022). CAAP will contribute to environmental conservation by promoting practices that reduce the use of excessive chemical inputs, conserve soil and water resources, and mitigate greenhouse gas emissions. The adoption of climate-resilient farming techniques also helps farmers contribute to climate change mitigation and adaptation efforts (Camillone et al., 2020). Through the promotion of entrepreneurship and the creation of market linkages, CAAP will stimulate economic development in rural areas. Also, the program will promote economic growth and poverty reduction in the region when additional income opportunities and enhanced agricultural value chains will be created (Jayne et al., 2023).

RECOMMENDATIONS AND CONCLUSION

The African Certified Agronomy Advisory Program (CAAP) represents a comprehensive approach to enhancing agricultural productivity and sustainability in Africa. CAAP will provide farmers with access to high-quality agronomy advisory services, promote sustainable farming practices, and foster community engagement. Therefore, CAAP has the potential to significantly improve livelihoods and food security across the continent. Further research is needed to assess the long-term impacts of CAAP interventions and identify areas for improvement. Additionally, studies on the scalability and replicability of CAAP models across different contexts and regions would be valuable for informing future program expansion efforts. CAAP offers a promising solution to the challenges facing smallholder farmers in Africa. By leveraging strategic partnerships, innovative technologies, and community participation, the program has the potential to catalyze transformative change in the agricultural food systems sector, leading to more resilient and sustainable food systems across the continent.

REFERENCES

Alston, J. M., Pardey, P. G., James, J. S., & Andersen, M. A. (2022). Research and Productivity Growth in Agriculture: A Broader Perspective. American Journal of Agricultural Economics, 104(3), 763-780.

Bambio, Y., & Agha, H. (2022). Adoption of Sustainable Agricultural Practices in Africa: The Role of Capacity Building. Journal of Development Studies, 58(6), 925-940.

Camillone, J., de Janvry, A., & Sadoulet, E. (2020). Certification and Agricultural Productivity: Evidence from a Field Experiment. World Development, 130, 104917.

Jayne, T. S., Chamberlin, J., & Benfica, R. (2023). Agriculture in Africa: Telling Myths from Facts. Food Policy, 104, 102102.

Masangano, C., & Mthinda, C. (2017). Agricultural Extension in Africa: Experiences from Malawi. Journal of Agricultural Education and Extension, 23(5), 385-401.

HIGH-THROUGHPUT FIELD PHENOTYPING OF ASCOCHYTA BLIGHT DISEASE SEVERITY IN CHICKPEA USING MULTISPECTRAL IMAGING

#11660

[1,2]Ibn El Mokhtar Fatima Zahrae, [1*]Krimibencheqroun Sanae, [1]Dahhane Younes, [1]Harkani Assia, [2]Houmairi Hafsa, [1]Idrissi Omar, [1*]El-Aissaoui Abdellah

[1] Regional Center of Agricultural Research of Settat, National Institute of Agricultural Research (INRA), Settat, Morocco

[2] Agri-food and Health Laboratory, Faculty of Science and Technology, Hassan First University of Settat, Settat, Morocco

[*]e-mail: abdellah.elaissaoui@inra.ma; sanae.krimibencheqroun@inra.ma

ABSTRACT

Ascochyta blight (AB) caused by *Ascochyta rabiei* (Pass.) Labr. is an important and widespread disease of chickpea (*Cicer arietinum* L.) worldwide. The disease is particularly severe under cool and humid weather conditions, leading to crop losses at all stages of chickpea growth. Screening for resistant cultivars remains the most effective, economic and ecological method of disease management. However, traditional phenotyping methods that relying on trained experts are slow, costly, labor-intensive, subjective, often involve destructive sampling. The development of high-throughput phenotyping methods for Ascochyta blight disease holds promise for precise and rapid data. In this study, 216 chickpea genotypes were screened in field trials to investigate the use of digital imaging to implement reliable phenotyping of Ascochyta blight resistance. An unmanned aerial system equipped with a 5-band multispectral camera was used to capture imagery of the tested genotype plots. Digital image processing was employed to extract the NDVI index. Our aim was to explore the correlation between the NDVI index and visual disease severity ratings for Ascochyta blight. Results revealed a consistent correlation between the NDVI index extracted from image features and disease severity with R^2 of 0.936. Genotypes were classified into resistant (R), moderately resistant (MR) susceptible (S) and highly susceptible categories based on their responses. These differences in genotypes response were utilized to developpe a predictive model for monitoring Ascochyta blight. Our findings highlight that rapid and precise image-based, high-throughput phenotyping can effectively differentiate responses to Ascochyta blight across many chickpea genotypes.

Keywords: Drone imaging, Ascochyta blight, severity, phenotyping, chickpea, NDVI,

INTRODUCTION

Chickpea (*Cicer arietinum L.*) is a highly valuable crop, providing an important source of protein and improving soil health through nitrogen fixation. However, its production is severely affected by various abiotic and biotic stresses, including drought and diseases. Among these, Ascochyta blight (AB), caused by *Ascochyta rabiei* (Kovatsch.) Arx, 1962, is a major biotic threat that significantly limits chickpea yield [1]. AB primarily affects the plant's foliar parts, causing lesions and tissue necrosis that reduce seed quality and overall crop productivity. The disease often begins in small patches within the field but can rapidly spread under favorable conditions of temperature and rainfall [2-3]. Weather plays a crucial role in AB development, particularly in cooler (15-

25°C) and humid environments (>70%) during the growing season. Additionally, factors such as inoculum type, virulence, concentration, and the plant's growth stage and resistance level influence the severity and spread of the disease [3].

Due to the polycyclic nature of AB, control often requires multiple fungicide applications, which are costly and pose risks to human health, wildlife, and ecosystems [4, 5]. Additionally, the overuse of fungicides may lead to contamination and the development of resistant pathogens. Consequently, the sustainable method for managing Ascochyta blight is based on breeding to select resistant cultivars. However, the traditional methods of phenotyping disease resistance, relying on human expertise, are often time and labor consuming, not cost-effective, and sometimes requires destructive sampling of plants. In this context, the use of high-throughput phenotyping (HTP) methods for Ascochyta blight is promising for developing precise and rapid disease assessment digital tool. The HTP based on using digital imaging, such as drones mounted thermal, multispectral (MSI), or hyperspectral (HIS) cameras, offers a non-invasive and consistent imaging process to monitor plant stresses and disease severity. Use of drone technologies, capturing high-resolution spectral data showed great opportunities to detect both biotic and abiotic stresses in different crops [6,7]. Different Indices like NDVI (Normalized Difference Vegetation Index) and GNDVI (Green Normalized Difference Vegetation Index), are commonly used to assess disease severity among different plant stresses due plant hydric state or plant health state.

Several authors [8-10] have been used digital methods for evaluating plant disease severity to provide greater accuracy, repeatability, and reproducibility compared to traditional techniques. This digital process involves image acquisition, analysis, processing, and validation through specialized software [8-10]. In fact, over the past three decades (1990-2020), significant advancements have been made in using digital tools for evaluating plants diseases severity. In the 1990s, cameras were first used to distinguish between healthy and diseased plants, such as in studies on Fusarium in corn [11] and maize streak virus (MSV) in resistant corn [12]. The 2000s saw the development of image analysis software like Assess [13] and ImageJ [14, 15], which improved the precision of disease quantification. By the 2010s, advanced imaging techniques, including thermal, hyperspectral (HIS), and multispectral (MSI) imaging, became widely used, offering early disease detection and more effective management compared to traditional visible spectrum imaging [16,17]. These imaging technologies, often mounted on drones, detect plant stress or disease by capturing temperature variations and multispectral data [18-19]. MSI cameras calculate spectral indices such as NDVI, which have been shown to strongly correlate with disease severity and plant health [20,21]. For instance, NDVI exhibited a strong negative correlation with disease severity in pineapple (-0.83 to -0.88) [22], and in chickpea, it correlated with leaf area index, chlorophyll content, and biomass [23]. Additionally, the correlation between visual disease ratings and NDVI in chickpea increased from -0.61 to -0.66 after 58 days, with NDVI’s correlation with yield ranging from 0.76 to 0.92 [24].

According to the short review stated above, an early and accurate disease detection remain essential for implementing timely management strategies. Furthermore, the digital methods require more improvements as it is often difficult to discriminate between biotic and abiotic stresses that may cause similar symptoms, making visual diagnosis challenging [25]. In fact, the use of these digital indices cannot differentiate between biotic and abiotic stresses without efforts from agronomic experts of relying on the indices data information to the main occurring stress and

avoiding spatial and temporal interference between two different stresses that can be potentially expressed in the same digital data taken from one image process acquisition [26, 27].
This study explores the use of digital imaging for reliable phenotyping of Ascochyta blight resistance in chickpea. Specifically, our innovative digital method aims for testing the correlation between disease severity and NDVI and boosting this correlation trough use of different plants/genotypes as checks for showing a gradient of resistance to AB severity and using it as reference model to predict the disease severity among a large sample of plants/genotypes that can be potentially tested for selection with reference to AB severity using NDVI information. This innovative digital method aims to developing a precise, automated phenotyping process for an effective disease management.

MATERIAL AND METHODS

Evaluation of AB disease severity using classic method of visual scale

A field trial was conducted in 2020-2021 at the Sidi El Aidi experimental station of the INRA Settat. A total of 216 chickpea genotypes with varied resistance to AB was tested, using a randomized complete block design (RCBD) augmented with nine blocks and four checks. Spores of *A. rabiei* was inoculated via foliar spraying, during vegetative stage. Disease severity was evaluated visually using a 0-9 scale [28]. The visual reading of AB disease severity was taken for comparison with digital method using drone multispectral imaging to promote as rapid evaluation of crops health by the plant pathologist.

Evaluation of AB disease severity using digital imaging and NDVI

The disease severity was evaluated also digitally using drone multispectral imaging. NDVI values were computed from multispectral data to assess plant health. The NDVI values were used to find potential correlation with the visual reading.

Reference model for calibration and prediction of disease severity

To test the response of the 216 chickpea genotypes to AB disease severity, four checks of chickpea genotypes were used as references to show a gradient of different responses from low to high resistance to AB disease severity. A tuning curve is generated from a gradient of response (4 checks, 9 levels of disease severity) to serve as a reference model for testing the responses of 216 genotypes. This model is then used to assess the potential for predicting AB disease severity among the tested genotypes.

RESULTS

Evaluation of AB disease severity using visual assessment and NDVI

Use of decision-making tools is essential for phytopathologists to effectively manage disease interventions by utilizing digital NDVI information to evaluate disease severity. To develop this tool, we assessed the correlation between Ascochyta blight (AB) disease severity and NDVI based on data from 216 plots of tested genotypes and 36 plots of reference genotypes. Where C1 represents the resistant check, C2 represents the susceptible check, and C3 and C4 represent the moderately resistant checks (Fig. 1)

Since AB is characterized by color changes, resulting from lesions on plant leaves, the use of digital imaging data has significantly distinguished the infected plants. The NDVI results of four checks clearly illustrate the varying responses of chickpea genotype plots, showing a gradual transition in leaf color from vibrant green (resistant check C1) to yellow, orange (moderately resistant C3 and C4), and ultimately red (susceptible check C2). This decrease in green coloration correlates with the severity of AB, highlighting the relative foliar changes in the infected plants (Fig. 2).

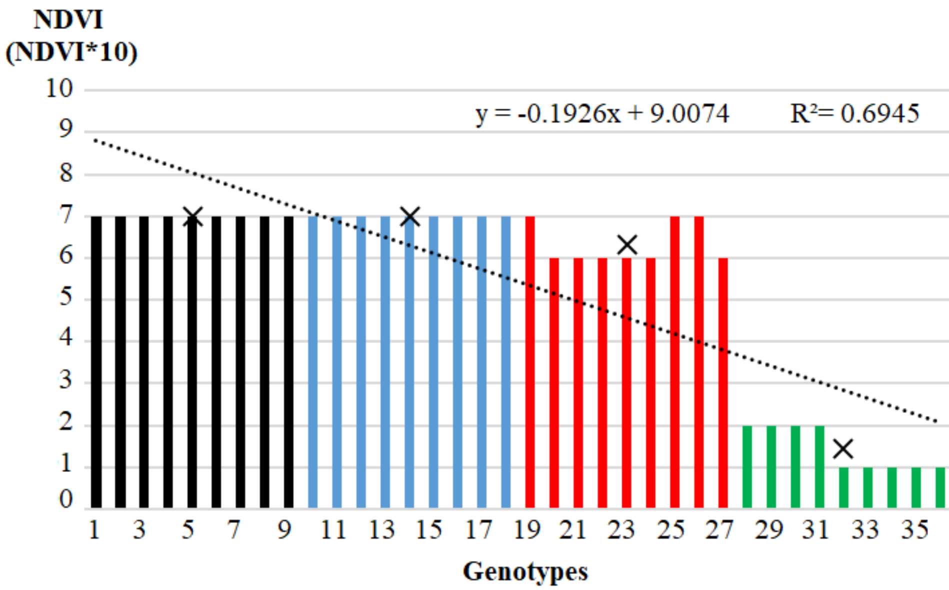


Figure 1. NDVI values relatives to 4 checks having different reaction to AB, resistant, moderate resistant or susceptible (36 plots relative to four checks with nine repetitions).

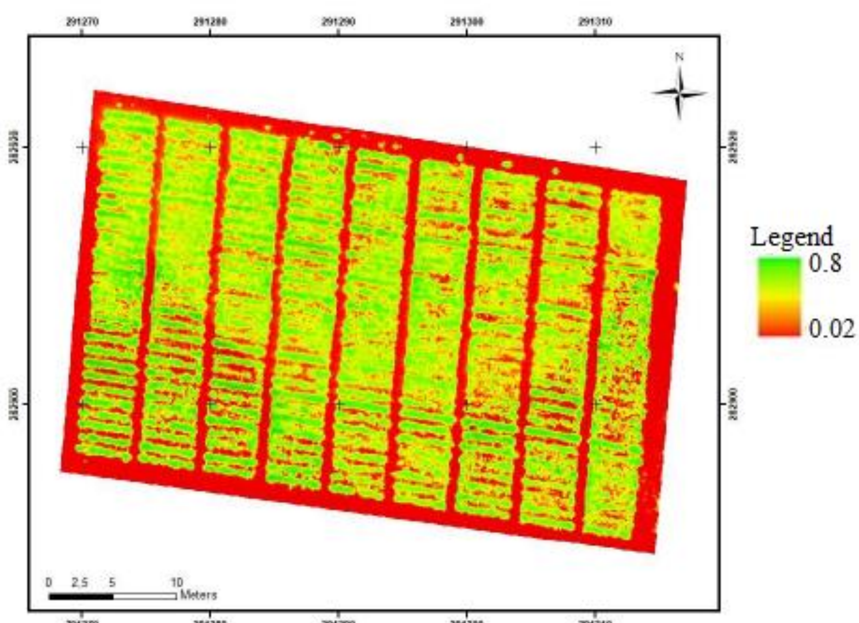


Figure 2. NDVI image illustrating 216 genotype plots with visual notation of 4 checks resistance to AB disease (S: susceptible, MR: Moderately Resistant and R: Resistant).

Reference model for calibration and prediction of disease severity

The correlation between NDVI and visual reading using data from the four checks used as reference genotypes facilitated the creation of an empirical model that can be used to predict AB disease severity using NDVI as an indicator (Eq. 1). The model equation is mounted as follows:

$$\textbf{Predicted Severity} = -0.9816 * \text{NDVI} + 9.983 \qquad (1)$$

The results showed existence of a strong correlation ($R^2 = 0.98$) between the actual visual rating scores and the predicted scores.

Prediction test of severity using the reference model

The severity of AB disease among the 216 genotype is predicted using the reference model to show how it is possible to find fitting between the predicted severity and the actual one.

Among the 216 genotypes, the correlation between measured severity and predicted severity showed a good fit using RMSE, MAE, and RE metrics (RMSE = 0.27, MAE = 0.15, RE = ±0.04), indicating its potential for practical application in assessing AB disease severity in crop fields based solely on NDVI data.

DISCUSSION

In this research, drone multispectral imaging was utilized to evaluate the severity of Ascochyta blight (AB) in 252 chickpea plots, comprising 216 genotypes and four check varieties. The NDVI (Normalized Difference Vegetation Index) was calculated to correlate with visual disease ratings, enabling field-scale assessment of AB severity. High-resolution orthophoto images revealed distinct differences between heavily infested and healthy plots, with consistent discoloration linked to increased plant mortality.

The study found a strong correlation between NDVI and AB severity, aligning with previous research indicating NDVI as a robust index for disease quantification. The relationship between NDVI and visual ratings showed an impressive R^2 value of 0.98. An empirical model was developed through linear regression, successfully predicting disease severity, validated by RMSE, MAE, and RE metrics.

The potential of NDVI as a decision-making tool for disease management was emphasized, facilitating timely interventions based on environmental conditions. Other studies highlighted the use of machine learning and decision support systems in disease detection and management, demonstrating significant accuracy in monitoring various crop diseases.

However, the accuracy of disease monitoring may be influenced by factors such as plant senescence, canopy density, and environmental conditions. Our study established a significant correlation between NDVI (Normalized Difference Vegetation Index) and the disease severity of four control genotypes with known reactions to Ascochyta blight. This finding highlights the potential of NDVI as a reliable tool for detecting biotic stress in crops. The use of NDVI for monitoring plant health has been widely reported as an effective indicator for assessing vegetation vigor and stress, particularly in response to pathogens [25]. By providing non-destructive, real-time monitoring capabilities, NDVI can serve as an early-warning system for managing disease outbreaks and guiding targeted interventions in precision agriculture [25]. Our results further validate the growing body of research that supports NDVI as a promising tool for assessing biotic stress in crops, allowing for efficient and sustainable crop management. In addition, the study underscored the need for calibrated images to increase accurate analysis and suggested further research to enhance the differentiation of disease symptoms using hyperspectral and multispectral sensing techniques.

CONCLUSION

This study showed that it is possible to adequately use NDVI derived from multispectral images and improve its fitting to effectively detect and assess the severity of Ascochyta blight on chickpeas. A strong correlation between NDVI and disease ratings allowed for the creation of an accurate predictive model. The prediction is greatly improved as the model calibration is referenced to a gradient of disease severity using four genotypes as checks to show a gradual response of disease severity.

The reference curve of the checks responses to AB disease showed that it is possible to implement robust predictive model for monitoring disease severity. In fact, the referencing of NDVI information to disease severity of known genotypes improved the model fitting. The digital monitoring of chickpea green cover can be greatly improved if the fitting of NDVI response to disease severity is calibrated with reference to use of checks gradient to assess AB disease severity. This innovative method based on calibration can potentially help the plant pathologists to overcome the problem of discriminating between NDVI responses to biotic and/or abiotic stresses by using specifically NDVI information to assess and control AB disease severity. The results highlight NDVI's potential for field-scale disease monitoring and high-throughput phenotyping, with future integration of deep learning offering further advancements in disease management.

REFERENCES

1. Pande S, Kishore GK, Upadhyaya HD, Rao JN. Identification of sources of multiple disease resistance in mini-core collection of chickpea. Plant Dis. 2006;90(9):1214-8. doi: 10.1094/PD-90-1214. PMID: 30781104.
2. Pande S, Sharma M, Gaur PM, et al. Development of screening techniques and identification of new sources of resistance to Ascochyta blight disease of chickpea. Australas Plant Pathol. 2011;40(2):149-56. doi: 10.1007/s13313-010-0024-8.
3. Pande S, Siddique K, Kishore G, Bayaa B, Gaur P, Laxmipathi Gowda C, et al. Ascochyta blight of chickpea (Cicer arietinum L.): A review of biology, pathogenicity, and disease management. Crop Pasture Sci. 2005;56(4):317-32. doi: 10.1071/AR04143.
4. Chang KF, Ahmed HU, Hwang SF, Gossen BD, Strelkov SE, Blade SF, et al. Sensitivity of field populations of Ascochyta rabiei to chlorothalonil, mancozeb, and pyraclostrobin fungicides, and effects of strobilurin fungicides on the progress of
5. Ascochyta blight of chickpea. Can J Plant Sci. 2007;87:937-44.

6. Gan YT, Siddique KHM, MacLeod WJ, Jayakumar P. Management options for minimizing the damage by ascochyta blight (Ascochyta rabiei) in chickpea (Cicer arietinum L.). Field Crops Res. 2006;97:121-34.
7. Zhao Y, Gu Y, Qin F, Li X, Ma Z, Zhao L, et al. Application of near-infrared spectroscopy to quantitatively determine relative content of Puccinia striiformis f. sp. tritici DNA in wheat leaves during the incubation period. J Spectrosc. 2017;2017:9740295. doi: 10.1155/2017/9740295.
8. Mahlein AK. Plant disease detection by imaging sensors—parallels and specific demands for precision agriculture and plant phenotyping. Plant Dis. 2016;100:241-51.
9. Kwack MS, Kim EN, Lee H, Kim JW, Chun SC, Kim KD. Digital image analysis to measure lesion area of cucumber anthracnose by Colletotrichum orbiculare. J Gen Plant Pathol. 2005;71:418-21.
10. Clément A, Verfaille T, Lormel C, Jaloux B. A new colour vision system to quantify automatically foliar discoloration caused by insect pests feeding on leaf cells. Biosyst Eng. 2015;133:128-40.
11. El Jarroudi M, Kouadio AL, Mackels C, Tychon B, Delfosse P, Bock CH. A comparison between visual estimates and image analysis measurements to determine Septoria leaf blotch severity in winter wheat. Plant Pathol. 2015;64:355-64.
12. Todd LA, Kommedahl T. Image analysis and visual estimates for evaluating disease reactions of corn to Fusarium stalk rot. Plant Dis. 1994;78:876-8.
13. Martin DP, Willment JA, Rybicki EP. Evaluation of maize streak virus pathogenicity in differentially resistant Zea mays genotypes. Phytopathology. 1999;89:695-700.
14. Sun H, Wei J, Zhang J, Yang W. A comparison of disease severity measurements using image analysis and visual estimates using a category scale for genetic analysis of resistance to bacterial spot in tomato. Eur J Plant Pathol. 2014;139:125-36.
15. Stewart EL, McDonald BA. Measuring quantitative virulence in the wheat pathogen Zymoseptoria tritici using high-throughput automated image analysis. Phytopathology. 2014;104:985-92.
16. Laflamme B, Middleton M, Lo T, Desveaux D, Guttman DS. Image-based quantification of plant immunity and disease. Mol Plant Microbe Interact. 2016;29:919-24.
17. Rumpf T, Mahlein AK, Steiner U, Oerke EC, Dehne HW, Plümer L. Early detection and classification of plant diseases with support vector machines based on hyperspectral reflectance. Comput Electron Agric. 2010;74:91-9.
18. Zhang D, Zhou X, Zhang J, Lan Y, Xu C, Liang D. Detection of rice sheath blight using an unmanned aerial system with high-resolution color and multispectral imaging. PLoS One. 2018;13
19. Gao D, Sun Q, Hu B, Zhang S. A framework for agricultural pest and disease monitoring based on internet-of-things and unmanned aerial vehicles. Sensors. 2020;20:148. doi: 10.3390/s20051487.
20. Bauriegel E, Herppich WB. Hyperspectral and chlorophyll fluorescence imaging for early detection of plant diseases, with special reference to Fusarium spec. infections on wheat. Agriculture. 2014;4:32-57.
21. Guo J, Hu Y, Xiong Z, Yan X, Ren B, Bu R. Spatiotemporal variations of growing-season NDVI associated with climate change in northeastern China's permafrost zone. Polish J Environ Stud. 2017;26:1521-9.

22. Pan S, Zhao X, Yue Y. Spatiotemporal changes of NDVI and correlation with meteorological factors in Northern China from 1985–2015. E3S Web Conf. 2019.
23. Wang M, Fu J, Wu Z, Pang Z. Spatiotemporal variation of NDVI in the vegetation growing season in the source region of the Yellow River, China. ISPRS Int J Geo Inf. 2020;9:282. doi: 10.3390/ijgi9040282.
24. Ajai MR, Kamat DS, Chaturvedi GS, Singh AK, Sinha SK. Spectral assessment of leaf area index, chlorophyll content, and biomass of chickpea. Photogramm Eng Remote Sens. 1983;49
25. Zhang C, Chen W, Sankaran S. High-throughput field phenotyping of Ascochyta blight disease severity in chickpea. Crop Prot. 2019;125:104885.
26. Prabhakar M, Prasad YG, Rao MN. Remote sensing of biotic stress in crop plants and its applications for pest management. In: Venkateswarlu B, Shanker A, Shanker C, Maheswari M, editors. Crop Stress and its Management: Perspectives and Strategies. Dordrecht: Springer; 2012. p. 449-62.
27. Rayhana R, Ma Z, Liu Z, Xiao G, Ruan Y, Sangha JS. A review on plant disease detection using hyperspectral imaging. IEEE Trans AgriFood Electron. 2023;1(2):108-34.
28. Chowhan P, Chakraborty AP. Remote sensing technology—A new dimension in detection, quantification, and tracking of abiotic and biotic stresses. In: Roy S, Mathur P, Chakraborty AP, Saha SP, editors. Plant Stress: Challenges and Management in the New Decade. Cham: Springer; 2022. p. 549-66.
29. Chen W, Coyne CJ, Peever TL, Muehlbauer FJ. Characterization of chickpea differentials for pathogenicity assay of ascochyta blight and identification of chickpea accessions resistant to Didymella rabiei. Plant Pathol. 2004;53:759-69.

EFFECTS OF ADOPTING FERTILIZER MANAGEMENT PRACTICES ON YIELD IN MAIZE-BASED SYSTEMS IN EMBU COUNTY, KENYA: AN INSTRUMENTAL VARIABLE REGRESSION APPROACH

#11303

[1*]Malcolm Gitau, [1]Rose Nyikal, [1]Evans Chimoita, [2]Onesmus Kitonyo
[1]Department of Agricultural Economics, University of Nairobi, Kenya
[2]Department of Plant Science and Crop Protection, University of Nairobi, Kenya
[*]e-mail: malcolmgitau@gmail.com; +254705534199

ABSTRACT

Global food security is increasingly becoming dependent on judicious fertilizer use. However, inefficient use by farmers has hindered yield potential and caused environmental pollution. The principles of "4R Nutrient Stewardship" promote best fertilizer management practices for enhanced economic, social and environmental outcomes. Despite widespread promotion of various fertilizer management practices under the 4R- framework, the empirical evaluation of their effects on yield remains limited. This study therefore employed an Instrumental Variable regression model to evaluate the nuanced effects of fertilizer management practices on yield. Results of the IV regression revealed that adoption of manure plus inorganic fertilizer, split application, soil testing and precision fertilization positively influence maize yield. Furthermore, practices such as intercropping, soil moisture conservation, crop rotation, and agroforestry positively influence yield, whereas minimum tillage has a negative effect. Efforts should be directed towards supporting and expediting the adoption of fertilizer management practices under the 4R- Nutrient Stewardship to increase maize yields among smallholder farmers.

Keywords: Maize, Fertilizer Management Practices, 4Rs, IV regression, Effects

INTRODUCTION

Food insecurity remains a pressing global issue, disproportionately affecting Africa (FAO *et al.*, 2023). In Kenya, it was projected that 4.4 million individuals are at a risk of facing acute food insecurity (IPC, 2022). In a world faced by pervasive hunger and malnutrition, global production of the world`s major grains like maize must double by 2050 in order to feed the growing population (Tian *et al.*, 2021). Maize (Zea mays L.), is a valuable cereal crops in Sub-Saharan Africa contributing significantly to dietary needs and supporting millions of smallholder farmers (FAO, 2021). Despite its indispensable role, maize productivity has not increased in a proportionate manner and significant gaps in yields are still evident.

Fertilizers play an important role in maize production and have been acknowledged for their potential in boosting yields by a substantial margin of between 40 to 60 percent (FAO, 2015). Nevertheless, escalating fertilizer prices have led to suboptimal utilization (Obour *et al.*, 2015). Excessive application, on the other hand, raises environmental concerns (Sapkota *et al.*, 2014). Additionally, farmers lack knowledge on fertilizer use and often apply excess or insufficient fertilizers (Aryal *et al.*, 2018 ; Kishore *et al.*, 2021). Recognizing the above limitations in fertilizer use, the Four Rights (4Rs) (*right rate, right source, right time, right place*) of fertilizer application were formulated through cross-sector collaborative efforts by the International Fertilizer Industry Association (IFA) and the International Plant Nutrition Institute (IPNI) as guidelines for optimal management of fertilizers worldwide (IPNI, 2014). Best fertilizer management practices under this study including soil testing, split application, combining manure with inorganic fertilizers, precision fertilization, and concurrent application of fertilizers and seeds during wet planting are inherently embedded within the 4R Nutrient Stewardship framework. They have been promoted for adoption in different regions. However, empirical evidence showing effects of adoption on maize yield among small-scale maize farmers remains sparse. This study therefore sought to assess effects of fertilizer management practices under the 4Rs on maize yield. Addressing this gap is important to get detailed insights into the best fertilizer types, applications rates, timings, and placement methods for maximum maize yield.

METHODOLOGY

Study area, data sources and sampling procedure

This study was conducted in Embu County, in upper Eastern Kenya. Embu is one of the strategic areas of African Plant Nutrition Institute owing to the strong interaction between water and nitrogen as key factors influencing yield in dryland maize-based crop systems. A household survey was conducted, and data was collected using structured questionnaires anchored on an android aided platform (Survey to go). A multistage stratified sampling technique was employed in selecting sample sub-locations and households. The study excluded higher wet zones, and dry lower zones where maize is not majorly grown. The agro-ecological zones were stratified into three transects (1, 2, and 3) encompassing the sub-locations.

There are about 5200 farmers within these transects (list provided by the Sub- County agriculture officers). This created a definite sampling frame and therefore the study adopted the Taro Yamane (1967) formula below. n=$\frac{N}{1+Ne^2}$ where: n = sample size, N = total population, and e = margin of error. The sample size was computed with a confidence level of 95%. n= $\frac{5200}{1+5200*(0.05)^2}$ = 371 maize farmers. Data cleaning was done thereafter to identify and remove duplicates and address outliers arriving at a final data set of 365 farmers.

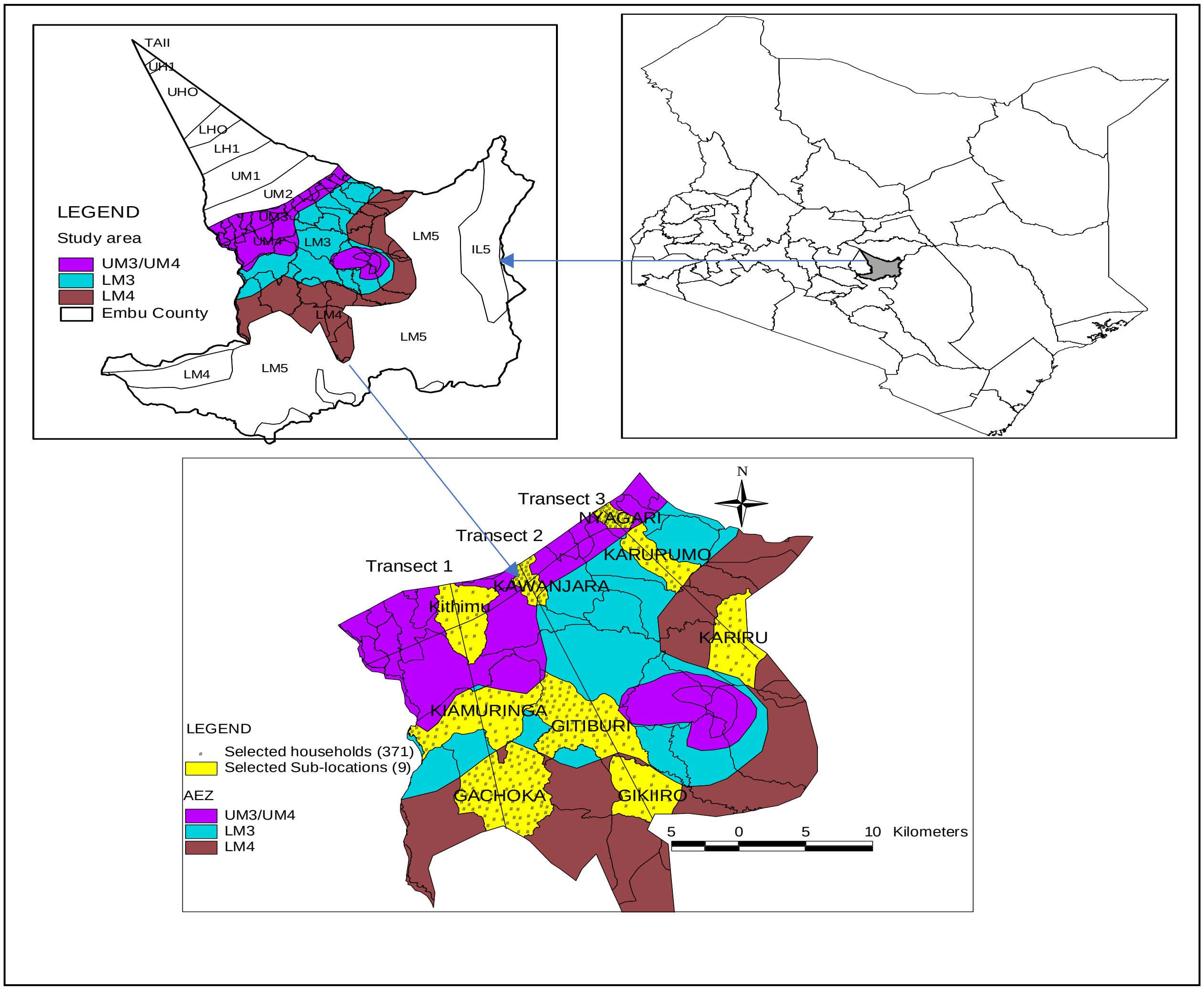


Figure 1. Map showing the study area. Source: Author`s compilation

RESULTS AND DISCUSSION

Effects of adopting fertilizer management practices on maize yield- IV regression

Results of the Instrumental Variable (IV) regression are presented in table 1 revealing the effects of four fertilizer management practices on maize yield. Adoption of manure plus inorganic fertilizer was found to increase maize yield by 306 kilograms/acre. This result highlights the importance of an integrated nutrient management approach, where organic nutrient sources such as manure are combined with inorganic fertilizers. It was further revealed that, compared to non-adopters, farmers adopting precision fertilization experienced significant increases in maize yield, of 294 kilograms per acre. Precision fertilization through side banding application involves placing fertilizer near the root zones ensuring efficient nutrient utilization. Adoption of this practice enhances efficient and targeted nutrient application, ensuring site-specific nutrient supply to maize. The IV regression analysis further revealed that adoption of soil testing had a positive and significant effect on maize yield, increasing yield by 1037 kilograms/ acre. Farmers leveraging soil testing can align their fertilizer applications precisely to meet specific soil deficiencies and requirements.

Table 1. Results of IV regression on effects of fertilizer management practices on yield

Variable	Manure + fertilizer	Precision fertilization	Soil testing	Split application
	Coefficient (Std error)			
Land tenure individual	-6.4029 (63.5392)	-43.3200 (60.4266)	-45.1778 (57.9350)	-42.9425 (60.7676)
Experience	-2.418957 (2.9040)	-2.9043 (2.8824)	-2.4473 (2.7452)	-2.9685 (2.9029)
Intercropping	600.2347 (92.3679) ***	612.856 (91.1396***	532.7773 (105.9075) ***	583.8539 (94.3519) ***
Minimum tillage	-222.1926 (82.6809) ***	-204.9583 (80.7194) **	-68.8440 (108.8409)	-214.660 9 (82.3724) ***
Monoculture	470.1703 (101.7040) ***	502.0999 (97.6594***	453.0867 (105.8808) ***	461.2402 (105.4477) ***
Moisture conservation	-85.85303 (72.4340)	-96.97673 (71.4337)	153.1873 (77.2872) **	-100.9195 (71.8379)
Conventional farming	-81.17338 (81.0702)	-57.7537 (79.0499)	46.8493 (100.5287)	-64.7622 (79.8595)
Crop rotation	691.5752 (83.3769) ***	677.5726 (87.9084) ***	641.7493 (102.1253) ***	670.0214 (90.6610) ***
Agroforestry	439.9163 (69.1065) ***	439.9945 (68.3584) ***	417.3008 (67.9312) ***	443.0685 (68.7047) ***
Farm demonstrations	Instrument **	Instrument 1**	Instrument 1**	Instrument 1**
Soil fertility training	17.0645(78.3552)	Instrument 2**	Instrument 2**	Instrument 2**
Farm experimentation	-4.4157(56.5874)	-8.5776(56.7589)	-31.5137 (60.4823)	-23.43488(59.6578)
Effect on maize yield	305.564 (168.339) *	294.2713 (177.0331) *	1037.811 (706.9282) **	295.1308 (179.2012) *
No. of observations	365	365	365	365
Wald χ2	χ2 (18) 161.33	χ2 (18) = 162.67	χ2 (18) = 171.73	χ2 (18) = 171.73
Prob > χ2	0.0000	0.0000	0.0000	0.0000
R-squared	0.2919	0.31	0.36	0.29

The practice of split application demonstrated a positive effect on maize yield, increasing yields by 295 kilograms per acre. Nutrient distribution at different growth stages maximizes nutrient availability when plants require them most, leading to vigorous growth and increased yield. This study further revealed that, practices such as intercropping, soil moisture conservation, crop rotation, and agroforestry positively influenced yield, whereas minimum tillage had a negative effect.

CONCLUSION AND RECOMMENDATIONS

This study assessed effects of adoption of fertilizer management practices on maize yield. The study used the Instrumental Variable regression model to assess effects of adoption. Average maize yield stood at 1552.05 kg/ha, which is significantly lower than the global average and potential yield. Adoption of practices like manure plus inorganic fertilizer, split application, precision fertilization (side banding) and soil testing positively influence maize yield. Other practices including intercropping, soil moisture conservation, crop rotation, and agroforestry also positively influence yield, while minimum tillage was associated with reduced yields. The findings from this research collectively highlight the important role of different fertilizer management practice under the 4R-Nutrient Stewardship in addressing the existing yield gaps and enhancing maize productivity in Embu County, addressing food insecurity concerns. Efforts should be directed towards supporting and expediating the adoption fertilizer management practices to increase maize yields among smallholder farmers in different regions.

REFERENCES

Aryal, J. P., Rahut, D. B., Maharjan, S., & Erenstein, O. (2018). Factors affecting the adoption of multiple climate-smart agricultural practices in the Indo-Gangetic Plains of India: Jeetendra Prakash Aryal, Dil Bahadur Rahut, Sofina Maharjan and Olaf Erenstein / Natural Resources Forum. Natural Resources Forum, 42(3), 141–158. https://doi.org/10.1111/1477-8947.12152

FAO. (2015). FAO statistical pocketbook 2015: World food and agriculture. Food and Agriculture Organization of the United Nations. http://www.fao.org/3/a-i4691e.pdf

FAO. (2021). FAOSTAT. Food and Agriculture Organization of the United Nations, Rome, Italy. https://www.fao.org/faostat/

FAO, IFAD, UNICEF, WFP, & WHO. (2023). STATE OF FOOD SECURITY AND NUTRITION IN THE WORLD 2023: Urbanization, agrifood system transformation. FOOD & AGRICULTURE ORG. https://doi.org/10.4060/cc3017en

IPC. (2022). KENYA : IPC Food Security & Nutrition Snapshot. https://www.ipcinfo.org/ipc-country-analysis/details-map/en/c/1155689/

IPNI. (2014, November 24). 4R Extension Handbook for Smallholder Farming Systems in Sub-Saharan Africa. http://ssa.ipni.net/article/AFR-3075

Kishore, A., Alvi, M., & Krupnik, T. J. (2021). Development of balanced nutrient management innovations in South Asia: Perspectives from Bangladesh, India, Nepal, and Sri Lanka. Global Food Security, 28, 100464. https://doi.org/10.1016/j.gfs.2020.100464

Obour, P. B., Dadzie, F. A., Kristensen, H. L., Rubæk, G. H., Kjeldsen, C., & Saba, C. K. S. (2015). Assessment of farmers' knowledge on fertilizer usage for peri-urban vegetable production in the Sunyani Municipality, Ghana. Resources, Conservation and Recycling, 103, 77–84. https://doi.org/10.1016/j.resconrec.2015.07.018

Sapkota, T. B., Majumdar, K., Jat, M. L., Kumar, A., Bishnoi, D. K., McDonald, A. J., & Pampolino, M. (2014). Precision nutrient management in conservation agriculture based wheat production of Northwest India: Profitability, nutrient use efficiency and environmental footprint. Field Crops Research, 155, 233–244. https://doi.org/10.1016/j.fcr.2013.09.001

Tian, Z., Wang, J., Li, J., & Han, B. (2021). Designing future crops: Challenges and strategies for sustainable agriculture. The Plant Journal, 105(5), 1165–1178. https://doi.org/10.1111/tpj.15107

GRAIN YIELD AND NITROGEN UPTAKE OF MAIZE AS AFFECTED BY SOIL MANAGEMENT PRACTICES AND THEIR INTERACTION ON CAMBISOLS AND CHERNOZEM

#11250

[1]Ashenafi Nigussie
[1]Department of Soil and Water Management, Wondo Genet Agriculture Research Center, Shashemene, Ethiopia.
*e-mail: nashenafinew@gmail.com; +251 09063256

ABSTRACT

Although numerous factors contribute to wide yield gaps, low external inputs, particularly N, and poor cropping practices such as soil tillage and monocropping are among the major factors affecting low maize production. In view of this, field experiments were implemented on two sites with Cambisols and Chernozem soil types in two consecutive years to evaluate the impacts of different soil management practices on the grain yield and quality, nitrogen uptake and selected soil properties. A three-factor experiment was arranged as a split-split plot arrangement randomized complete block design with three replications. The minimum tillage (MT) and conventional tillage (CT) were used as the main plot, haricot bean-maize rotation, and maize monocropping as a subplot, and four levels of nitrogen fertilization (Control, 20 t ha^{-1} compost, 46 kg N ha^{-1} + 10 t ha^{-1} compost, and 92 kg N ha^{-1}) as the sub-sub plot. Analysis of variance showed that soil management practices were significantly affecting grain yield, N-uptake and soil properties. In sites, the conventional tillage and rotation system increased the grain yield, and N-uptake in contrast to the minimum and monocropping, respectively. Similarly, nitrogen evidently affected the grain yield, N- uptake, and selected soil properties. However, tillage methods differed in their effects on soil chemical properties; soil organic carbon and total nitrogen concentrations were improved through MT compared to CT. Grain yield was significantly associated with NDVI, grain N-content and N-uptake. Therefore, a CT plus haricot bean-maize rotation system with the addition of solely 92 kg N ha^{-1} and integrated 46 kg N ha^{-1} + 10 t compost ha^{-1} could be recommended for Hawassa Zuria (Cambisols) and Meskan (Chernozem) districts, respectively. However, to ensure sustainable maize production in the investigated areas, an integrated N-treatment with MT and a rotation system may be recommended, which could improve soil properties.

Keywords: maize, tillage, cropping systems, fertilization, grain yield and quality, nitrogen uptake

INTRODUCTION

Maize or corn (*Zea mays* L.) is one of the world's leading cereals, ranking second in production after wheat (FAO, 2019). Ethiopia is the seventh maize-producing country in Africa. It is the second in area coverage next to tef (*Eragrostis tef* (Zucc.), with total land area of 10,478,217 ha being under cereals, of which maize covered about 17.68% (2,274,305.93 ha) (CSA, 2019). Despite the large area under maize production, its current national average yield is about 4.2 t ha^{-1} (CSA, 2019), which is far below the world's average yield of 5.8 t ha^{-1} (FAO, 2019). Although numerous factors contribute to wide yield gaps, low external inputs, particularly N, poor soil fertility, reduced water-holding capacity of the soil, and poor soil infiltration problems are among the major factors paid for low maize productivity (Chimdi et al., 2012; Mourice et al., 2015; Teklewold et al., 2013). Moreover, frequent tillage, monocropping, and complete removal of crop residues are also the governing factors for low productivity (Kassie et al., 2013). However, there is scarce information about the effects of tillage, cropping systems, nitrogen fertilization and their interaction on the yield, nitrogen uptake of maize, as well as soil chemical properties. Therefore, the present study was instigated to evaluate the effects of different soil management practices on the maize grain yield and quality, nitrogen uptake and selected soil chemical properties in the central Rift valley of Ethiopia, under two soil types - Cambisols and Chernozem.

MATERIALS AND METHODS

The field experiments were conducted for two consecutive years (2019 and 2020) in Hawassa Zuria and Meskan districts of the Central rift valley of Ethiopia. The Hawassa Zuria site is geographically situated at 07° 1' 0.83" N Latitude and 38° 22' 26" E Longitude with an altitude of 1713 m above sea level (asl). The experimental site at Meskan is found at 08° 05' 33" N Latitude and 38° 26' 75" E Longitude with an altitude of 1841 m asl. The soil types for the field trial were Cambisols for Hawassa Zuria and Chernozem for Meskan, according to the WRB soil classification system (IUSS Working Group, 2015).

Two tillage methods (TM) were evaluated: conventional tillage (CT) and minimum tillage (MT). The two tillage practices were combined with two cropping systems (CS): haricot bean-maize rotation (RCS) and maize monocropping (MCS). In addition, four levels of nitrogen fertilization (NF) (0, 20 t compost ha^{-1}, 46 kg N ha^{-1} + 10 t compost ha^{-1}, and 92 kg N ha^{-1}) were combined with tillage practices and cropping systems. Treatments were arranged as Split-split plot arrangement randomized as a RCBD (randomized complete block design), with tillage methods as the main (whole) plots, cropping systems as sub-plots, and nitrogen fertilization treatments as sub-sub-plots, with three replicates: making 48 sub-sub-plots for each experimental site.

Yield and yield related data were collected from a net plot area of 4 m^2 (1.25 m x 3.2 m) by rejecting the border rows, from three replications. The harvested grain yield was adjusted to a 12.5% moisture level (Nelson et al., 1985) and it was converted into hectare bases. Twenty grams of grain samples were taken from each experimental unit. The grains were oven-dried to constant weight thereafter; and the samples were ground and passed through a 0.5 mm sieve. The nitrogen content in the grain was analyzed using the Kjeldahl procedure after wet digestion by H_2SO_4/H_2O_2 (Nelson and Sommers, 1982).

Before the analysis of variance (ANOVA), the normality of the data was checked using the Shapiro-Wilk normality test. Despite the two experimental sites were distinctly different in their soil fertility status, subsequently the statistically analysis was done independently for each location, using the SAS 9.3 software package (SAS Institute, 2014), considering the experimental treatment as a fixed factor and replication as a random factor. At a probability level of $P \leq 0.05$, differences between treatments means were separated using the protected Fisher’s least significant difference (LSD) (Steel and Torrie, 1980). The LSD differences for the main factors and interaction effects comparisons were calculated using the appropriate standard error terms.

RESULTS AND DISCUSSION

Effects of tillage methods, Cropping systems and nitrogen fertilization on NDVI, grain yield, grain N-content and uptake and grain protein content

Tillage had revealed a statistically significant ($P < 0.05$) effect on maize grain yield At Hawassa Zuria, but not Meskan site, despite the higher yield which was gained from the CT (3855.5 kg ha^{-1}) and (7094.9 kg ha^{-1}) for Hawassa Zuria and Meskan, respectively (Table 1). In this study, grain yield increased by 5.2 and 0.1% in CT over MT at Hawassa Zuria, and Meskan. The positive result of CT on maize grain yield was possibly due to improved soil physical conditions, root growth, infiltration of water, nutrient mineralization and suppressing weed growth. Correspondingly, Simić et al. (2020); Salem et al. (2015); Wang et al. (2015) reported that CT in a short-term study increased corn grain yield compared to a minimum or zero tillage due to less soil compaction, which improved soil aeration and organic matter mineralization. In both locations, the N-content and N-uptake parameters responded positively to CT, possibly due to the stimulation of N-mineralization from organic matter and thereby improved soil mineral N-availability for crop uptake. Similarly, Simić et al. (2020) verified the benefit of conventional tillage for better maize grain yield and enhancement in grain protein content.

At Hawassa Zuria, the cropping system had a significant (P < 0.05) effect on grain yield, grain nitrogen content, nitrogen uptake, and protein content. However, at Meskan, while grain yield was affected, the other parameters did not show statistically significant differences (Table 1). The haricot bean-maize rotation system increased maize grain yield, N-content, N-uptake and protein content by 1.1, 2.7, 17.8, 21.1 and 17.9% in Hawassa Zuria and 1.3, 0.25, 10, 12.1 and 13.7% in Meskan, respectively, compared to maize monocropping (Table 1). This was possibly due to the change in inorganic N-availability in the soil solution caused by previous atmospheric N_2 fixation and legume residue decomposition since legume residues had better quality and a narrow C:N ratio, which results in rapid release of N from the residues (Adesoji et al., 2015; Lupwayi et al., 2011; Tolera et al., 2009). Our result is in covenant with Lafond et al. (2006) who stated that legumes offer a positive contribution to soil TN and thus improved its availability.

Analysis of variance depicted that the grain yield differed significantly ($P < 0.001$) among N-treatments in both sites. The highest grain yields of 1180.5 kg ha^{-1} and 8169.1 kg ha^{-1} were obtained from the application of 92 kg N ha^{-1} and 46 kg N ha^{-1} + 10 t ha^{-1} compost at Hawassa Zuria and Meskan sites, respectively. Similarly, Kaplan et al. (2019) proved that the grain yield increased with increasing the N level. Like grain yield, N-fertilization had revealed significant effects on GNC, GNU, and GPC (Table 1). In both locations, the integrated use of inorganic nitrogen and compost at a rate of 46 kg N ha^{-1} + 10 t ha^{-1} remarkably increased GNC, GNU and GPC by 35.1, 61.6 and 35.3% at Hawassa Zuria and 23.2, 68.2 and 21.6% at Meskan, respectively, when compared to the unfertilized treatment. Our result is in covenant with findings of Dunjana et al. (2012); Negassa et al. (2005); Rusinamhodzi et al. (2013), who stated that integrated application of organic and mineral fertilizers at appropriate rates can be an effective approach to improve maize N uptake.

Table 1. The effects of tillage methods, cropping systems, and N-fertilization on NDVI, grain yield, N-content, N-uptake and grain protein content of maize at the two sites

Investigated factors	Hawassa Zuria				Meskan			
	GY kg ha^{-1}	GNC g kg^{-1}	GNU kg ha^{-1}	GPC %	GY kg ha^{-1}	GNC g kg^{-1}	GNU kg ha^{-1}	GPC %
Tillage methods								
MT	3662.6^{b}	9.6	35.6^{b}	6.0	7061.0	12.1	89.0	7.8
CT	3855.5^{a}	9.9	39.1^{a}	6.2	7091.9	12.5	89.7	7.8
LSD (0.05)	112.6	ns	1.89	ns	ns	ns	ns	ns
Cropping systems								
RCS	3835.1^{a}	10.6^{a}	10.9^{a}	6.6^{a}	7101.0	13.2^{a}	91.5^{a}	8.3^{a}
MCS	3683.5^{b}	9.0^{b}	33.7^{b}	5.6^{b}	7083.2	12^{b}	81.3^{b}	7.3^{b}
LSD (0.05)	128.8	0.1	3.8	0.21	ns	0.03	5.6	0.2
Nitrogen fertilization								
Control	3273.3^{d}	8.2^{d}	26.8^{c}	5.1^{d}	5987.9^{d}	11.2^{d}	66.9^{d}	6.9^{d}
20 t ha^{-1} Compost	3628.2^{c}	9.1^{c}	31.2^{b}	5.9^{c}	6169.2^{c}	11.8^{c}	75.8^{c}	7.1^{c}
46 kg N ha^{-1} +10 t ha^{-1} Compost	3951.1^{b}	11.1^{a}	11.1^{a}	6.9^{a}	8169.1^{a}	13.8^{a}	112.5^{a}	8.6^{a}
92 kg N ha^{-1}	1180.5^{a}	10.5^{b}	11.1^{a}	6.6^{b}	7711.8^{b}	13^{b}	102.1^{b}	8.3^{b}
LSD (0.05)	113.7	0.6	2.62	0.35	310.1	0.01	1.2	0.25

Values of a parameter means followed by the same letter did not differ significantly across the tillage methods, cropping systems and N-fertilization at $P \leq 0.05$ according to LSD test.

Effects of tillage, cropping systems and nitrogen fertilization on soil organic carbon and total nitrogen

There were no significant changes in organic carbon concentrations across tillage methods and cropping systems in either location (Table 2). This could be because the samples were gathered two years after the field trial, which is a short time to oversee the effect of tillage on soil OC. A similar observation was reported by Geisseler and Horwath (2009). Conversely, organic carbon content was significantly affected by N fertilization (Table 2). The addition of 20 t ha^{-1} compost provided the higher OC at Hawassa Zuria, which was statistically comparable with the integrated N-treatment. The increase in soil OC after the application of compost is due to the composting material and the rich microbial community, which contributes to the formation of soil organic carbon (Deepak et al., 2017; Dhillon et al., 2018; Lorenz and Lal., 2016).

Tillage practices had a significant effect on soil total N in both locations, with minimum tillage contributing more to total N than the conventional tillage (Table 2). This could be owing to enhanced N protection inside micro and macro aggregates, resulting in lower N losses due to leaching and organic matter decomposition (Wyngaard et al., 2012). Likewise, the cropping systems was significantly affected the soil total N at Meskan, but remarkable variation not observed at Hawassa Zuria. However, in both sites there was a tendency for better soil total N in the RCS compared to MCS (Table 2). The findings of this study agree with those of Kirkegaard et al. (2008) and Lupwayi et al. (2011). Total nitrogen content was significantly affected by nitrogen fertilization (Table 2). The integrated N treatment had the highest TN (0.26% and 0.39% for Hawassa Zuria and Meskan, respectively), indicating that more N was released through mineralization of the compost added to the soil and due to the existence of high levels of respective total N in the compost. Our findings are in line with those of Ashenafi et al. (2021) and Yan et al.

(2007), who found that inorganic nitrogen influences most soil biological processes by promoting microbial carbon use, which is critical for mineralization and nutrient transformation activities.

Table 2. Main effects of tillage, cropping systems and nitrogen fertilization on soil reaction, organic carbon and total nitrogen contents of the surface layer of soils (0-20 cm)

Treatments	Hawassa Zuria (Cambisols)				Meskan (Chernozem)			
	pH	**OC (%)**	TN (%)	**C: N**	**pH**	**OC (%)**	TN (%)	**C: N**
Tillage methods								
MT	6.1^{b}	2.61	0.25^{a}	10.52^{b}	6.8	1.00	0.36^{a}	11.31^{b}
CT	6.2^{a}	2.59	0.23^{b}	11.18^{a}	6.8	3.98	0.33^{b}	12.11^{a}
LSD (0.05)	0.06	ns	0.01	0.33	ns	ns	0.02	0.83
Cropping systems								
RCS	6.1	2.61	0.25	10.72	6.8	3.99	0.35^{a}	11.18^{b}
MCS	6.2	2.60	0.21	10.97	6.8	3.99	0.31^{b}	11.97^{a}
LSD (0.05)	ns	ns	ns	ns	ns	ns	0.01	0.37
Nitrogen fertilization								
Control	6.0^{b}	2.51^{c}	0.21^{c}	11.81^{a}	6.6^{d}	3.83^{d}	0.32^{c}	11.91^{b}
20 t ha^{-1} Compost	6.3^{a}	2.68^{a}	0.21^{b}	10.73^{b}	7.0^{a}	1.11^{b}	0.32^{c}	13.02^{a}
16 kg N ha^{-1} +10 t ha^{-1} Compost	6.2^{a}	2.66^{a}	0.26^{a}	10.19^{c}	6.9^{b}	1.11^{a}	0.39^{a}	10.57^{d}
92 kg N ha^{1}	6.1^{b}	2.58^{b}	0.25^{ab}	10.63^{bc}	6.7^{c}	3.88^{c}	0.31^{b}	11.37^{c}
LSD (0.05)	0.1	0.01	0.01	0.17	0.08	0.03	0.01	0.53

Within the columns, means followed by the same letters are not significantly different at $P < 0.05$ according to LSD test.

CONCLUSION

Soil management practices play a crucial role in influencing grain yield, nitrogen content, nitrogen uptake, and grain protein content, as well as certain soil chemical properties. At both sites, the conventional tillage and crop rotation system resulted in higher grain yield, nitrogen content, uptake, and protein content compared to minimum tillage and monocropping systems. Additionally, nitrogen fertilization had a significant impact on grain yield, nitrogen content, and uptake, with the application of 92 kg N ha^{-1} and 46 kg N ha^{-1} + 10 t compost ha^{-1} showing superior results at the Hawassa Zuria and Meskan sites, respectively. Consequently, a conventional tillage combined with a haricot bean-maize rotation system, supplemented with either 92 kg N ha^{-1} alone or 46 kg N ha^{-1} + 10 t compost ha^{-1}, is recommended for the Hawassa Zuria (Cambisols) and Meskan (Chernozem) districts, respectively, to achieve optimal yield and nitrogen uptake. However, for sustainable maize production in these areas, it is advisable to adopt an integrated nitrogen treatment along with minimum tillage and legume-based crop rotation to enhance soil properties, ultimately improving yields and nitrogen uptake.

REFERENCES

Adesoji, A.G., Abubakar, I.U. and Labe, D.A. 2015. Influence of incorporated legumes and nitrogen fertilization on maize (Zea mays L.) nutrient uptake in a Semi-Arid environment. Journal of Agriculture and Veterinary Science 8(3): 01-08.

Ashenafi, N., H. Wassie, A. Getachehu, and K. Alemayehu. 2021. Growth, Nitrogen Uptake of Maize (Zea mays L.) and Soil Chemical Properties, and Responses to Compost and

Nitrogen Rates and Their Mixture on Different Textured Soils: Pot Experiment. Applied and Environmental Soil Science. Pp. 12 https://doi.org/10.1155/2021/9931763

Benton, J.J. 2003. Agronomic handbook: Management of crops, soils, and their fertility. CRC Press LLC, 2000 N.W. Corporate Blvd., Boca Raton, Florida.

Chimdi, A., Gebrekidan, H., Kibret, K., Tadesse, A. 2012. Status of selected physio-chemical properties of soil under different land use system of Western Oromia, Ethiopia. Journal of Biological and Environmental Sciences 2(3):57-71.

CSA (Central Statistics Agency). 2019. Agricultural Sample Survey 2018/2019. Volume I. Report on Area and Production of Major Crops (Private Peasant Holdings, Meher Season). Statistical Bulletin 586. Addis Ababa.

Deepak, K.G., M.B. Roshan and K.S. Bishal. 2017. Effects of Biochar and Farmyard Manure on Soil Properties and Crop Growth in an Agroforestry System in the Himalaya. Sustainable Agriculture Research Journal 6: 1.

Dhillon, J., M. R. Del Corso, B. Figueiredo, E. Nambi, and W. Rau. 2018. Soil organic carbon, total nitrogen, and soil pH in a long-term continuous winter wheat (Triticum Aestivum L.) experiment. Communications in Soil Science and Plant Analysis. 19:803–13.

Dunjana, N.; Nyamugafata, P.; Shumba, A.; Nyamangara, J.; Zingore, S. 2012. Effects of cattle manure on selected soil physical properties of smallholder farms on two soils of Murewa, Zimbabwe. Soil Use Manag. 28: 221–228.

FAO (Food and Agricultural Organization) 2019. FAOSTAT statistical database and data sets of the Food and Agriculture Organization of the United Nations. Available at: http://www.faostat.fao.org.

Geisseler, D., W.R. Horwath. 2009. Short-term dynamics of soil carbon, microbial biomass, and soil enzyme activities as compared to longer-term effects of tillage in irrigated row crops. Biol. Fertil. Soils 16:65-72.

Hazelton P and Murphy B. 2007. Interpreting soil test results: What do all numbers mean? CSIRO publishing: Melbourne.

Kaplan, M., Karaman, K., Kardes, Y.M., Kale, H. 2019. Phytic acid content and starch properties of maize (Zea mays L.): Effects of irrigation process and nitrogen fertilizer. Food Chem. 283: 375–380.

Kassie, B.T., Hengsdijk, H., Rötter, R.P., Kahiluto, H., Asseng, S., and Ittersum, M.K.V. 2013. Adapting to climate variability and change: Experiences from cereal-based farming in the Central Rift and Kobo valleys, Ethiopia. Environ. Manag. 52:1115–1131.

Kirkegaard, J.A., O. Christen, J. Krupinsky, D. B. Layzell. 2008. Break crop benefits in temperate wheat production. Field Crops Research 107, 185–195. doi:10.1016/j.fcr.2008.02.010.

Lafond, G.P., May, W.E., Stevenson, F.C., Derksen, D.A. 2006. Effects of Tillage Systems and Rotations on Crop Production for a Thin Black Chernozem in the Canadian Prairies. Soil Tillage Res. 89: 232–215.

Lorenz, K. and R. Lal. 2016. Environmental Impact of Organic Agriculture. Adv. Agron. 139: 99-152.

Lupwayi, N. Z., A. C. Kennedy, and R. M. Chirwa. 2011. Grain legume impacts on soil biological processes in sub-Saharan Africa. Afr. J. Plant Sci. 5(1): 1-7.

Mourice, S.K., Tumbo, S.D., Nyambilila, A., Rweyemamu, C.L. 2015. Modeling potential rain-fed maize productivity and yield gaps in the Wami River subbasin, Tanzania. Acta Agriculturae Scandinavica, Section B: Soil and Plant Science, 65(2):132-110.

Negassa, W., Gebrekidan, H., Friesen, D.K. 2005. Integrated use of farmyard manure and NP fertilizers for maize on farmers' fields. J. Agric. Rural Dev. Trop. Subtrop. 106: 131–111.

Nelson, D.W. and Sommers, L.E. 1982. Total carbon, organic carbon, and organic matter. In: A. L. Page, R. H. Miller & D. R. Keeney, (eds.). Methods of Soil Analysis, Part 2 Chemical and microbiological properties. Agronomy monograph 9, Am. Society of Agronomy and Soil Science Society of America, Madison, Wisconsin, USA, pp. 539-591.

Nelson, L.A., Voss, R.D. and Pesek, J. 1985. Agronomic and statistical evaluation of fertilizer response. Pp. 89.

Rusinamhodzi, L., Corbeels, M., Zingore, S., Nyamangara, J., Giller, K.E. 2013. Pushing the envelope? Maize production intensification and the role of cattle manure in the recovery of degraded soils in smallholder farming areas of Zimbabwe. Field Crop. Res. 117: 10–53.

Salem, H.M., Valero, C., Muñoz, M.A., Rodríguez, M.G. and Silva, L.L. 2015. Short-term effects of four tillage practices on soil physical properties, soil water potential, and maize yield. Geoderma 237-238: 60-70.

SAS (Statistical Analysis System) 2001. SAS/STAT Software Syntax, Version 9.0. SAS Institute, Cary, NC. USA. 751pp.

Simić M, Dragičević V, Mladenović Drinić S, Vukadinović J, Kresović B, Tabaković M, Brankov M. 2020. The Contribution of Soil Tillage and Nitrogen Rate to the Quality of Maize Grain. Agronomy. 10(7):976. https://doi.org/10.3390/agronomy10070976.

Steel, R.G.D. and Torrie, J.H. 1980. Principles and Procedures of Statistics: a Biometrical Approach. 2nd Edition. McGraw-Hill. New York. Pp. 631.

Teklewold, H., Kassie, M., Shiferaw, B. 2013. Adoption of multiple sustainable agricultural practices in rural Ethiopia. J. Agric. Econ. 61: 597–623.

Tolera, A., Daba, F. and Friesen, D.K. 2009. Effects of Crop rotation and N-P Fertilizer Rate on Grain Yield and related characteristics of Maize and Soil Fertility at Bako Western Oromia, Ethiopia. East African Journal of Science 3: 70-79.

Wang, X., Zhou, B., Sun, X., Yue, Y., Ma, W., Zhao, M. 2015. Soil Tillage Management Affects Maize Grain Yield by Regulating Spatial Distribution Coordination of Roots, Soil Moisture and Nitrogen Status. Plops ONE 10 e0129231.

Wyngaard, N., H. Echeverrıa, H. R. Sainz Rozas, and G. A. Divito. 2012. Fertilization and tillage effects on soil properties and maize yield in a Southern Pampas Argiudoll. Soil and Tillage Research. 119: 22–30.

Yan D, Wang D and Yang L, 2007. Long-term effect of chemical fertilizer, straw, and manure on labile organic matter fractions in paddy soil. Biol. Fertil. Soils, 11(1):93-101.

POLICY IMPLICATIONS OF THE ADOPTION OF PRECISION AGRICULTURE IN NIGERIA

[1*]Oyedepo, Elizabeth Omolola, [2]Oyedepo, John Adebayo
[1]Augustine University, Ilara-Epe; [2]Federal University of Agriculture, Abeokuta, Nigeria
e-mail: lolaoyedepo1@gmail.com; +2348038648941

ABSTRACT

This paper examines the policy implications of adopting Precision Agriculture (PA) in Nigeria, emphasizing infrastructure, capacity-building, data regulation, and financial support. It highlights the transformative potential of PA and recommends policy frameworks to facilitate its sustainable integration into the agricultural sector. In Nigeria, where agriculture faces challenges including outdated practices, inadequate infrastructure, and climate vulnerabilities, PA offers a promising solution. Southwest States with soil health and irrigation technologies, lead adoption while regions like Sokoto in the Northwest leverage smart irrigation through donor-supported projects. Despite these advancements, significant barriers such as limited internet penetration, high costs, and low digital literacy hinder widespread uptake. Policy reforms are crucial, focusing on infrastructure development, financial incentives, specialized training, and data governance. Socioeconomic benefits of PA include improved yields, reduced waste, and environmental conservation, but equitable access for smallholder farmers is essential to ensure inclusive growth. Recommendations include public-private partnerships for infrastructure, pilot programs in agricultural belts, and capacity-building collaborations with international organizations. This will help Nigeria to transit towards sustainable agriculture.

Keywords: Precision Agriculture, Policy, Nigeria, Sustainable Development, Agricultural Technology

INTRODUCTION

Precision agriculture (PA) represents a paradigm shift in modern farming, leveraging technology for improved productivity, efficient resource use, and sustainability [1]. In Nigeria, agricultural productivity has remained suboptimal due to outdated farming practices, inadequate infrastructure, and climate vulnerabilities [2]. The adoption of PA could without doubt, revolutionize Nigerian agriculture, this is because precision agriculture integrates advanced technologies such as GPS, IoT, and data analytics to enhance farming efficiency and environmental sustainability [3].

However, these technologies are inadequate in Nigeria; and to successfully adopt PA in Nigeria will therefore require that robust policy frameworks addressing infrastructural deficits, financial support, and human capital development be put in place [4, 5]. Nigeria, is a country still grappling with food insecurity, land degradation, and climate change impacts and economic downturn. Adoption of PA therefore presents an opportunity as well a challenge.

Currently, data on the precise number of farmers using precision agriculture in Nigeria has not been systematically aggregated across the country. However, there are indications of growing adoption in specific locations and contexts.

While these examples highlight advancements, barriers such as limited internet penetration, high technology costs, and low digital literacy remain significant challenges. Some locations might be seeing progress due to private initiatives in solar-powered irrigation and market access platforms. This paper is therefore an attempt to do a political economic analysis of the adoption of Precision Agriculture in Nigeria. There is equally the need to do an x-ray of policy challenges and needs of transition from traditional agriculture to hi-tech agriculture like PA.

Digital agriculture tools such as AI-powered crop monitoring, mobile apps, and precision farming methods are gaining traction but remain concentrated in areas with better connectivity and infrastructure [6]. Statistics on farmers using high-tech agricultural practices in Nigeria vary by state and depend on factors like technology availability, education, and crop focus. In Northern Nigeria, High-tech adoption is driven by large-scale farmers' programs like the Anchor Borrowers. In South-West Nigeria, there is moderate adoption of precision agriculture, with emphasis on soil testing kits, mobile apps, and IoT tools for smart irrigation, largely facilitated by research collaborations and local government interventions. In the South-East farmers are notable for engaging in digital agriculture practices. The South-South region however, exhibit varied adoption rates. Niger and Benue States demonstrate efforts in deploying agricultural drones and mobile platforms for cassava farming, reflecting state-supported projects aimed at boosting crop yields [7]. Despite these efforts, challenges like inadequate infrastructure, cost barriers, and lack of technical training hinder broader adoption across most states.

Policy Challenges and Needs

- **Infrastructure Development**: A major bottleneck is the lack of basic infrastructure such as reliable power, high-speed internet, and rural connectivity. Policies must prioritize infrastructure investments that support PA technologies.
- **Education and Training**: A skilled workforce is critical for PA adoption. Government and private sector collaboration is needed to develop specialized training programs and integrate PA concepts into agricultural curricula.
- **Financial Support**: Many smallholder farmers lack the financial capacity to invest in PA technologies. Policies should introduce subsidies, grants, and low-interest loans to make these technologies accessible.
- **Regulatory Framework for Data Governance**: PA relies heavily on data collection and analysis. A regulatory framework is needed to address data ownership, privacy, and sharing protocols, ensuring farmer protection and fostering innovation.

Socioeconomic Impacts

Adopting PA in Nigeria could increase crop yields, reduce waste, and optimize input use, addressing food insecurity while conserving environmental resources. However, the transition must consider the digital divide and ensure equitable access for smallholder farmers, who constitute the bulk of Nigeria's agricultural workforce.

MATERIALS AND METHODS

Thirteen states within Nigeria were selected based on the higher level of food crop production taking place in these regions compared to other areas in Nigeria and due to the relative proximity of the ADPs (Agricultural Development Programmes) in the states which helped give direct access to the farmers who were the main target group of the research. Primary data collected with electronic means (smart phones with installed ODK apps) were mainly on level of adoption of climate smart agriculture, barriers mitigating the adoption of precision agriculture and level of internet connectivity in farming areas. Three local government areas (LGAs) with the highest record of climate-induced stress were purposively selected in each state based on the advice of state Agricultural Development Programme ADPs). In each selected LGA, four (4) villages were randomly selected and thirty (30) farming households were selected per village. With twelve villages per state and thirty farm households per village. A total of three hundred and sixty farm households were selected per state and this makes up a total sample a sample size of 4,680 households (respondents) interviewed for the study. Descriptive statistics such as frequencies, means and percentages were used to analyse the data and the results are presented below.

RESULTS AND DISCUSSION

Table 1 shows the distribution of respondents according to their personal characteristics. The results revealed that majority of the farm household heads were male (67.43 %). This showed that men dominated farming activities in the study area. This result is also in line with [9] who implied that men dominated farming activities in Nigeria. In terms of age, majority of the respondents (about 80%) are young, falling between ages 18 and 59 years. About 21% of the respondents are within the age group of 60 years and above. This result show that majority of the farmers are able bodied young people within their economically active years of life. In terms of level of literacy, 17.5% of the respondents revealed that they had no form of formal education. However, 30.97% of the respondents had primary education, 28.13 % had secondary education while only 17.43% had tertiary education. This result shows that majority of the respondents were literate with at least primary education. Literacy will enable farmers to easily adopt new techniques of solving problems of climate change impact on their farms.

Table 2 show distribution of respondents according to access to telecommunication services and type of climate change risks experienced in the study area. Results revealed that in terms of access to telecommunication services in the study area, more than half of the respondents had no regular access to telecommunication services and 17.78 % of the respondents had smart phones. Majority of the respondents had no regular access to telecommunication services.

Results on variability to climate change revealed that 64.8 % of the respondents reported they experienced increased temperature and 78.3% reported they experienced decreased rainfall duration and intensity. About 34.3% of the respondents reported a disappearance in vegetation cover due to the climate change experienced. The respondents noted they experienced prolonged dry spell after the early rains which led to increased temperature and loss of crops.

Table 1. Distribution of respondents according to socioeconomic characteristics.

Variables	Frequency	Percentages	Mean category
Sex			
Male	3,156	67.43	
Female	1,524	32.57	
Age (years)			
18 – 31	500	10.68	
32 – 45	1,798	38.41	32 -45
46 – 59	1,339	28.61	
60 – 73	864	18.47	
74 and above	179	3.82	
Level of Education			
No formal education	858	18.33	
Primary education	1,449	30.96	
Secondary education	1,557	33.27	
Tertiary education	815	17.43	
Household size			
0 – 4	809	17.29	
5 - 9	2,613	55.83	5 – 9
10 – 14	998	21.32	
15 & above	260	5. 56	
Years of farming experience			
1 – 10	1,021	21.81	
11 – 20	1,670	35.69	11 – 20
21 – 30	974	20.83	
31 – 40	624	13.34	
41 and above	390	8.33	

Source: Field Survey

Table 2. Distribution of respondents according to access to telecommunication services and type of climate change risks experienced in the study area.

Variables	Frequency	Percentages
Category of mobile phone used		
Ordinary phone	3,760	80.34
Smart phone	832	17.78
No phone	88	1.88
Access and availability of telecommunication services		
No	3,878	82.86
Yes	802	17.15
Variability in climate change experienced?		
Increased temperature	3,033	64.8
Decreased temperature	744	15.9
Increased rainfall duration and intensity	1,048	22.4
Decreased rainfall duration and intensity	3,664	78.3
Increased sunlight intensity	2,3112	49.4
Decreased sunlight intensity	491	10.5
Disappearance of vegetation cover	1,605	34.3
Increased changes in vegetation type	997	21.3

Source: Field Survey

Table 3 reveals the extent to which climate change risks is experienced in the study area. About 43.64% of the respondents reported they always experience inadequate rainfall while 47.57 reported an occasional dry spell. More than half of the farmers (55.14 %) reported they occasionally experienced frequent crop failure due to erratic rain distribution of rainfall. About 65% reported an occasional shortage of food for households. Majority of the respondents reported an always or occasional experience of climate change risks in the study area. Only few of the respondents indicated they have never experienced any of the climate change risks identified except in cases of death of livestock and extinction of fishes and aquatic life due to climate change.

Table 3. Extent to which climate change risks is experienced.

Variables	**Always (%)**	**Occasionally (%)**	**Never (%)**
Inadequate rainfall	43.54	47.57	8.89
Frequent crop failure due to erratic distribution and dwindling rainfall	37.01	55.14	7.85
Incessant flood	37.57	55.83	6.60
Frequent crop failure due to incessant flood	8.88	59.72	31.39
Shortage of food for households	17.78	65.0 0	17.22
Reduction of forest cover and degradation of natural resources	22.29	62.6	15.07
Extinction of fishes and aquatic life	11.39	54.79	33.82
Death of livestock	11.04	38.40	50.56
Cattle invasion on farm due to inadequate grasses	31.04	48.82	20.14

Source: Field Survey

Recommendations

- Develop public-private partnerships to fund rural broadband and power projects.
- Establish centers for PA research and demonstration across the country.
- Create incentive schemes for local startups to develop affordable PA solutions tailored to Nigeria’s agro-ecological zones.
- Implement pilot PA programs in key agricultural belts to assess scalability and economic impact.
- Encourage collaborations with international organizations for knowledge transfer and capacity-building initiatives.

CONCLUSION

The adoption of precision agriculture in Nigeria presents a pathway to achieving sustainable agricultural intensification, food security, and environmental conservation. Policymakers must create an enabling environment that bridges infrastructure gaps, fosters innovation, and ensures equitable access to PA technologies. The future of Nigerian agriculture depends on its ability to harness the transformative potential of precision farming.

REFERENCES

1. Somashekar, K. S., Belagalla, N., Srinatha, T. N., Abhishek, G. J., Kumar, V., & Tiwari, A. (2024). Revolutionizing Agriculture: Innovative Techniques, Applications, and Future Prospects in Precision Farming. Journal of Scientific Research and Reports, 30(8), 405-419.
2. Oladoyinbo, O. B. (2023). Comprehensive synthesis and integrative review of agricultural dynamics in southwest Nigeria: Assessing economic viability, technological advances, and rural development approaches. Technological Advances, and Rural Development Approaches (December 4, 2023).
3. Ani, O., Chukwuma, K., Okoro, G., & Oyiga, A. (2019). Applications of Mechatronics and Autonomous Systems in Smart Agriculture: Potentials and Challenges for Nigeria. no. November.
4. Abdullahi, H. S., & Sheriff, R. E. (2017). Case study to investigate the adoption of precision agriculture in Nigeria using simple analysis to determine variability on a maize plantation. Journal of Agricultural Economics and Rural Development, 3(3), 279-292.
5. John, D., Hussin, N., Shahibi, M. S., Ahmad, M., Hashim, H., & Ametefe, D. S. (2023). A systematic review on the factors governing precision agriculture adoption among small-scale farmers. Outlook on Agriculture, 52(4), 469-485.
6. Lawal, S. (2023). Digital agriculture: Transforming the landscape in Nigeria. Available online at: https://farmingfarmersfarms.com/2023/12/digital-agriculture-transforming-the-landscape-in-nigeria/
7. Nkwuagba, J. A., & Nkamnebe, A. D. (2024). Predictors of Agricultural Technology Adoption Among the Cassava Farmers in the North-Central Nigeria. International Journal of Small Business and Entrepreneurship Research, 12(2), 72-124
8. Nyaga, J.M., Onyango, C.M., Wetterlind, J. et al. Precision agriculture research in sub-Saharan Africa countries: a systematic map. Precision Agric **22**, 1217–1236 (2021). https://doi.org/10.1007/s11119-020-09780-w
9. Sadiq MS, Yakassai MT, Ahmad MM, Lakpene TY, Abubakar M. Profitability and production efficiency of small-scale maize production in Niger state, Nigeria. IOSR Journal of Applied Physics (IOSR-JAP). 2013;3(4):19-23.

ARTIFICIAL INTELLIGENCE (AI) IN AGRICULTURE

AN ENSEMBLE-BASED DEEP LEARNING APPROACH FOR EARLY AND ACCURATE WHEAT DISEASE DETECTION

#11635

[1]Tagel Aboneh, [1]Prof. Abebe Rorissa, [2]Prof. Ramasamy Srinivasagan
[1]Addis Ababa Science and Technology University
[2]Professor & Director, School of Information Sciences Associate Dean for Faculty Affairs
College of Communication and Information the University of Tennessee, Knoxville

ABSTRACT

Crop diseases are the primarily cause for yield loss and a factor for food security issue around the globe. Crop diseases caused by pathogens pose a significant threat to global food security, the challenge become worst particularly in developing countries like Ethiopia. Rapid population growth and accurate disease identification is crucial for timely intervention and minimizing crop losses. However, traditional methods often rely on expert analysis, which can be time-consuming and resource intensive. The state of the art in agriculture employed AI enable crop diseases early detection technologies to support the agriculture domain area. Currently machine learning based solutions plays significant role to detect and classify crop diseases as early as possible. In this study, we proposed ensemble-based deep learning approaches for crop diseases classification purpose. Ensemble Deep Learning is a cutting-edge technique in machine learning that combines the strengths of multiple deep learning models to achieve superior performance compared to any individual model. The proposed model leverages the strengths of pre-trained models such as ResNet50, EfficientNetB4, DenseNet, ViT-Base and VGG19. To train the base models, more 23,000 crop images are acquired from various sources. The trained models are combined using ensemble learning method adjustable weighted average techniques to create a robust and generalizable model.We done model performance assessment based on optimization, scalability, and mitigation of model drifting issues to enhance the overall generalizability. From experimental results, the proposed ensemble model demonstrated a promising performance with 99.48% for training data and 99.23% for validation accuracy respectively. This research signifies a crucial step towards developing a practical and reliable tool for early crop disease detection in resource-constrained environments.

INTRODUCTION

The rapid population growth, a constant decline in arable land size per capital, and dynamic environmental change are the main constraints in the agriculture process. On the other hand, fighting against plant diseases is crucial activity in the agriculture sector to maintain crop productivity. In this regards, researchers are attempting new methods and technology to support the identification of crop diseases(Jasim & Al-Tuwaijari, 2020). The research findings in the domain area reveal that the application of technology would enhance agriculture production quality. In this regard, classical farming approaches, resources optimization, dynamic weather condition, severity of different pathogens are the main cause for y(Habiba & Islam, 2021)ield variation in the case of Ethiopia. In this study, we proposed ensemble based deep learning approach to classify crop diseases into the respective categories. Based on different literature review reports, about 20 to 40\% yield loss because of crop diseases. This is a significant effect which demand appropriate action by stakeholder. On the other hand, climate change also a critical factor for crop production and a cause for food insecurity issue. Thus, the sector demands an AI enabled system at least to minimize its consequence on food security.

CONTRIBUTION

The proposed ensemble-based deep learning model holds significant potential to empower farmers and agricultural stakeholders with the ability to rapidly identify and address crop diseases, ultimately contributing to improved food security and agricultural sustainability. The proposed model are converted smart phone application to support smallholder farmers. An ensemble-based deep learning approaches are designed to develop generalizable models to improve the limitations of crop diseases early detection(Fuentes et al., 2017). The proposed model can be used for others crop disease detection and reference for wheat disease management work. Similarly, the proposed model can be used as decision support tool for different stakeholder in the domain area.

MATERIALS AND METHODS

In this research, an empirical research approach has been used to implement an ensemble deep learning framework to efficiently detect plant diseases(Reddy et al., 2021). In this work our main focus is to build generalizable(Ferreira et al., 2020) machine learning model for the purpose of crop diseases detection as early as possible. Figure 4.4 below illustrate the proposed system general system architecture.

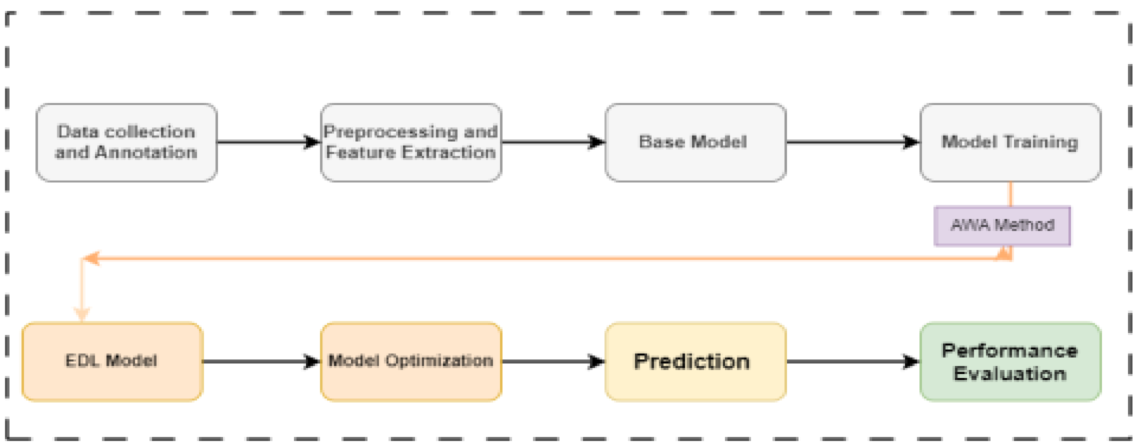


Figure 1. Ensemble based deep learning model data flow

DATASETS

To implement the experiment work, we have collected more than 25 thousand image datasets from kaggle repository and 1500 wheat image (RGB) dataset from our previous research study entitle with ’computer vision approach for wheat diseases classification using GPU infrastructure’. The datasets are structure into 4 major categories namely corn, wheat, potatoes and tomato. These categories are further classified into 20 classes (Figure 2).

SN	D. Main categories	Diseases Subcategories	Classes
1	Tomato Diseases	Yellow-leaf-curv-virus	1
		Mosaic-virus	2
		Target-spot	3
		Spider-mites	4
		Septoria-leaf-spot	5
		Leaf-mold	6
		Late-blight	7
		Healthy-tomato	8
2	Corn Diseases	North-leaf-blight	9
		Health-corn	10
		Common-rust	11
		Cercospora-leaf-spot	12
3	Potato Diseases	late-blight	13
		healthy	14
		early-blight	15
		Bacterial-spot	16
4	Wheat Diseases	Healthy weath	17
		leaf rust	18
		yellow rust	19
		stem rust	20

Figure 2.

Data processing for feature extraction (Jasim & Al-Tuwaijari, 2020) and selection are the important task before build the proposed model. In this regard, we have covered dimensional, removal of the least relevant features, image normalization, formatting, removal of poor-quality images, re-scaling or image resizing, and cropping of irrelevant parts of the image. Similarly, re-scaling pixel intensities values ranging from 0 to 255. Furthermore, we transformed the data by re scaling and setting the dimensions of the images at $224 \times 224 andchannel = 3$ to standardize the data set. We have used well annotated crop image data to train our model, and the data sources are organized into training, testing and validation dataset. Then, we have selected five different deep learning model as a base learner namely ResNet50, EfficientNetB4, DenseNet, ViT-Base and VGG19 models (Rasti & Bleakley, 2020) (Figure 3). We have considered the following criteria, such as the size and quality of the data set, computational resources, disease types and crops, and accuracy requirements to select the base models. In line with ensemble learning method, the issue of computation infrastructure is very critical. To solve this challenge, we have used NVIDIA GeforceRTX3036 GPU facility to handle computational cost. Adjustable weighted average method has been used to readjust the weight of individual based models based on the validation loss accuracy.

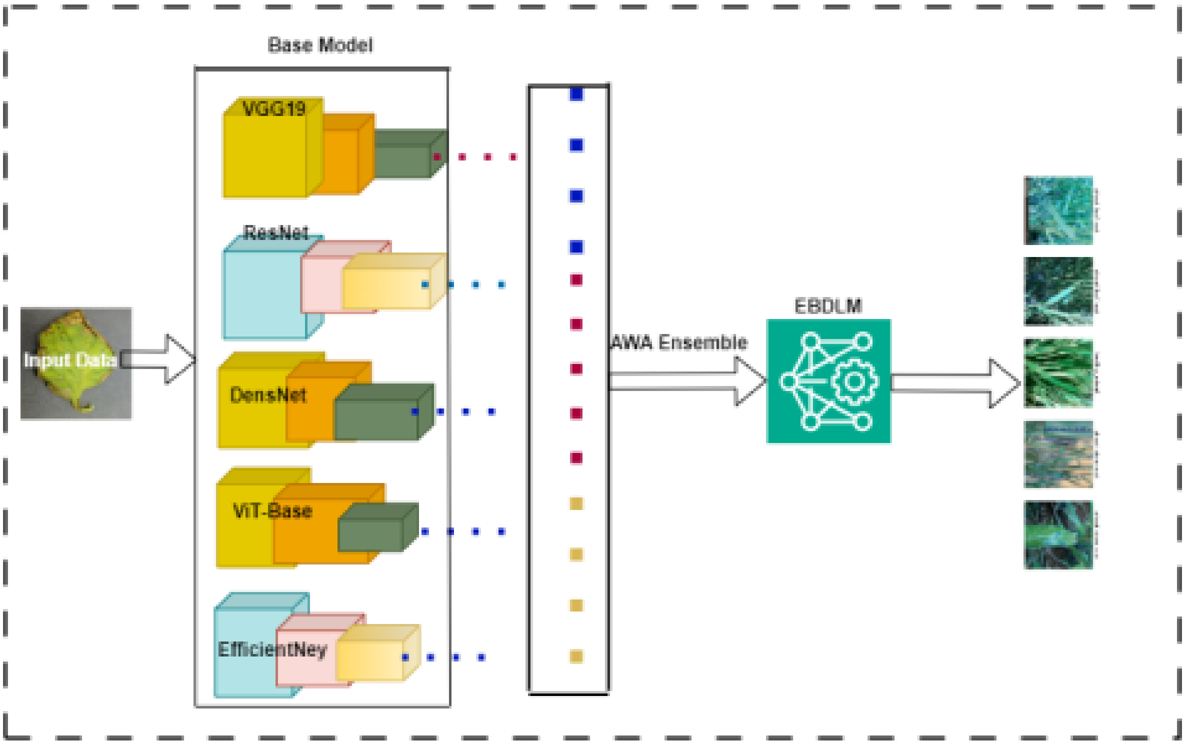


Figure 3.

In case of ensemble learning method, evaluating pairwise correlation between base models is very important before proceeding to build an ensemble model. In this regard, we computed the pairwise correlation between the output probabilities or predicted labels of each model. On Figure 4, we illustrated the model crop diseases prediction accuracy of 99.48% training and 99.23% validation accuracy respectively. From the experiment results, we can conclude that the proposed model has learned the underlying patterns in the on the unseen dataset perfectly.

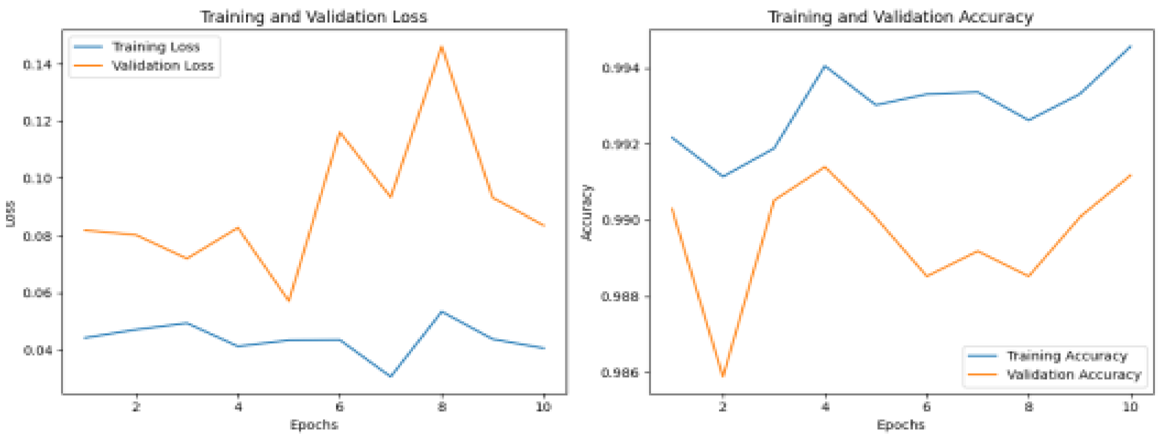


Figure 4. Ensemble model training and validation accuracy

We have used confusion matrix to understand the distribution of predictions across different classes which helps us to make informed decisions, such as adjusting the threshold for specific classes or focusing efforts on improving the model's performance for critical classes. Similarly, we have computed model drifting based the validation dataset to assess how the model's performance has changed over time. Finally, we have made comparison analysis between the proposed model and similar studies in the domain area.

Ensemble learning is a powerful technique in machine learning where multiple models are combined to produce a single superior model.

CONCLUSION

Crop diseases also remain as a major threat to food security. However, rapid disease detection remains a home job for many developing countries such as Ethiopia. Different evidence reveal that proportion of yield loss due crop diseases is significant. Currently, machine learning based solutions plays significant role to detect and classify crop diseases as early as possible. In this study, we proposed ensemble-based deep learning approaches for crop diseases classification purpose. The underlying principle is that the collective decision of the committee tends to exhibit superior overall accuracy compared to any individual member. From the experiment results, the proposed model classifies the type of crop diseases with optimal accuracy. To further justify model's performance, we have used different scalability assessment on the proposed model.

REFERENCES

Ferreira, J. R., Armando Cardona Cardenas, D., Moreno, R. A., De Fatima De Sa Rebelo, M., Krieger, J. E., & Antonio Gutierrez, M. (2020). Multi-View Ensemble Convolutional Neural Network to Improve Classification of Pneumonia in Low Contrast Chest X-Ray Images. Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBS, 2020-July, 1238–1241. https://doi.org/10.1109/EMBC44109.2020.9176517

Fuentes, A., Yoon, S., Kim, S. C., & Park, D. S. (2017). A robust deep-learning-based detector for real-time tomato plant diseases and pests recognition. Sensors (Switzerland), 17(9). https://doi.org/10.3390/s17092022

Habiba, S. U., & Islam, M. K. (2021). Tomato Plant Diseases Classification Using Deep Learning Based Classifier from Leaves Images. 2021 International Conference on Information and Communication Technology for Sustainable Development, ICICT4SD 2021 - Proceedings, 82–86. https://doi.org/10.1109/ICICT4SD50815.2021.9396883

Jasim, M. A., & Al-Tuwaijari, J. M. (2020). Plant Leaf Diseases Detection and Classification Using Image Processing and Deep Learning Techniques. Proceedings of the 2020 International Conference on Computer Science and Software Engineering, CSASE 2020, 259–265. https://doi.org/10.1109/CSASE48920.2020.9142097

Rasti, S., & Bleakley, C. J. (2020). Crop growth stage estimation prior to canopy closure using deep learning algorithms. 6. https://doi.org/10.1007/s00521-020-05064-6

Reddy, D. B. R. S., Madhavi, D. G. B., Lakshmi, C. H. S., Nagendra, D. K. V., & Sridevi, D. R. (2021). Detection of Disease in Maize Plant Using Deep Learning. Alinteri Journal of Agriculture Sciences, 36(2), 82–88. https://doi.org/10.47059/alinteri/v36i2/ajas21118

More references are available in the main content ….

MULTIVARIATE REGIONAL DEEP LEARNING PREDICTION OF SOIL PROPERTIES FROM NEAR-INFRARED, MID-INFRARED AND THEIR COMBINED SPECTRA

#11647

[1,2*]Rumbidzai W. Nyawasha, [3]Alexandre M.J.-C. Wadoux, [4,5]Pierre Todoroff, [1,6]Regis Chikowo, [1,2,5,7]Gatien N. Falconnier, [4,5]Maeva Lagorsse, [5,8]Marc Corbeels, [1,2,5]Rémi Cardinael
[1]Plant Production Sciences and Technology, University of Zimbabwe, Harare, Zimbabwe
[2]CIRAD, UPR AIDA, Harare, Zimbabwe
[3]LISAH, Université de Montpellier, INRAE, IRD, Institut Agro, Montpellier, France
[4]CIRAD, UPR AIDA, F-97410 Saint-Pierre, Réunion, France
[5]AIDA, Univ Montpellier, CIRAD, Montpellier, France
[6]Plant, Soil and Microbial Sciences Department, Michigan State University, East Lansing, MI 48824, USA
[7]International Maize and Wheat Improvement Centre (CIMMYT)-Zimbabwe, Harare, Zimbabwe
[8]IITA, International Institute of Tropical Agriculture, PO Box 30772, Nairobi 00100, Kenya
[*]e-mail: rumbidzaiwnyawasha@yahoo.com; +263 776 163 414

ABSTRACT

Artificial neural network (ANN) models have been successfully used in infrared spectroscopy research for the prediction of soil properties. They often show better performance than conventional methods such as partial least squares regression (PLSR). In this paper we develop and evaluate a multivariate extension of ANN for predicting correlated soil properties: total carbon (C), total nitrogen (N), clay, silt, and sand contents, using visible near-infrared (vis-NIR), mid-infrared (MIR) or combined spectra (vis-NIR + MIR). We hypothesize that accounting for the correlation through joint modelling of soil properties with a single model can eliminate “pedological chimera”: unrealistic values that may arise when properties are predicted independently such as when calculating ratio or soil texture values. We tested two types of ANN models, a univariate (ANN-UV) and a multivariate model (ANN-MV), using a dataset of 228 soil samples collected from Murehwa district in Zimbabwe at two soil depth intervals (0 – 20 and 20 - 40 cm). The models were compared with results from a univariate PLSR (PLSR-UV) model. We found that the multivariate ANN model was better at conserving the observed correlations between properties and consequently gave realistic soil C:N and C:Clay ratios, but that there was no improvement in prediction accuracy over using a univariate model (ANN or PLSR). The use of combined spectra (vis-NIR + MIR) did not make any significant improvements in prediction accuracy of the multivariate ANN model compared to using the vis-NIR or MIR only. We conclude that the multivariate ANN model is better suited for the prediction of multiple correlated soil properties and that it is flexible and can account for compositional constrains. The multivariate ANN model helps to keep realistic ratio values – with strong implications for assessment studies that make use of such predicted soil values.

INTRODUCTION

Soils and soil properties vary over space in relation to the parent material, climate, topography, among others, and change over time in response to natural processes and human activities (Jenny, 1994; Beillouin et al., 2023). Sampling and monitoring of soils is costly and time consuming, as it usually requires a large number of measurements and laboratory analyses (Webster and Lark, 2013). To adequately capture the spatial and temporal variations of soils, effective and less costly methods of data collection and analysis have been developed, including the use of visible and near-infrared (vis-NIR) and mid-infrared (MIR) spectroscopy (Nocita et al., 2015). Statistical models can then be employed to establish a predictive relationship between the spectral characteristics and values of soil properties for which corresponding laboratory measurements are available (Barra et al., 2021). Partial least squares regression (PLSR) has become the most popular regression model in soil spectroscopy (Viscarra Rossel and Lark, 2009; Soriano-Disla et al., 2014). It has been shown to perform well in many situations (Janik et al., 1998; Viscarra Rossel et al., 2006; Cambou et al., 2016; Allo et al., 2020; Bachion de Santana and Daly, 2022). Usually, each soil property is modelled independently, ignoring the correlations that exist between properties. In cases where multiple dependent properties are predicted, this can result in inconsistent predictions and the occurrence of “pedological chimera” as defined by Lagacherie et al. (2022). As a solution, multivariate counterparts of PLSR have been developed, the most common being the PLS2 regression model, a modification of PLSR developed by Wold et al. (1983) and Martens and Naes (1987). However, in terms of predictive accuracy, PLS2 usually performs worse than a model fitted for an individual variable. Several studies, (Pedro and Ferreira, 2007; Blanco and Peguero, 2008; Mishra and Passos, 2022), acknowledged that the univariate model gave higher prediction accuracy than PLS2.

Recently, data-driven models and algorithmic tools from the field of machine learning have become popular for predicting soil properties from spectral data (Meza Ramirez et al., 2021). Commonly used algorithms in soil spectroscopy are support vector machines (Demattê and da Silva Terra, 2014; Deiss et al., 2020), cubist (Minasny and McBratney, 2008; Clergue et al., 2023), random forest (Viscarra Rossel and Behrens, 2010; McDowell et al., 2012; Wadoux, 2023), and artificial neural networks (ANNs) (Daniel et al., 2003; Wijewardane et al., 2018). The use of ANNs has been successful for soil property prediction and showed better performance than conventional methods such as PLSR in several studies (Daniel et al., 2003; Viscarra Rossel and Behrens, 2010; Ng et al., 2019; Padarian et al., 2019). The main advantages of ANNs over conventional regression models are the ability to extract relevant information in high-dimensional datasets, the modelling of non-linear relationships between spectra and soil properties, and a flexibility in the definition of the algorithm and objective function (Ludwig et al., 2019; Margenot et al., 2020). Despite its flexibility, to date very few studies have attempted to understand whether a multivariate ANN model accounts for the correlations that exist amongst soil properties, although promising results were found in Mishra and Passos (2022), Ng et al. (2019), and Ramsundar et al. (2015).

In this paper we develop, further expand, and test the multivariate extension of ANNs for predicting soil properties from their vis-NIR, MIR and combined spectra (vis-NIR + MIR). After model development, we investigate the ability of the multivariate model to predict correlated soil properties, as compared to a model that predicts each property individually. The methodology is tested for total carbon, total nitrogen, sand, silt, and clay contents in soils from Murehwa district located in the sub-humid region of Zimbabwe. We hypothesize that combined modelling of several soil properties can eliminate “pedological chimera” by accounting for the correlations between the properties. The comparison between observed and predicted soil properties from a univariate and a multivariate model is made using vis-NIR, MIR or combined vis-NIR + MIR spectra.

METHODOLOGY

The study was done in Murehwa district (17°39'S, 31°47'E), a smallholder farming area situated about 80 km northeast of Harare, the capital city of Zimbabwe. Soil samples were collected in three villages randomly selected from Ward 28 of the district. 50 % of the households in the three villages were then randomly selected to give a total of 183 farming households. Soil samples were collected from all agricultural fields belonging to the selected households. Samples were also collected from common lands – lands that are available for all villagers and used for grazing, collecting firewood, litter, and wild fruits. Soil samples were collected between June and July 2021 at two depths i) 0 – 20 cm ii) 20 – 40 cm. Sampling was carried out following a zig-zig transect covering each field, with a sub-sample being collected at 10 m distance using an auger and all the sub-samples were mixed to obtain a composite per field and depth.

Spectra were acquired at the laboratory of the French Agricultural Research Centre for International Development (CIRAD) in Saint Denis, La Réunion, on all soil samples ground to 200µm. The MIR spectra were measured using an Agilent 4300 handheld FTIR spectrometer (Agilent Technologies, Santa Clara, CA) over a wavenumber range between 650 – 4000 cm^{-1} with a measurement interval of 4 cm^{-1}, vis-NIR spectra were measured using a LabSpec 5000 (Analytical Spectral Devices, Inc. Boulder, CO, USA) with an optical fibre connected to the internal light (adapted to small sample sizes) over a wavelength of 350 – 2500nm and spectral resolution of 3 nm at 700 nm and 10 nm at 1400/2100 nm. Spectral pre-processing was done to ensure the removal of any variations caused by light scattering and to enhance some features within the spectra (Wadoux et al., 2021). The MIR spectra were trimmed to remove the noise at the edges leaving the range between 800-4000 cm^{-1} whereas vis-NIR spectra were trimmed to 20000 – 4080 cm^{-1}. The MIR and vis-NIR datasets were then combined using spectra concatenation to create a third dataset (vis-NIR + MIR) ranging between 10000 - 800 cm^{-1}. A For laboratory analysis, a subset of 230 soil samples, corresponding to 17 % of the total number of samples, was selected. The selection was based on spectra similarity and the most representative spectra were chosen using the Kennard Stone algorithm as implemented in the Unscrambler X 10.5 Software (CAMO Software Inc., Oslo, Norway). Total carbon and total nitrogen were determined by the Dumas elemental dry combustion method using an Elementar VarioMax Cube. Soil texture analysis was done using the hydrometer method following Gee and Bauder (1986).

Two types of ANN models were built, a univariate model which predicts one soil property at a time, and a multivariate model which predicts more than one property at the same time. The univariate model was made up of one input layer, three hidden layers and one output layer. The multivariate model was made up of one input layer, four hidden layers and an output layer predicting five outputs simultaneously. The models were trained using vis-NIR, MIR and the combined vis-NIR + MIR data. The two ANN models were compared to a univariate PLSR model to gauge their performance against a conventional model. The ANN models in this study were built using the *keras* package (Allaire and Chollet, 2023) in R with *tensorflow* as backend (Allaire and Tang, 2023) and the PLSR was built using the *pls* package (Liland et al., 2023) also in R. The measured values of the soil properties from the laboratory analyses were used to fit the models. The measured values were split into training and validation sets using k-fold cross-validation to assess prediction accuracy of the model predictions on unseen data. Validation statistics – i.e. mean error (ME), the root mean square error (RMSE) and the coefficient of determination R^2 - were calculated from the pairwise comparison of measured and predicted values obtained from all folds as each represents a specific aspect of prediction quality.

RESULTS AND DISCUSSION

The best prediction models were obtained using MIR spectra, followed by vis-NIR + MIR spectra and lastly by vis-NIR spectra. Model predictions based on MIR spectra had consistently higher R^2 values and lower RMSE values, and this difference was significant when compared to predictions based on vis-NIR spectra (Table 1). This can be attributed to the presence of fundamental vibrations in the MIR region whereas only overtones and combinations bands are present in the vis-NIR regions. Other studies report similar results, particularly for soil carbon predictions where MIR outperforms vis-NIR (Viscarra Rossel et al., 2006; Vohland et al., 2014; Wijewardane et al., 2018). The use of combined vis-NIR + MIR spectra did not improve the predictive accuracy of soil properties in this study. There are varying results on this - a study conducted by Johnson et al. (2019) reported an improved accuracy with combined spectra for several soil properties whereas others report that because the predictions with MIR spectra alone are already highly accurate, combining spectra either results in slightly worse results (Viscarra Rossel et al., 2006; Shao and He, 2011; Ng et al., 2019) or produces results that are equally comparable to MIR alone (Knox et al., 2015).

Table 1. Comparison of the PLSR-UV, ANN-UV and ANN-MV models for three spectral datasets, vis-NIR, MIR and combined vis-NIR + MIR using mean error (ME), root mean square error (RMSE) and coefficient of determination (R^2)

	vis-NIR				MIR				vis-NIR + MIR			
	Model	ME	RMSE	R^2	Model	ME	RMSE	R^2	Model	ME	RMSE	R^2
Total C	PLSR-UV	0.07	4.78	0.74	PLSR-UV	0.09	2.87	0.91	PLSR-UV	0.05	3.99	0.82
	ANN-UV	−0.24	5.41	0.66	ANN-UV	0.52	3.13	0.89	ANN-UV	0.06	4.99	0.71
	ANN-MV	−2.69	6.66	0.49	ANN-MV	−0.79	3.09	0.89	ANN-MV	−1.13	4.23	0.79
Total N	PLSR-UV	0.00	0.35	0.72	PLSR-UV	0.01	0.24	0.87	PLSR-UV	0.01	0.31	0.78
	ANN-UV	0.05	0.43	0.59	ANN-UV	0.01	0.28	0.83	ANN-UV	0.02	0.41	0.64
	ANN-MV	−0.18	0.48	0.48	ANN-MV	−0.09	0.26	0.85	ANN-MV	−0.07	0.31	0.78
Sand	PLSR-UV	0.12	9.19	0.63	PLSR-UV	0.19	6.68	0.80	PLSR-UV	0.05	7.08	0.78
	ANN-UV	−2.86	10.38	0.52	ANN-UV	−1.04	7.28	0.77	ANN-UV	−0.48	9.38	0.61
	ANN-MV	2.63	10.2	0.54	ANN-MV	0.17	7.15	0.77	ANN-MV	1.39	7.72	0.74
Clay	PLSR-UV	−0.07	7.15	0.59	PLSR-UV	−0.07	5.68	0.74	PLSR-UV	−0.03	5.82	0.73
	ANN-UV	−0.13	7.53	0.55	ANN-UV	−0.65	6.18	0.69	ANN-UV	−0.98	6.62	0.65
	ANN-MV	−1.75	7.83	0.51	ANN-MV	−0.08	5.81	0.73	ANN-MV	0.98	5.92	0.72
Silt	PLSR-UV	−0.06	4.15	0.36	PLSR-UV	−0.02	3.49	0.55	PLSR-UV	0.05	3.67	0.50
	ANN-UV	−0.27	5.29	0.68	ANN-UV	−0.56	3.56	0.53	ANN-UV	0.06	4.99	0.71
	ANN-MV	−0.83	4.31	0.31	ANN-MV	−0.04	3.42	0.57	ANN-MV	−0.35	3.71	0.49

We also studied the predictions of two key ratios: *(1)* soil C:N ratio, which is calculated using total carbon and total nitrogen values and is a sensitive indicator of soil quality and for assessing the carbon and nitrogen nutrition balance of soils; and *(2)* the C:Clay ratio, calculated using soil carbon and clay content, which has been proposed as an indicator for soil organic carbon status and soil structure quality (Poeplau and Don, 2023). The range of values for the soil C:N ratio was all within the range between 10 – 25, comparable to the measured values, whereas the ANN-UV model gave more unrealistic values including some negative ones. Previous studies in the study area have shown that soil carbon concentrations in the most fertile soils rarely exceed 10 g C kg^{-1} (Masvaya et al., 2010; Zingore et al., 2011). For the C:Clay ratios the predictions made by the ANN-MV model gave significantly better results (Figure 2). Soil clay content plays an important role in the stabilization of SOC since clay minerals have a high specific surface area and carry a charge, enabling them to bind, and thereby chemically stabilize, organic matter. Clay aggregates also provide micropores for the physical protection of soil organic carbon (Wattel-Koekkoek et al., 2001). The C:Clay ratios obtained in this study range between 1:10 – 1:13 and sometimes even lower, which suggests that these soils are degraded (Poeplau and Don, 2023). This is accurate as these soils are granitic derived. A low clay plus silt fraction usually provides little physical protection of organic matter to influence soil physical properties (Feller and Beare, 1997; Nyamangara et al., 2014). Moreover, clay content is not an accurate predictor of SOC, particularly in tropical soils with high concentrations of aluminium and iron oxides (Khomo et al., 2017; Kirsten et al., 2021).

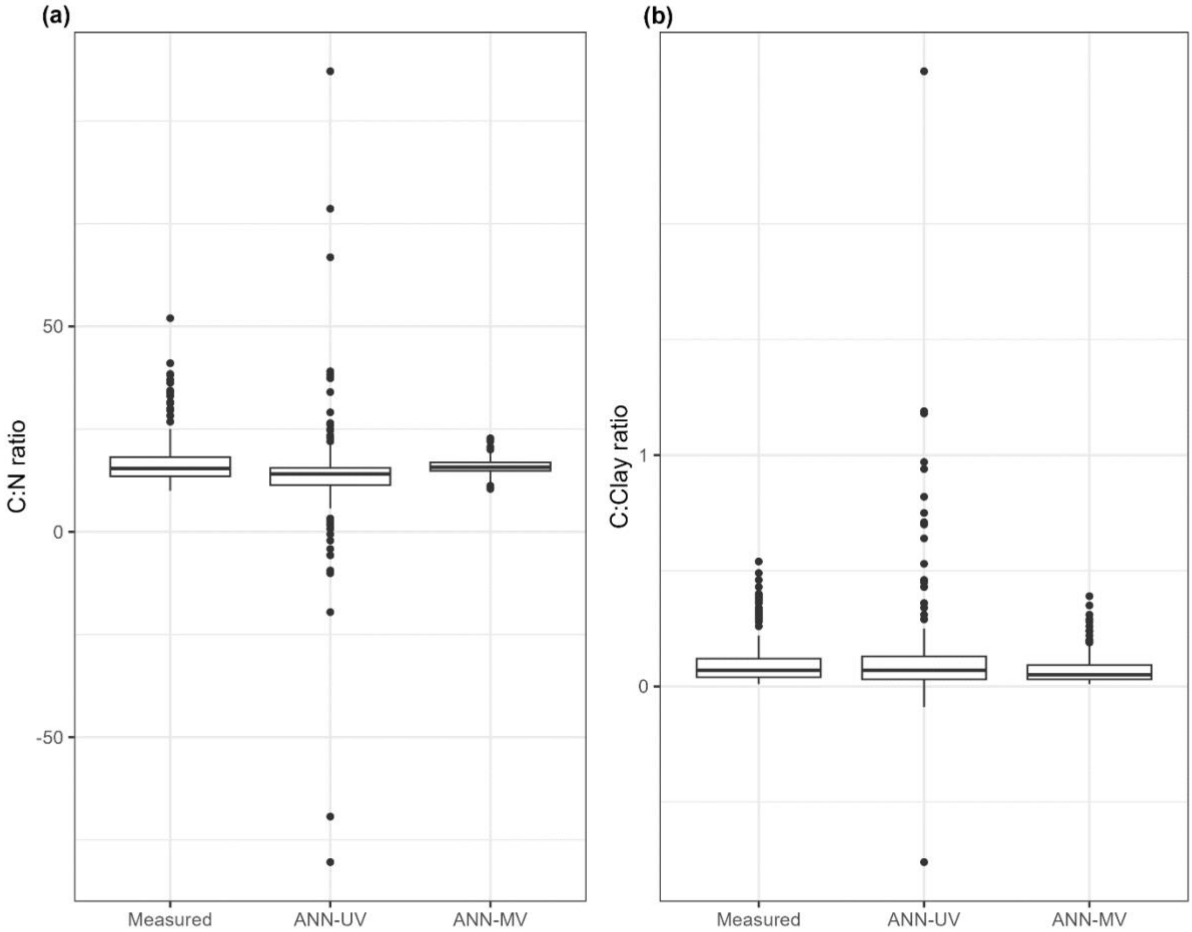


Figure 1. Boxplots of a) soil C:N ratio and b) C:Clay ratio calculated with measured values and the two ANN models

REFERENCES

Allaire, J.., Chollet, F., 2023. Keras: R interface to 'Keras' [WWW Document]. URL https://github.com/rstudio/keras (accessed 8.23.23).

Allaire, J., Tang, Y., 2023. Tensorflow: R Interface to 'TensorFlow' [WWW Document]. R Packag. version 2.11.0.9000. URL https://github.com/rstudio/tensorflow%0A (accessed 8.23.23).

Allo, M., Todoroff, P., Jameux, M., Stern, M., Paulin, L., Albrecht, A., 2020. Prediction of tropical volcanic soil organic carbon stocks by visible-near- and mid-infrared spectroscopy. Catena 189, 104452. https://doi.org/10.1016/j.catena.2020.104452

Bachion de Santana, F., Daly, K., 2022. A comparative study of MIR and NIR spectral models using ball-milled and sieved soil for the prediction of a range soil physical and chemical parameters. Spectrochim. Acta - Part A Mol. Biomol. Spectrosc. 279, 121441. https://doi.org/10.1016/j.saa.2022.121441

Barra, I., Haefele, S.M., Sakrabani, R., Kebede, F., 2021. Soil spectroscopy with the use of chemometrics, machine learning and pre-processing techniques in soil diagnosis: Recent advances–A review. TrAC - Trends Anal. Chem. 135, 116166. https://doi.org/10.1016/j.trac.2020.116166

Beillouin, D., Corbeels, M., Demenois, J., Berre, D., Boyer, A., Fallot, A., Feder, F., Cardinael, R., 2023. A global meta-analysis of soil organic carbon in the Anthropocene. Nat. Commun. 14, 1–10. https://doi.org/10.1038/s41467-023-39338-z

Blanco, M., Peguero, A., 2008. An expeditious method for determining particle size distribution by near infrared spectroscopy: Comparison of PLS2 and ANN models. Talanta 77, 647–651. https://doi.org/10.1016/j.talanta.2008.07.015

Cambou, A., Cardinael, R., Kouakoua, E., Villeneuve, M., Durand, C., Barthès, B.G., 2016. Prediction of soil organic carbon stock using visible and near infrared reflectance spectroscopy (VNIRS) in the field. Geoderma 261, 151–159. https://doi.org/10.1016/j.geoderma.2015.07.007

Clergue, T.C., Saby, N.P.A., Wadoux, A.M.J.-C., Barthès, B.G., Lacoste, M., 2023. Estimating soil aggregate stability with infrared spectroscopy and pedotransfer functions. Soil Secur. 11, 100088. https://doi.org/10.1016/j.soisec.2023.100088

Daniel, K.W., Tripathi, N.K., Honda, K., 2003. Artificial neural network analysis of laboratory and in situ spectra for the estimation of macronutrients in soils of Lop Buri (Thailand). Aust. J. Soil Res. 41, 47–59. https://doi.org/10.1071/SR02027

Deiss, L., Margenot, A.J., Culman, S.W., Demyan, M.S., 2020. Tuning support vector machines regression models improves prediction accuracy of soil properties in MIR spectroscopy. Geoderma 365, 114227. https://doi.org/10.1016/j.geoderma.2020.114227

Demattê, J.A.M., da Silva Terra, F., 2014. Spectral pedology: A new perspective on evaluation of soils along pedogenetic alterations. Geoderma 217–218, 190–200. https://doi.org/10.1016/j.geoderma.2013.11.012

Feller, C., Beare, M.H., 1997. Physical control of soil organic matter dynamics in the tropics. Geoderma 79, 69–116. https://doi.org/10.1016/S0016-7061(97)00039-6

Gee, G.W., Bauder, J.W., 1986. Particle-size Analysis, in: Klute, A. (Ed.), Methods of Soil Analysis, Part 1. Physical and Mineralogical Methods-Agronomy. Agronomy Society of America/Soil Science Society of America, Madison, Wisconsin, pp. 384–411.

Janik, L.J., Merry, R.H., Skjemstad, J.O., 1998. Can mid infrared diffuse reflectance analysis replace soil extractions? Aust. J. Exp. Agric. 38, 681–696. https://doi.org/10.1071/EA97144

Jenny, H., 1994. Factors of Soil Formation A System of Quantitative Pedology. Courier Corporation.

Johnson, J.M., Vandamme, E., Senthilkumar, K., Sila, A., Shepherd, K.D., Saito, K., 2019. Near-infrared, mid-infrared or combined diffuse reflectance spectroscopy for assessing soil fertility in rice fields in sub-Saharan Africa. Geoderma 354, 113840. https://doi.org/10.1016/j.geoderma.2019.06.043

Khomo, L., Trumbore, S., Bern, C.R., Chadwick, O.A., 2017. Timescales of carbon turnover in soils with mixed crystalline mineralogies. Soil 3, 17–30. https://doi.org/10.5194/soil-3-17-2017

Kirsten, M., Mikutta, R., Vogel, C., Thompson, A., Mueller, C.W., Kimaro, D.N., Bergsma, H.L.T., Feger, K.H., Kalbitz, K., 2021. Iron oxides and aluminous clays selectively control soil carbon storage and stability in the humid tropics. Sci. Rep. 11, 1–12. https://doi.org/10.1038/s41598-021-84777-7

Knox, N.M., Grunwald, S., McDowell, M.L., Bruland, G.L., Myers, D.B., Harris, W.G., 2015. Modelling soil carbon fractions with visible near-infrared (VNIR) and mid-infrared (MIR) spectroscopy. Geoderma 239–240, 229–239.

https://doi.org/10.1016/j.geoderma.2014.10.019
Lagacherie, P., Buis, S., Constantin, J., Dharumarajan, S., Ruiz, L., Sekhar, M., 2022. Evaluating the impact of using digital soil mapping products as input for spatializing a crop model: The case of drainage and maize yield simulated by STICS in the Berambadi catchment (India). Geoderma 406, 115503. https://doi.org/https://doi.org/10.1016/j.geoderma.2021.115503.
Liland, K.., Mevik, B.-H., Wehrens, R., Hiemstra, P., 2023. pls: Partial Least Squares and Principal Component Regression [WWW Document]. 2.8-2. URL https://github.com/khliland/pls (accessed 8.23.23).
Ludwig, B., Murugan, R., Parama, V.R.R., Vohland, M., 2019. Accuracy of Estimating Soil Properties with Mid-Infrared Spectroscopy: Implications of Different Chemometric Approaches and Software Packages Related to Calibration Sample Size. Soil Sci. Soc. Am. J. 83, 1542–1552. https://doi.org/10.2136/sssaj2018.11.0413
Margenot, A., O' Neill, T., Sommer, R., Akella, V., 2020. Predicting soil permanganate oxidizable carbon (POXC) by coupling DRIFT spectroscopy and artificial neural networks (ANN). Comput. Electron. Agric. 168, 105098. https://doi.org/10.1016/j.compag.2019.105098
Martens, H., Naes, T., 1987. Multivariate calibration by data compression, in: Williams, P.., Norris, K. (Eds.), Near-Infrared Technology in the Agricultural and Food Industries. American Association of Cereal Chemists, St. Paul, MN, pp. 57–87.
Masvaya, E.N., Nyamangara, J., Nyawasha, R.W., Zingore, S., Delve, R.J., Giller, K.E., 2010. Effect of farmer management strategies on spatial variability of soil fertility and crop nutrient uptake in contrasting agro-ecological zones in Zimbabwe. Nutr. Cycl. Agroecosystems 88, 111–120. https://doi.org/10.1007/s10705-009-9262-y
McDowell, M.L., Bruland, G.L., Deenik, J.L., Grunwald, S., Knox, N.M., 2012. Soil total carbon analysis in Hawaiian soils with visible, near-infrared and mid-infrared diffuse reflectance spectroscopy. Geoderma 189–190, 312–320. https://doi.org/10.1016/j.geoderma.2012.06.009
Meza Ramirez, C.A., Greenop, M., Ashton, L., Rehman, I. ur, 2021. Applications of machine learning in spectroscopy. Appl. Spectrosc. Rev. 56, 733–763. https://doi.org/10.1080/05704928.2020.1859525
Minasny, B., McBratney, A.B., 2008. Regression rules as a tool for predicting soil properties from infrared reflectance spectroscopy. Chemom. Intell. Lab. Syst. 94, 72–79. https://doi.org/10.1016/j.chemolab.2008.06.003
Mishra, P., Passos, D., 2022. Multi-output 1-dimensional convolutional neural networks for simultaneous prediction of different traits of fruit based on near-infrared spectroscopy. Postharvest Biol. Technol. 183, 111741. https://doi.org/10.1016/j.postharvbio.2021.111741
Ng, W., Minasny, B., Montazerolghaem, M., Padarian, J., Ferguson, R., Bailey, S., McBratney, A.B., 2019. Convolutional neural network for simultaneous prediction of several soil properties using visible/near-infrared, mid-infrared, and their combined spectra. Geoderma 352, 251–267. https://doi.org/10.1016/j.geoderma.2019.06.016
Nocita, M., Stevens, A., van Wesemael, B., Aitkenhead, M., Bachmann, M., Barthès, B., Dor, E. Ben, Brown, D.J., Clairotte, M., Csorba, A., Dardenne, P., Demattê, J.A.M., Genot, V., Guerrero, C., Knadel, M., Montanarella, L., Noon, C., Ramirez-Lopez, L., Robertson, J., Sakai, H., Soriano-Disla, J.M., Shepherd, K.D., Stenberg, B., Towett, E.K., Vargas, R., Wetterlind, J., 2015. Soil Spectroscopy: An Alternative to Wet Chemistry for Soil Monitoring. Adv. Agron. 132, 139–159. https://doi.org/10.1016/bs.agron.2015.02.002
Nyamangara, J., Marondedze, A., Masvaya, E.N., Mawodza, T., Nyawasha, R., Nyengerai, K., Tirivavi, R., Nyamugafata, P., Wuta, M., 2014. Influence of basin-based conservation

agriculture on selected soil quality parameters under smallholder farming in Zimbabwe. Soil Use Manag. 30, 550–559. https://doi.org/10.1111/sum.12149

Padarian, J., Minasny, B., McBratney, A.B., 2019. Using deep learning to predict soil properties from regional spectral data. Geoderma Reg. 16, e00198. https://doi.org/10.1016/j.geodrs.2018.e00198

Pedro, A.M.K., Ferreira, M.M.C., 2007. Simultaneously calibrating solids, sugars and acidity of tomato products using PLS2 and NIR spectroscopy. Anal. Chim. Acta 595, 221–227. https://doi.org/10.1016/j.aca.2007.03.036

Poeplau, C., Don, A., 2023. A simple soil organic carbon level metric beyond the organic carbon-to-clay ratio. Soil Use Manag. 39, 1057–1067. https://doi.org/10.1111/sum.12921

Ramsundar, B., Kearnes, S., Riley, P., Webster, D., Konerding, D., Pande, V., 2015. Massively Multitask Networks for Drug Discovery, in: International Conference on Machine Learning. https://doi.org/10.48550/arXiv.1502.02072

Shao, Y., He, Y., 2011. Nitrogen, phosphorus, and potassium prediction in soils, using infrared spectroscopy. Soil Res. 49, 166–172. https://doi.org/10.1071/SR10098

Soriano-Disla, J.M., Janik, L.J., Viscarra Rossel, R.A., MacDonald, L.M., McLaughlin, M.J., 2014. The performance of visible, near-, and mid-infrared reflectance spectroscopy for prediction of soil physical, chemical, and biological properties. Appl. Spectrosc. Rev. 49, 139–186. https://doi.org/10.1080/05704928.2013.811081

Viscarra Rossel, R.A., Behrens, T., 2010. Using data mining to model and interpret soil diffuse reflectance spectra. Geoderma 158, 46–54. https://doi.org/10.1016/j.geoderma.2009.12.025

Viscarra Rossel, R.A., Lark, R.M., 2009. Improved analysis and modelling of soil diffuse reflectance spectra using wavelets. Eur. J. Soil Sci. 60, 453–464. https://doi.org/10.1111/j.1365-2389.2009.01121.x

Viscarra Rossel, R.A., Walvoort, D.J.J., McBratney, A.B., Janik, L.J., Skjemstad, J.O., 2006. Visible, near infrared, mid infrared or combined diffuse reflectance spectroscopy for simultaneous assessment of various soil properties. Geoderma 131, 59–75. https://doi.org/10.1016/j.geoderma.2005.03.007

Vohland, M., Ludwig, M., Thiele-Bruhn, S., Ludwig, B., 2014. Determination of soil properties with visible to near- and mid-infrared spectroscopy: Effects of spectral variable selection. Geoderma 223–225, 88–96. https://doi.org/10.1016/j.geoderma.2014.01.013

Wadoux, A.M.J.-C., 2023. Interpretable spectroscopic modelling of soil with machine learning. Eur. J. Soil Sci. 74, 1–14. https://doi.org/10.1111/ejss.13370

Wadoux, A.M.J.-C., Malone, B., Minasny, B., Fajardo, M., McBratney, A.B., 2021. Soil Spectral Inference with R: Analysing Digital Soil Spectra Using the R Programming Environment, Springer International Publishing AG, Cham.

Wattel-Koekkoek, E.J.W., Van Genuchten, P.P.L., Buurman, P., Van Lagen, B., 2001. Amount and composition of clay-associated soil organic matter in a range of kaolinitic and smectitic soils. Geoderma 99, 27–49. https://doi.org/10.1016/S0016-7061(00)00062-8

Webster, R., Lark, R.M., 2013. Field Sampling for Environmental Science and Management. Routledge, New York. https://doi.org/10.4324/9780203128640

Wijewardane, N.K., Ge, Y., Wills, S., Libohova, Z., 2018. Predicting Physical and Chemical Properties of US Soils with a Mid-Infrared Reflectance Spectral Library. Soil Sci. Soc. Am. J. 82, 722–731. https://doi.org/10.2136/sssaj2017.10.0361

Wold, S., Albano, C., Dunn III, W.J., Esbensen, K., Hellberg, S., Johansson, E., Sjorstrom, S., 1983. Pattern recognition: Finding and using regularities in multi-variate data, in: Martens, H., Russwurm, Jr, H. (Eds.), Food Research and Data Analysis. Applied Science Publishers, London, pp. 147–188.

Zingore, S., Tittonell, P., Corbeels, M., van Wijk, M.T., Giller, K.E., 2011. Managing soil fertility diversity to enhance resource use efficiencies in smallholder farming systems: A case from Murewa District, Zimbabwe. Nutr. Cycl. Agroecosystems 90, 87–103. https://doi.org/10.1007/s10705-010-9414-0

CLIMATE SMART AGRICULTURE

PREDICTING THE DISTRIBUTION OF GROUNDNUT PHYTOPATHOGENS UNDER CURRENT AND FUTURE CLIMATIC SCENARIOS IN ZIMBABWE

#11736

[1]Hardlife Chinwa, [1]Elizabeth Ngadze, [1]Juliet Murimwa, [2,3]Eliel Belchrist Sossou, [4]Clara Machokoto, [1]Regis Chikowo, [1*]Casper Nyaradzai Kamutando
e-mail: Kamutandocn@gmail.com; 00263713232033

ABSTRACT

Groundnut (*Arachis hypogaea* L.) is an important oil seed crop with immense nutritional and economic benefits, but its productivity in sub-Saharan Africa (SSA) is threatened by a plethora of phytopathogens such as groundnut rosette virus, Alternaria leafspots, early leafspots and peanut rust. In Zimbabwe, ecological niches and epidemiology of these pathogenic microbial strains, particularly under the current and predicted climate change scenarios, are still poorly understood. Yet, this information is vital in crafting effective and sustainable disease management approaches for production of this important crop. Here, a field survey was conducted on small-scale farms across a climate gradient during the 2023-24 and 2024-25 summer cropping seasons, to predict the current and future (2050) distribution of groundnut phytopathogens in Zimbabwe. Three out of the five main agro-ecological regions (AER) of Zimbabwe (i.e., AERII, AERIII and AERIV) were used as sampling sites. Georeferenced data was subjected to maximum entropy (MaxEnt) algorithm for species distribution modelling. The model identified isothermality, precipitation and temperature seasonality as the major environmental variables governing suitability of groundnut phytopathogens occurrence across the diverse agro ecologies of Zimbabwe. Distribution of groundnut phytopathogens in Zimbabwe was predicted to vary with change in climatic conditions, in particular, rainfall and temperature-based bio-climatic variables. In conclusion, groundnut phytopathogens are widely distributed in Zimbabwe and climate change under current and future climate scenarios will influence their distribution posing significant threat to food security.

Keywords: Phytopathogens; Groundnut; Zimbabwe; Climate change; MaxEnt

INTRODUCTION

Foliar diseases are one of the major biotic stresses impacting the productivity of groundnuts, a potential crop widely grown for food and nutrition security by small scale farmers in sub-Saharan Africa (SSA) [1]. Renown biotypes of economic importance are (1) groundnut rosette virus (GRV), the most devastating viral phytopathogen cosmopolitan to SSA, (2) *Nothopassalora arachidicola* (late leafspot), (3) *Passalora arachidicola* (early leafspot), (4) *Puccinia arachidis* (peanut rust) and (5) Alternaria species (i.e., *A. alternata* (Fr.) Keissler., *A. tennuissima*, *A arachidis* and *A. longipse* (leaf blights)) [2-5]. Groundnut rosette alone can cause 100% yield losses while leafspots can cause >50% yield losses [6, 7]. In Ghana, yield losses between 78-88% due to GRV on groundnuts was reported by Appiah, Offei (3). In 2003, Nutsugah, Oti-Boateng (8) reported yield loss of up to 80% on pod yield due to early and late leafspot in Ghana. Mau and Ndiwa (9) reported yield loss of up to 57% due to the co-infection of peanut rust and late leafspot in Indonesia. As groundnut is a cash crop and source of nutrition for thousands of smallholder farmers in Zimbabwe, groundnut phytopathogens through yield losses can obscure the roadmap towards food and nutrition security patronaged by the sustainable development goals (SDG2 and SDG3) of the United nations [10-12].

Due to wide range of hosts, exchange of planting materials, spatial production of landraces, evolution of pathogens as well as the inadvertent sporadic weather patterns, and lack of resistant varieties, the environmental suitability of groundnut phytopathogens in Zimbabwe is likely to increase significantly [13, 14]. Exacerbated by climate change, various agro-ecological regions in Zimbabwe are likely to share similar environmental characteristics favoured by foliage disease-causing microbes for groundnuts.

Understanding the epidemic and conducive environmental conditions promoting the pathogenicity of groundnut diseases in Zimbabwe is a first line of defence against future potential yield losses and inoculum build-up as it helps policy makers in deciding whether to go for new varieties or improved plant and soil health. State-of-the-art species distribution models such as correlative (also referred to as bioclimatic), and mechanistic models have been developed to pacify our comprehension on the spread of a species as a function of environmental variables through the use of computer algorithms [15]. Predicting the distribution of species under climate change using mathematical models is useful in: (i) revealing the biogeographical patterns of a species, (ii) finding suitable areas of re-introduction of endangered species, (iii) assessing how environmental conditions influence the occurrence or abundance of species, and (iv) ecological forecasting [13, 14]. In this study, a field survey was conducted on smallholder groundnut farmers across a climate gradient in Zimbabwe to predict the potential spatial distribution of groundnut phytopathogens under current and future climates. We hypothesize that, the distribution of groundnut phytopathogens in Zimbabwe is influenced by current and future climates.

MATERIALS AND METHODS

Occurrence data

Presence only (PO) data were collected as input data across a climate gradient, encompassing three out of the five agro-ecological regions of Zimbabwe from a total of 445 occurrence points during the 2023-24 and 2024-25 summer cropping season.

Disease confirmation under compound microscope

Symptomatic diseased groundnut samples were brought to the laboratory for further confirmation through the aid of a compound microscope. Fungi specimen was cultured in an incubator at 25 ℃ using potato-dextrose agar until spores were developed.

Data for environmental variables

Worldclim's (www.worldclim.org) nineteen (19) bioclimatic variables (BIO1-BIO19) from 1970-2000 were downloaded from database as raster layers. Four socio-economic pathways (SSPs) namely, SSP5-8.5 (highest scenario), SSP3-7.0 (high scenario), SSP2-4.5 (medium scenario) and SSP1-2.6 (low scenario) for greenhouse gas (GHG) emissions, released by the Intergovernmental Panel on Climate Change (IPCC) in 2013, were selected from Australia ACCESS CM2 of the Coupled Model Intercomparison Project Phase 6 (CMIP6) for the year 2050 (2040-2060).

MaxEnt model simulation

To simulate the model, the maximum entropy (MaxEnt) ver 3.4.3. algorithm was employed [16]. The software is open source with high accuracy, and it can work with as little as 20 occurrences to predict the distribution of species.

Determination of suitable and unsuitable areas

Output maps from the MaxEnt software in .asc format were uploaded into QGIS together with the country shapefile downloaded from diva-gis. Uploaded layers under symbology were changed from single band Gray to single band pseudo-colour in-which turbo colour ramp was selected to generate colourful continuous maps. To generate binary maps, linear interpolation was changed to discrete. The raster calculator in QGIS was used to assign the binary values (classes) of 1 and 0 to the variables.

RESULTS

Model and variable performances

The model had an excellent performance with an accuracy value of 0.965 and a standard deviation of 0.041. The bioclimatic variables which reduced the model gain the most when excluded was BIO3 (isothermality, Figure 1).

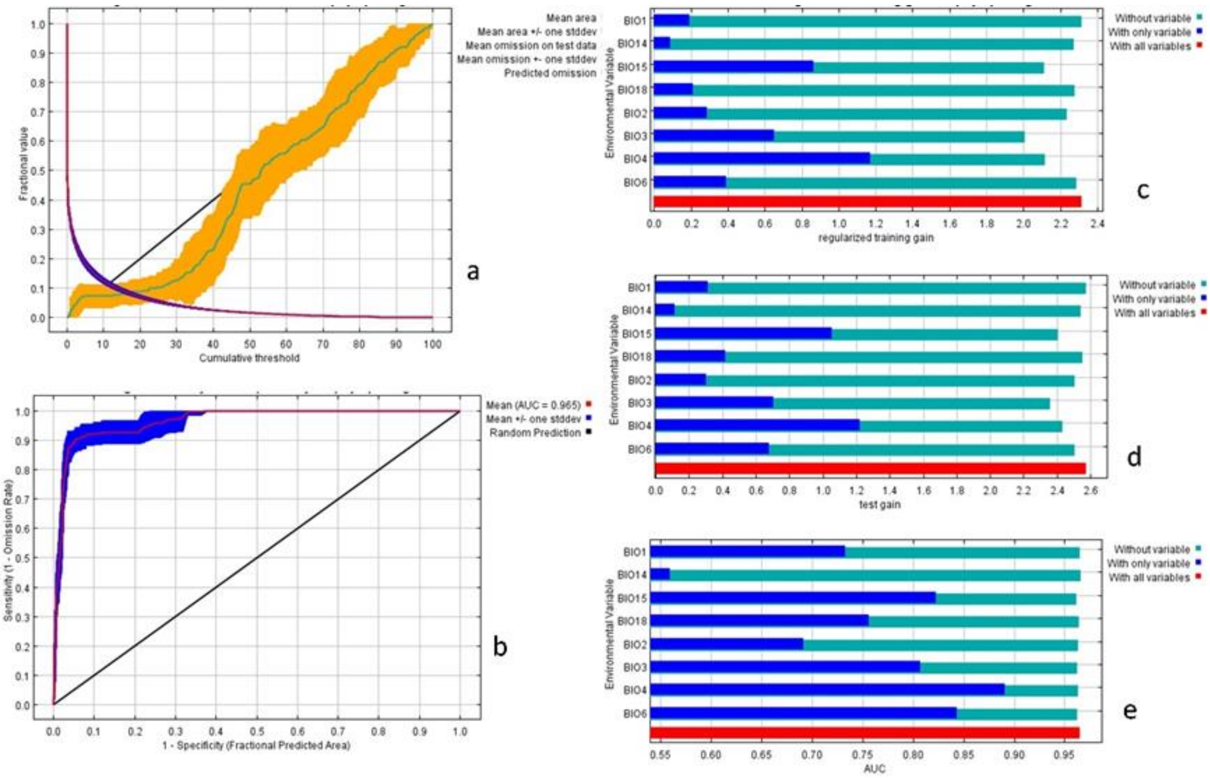


Figure 1. Model and variable performance based on area under curve (AUC) of the receiver operating curve (ROC), omission rate and Jackknife tests

Groundnut phytopathogens under current and future climatic scenarios

Under current climatic conditions, the ecological niche model (ENM) revealed that, the unsuitable area (unsuitable = 0%) was far less than the total suitable area (suitable > 90%). The analysis based on projecting the final model into the future climate scenarios (2050) revealed no predicted increase of unsuitable areas for groundnut phytopathogens under low carbon concentration (Figure 2).

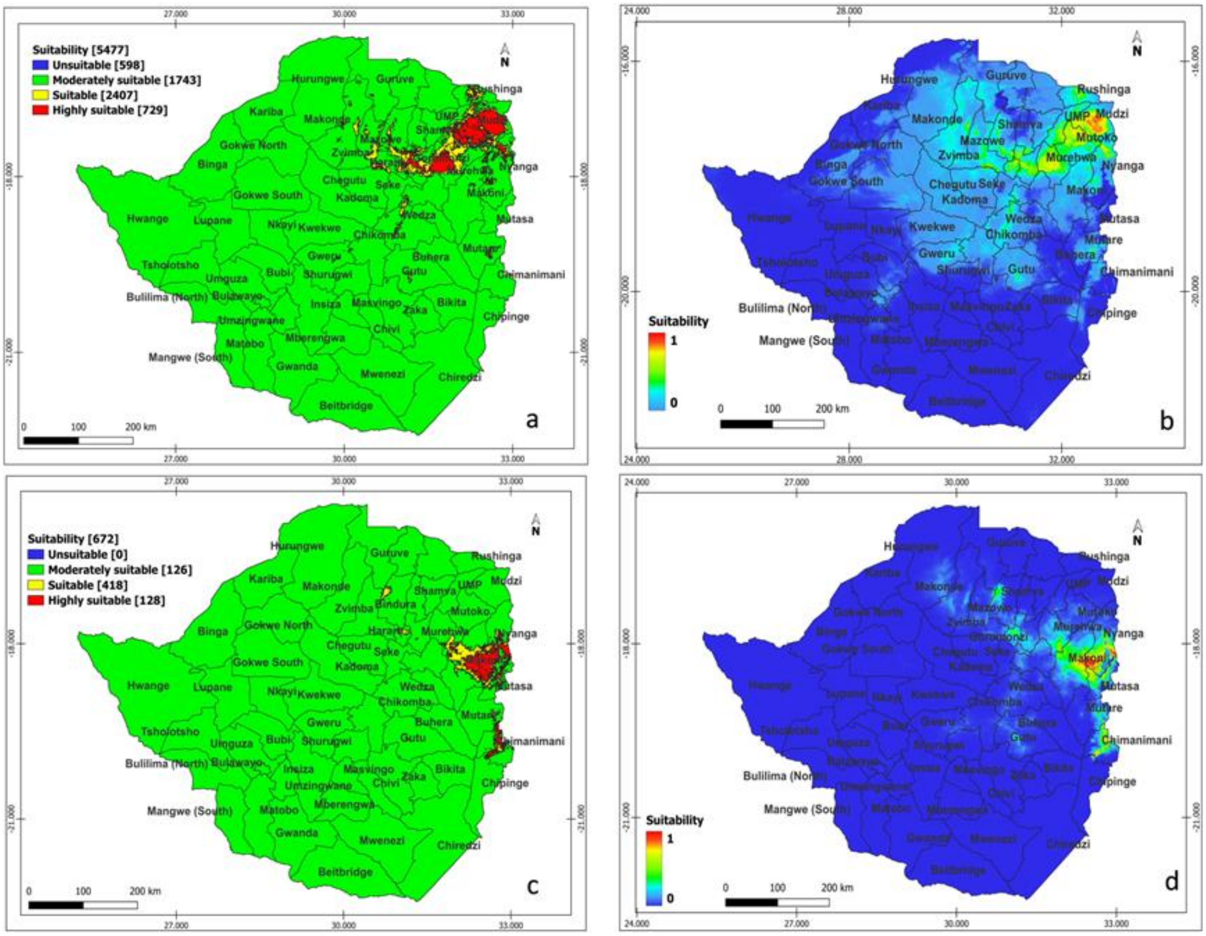


Figure 2. Suitable areas for groundnut phytopathogens in Zimbabwe under current climate and future scenario (SSP1-2.6)

DISCUSSION

The current and future distribution of groundnut phytopathogens in Zimbabwe could be attributed to several factors including: (i) host distribution and susceptibility, (ii) pathogen evolution, (iii) vector distribution and life cycle, (iv) management and farming systems, and (v) government policy.

Host distribution and susceptibility

The distribution of groundnut phytopathogens under current and future climates is likely to be influenced by the distribution of the hosts and their susceptibility. The study concurred with the findings reported in Kenya by Mabele, Were (13) that, legumes including groundnut and non-legume crops were susceptible to GRV.

Management and farming systems

Other elements which are likely to propel the distribution of groundnut phytopathogens in Zimbabwe are management and farming systems currently used by farmers. Commonest farming systems such as crop rotations, intercropping and mulching may be inappropriate in the future as they can serve as vehicles for spreading disease inoculum [17].

CONCLUSION

The Maxent algorithm successfully predicted the current and future distribution of groundnut phytopathogens under the current and future climates in Zimbabwe. Among those environmental factors, isothermality, precipitation and temperature seasonality emerged as the top factors associated with groundnut phytopathogens distribution. Therefore, current and future climatic conditions helped to determine the potential range of the phytopathogens and hotspot areas where proactive measures may be necessary to prevent severe yield losses

REFERENCES

1. Kumar V, Thirumalaisamy P. Diseases of groundnut. New Delhi: Indian Phytopathological Society, Today, Tomorrow's Printers Publishers; 2016. 459-87 p.
2. Prabhu R, Manivannan N, Mothilal A, Ibrahim SM. Artificial screening for foliar fungal diseases in groundnut (Arachis hypogaea L.). Adv Life Sci. 2016;5(14):5634-8.
3. Appiah AS, Offei SK, Tegg RS, Wilson CR. Varietal response to groundnut rosette disease and the first report of Groundnut ringspot virus in Ghana. Plant Dis. 2016;100(5):946-52.
4. Sudini H, Upadhyaya HD, Reddy SV, Naga Mangala U, Rathore A, Vijay Krishna Kumar K. Resistance to late leaf spot and rust diseases in ICRISAT's mini core collection of peanut (Arachis hypogaea L.). Australas Plant Pathol. 2015;44:557-66.
5. Kumar N, Ajay BC, Jadon KS, Gangadhara K, Kona P, Rathanakumar AL, et al. Genetic variability for Alternaria leaf blight resistance in groundnut genotypes. 2020.
6. Amoah RA, Akromah R, Asibuo JY, Oppong A, Nyadanu D, Agyeman A, et al. Genetic control of resistance to rosette virus disease in groundnut (Arachis hypogaea L.). Journal of Plant Breeding and Crop Science. 2016;8(6):87-93.
7. Gaikpa DS, Akromah R, Asibuo JY, Appiah-Kubi Z, Nyadanu D. Evaluation of yield and yield components of groundnut genotypes under Cercospora leaf spots disease pressure. International Journal of Agronomy and Agricultural Research. 2015;7(3):66-75.
8. Nutsugah SK, Oti-Boateng C, Tsigbey FK, Brandenburg RL. Assessment of yield losses due to early and late leaf spots of groundnut (Arachis hypogaea L.). Ghana Journal of Agricultural Science. 2007;40(1):21-7.
9. Mau YS, Ndiwa ASS. Field evaluation of late leaf spot and leaf rust resistance and the associated yield losses in Indonesian groundnut genotypes. Asian J Plant Sci. 2018;17(3):134-41.
10. Katema T, Hanyani-Mlambo EMBT, Gomera MR, Chamboko T. An Analysis of the Profitability of Groundnut Production by Small-holder Farmers in Chegutu District, Zimbabwe. J Econ Sustain Dev. 2017;8:167-75.
11. Allahyari MS, Sadeghzadeh M. Agricultural extension systems toward SDGs 2030: zero hunger. Zero hunger. 2020:41-52.
12. Mollier L, Seyler F, Chotte J-L, Ringler C. End hunger, achieve food security and improved nutrition and promote sustainable agriculture: SDG 2. A Guide to SDG Interactions: From Science to Implementation Paris, France: ICSU; 2017. p. 34-80.
13. Mabele AS, Were HK, Ndong'a MF, Mukoye B. Distribution, molecular detection and host range of groundnut rosette assistor virus in western Kenya. Journal of Plant Sciences. 2019;7(5):100-5.
14. van Niekerk J, Wynberg R. Traditional seed and exchange systems cement social relations and provide a safety net: A case study from KwaZulu-Natal, South Africa. Agroecol Sustain Food Syst. 2017;41(9-10):1099-123.

15. Kearney MR, Wintle BA, Porter WP. Correlative and mechanistic models of species distribution provide congruent forecasts under climate change. Conservation letters. 2010;3(3):203-13.
16. Phillips SJ, Dudík M. Modeling of species distributions with Maxent: new extensions and a comprehensive evaluation. Ecography. 2008;31(2):161-75.
17. Juroszek P, Von Tiedemann A. Potential strategies and future requirements for plant disease management under a changing climate. Plant Pathol. 2011;60(1):100-12.

DECISION SUPPORT SYSTEMS, SOFTWARE AND MOBILE APPLICATIONS

EMPOWERING FARMERS TO SUSTAINABLE AGRICULTURAL PRODUCTIVITY IN WEST AFRICA: FESERWAM, A DIGITAL ADVISOR FOR FARMERS

#11359

J. Toviho, I. Brou, K. Kouassi
International Fertilizer Development Center, EnGRAIS project, Ghana
e-mail: jtoviho@ifdc.org; (229) 97 27 94 71

ABSTRACT

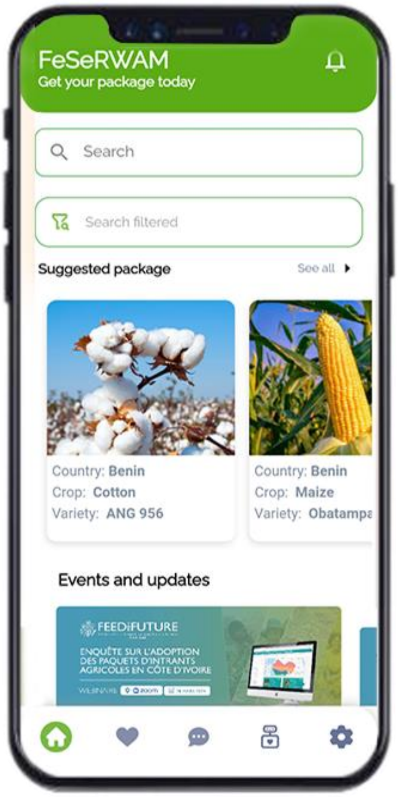
Smallholder farmers in West Africa frequently face challenges in accessing critical information about agricultural inputs and practices. To address this issue, EnGRAIS/IFDC and CORAF, with funding from USAID, developed the *Fertilizer and Seed Recommendations Map for West Africa* (FeSeRWAM) mobile application. FeSeRWAM App is a digital agricultural tool for West Africa, offering tailored Agricultural Input Packages (AIP) with recommendations on fertilizers, seeds and good agricultural practices based on country specific agroecological zones. Built on the FeSeRWAM web platform developed by IFDC and CORAF with USAID funding and technical inputs from National Agricultural Research Structures, the app provides guidance for over 650 AIP on 21 crops, 578 varieties and 62 fertilizer grades for 15 ECOWAS countries, as well as Mauritania and Chad. Designed for ease of use, the app allows farmers, extension agents, and agrodealers to access critical information offline and on the go. The app's success is attributed to its regional customization and the collaborative effort of over 350 stakeholders. Additionally, it aligns with the ECOWAS Regional Agricultural Input Strategy. EnGRAIS has played a pivotal role in this initiative by training 50 regional trainers and 5,000 national trainers, reaching a total of 600,000 farmers to promote FeSeRWAM application. Moving forward, the project plans to further integrate a decision support tool (DST) based on economic returns for smart AIPs selection, to continue boosting agricultural productivity in the region.

Keywords: FeSeRWAM, Fertilizers, Seeds, Good agricultural practices, Agroecological zones.

INTRODUCTION

Agriculture remains a cornerstone of the West African economy, providing livelihoods for millions and contributing significantly to the region's GDP. Many smallholder farmers in West Africa continue to produce below capacity due to their inability to access the the right information on appropriate agricultural inputs and practices to unlock existing potential, make better decisions and get more dividends on their investments. Various efforts have been made over the years by value chain actors to change the trend, but not many of these efforts have yielded the expected results. Ideally, extension agents are supposed to provide this information to farmers. However, there are not enough extension agents, and those available often lack access to the right information on farm inputs. Meanwhile, the information available in research centers is not disseminated. In this condition, farmers often get their information from agrodealers and more educated people in their communities, but this actor is also struggle to find the correct information.

To address these issues and boost agricultural productivity sustainably, technological innovations are increasingly recognized as essential. Among these innovations is FeSeRWAM. FeSeRWAM, an acronym for the *Fertilizer and Seed Recommendations Map for West Africa*, is a comprehensive digital app developed to support farmers in West Africa. This digital tool aims to empower farmers by providing site-specific recommendations on seeds, fertilizers, and best agricultural practices, thereby promoting sustainable agricultural productivity in the region.



MATERIALS AND METHODS

The development of FeSeRWAM involved a collaborative effort between various stakeholders, including the International Fertilizer Development Center (IFDC) and the West and Central African Council for Agricultural Research and Development (CORAF). Funded by USAID through the Feed the Future *Enhancing Growth through Regional Agricultural Input Systems* (EnGRAIS) and *Partnership for Agricultural Research, Education, and Development* (PAIRED) projects, FeSeRWAM App builds on the FeSeRWAM website's is ton and tons of agronomic data. It utilizes big data technologies, is mobile, is in the hands of the user, accessible instantaneously to deliver site-specific recommendations. The application integrates data from over 350 stakeholders across national and regional organizations. It provides recommendations for more than 650 agro-input packages (AIPs) on 21 crops, and 578 seed varieties and 62 fertilizer grades for 15 ECOWAS countries as well as Mauritania and Chad. The tool is designed to be user-friendly, enabling farmers, extension agents, and agro-input dealers to access critical information easily.

- **Technological Infrastructure:** It is accessible via mobile applications on Android (feserwam – Applications Android sur Google Play), and iOS for iPhone and iPad (FeSeRWAM on the App Store (apple.com)) devices. The entire system is hosted on a cloud platform, allowing for scalable processing power, data storage, and real-time analytics.

- **Data sources and analysis:** It utilizes big data technologies to process vast amounts of agronomic data to generate accurate and localized recommendations. The information presented on the FeSeRWAM mobile app is sourced directly from the agricultural research institute's databases.
- **Training Materials and support:** Educational resources, including user manuals, video tutorials, and community workshops, were developed to ensure effective use of FeSeRWAM by farmers. These materials address both technological and agricultural literacy. Farmers receive training on using FeSeRWAM through workshops and online resources. Ongoing support is provided via a dedicated helpdesk and community forums.
- **User Interaction**: Farmers interact with FeSeRWAM through a user-friendly interface on their mobile devices. The app provides personalized advice based on the specific needs of their farms.
- **Cost**: The mobile app requires a smartphone and an internet connection to use. Currently, it is free for users because it was developed as part of a project.

RESULTS AND DISCUSSION

Increased capacity of extension services

The FeSeRWAM app plays a key role in disseminating knowledge and best practices by extending the reach of agricultural extension services. The mobile application's guidance on good agricultural practices and nutrient management are particularly valued. FeSeRWAM also promotes sustainable agricultural practices. The application facilitates better resource management, reducing the environmental impact of farming activities.

Enhanced Productivity

Since its launch and its implementation, FeSeRWAM has demonstrated significant improvements in agricultural productivity in West Africa. The app has enabled over 600,000 farmers to access vital information on improved seeds and appropriate fertilizers, leading to increased crop yields and enhanced food security. By providing specific recommendations, FeSeRWAM helps farmers make informed decisions, optimize input use, and adopt sustainable agricultural practices.

The FeSeRWAM mobile application has shown promising potential to enhance agricultural productivity through improved advice and guidance. While it may be premature to claim definitive yield increases directly attributable to the app, early indications suggest farmers who have adopted the recommended practices are experiencing positive outcomes.

For instance, in collaboration with the Institut Togolais de Recherches Agronomiques (ITRA) and the Institut de Conseil et d'Appui Technique (ICAT), the EnGRAIS project trained many extension agents to support farmers in using the FeSeRWAM app and adopting the recommended agricultural best practices. Bakoundi Ayékénam Nadège, a rice and maize farmer who is part of a 19-member cooperative at Akaglakopé, participated in one of these training programs covering soil preparation, sowing, fertilizer application, and other good practices. She reported that, “after adopting these practices, her cooperative's rice yields doubled from one-and-a-half tons per hectare to three metric tons per hectare.”

Economic Impact

FeSeRWAM has shown positive economic potential for farming communities. There is a direct cause between using the app and increased incomes has not yet been conclusively demonstrated, the improved agricultural practices enabled by FeSeRWAM can reasonably be expected to lead to enhanced productivity and farm revenues.

DISCUSSION

Empowering Farmers

FeSeRWAM represents a significant advancement in the digitalization of agriculture in West Africa by empowering farmers with timely and relevant information. By leveraging technology to provide tailored agricultural advice, the App addresses key challenges faced by farmers, such as low yields and limited access to quality inputs. The FeSeRWAM is designed to be accessible to all farmers including women and youth. The FeSeRWAM is especially friendly to women and youth users. The success of FeSeRWAM underscores the importance of digital tools in enhancing agricultural productivity and sustainability. However, the FeSeRWAM's effectiveness depends on regular updates. Ensuring that farmers are aware of and can access FeSeRWAM is crucial for its sustained impact. The innovative training programs and awareness campaigns can help increase the adoption of the tool among farmers and other stakeholders. Moreover, expanding the app's capabilities to include more crops and regions can further enhance its utility. Collaboration with local agricultural organizations and continuous feedback from users will be essential in refining and improving FeSeRWAM.

Addressing Challenges

While FeSeRWAM has shown considerable benefits, challenges remain. Accessibility to technology in remote areas, variability in digital literacy, and infrastructure limitations are notable hurdles. Addressing these challenges requires continued investment in digital infrastructure, targeted training programs, and support for low-tech solutions.

Prospects

Looking ahead, FeSeRWAM can be enhanced with additional features such as agricultural-based technologies that improve Nutrient Use Efficiency (NUE) and integration of a decision support tool (DST) based on economic returns for smart AIPs selection. Expanding its reach and functionality could further bolster agricultural sustainability and productivity in the region.

REFERENCES

IFDC, 2024. Enhancing Agricultural Productivity in West Africa by Empowering Women Aggregators. Empowering Women Aggregators through Training - IFDC

IFDC, 2022. IFDC and CORAF Release Updated Online Tool to Promote Use of Innovative Technologies for West African Farmers to Increase Agricultural Productivity and Profits. IFDC and CORAF Release Updated Online Tool to Promote Use of Innovative Technologies for West African Farmers to Increase Agricultural Productivity and Profits - IFDC

IFDC, 2021. EnGRAIS and PAIRED Validate Strategy and Action Plan for FeSeRWAM and AIP's Dissemination. EnGRAIS and PAIRED Validate Strategy and Action Plan for FeSeRWAM and AIP's Dissemination - IFDC

IFDC, 2020. FeSeRWAM, a New Digital for Agriculture (D4AG) Tool Launched. FeSeRWAM, a New Digital for Agriculture (D4AG) Tool Launched - IFDC

A FRAMEWORK FOR A CROP YIELD PREDICTION MODEL BASED ON DECISION TREE AND MIN-MAX SCALING

S.A. Audu, A.A. Rabiu, G.I.O. Aimufua, M. Samaila, A.M. Umar, and M.A. Yau
[1,2,3,5,6]Department of Computer Science, Nasarawa State University, Keffi, Nigeria
[4]Department of Computer Science, Federal University Gusau, Zamfara, Nigeria
e-mail: samailaagp@gmail.com; +234 8065670727

ABSTRACT

The prediction of crop yield has become critical for enhancing global food security. This study presents a framework for agricultural yield prediction, employing a decision tree-based mathematical model integrated with Min-Max scaling. A dataset comprising 28,241 entries was collected from the Food and Agriculture Organisation (FAO) and the World Data Bank (WDB). Variables include nation, crop type, year, rainfall, pesticide usage, and temperature. The model achieved an accuracy of 97.8%, demonstrating that crop variety significantly influences agricultural output, while temperature and pesticide usage impact yield more than rainfall. The findings provide actionable insights into optimizing agricultural productivity by identifying key influencing factors. This research offers a robust decision-making tool for stakeholders aiming to enhance food security and agricultural efficiency.

Keywords: Crop yield, decision tree, prediction framework, Min-Max scaling, agricultural productivity.

INTRODUCTION

The agricultural sector faces numerous challenges, including climate variability, environmental degradation, labor costs, resource limitations, and conflicts such as herdsmen-farmer clashes and banditry. Additionally, the need to sustain agricultural practices while preserving the environment complicates efforts to meet food demands for growing populations. These challenges underscore the importance of technological innovations for improving crop productivity without compromising quality (Mittal et al., 2020).

Crop yield forecasting is vital for achieving food security. It supports decision-making for farmers, industries, and governments by estimating production levels based on various factors, such as soil properties, fertilizer use, irrigation management, and climatic variables like temperature and rainfall (Khaki et al., 2020). Optimizing these factors, coupled with effective policies, can significantly enhance agricultural productivity.

This study focuses on yield management, which integrates all agricultural processes into the final productivity outcome. By leveraging predictive modeling, stakeholders can improve agricultural efficiency, meet growing food demands, and inform government decisions regarding food imports (Juvanna et al., 2021). This research aims to develop a framework for crop yield prediction, emphasizing the role of climatic and agronomic variables. Beyond a shadow of a doubt, predicting crop yield is another way of increasing the productivity of agricultural products to meet the growing demand for food and to advise the government on the amount of food to be imported based on the estimated yield as outlined in the study by (Juvanna et al., 2021)

MATERIALS AND METHODS

The crop yield prediction framework integrates climatic, agronomic, and other variables (Figure 1). Key variables include temperature, precipitation, seed variety, soil water content, and soil fertility rate.

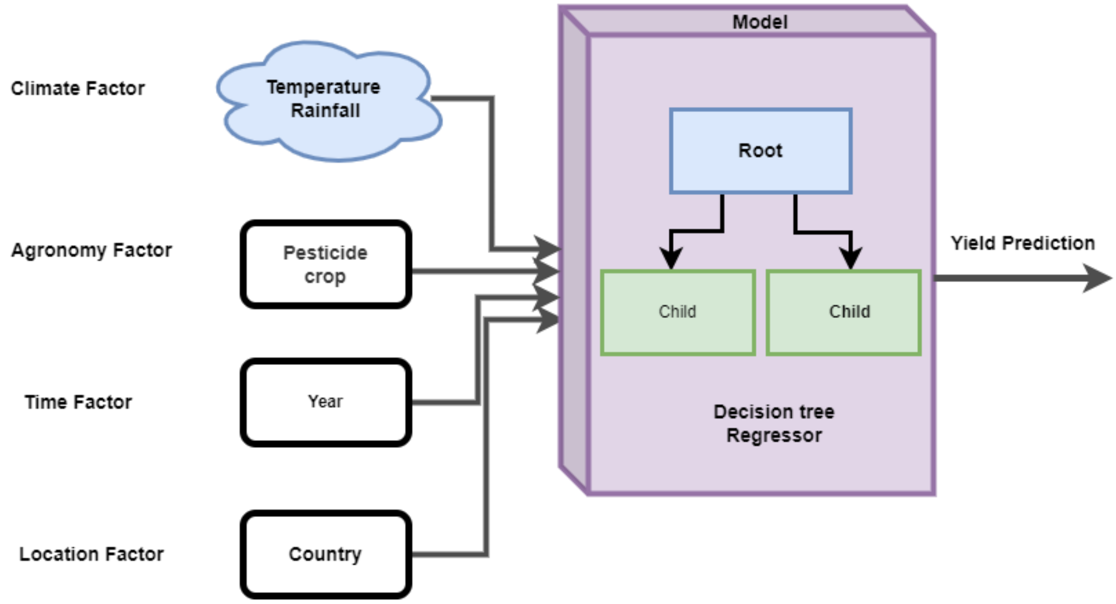


Figure 1. Crop Yield Prediction Framework.

Climatic Factors

Temperature and precipitation are pivotal to crop yield. Studies reveal that extreme climatic conditions, such as high temperatures and limited precipitation, adversely affect agricultural productivity (Beillouin et al., 2020; Guo et al., 2021).

Agronomic Factors

Pesticides play a critical role in mitigating crop losses. Research by Tudi et al. (2021) highlights that pesticide use prevents substantial losses in global fruit, vegetable, and grain production. Thus, pesticides significantly contribute to higher agricultural yields by minimizing the impact of pests and diseases.

Other Variables

Additional factors include the type of crop, the country of cultivation, and historical yield data. These variables are critical inputs for the proposed framework.

Decision Tree-Based Crop Yield Model Development

The proposed system architecture (Figure 2) outlines the stages from data collection to model training. Data preprocessing includes normalization using Min-Max scaling to ensure uniformity. The normalized dataset is split into training and testing subsets, with the decision tree (DT) regressor trained on the former. The model predicts crop yield using the trained DT algorithm.

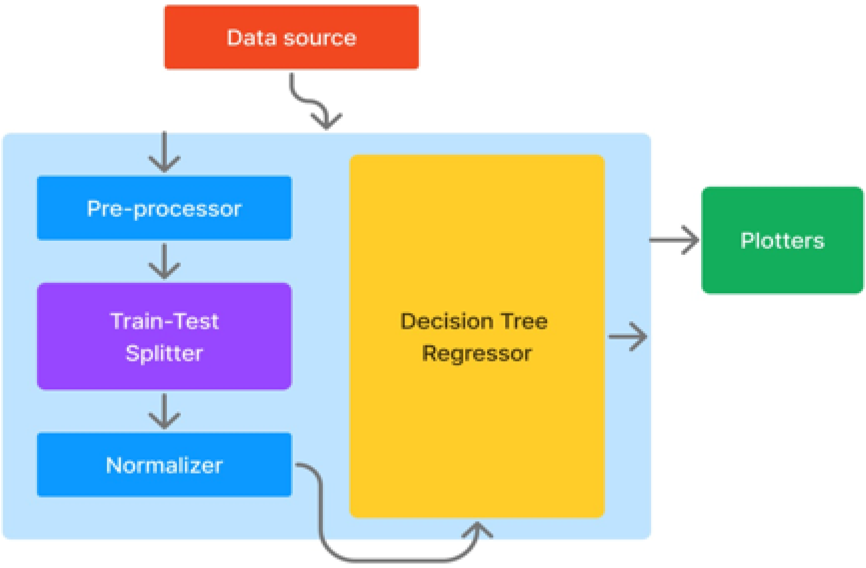


Figure 2. System Architecture for Decision Tree based Crop Prediction.

RESULTS AND DISCUSSION

The model's performance was evaluated using training and validation scores, which demonstrated its accuracy and generalization capability (Figure 3). Variable importance was assessed using the regressor feature_importances_ function, revealing that crop type is the most significant predictor of yield. Temperature and pesticide usage follow closely, with rainfall contributing less than expected (Figure 4).

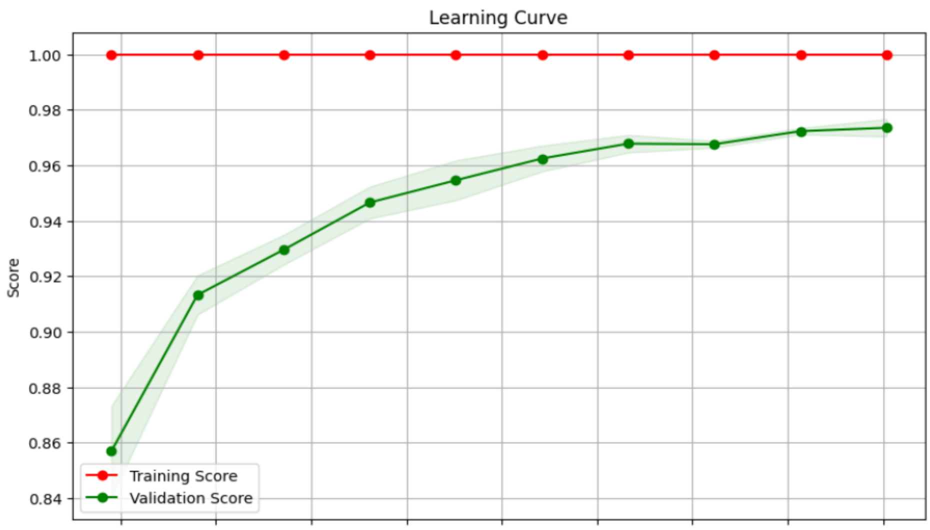


Figure 3. The Validation and the Learning Curve

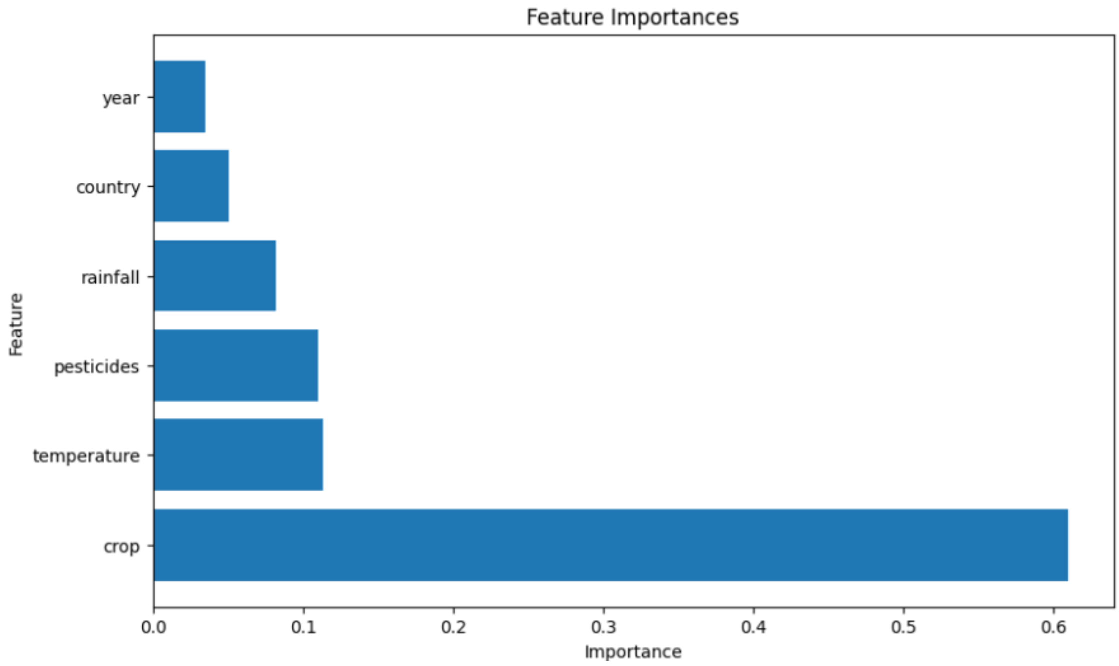


Figure 4. Bar Chart of order of Importance of the Features.

The results underscore the importance of integrating agronomic and climatic factors in predictive models. The high accuracy (97.8%) indicates the model's potential as a decision-support tool for policymakers and farmers to enhance agricultural productivity.

CONCLUSION

This study developed a decision tree-based crop yield prediction framework incorporating Min-Max scaling. The findings highlight the dominant role of crop variety, temperature, and pesticide usage in determining yield. The framework provides a reliable tool for stakeholders to optimize agricultural output and address food security challenges. Future research could explore integrating additional variables, such as soil texture and socio-economic factors, to further refine predictive accuracy.

REFERENCES

Beillouin, D.; Schauberger, B.; Bastos, A.; Ciais, P.; and Makowski, D. (2020). Impact of extreme weather conditions on European crop production in 2018: Random forest - Yield anomalies. Philosophical Transactions of the Royal Society B: Biological Sciences, 375(1810). https://doi.org/10.1098/rstb.2019.0510

Cunha, R. L. D. F.; and Silva, B. (2020). Estimating Crop Yields with Remote Sensing and Deep Learning. 2020 IEEE Latin American GRSS and ISPRS Remote Sensing Conference, LAGIRS 2020 - Proceedings, 273–278. https://doi.org/10.1109/LAGIRS48042.2020.9165608

Guo, Y. ; Xiang, H. ; Li, Z. ; Ma, F. ; and Du, C. (2021). Prediction of rice yield in east China based on climate and agronomic traits data using artificial neural networks and partial least squares regression. Agronomy, 11(2). https://doi.org/10.3390/agronomy11020282

Juvanna, I.; Yuvesh, Balaji V. G.; Sri Raam, M. A.; and Karthikeyan, T. (2021). A Novel Framework Crop Yield Prediction Using Data Mining. Turkish Journal of Computer and Mathematics Education, 12(10), 350–356.

Kavitha, M.; Anusha, K.; Santhi, M. V. B. T.; Rajesh, N.; and Choragudi, F. (2020). Predicting Crop Yield using Neural Network with Optimal. 32(2), 3028–3036.

Khaki, S.; Wang, L.; and Archontoulis, S. V. (2020). A CNN-RNN Framework for Crop Yield Prediction. Frontiers in Plant Science, 10(January), 1–14. https://doi.org/10.3389/fpls.2019.01750

Martinez-Ferrer, L.; Piles, M.; and Camps-Valls, G. (2020). Crop Yield Estimation and Interpretability With Gaussian Processes. IEEE Geoscience and Remote Sensing Letters, XX(1), 1–5. https://doi.org/10.1109/lgrs.2020.3016140

Mittal, D.; Kaur, G.; Singh, P.; Yadav, K.; and Ali, S. A. (2020). Nanoparticle-Based Sustainable Agriculture and Food Science: Recent Advances and Future Outlook. Frontiers in Nanotechnology, 2(December). https://doi.org/10.3389/fnano.2020.579954

Nishant P. S.; Venkat P.S,; Avinash B. L.; and Jabber B., "Crop Yield Prediction based on Indian Agriculture using Machine Learning," 2020 International Conference for Emerging Technology (INCET), 2020, pp. 1-4, DOI: 10.1109/INCET49848.2020.9154036

Nosratabadi, S.; Ardabili, S.; Lakner, Z.; Mako, C.; and Mosavi, A. (2021). Prediction of food production using machine learning algorithms of multilayer perceptron and anfis. *Agriculture* (Switzerland), 11(5) pp. 1-13. https://doi.org/10.3390/agriculture11050408

Tudi, M.; Ruan, H. D.; Wang, L.; Lyu, J.; Sadler, R.; Connell, D.; and Chu, C. (2021). Agriculture Development, Pesticide Application and Its Impact on the Environment. PP. 1–23.

EDUCATION AND ENGAGEMENT IN PRECISION AGRICULTURE

INTER-COUNTRY COOPERATION CAN TRANSFORM PRECISION AGRICULTURE EDUCATION AND RESEARCH IN AFRICA

#11628

Kwame Agyei Frimpong
African Plant Nutrition Institute (APNI)
e-mail: k.frimpong@apni.net

ABSTRACT

The productivity and profitability of sub-Saharan (SSA) agriculture can be greatly enhanced by the adoption of precision agriculture technologies and tools. However, until 2020 when the African Plant Nutrition Institute (APNI) established the African Association for Precision Agriculture (AAPA), most SSA PA enthusiasts worked in isolation. The AAPA was formed to innovate Africa's agricultural industry by connecting PA science to its practice and disseminating PA tailored to the needs and aspirations of the African people. This paper highlights the leverage that intra-Africa cooperation such as the AAPA offers to transform PA education, research, and outreach in Africa. The paper further presents activities and milestones that the AAPA has chalked in the last two years. So far, the AAPA has provided opportunities for members to engage in research, extension, education, and training activities to promote the advancement and dissemination of PA tailored to the needs and aspirations of the African people and the furtherance of international collaborations. These opportunities include a Global Challenge Research Fund networking forum, and EU funding to promote leadership skills development, advocacy, and engagement among five African universities and a European partner. In conclusion, intra-Africa cooperation through AAPA has catalyzed the enthusiasm and willingness of universities in African countries to work together to develop and scale precision agriculture (PA) education, research, and outreach to reduce skill gaps and tackle food and nutritional security challenges in African countries.

INTRODUCTION

Precision agriculture (PA) has gained considerable recognition as a farm management strategy to improve resource economy, farm productivity, and profitability to enhance the sustainability of agricultural production systems (Wang et al., 2023; Ofori and El-Gayar, 2021). However, the application of PA technologies is yet to be widely adopted in smallholder farms in sub-Saharan Africa (SA). The World Bank (2021) estimated that agriculture employs 52% of the SSA adult population and contributes to about 17% of the region's gross domestic product (GDP). Despite the critical contribution of the agricultural sector to the economic development of the continent, the sector is inherently characterized by low productivity and low income for farmers (Abay et al., 2023; Marinus et al., 2022), and so the agriculture industry is unattractive for the youth. The burgeoning SSA population growth (World Bank, 2022b), and the impacts of climate change make it imperative for the adoption of innovative agricultural technologies to meet food and nutrition demands in the region. Adoption of precision agriculture is a promising pathway to transform agricultural productivity and profitability in SSA and incentivize the youth in the region to embrace agricultural production as a profitable livelihood option. Nyaga et al. (2021) contended that the low adoption rate of PA in SSA could be attributed to the lack of awareness and information among smallholder farmers and other agriculture stakeholders in SSA.

Therefore, there is a need to equip farmers, extension agents, and the youth in SSA with the relevant information and knowledge and provide the necessary tools to drive PA use for sustainable agriculture in the continent. Studies have been done on the potential for PA to improve farm productivity and profitability (Wang et al., 2023) adoption decisions (John et al., 2023; DeLay et al., 2022; Lowenberg-DeBoer and Erickson, 2019), the opportunities and challenges of precision agriculture for farmers (Khanna et al., 2022; Bosompem, 2021; Nyaga et al., 2021; Ofori and El-Gayar, 2021) and the role of data management for the deployment of precision agriculture (Gobezie and Biswas, 2023). However, there is a paucity of information about how African countries can leverage the power of collaboration and networking to transform agricultural production in their countries through inter-country collaboration. The objective of this paper was to highlight the potential of inter-country cooperation to transform precision agriculture education and research in Africa. Specifically, this paper provides practical examples of inter-country collaboration in the region, which have amply demonstrated that these collaborations can foster co-development and co-implementation of PA research, education, and outreach actions to increase awareness, motivate, and build the capacity of farmers, extension agents and students in the region.

MATERIALS AND METHODS

The paper presents an overview of three examples of inter-country collaborations – The African Association for Precision Agriculture (AAPA), the Global Challenge Research Fund (GCRF) networking forum, and the EU-funded 'Capacity Building of African Young Scientists in Precision Agriculture Through Cross-Regional Academic Mobility for Enhanced Climate-Smart Agri-Food System' (PATH) project, which have provided opportunities for faculty, postgraduate students, and staff of some African universities to engage in advocacy and networking fora to promote the advancement and dissemination of PA tailored to the needs and aspirations of the African people. The paper highlights some successes that the AAPA has achieved since its formation in 2020. The overview is supported by information from published and grey literature.

RESULTS AND DISCUSSION

The inter-country collaborations among African countries within the AAPA is a typical example of how such cooperation can promote PA education, research and outreach in the continent. The AAPA was formed by the African Plant Nutrition Institute (APNI) in 2020. The AAPA boasts of a membership of 628 registered members from 51 countries. The objectives, activities and board composition of the AAPPA are summarised in Table 1.

The AAPA have organised webinars and published newsletters, as well as supported the organization of the African Conference for Precision Agriculture in 2020 and 2022. Another example of inter-country collaboration is the GCRF-funded networking forum that was held at the University of Cape Coast in Ghana. The forum was a collaborative project between the Harper Adams University of the United Kingdom, the University of Cape Coast, and the University for Development Studies, both in Ghana, the University of Abomey Calavi in Benin, and the Institute of Agricultural Research and Training in Nigeria. The forum attracted participants from the Ministry of Food and Agriculture, Ghana, Non-governmental organizations, and agro-input dealers. An important outcome of the networking forum is the EU-funded PATH. Project, which is a collaborative project among four universities from West, East, and Southern Africa, a northern African associate partner, and a European technical partner, respectively, to promote leadership skills development, advocacy, postgraduate education, and research. The partnering institutions, objectives, and target crops of the PATH project are presented in Table 2.

Table 1. Objectives, activities and board membership of the AAPA

Objectives	Activities	Board membership
The AAPA provides opportunities for members to engage in research, extension, education, and training activities to promote the advancement and dissemination of PA tailored to the needs and aspirations of the African people; the furtherance of international collaborations; leadership skills development; advocacy; and engagement with policymakers toward creating the enabling environment needed to advance the knowledge of the science and practice of PA in Africa.	Publishes a quarterly newsletter; leads professional community within the International Society of Precision Agriculture (ISPA); and organizes workshops and symposiums at the African Conference on Precision Agriculture (AfCPA), and the International Conference on Precision Agriculture (ICPA). AAPA also organizes and hosts webinars on various topics in precision agriculture.	• President (Nigeria) • Past President (Ghana) • President-elect (Benin): • Executive secretary (Morocco) • Regional Representatives North Africa (Tunisia), West Africa (Togo), Central Africa (Cameroon), East Africa (Tanzania), and Southern Africa (Zimbabwe): • Founder: Steve Phillips (APNI)

Table 2. Capacity Building of African Young Scientists in Precision Agriculture Through Cross-Regional Academic Mobility for Enhanced Climate-Smart Agri-Food System (PATH) Project

Objectives	Universities involved	Countries involved	Target crops
• Training 32 MSc and 12 PhD African scholars in Precision Agriculture (PA) to upgrade the continent's capability • Building the capacity of 10 young African trainees and 10 staff in PA and entrepreneurship • Improving PAAC and ICT4Ag curricula and research at the participating African Higher • Education Institutions (HEIs) to address more efficiently the current challenges of agriculture and climate change • Developing a network of HEIs in Africa involved in PAAC research and training	• University of Abomey Calavi • University of Cape Coast • University of Rwanda • University of Eswatini • University of Mohammed VI Polytechnic • Laboratoire Univers et Particules de Montpellier	• Benin (lead) • Ghana (Co-lead) • Rwanda (Co-lead) • Eswatini (Co-lead) • Morocco (Associate partner) • France (Technical partner)	• soybean, rice, tomato and pineapple between Ghana and Benin • groundnut between Benin and Eswatini • rice and potato between Benin and Rwanda • beans between Eswatini and Rwanda • taro and sweet potato between Ghana and Eswatini • sorghum and taro between Ghana and Rwanda

Potential benefits from Intra-Africa collaboration

African countries can harness available skills, expertise, and infrastructure in their countries to drive the PA agenda through knowledge sharing, and a culture of collaborative learning. Inter-country cooperation can also foster mutual deployment of digital technologies to enhance agricultural productivity, increase access to markets and finance, and improve food security. An analysis of the Baobab Insights companies' 2015 database showed that more than 40 innovative start-ups are established in Africa that provide various precision farming technologies and services with t 50% of these companies based in Nigeria, Kenya and South Africa. Universities, and other agricultural organizations in Africa can pool resources, coordinate their research efforts to avoid duplication of efforts and harmonize common research actions, and develop comprehensive training programs for farmers, extension workers, and students. The "Digital Transformation Strategy for Africa (2020-2030) of the African Union outlines the vision and objectives for Africa to leverage digital technologies for economic and social development (African Union, 2020). In June 2021, a high-level dialogue among Head of States of African countries on Feeding Africa pointed out the need for technology-led agriculture that can increase crop productivity, and improve product quality including post-harvest losses reduction while mitigating the negative effects of climate changes (drought, flooding, pest outbreak etc.

Challenges and the way forward

Intra-Africa cooperation in PA education, research and outreach is constrained by the lack of PA expertise, tools, and facilities in SSA education and research institutions, Further, there are limited financial commitments and enabling policies towards integrating PA into ongoing country-specific agricultural development programmes. Other challenges that inter-country cooperation face include the high costs of mobile technology and internet, which is exacerbated by unreliable electricity supply, low ICT literacy levels, and lack of financial resources to secure the use of ICTs.

CONCLUSION

Inter-country cooperation is crucial to support the farmers and other agriculture stakeholders in SSA. These cooperations can promote co-learning and sharing of scientific, technical, and market information. Thus, it is imperative to link universities and other agricultural institutions in Africa to tackle knowledge and skills gaps, while facilitating participatory research, and enhancing results dissemination. Inter-country cooperation can stimulate investment in digital infrastructure, technical capacity building, and policy support to unlock the potential of PA to improve the productivity and profitability of agriculture in Africa.

REFERENCES

1. Abay, K. A., Wossen, T., & Chamberlin, J. (2023). Mismeasurement and efficiency estimates: Evidence from smallholder survey data in Africa. Journal of Agricultural Economics, 74(2), 413-434.
2. Bosompem, M. (2021). Potential challenges to precision agriculture technologies development in Ghana: Scientists' and cocoa extension agents' perspectives. Precision Agriculture, 22(5), 1578-1600
3. DeLay, N. D., Thompson, N. M., & Mintert, J. R. (2022). Precision agriculture technology adoption and technical efficiency. Journal of Agricultural Economics, 73(1), 195-219.

4. Khanna, M., Atallah, S. S., Kar, S., Sharma, B., Wu, L., Yu, C., ... & Guan, K. (2022). Digital transformation for a sustainable agriculture in the United States: Opportunities and challenges. Agricultural Economics, 53(6), 924-937.
5. Lowenberg-DeBoer, J. (2019). The economics of precision agriculture. In Precision agriculture for sustainability (pp. 481-502). Burleigh Dodds Science Publishing
6. Marinus, W., Thuijsman, E. S., van Wijk, M. T., Descheemaeker, K., van de Ven, G. W., Vanlauwe, B., & Giller, K. E. (2022). What farm size sustains a living? Exploring future options to attain a living income from smallholder farming in the East African Highlands. Frontiers in Sustainable Food Systems, 5, 759105.
7. Nyaga, J. M., Onyango, C. M., Wetterlind, J., & Söderström, M. (2021). Precision agriculture research in sub-Saharan Africa countries: A systematic map. Precision Agriculture, 22, 1217-1236.
8. Ofori, M., & El-Gayar, O. (2021). Drivers and challenges of precision agriculture: a social media perspective. Precision Agriculture, 22, 1019-1044.
9. Wang, T., Jin, H., Sieverding, H., Kumar, S., Miao, Y., Rao, X., ... & Cheye, S. (2023). Understanding farmer views of precision agriculture profitability in the US Midwest. Ecological Economics, 213, 107950.

ADVANCING PRECISION AGRICULTURE EDUCATION IN SUB-SAHARAN AFRICA: EXPLORING FACTORS FOR SUCCESS AND OBSTACLES

#12326

F.J. Adekoya, B.V. Bamidele, T.E. Adefare
Integrated Aerial Precision, Lagos, Nigeria
e-mail: femi@iaprecision.com; 2348136163231

ABSTRACT

Precision Agriculture (PA) is a critical tool for addressing food security challenges, yet its adoption in Sub-Saharan Africa (SSA) remains low. This study examines the role of education in advancing PA adoption, focusing on barriers and opportunities for integrating PA into the agricultural curriculum in SSA, with Nigerian institutions as a case study. A mixed-methods approach was employed, involving 227 respondents comprising faculty, undergraduate, and postgraduate students from tertiary institutions. Quantitative surveys assessed awareness, familiarity, and factors influencing PA adoption, while qualitative interviews explored curriculum integration and potential solutions.

Findings reveal a significant gap in PA education, with 57.71% of respondents reporting no exposure to PA-related courses. Familiarity with basic tools such as GPS and drones was moderate, while advanced technologies like robotics and telemetry were largely unfamiliar. Key barriers include limited curriculum integration, inadequate digital infrastructure, and insufficient faculty expertise.

The study underscores the importance of updating agricultural curricula to incorporate PA concepts, enhancing digital infrastructure for practical learning, and providing faculty development programs through workshops and certifications. These reforms are essential to equip future agricultural professionals with the skills needed to adopt and implement PA, thereby fostering a skilled workforce capable of leveraging advanced technologies for sustainable agriculture. This research highlights the transformative potential of education in overcoming barriers to PA adoption, contributing to enhanced agricultural productivity and food security in SSA.

Keywords: Precision Agriculture, Sub-Saharan Africa, Agricultural Education, Technology Adoption.

INTRODUCTION

Globally, food production is projected to increase by 50% by 2050 to meet the needs of the rapidly growing population (FAO, 2020). Achieving this demand is unlikely without advanced technologies to improve food security, as traditional methods alone may fall short. Precision Agriculture (PA) has emerged as a vital approach to meet these challenges, focusing on efficiency, sustainability, and productivity. It relies on advanced technologies, including Geographic Information Systems (GIS), remote sensing, drone technology, and data analytics, to improve crop production while minimizing environmental impact (Gebbers & Adamchuk, 2010).

While Precision Agriculture (PA) is gaining momentum in developed countries due to advancements in technology and infrastructure (Fountas et al., 2020; Roberts et al., 2021), Sub-

Saharan Africa (SSA) has been slower to adopt these innovations due to barriers such as limited digital infrastructure, high costs, and a lack of technical expertise (Mabaya et al., 2022; Tsan et al., 2019).

The education sector plays a crucial role in accelerating PA adoption by equipping farmers, agronomists, and extension workers with the skills necessary to implement these advanced technologies. With a growing population and the urgent need for food security, particularly in Sub-Saharan Africa (SSA), PA presents significant potential for improving agricultural productivity in the region. However, the successful adoption and implementation of PA largely depends on the level of education, awareness, and skill proficiency of the agricultural workforce (Tsan et al., 2019).

Precision agriculture education when incorporated into the Education curricula could increase the adoption of data-driven technologies and enhance the quality of agricultural education in Sub-Saharan Africa (SSA). However, for SSA where agriculture is a key livelihood and food security is a priority, this incorporation would mean that students enter the workforce well-prepared to contribute to resilient, productive agricultural systems.

This study aims to access the level of knowledge about precision agriculture in the education system in Sub-Saharan Africa, using university faculty, undergraduate, and postgraduate students in Nigeria as a case study to examine the familiarity with PA tools and technologies, and the factors and barriers influencing their willingness to adopt PA or become an expert in PA tools and the extent of PA integration in the academic curriculum.

MATERIAL AND METHODOLOGY

This study which was conducted in Nigeria adopted a mixed-method approach to retrieve data from penultimate year students, final-year students, postgraduate students, and lecturers of the Faculty of Agriculture across tertiary institutions in Nigeria. Quantitative data were gathered through a structured questionnaire, while qualitative data was collected using an in-depth interview.

The questionnaire was structured to gather information from respondents regarding their socio-economic characteristics, awareness and familiarity with Precision agriculture tools, and factors influencing their willingness to adopt PA or become an expert in PA tools. In addition, the qualitative interview contained questions regarding the integration of PA into educational curriculum as well as recommendations to the government and educational institutions. The study employed a purposive sampling method to collect data from 227 respondents across six geopolitical zones and analyzed using STATA. The analytical approaches used were descriptive statistics such as percentage and frequencies to examine the socio-economic characteristics, likert scale to measure level of familiarity with precision tools and willingness to adopt precision agriculture tools was analyzed using linear regression. The qualitative responses were then analyzed using thematic analysis.

RESULT AND DISCUSSION

The discussion shows that most respondents are male (62.55%). This agrees with (Luka et al., 2023; Omotosho et al., 2020) who conducted a survey and found higher male participation in agricultural-related careers. A greater proportion of the respondents (62.55%) fall within the age bracket of 18-30. This is like the findings of (Luka et al., 2023) who found the mean age of agricultural students in Bauchi state to be 27 years indicating that their mean age is between 18 -30 years.

Based on the proportion of respondents who had been taught or taken any course relating to Precision Agriculture, most of the respondents (57.71%) had never taught or taken any course relating to PA. This likely implies that most of the agricultural students in Nigeria have not been exposed to the concept of precision agriculture via their institutions. This agrees with the findings of Adepoju et al., 2022 and Nyaga et al., 2021 who found in their studies that a significant gap exists in the learning and teaching of precision agriculture in tertiary institutions in Nigeria as many students have not been exposed to courses relating to PA.

Table 1. Demographic characteristics of respondents.

Variables	Categories	Frequency	Percentage
Sex	Female	85	**37.44**
	Male	142	**62.56**
Age	18-30	142	**62.55**
	31-50	79	**34.80**
	51-65	6	**2.6**
	Min	18	
	Max	62	
Category of respondents	Finalist	62	27.31
	Lecturer/staff	42	18.50
	Penultimate year	28	12.33
	Post graduate Student	95	41.85
Taught or taken any course in Precision Agriculture	No	131	**57.71**
	Yes	96	**42.29**

Table 2. Level of familiarity with precision agriculture tools.

PA Tool	Extremely Familiar	Moderately Familiar	Not Familiar At All
Variable Rate Application	9 (3.96)	85 (37.44)	116 (51.10)
GPS/GNSS	9 (3.96)	98 (43.17)	85 (37.44)
Yield and Soil Moisture Sensor	6 (2.64)	78 (34.36)	120 (52.86)
Drones	6 (2.64)	98 (43.17)	86 (37.89)
GPS Tracker	9 (3.96)	92 (40.53)	80 (35.24)
Digital Fencing	6 (2.64)	81 (35.68)	121 (53.13)
Field Sensor	5 (2.26)	85 (37.44)	113 (49.78)
Data Analytics	7 (3.08)	105 (46.26)	86 (37.88)
Digital Soil maps	6 (2.64)	80 (35.24)	119 (52.42)
Telemetry Systems and Automation Tech	6 (2.64)	48 (21.15)	165 (72.69)
Machine Vision Tech for livestock	4 (1.76)	53 (23.35)	159 (70.04)
Automated Feeding System for Livestock	7 (3.08)	96 (42.29)	89 (39.21)
Robotic Milking Systems	4 (1.76)	7 (33.04)	131 (57.71)
Electronic Identification for Livestock	6 (2.64)	79 (34.80)	12.5 (55.07)

The survey reveals that the respondents are familiar with basic tools such as GPS, Drones, and Data Analytics in Precision Agriculture and less familiar with advanced tools like Robotic Milking systems, Telemetry systems, and automation technology.

Willingness to adopt precision agriculture tools

Performance expectancy (PE): For every one-unit increase in Performance Expectancy, the behavioural intention to adopt PA increases by approximately 0.752 units. This strong positive relationship suggests that respondents believe that adopting PA will significantly enhance their performance, making this factor crucial in influencing their willingness to engage with PA technologies. This finding is like the result of Eweoya et al., 2021, who conducted a survey and found that performance expectancy is the most significant factor that influences the adoption of e-agriculture in Nigeria. In addition, Lee et al. (2023) highlights that performance expectancy significantly predicts professionals' intention to adopt precision agriculture technologies. This emphasizes the importance of demonstrating clear and tangible benefits of such technologies to potential users.

Effort Expectancy (EE): the coefficient of 0.214 indicates that EE positively influences adoption, though its effect is smaller compared to PE. This suggests that when PA technologies are perceived as easier to use, the students and lecturers are more likely to consider adoption ($p < .01$) or become experts in PA technology. This agrees with Al-zboon et al., 2022, that effort expectancy is positive and significant to the attitude of science and mathematics teachers towards integrating ICT in their teaching activities.

Social influence: The result shows that SI, with a coefficient of 0.048, is not statistically significant ($p = .292$), implying that social factors—such as recommendations from others do not have a strong impact on adoption intentions for Precision agriculture technology. This agrees with Tey and Brindal (2012), that while social factors like recommendations can play a role, they are typically weaker predictors of technology adoption in precision agriculture compared to economic and technical factors, such as perceived financial benefits, ease of use, and productivity improvements.

Facilitating Conditions: The coefficient of 0.248 for FC is significant, indicating that when supportive resources or infrastructure are available, the likelihood of adoption or tendency to become an expert by the respondents, increases ($p < .01$). This is like the findings of Reichardt and Jurgens, (2009). In their research, Reichardt and Jürgens found that access to supportive infrastructure, such as technical resources and financial support, significantly enhances the adoption of precision agriculture technologies. Their findings highlight that when farmers have the necessary resources and infrastructure, they are more likely to adopt precision farming practices and improve their expertise over time.

Perceived Challenges: Having a negative coefficient of -0.217, PC significantly reduces the willingness to adopt or become an expert in PA. This suggests that the more challenges (e.g., high costs, technical difficulties) individuals perceive, the less inclined they are to adopt PA ($p < .01$). This agrees with Paustian and Theuvsen, 2017. In their study, they found that perceived challenges (e.g., high initial costs, complexity of use) were significant barriers to adopting precision agriculture technologies. Their analysis suggests that as perceived difficulties increase, farmers are less likely to adopt these technologies, highlighting a negative association between perceived challenges and adoption intentions.

Predictor Variables		Coefficient	Standard Error	T value	P value
Performance Expectancy average		0.752***	0.048	15.69	0.0000
Effort Expectancy average		0.214***	0.051	4.18	0.000
Social Influence average		0.048	0.046	1.06	0.292
Facilitating Condition average		0.248***	0.033	7.61	0.0000
Perceived Challenges average		-0.217***	0.041	-0.526	0.0000
Constant		-0.995	0.277	-0.360	0.0000
Mean dep Variable	484.495				
R- squared	1.000				
F-test	3460540.518				

Summary of the Qualitative Interview

Results of the qualitative interview show the perceived benefits of precision agriculture as it enhances speed and accuracy in farming, reduces the workload of the farmers and assists in farm-data collection. The Finalists and Postgraduate students cited drone technology, GPS, and sensors as the technology they are most familiar with. The respondents gave high cost and gap in knowledge as the major barriers in the adoption of the PA tools. The respondents further noted that the integration of PA into their educational curriculum was very low. In terms of the respondent's willingness to adopt or become experts in Precision Agriculture, the respondents noted that the provision of education and training to the younger generation will attract students to agriculture. As stated by one of the respondents “I have passion for training farmers. If I gain more knowledge, I will be able to train others” shows a willingness to enhance their knowledge and educate others too on precision agriculture.

CONCLUSION AND RECOMMENDATIONS

This study underscores the critical role of education in advancing Precision Agriculture (PA) adoption in Sub-Saharan Africa, with Nigeria as a case study. The findings reveal a significant gap in PA education, as many agricultural students lack exposure to PA concepts and tools due to insufficient curriculum integration. Despite these challenges, there is growing awareness among students and faculty about PA’s potential to transform farming practices and enhance food security. The study highlights performance expectancy, effort expectancy, and facilitating conditions as key drivers of PA adoption, while perceived challenges deter progress.

To address these gaps, educational institutions in SSA must prioritize updating agricultural curricula to integrate PA concepts and tools. Providing students with practical training on technologies such as drones, GPS systems, and data analytics is essential to preparing them for the evolving demands of modern agriculture. Investment in digital infrastructure is critical to ensure access to the necessary tools for hands-on learning.

Additionally, supporting faculty development through workshops, seminars, and certifications will enhance their ability to teach PA effectively and bridge existing knowledge gaps. By equipping both students and educators with the skills and resources required for PA adoption, institutions can foster a skilled workforce capable of leveraging advanced technologies for sustainable agriculture and improved food security.

REFERENCES

Adepoju, O., Esan, O., and Akinyomi, O. (2022). Food Security in Nigeria: Enhancing Workers' Productivity in Precision Agriculture. Journal of Digital Food, Energy & Water Systems. https://doi.org/10.36615/digital_food_energy_water_systems.v3i2.

Ajao, H., Alegbeleye, I., and Westfall-Rudd, D. (2022). Curriculum Design In An Agricultural Education Program In Nigeria: Towards Advancing Career Readiness. Advancements in Agricultural Development, 3(2), 17-30. https://doi.org/10.37433/aad.v3i2.159

Chaudhary, S., Patel, J., and Raval, K. (2023). Attitude And Aspiration Of Undergraduate Agricultural Students. Gujarat Journal of Extension Education. https://doi.org/10.56572/gjoee.2023.35.2.0007.

Ekea, U. U. (2019). Weed Science Education At The Tertiary Educational Level In Nigeria. Agriculture, Forestry And Fisheries, 8(1), 27. https://doi.org/10.11648/j.aff.20190801.15

Eweoya, I., Okuboyejo, S., Odetunmibi, O., and Odusote, B. (2021). An empirical investigation of acceptance, adoption and the use of E-agriculture in Nigeria. Heliyon, 7. https://doi.org/10.1016/j.heliyon.2021.e07588.

Food and Agriculture Organization (FAO). (2020). The State of Food Security and Nutrition in the World 2020.

Fountas, S., Mylonas, N., Malounas, I., Gemtos, T. A., & Blackmore, S. (2020). Precision Agriculture Technology in Fruit Production: Status, Challenges and Future Trends. Computers and Electronics in Agriculture, 170, 105309

Gebbers, R., & Adamchuk, V. I. (2010). Precision agriculture and food security. Science, 327(5967), 828-831.

Lee, C., Strong, R., Briers, G., Murphrey, T., Rajan, N., and Rampold, S. (2023). A Correlational Study of Two U.S. State Extension Professionals' Behavioral Intentions to Improve Sustainable Food Chains through Precision Farming Practices. Foods, 12. https://doi.org/10.3390/foods12112208.

Luka, J., Murtala, N., and Sani, M. H. (2023). Socio-Economic Factors Influencing Choice Of Agribusiness As Career Option After Graduation Among Agricultural Students Of Tertiary Institutions In Bauchi State, Nigeria. Nigerian Journal of Agriculture and Agricultural Technology, 3(1), 85-96.

Mabaya, E., & Gahakwa, D. (2022). Precision Agriculture in Africa: Addressing Food Security and Economic Transformation. African Journal of Science, Technology, Innovation and Development, 14(1), 50-58.

Nyaga, J., Onyango, C., Wetterlind, J., and Söderström, M. (2021). Precision agriculture research in sub-Saharan Africa countries: a systematic map. Precision Agriculture, 1-20. https://doi.org/10.1007/S11119-020-09780-W.

Nguyen, L., Khuu, D., Halibas, A., and Nguyen, T. (2023). Factors That Influence the Intention of Smallholder Rice Farmers to Adopt Cleaner Production Practices: An Empirical Study of Precision Agriculture Adoption.. Evaluation review, 193841X231200775. https://doi.org/10.1177/0193841X231200775.

Obi, B., and Oladokun, B. (2023). Security Measures in Meeting Information Needs and Seeking Behaviour of Agricultural Science Students in Nigerian Universities. Southern African Journal of Security. https://doi.org/10.25159/3005-4222/14383.

Omotosho, A., Emmanuel, A., Ayegba, P., and Ayoola, J. (2020). Impact of Agricultural Education on Students' Career Choice: A Survey. Int. J. Emerg. Technol. Learn., 15, 51-61. https://doi.org/10.3991/ijet.v15i03.11260.

Paustian, M., & Theuvsen, L. (2017). Adoption of precision agriculture technologies by German crop farmers. Precision Agriculture, 18(5), 701–716. https://doi.org/10.1007/s11119-016-9482-5

Reichardt, M., & Jürgens, C. (2009). Adoption and future perspective of precision farming in Germany: Results of several surveys among different agricultural target groups. Precision Agriculture, 10(1), 73–94. https://doi.org/10.1007/s11119-008-9101-1

Roberts, M. J., Schimmelpfennig, D., & Livingston, M. (2021). Precision Agriculture Adoption and Technical Efficiency. American Journal of Agricultural Economics, 103(2), 589–615

Tey, Y. S., and Brindal, M. (2012). Factors influencing the adoption of precision agricultural technologies: A review for policy implications. Precision Agriculture, 13(6), 713–730. https://doi.org/10.1007/s11119-012-9273-6

Tsan, M., Totapally, S., Hailu, M., & Addom, B. K. (2019). The Digitalisation of African Agriculture Report 2018–2019. CTA. Retrieved from https://cgspace.cgiar.org/handle/10568/101498

Yekinni, O., Ladigbolu, T., Adeniyi, R., and Oluwasusi, S. (2021). Information and Communication Technologies Usage among Agricultural Students of Tertiary Institutions in Southwest of Nigeria. The Journal of Agricultural Extension, 24, 1-10. https://doi.org/10.4314/JAE.V25I1.1.

YIELD OF MAIZE (*Zea mays* L.) VARIETIES AS AFFECTED BY NEEM OIL COATED UREA APPLICATION IN SOUTHERN BENIN

#11624

*Fassinou Hotegni V. Nicodeme, Houessou C. Gildas, Linkpon F. Orthia, Tchokponhoue A. Dedeou, Houdegbe Carlos, Adje Charlotte, Achigan-Dako Enoch
Genetics, Biotechnology and Seed Science Unit (GBioS), Laboratory of Crop Production, Physiology and Plant Breeding (PAGEV), Faculty of Agronomic Sciences, University of Abomey-Calavi, 01 P.O. Box 526, Cotonou, Republic of Benin.
*e-mail: nicodemef@gmail.com

ABSTRACT

Maize is one of the most important cereals grown and consumed in Benin Republic. In maize cultivation, huge amount of nitrogen is used contributing to soil and environment pollution. Despite such huge level of applied nitrogen, maize grain yield is still below 2 ton/ha. The aim of this study was to make available to the maize grain's farmers, an eco-friendly practice based on the use of Neem Oil Coated Urea (NOCU) for a high maize grain yield in Benin. An experiment was carried out from April 2023 to August 2023 using a split plot with four blocks design. The treatments consisted of the combination of four varieties (V1: DMR ESR-W, V2: EVDT 97 STR W, V3: 2000 SYN EE-W and V4: ABONTEM) and five levels of fertilization (T0: the control, T1: Urea only, T2: NOCU at 1%, T3: NOCU at 3% and T4: NOCU at 6%). Yield data were collected. Results showed that with the application of the NOCU at the rate of 3% (200 Kg/ha of NPK and 75 Kg/ha of urea + 3ml of neem oil), V1 and V4 showed the highest maize grain yield (3.82 ton/ha) and (4.71 ton/ha) respectively. With the application of the NOCU rate at 6% (200 Kg/ha of NPK and (75 Kg/ha of urea + 6ml of neem oil), V2 and V3 showed the highest maize grain yield (5 ton/ha) and (4.07 ton/ha) respectively. These results suggest that the NOCU at 3% (200 Kg/ha of NPK and (75 Kg/ha of urea + 3ml of neem oil) and 6% (200 Kg/ha of NPK and (75 Kg/ha of urea + 6ml of neem oil) can be used for the maize production in Benin. Further studies should be conducted to depict the post-harvest behavior of produced maize from NOCU.

INTRODUCTION

In Benin Republic, maize contributes to 6.54% to the Gross Domestic Product (GDP) and is listed among the crop being promoted in four Agricultural Development Territorial Agency (ATDA) (6, 5, 4, 3 and 2) out of the seven ATDAs established by Benin government. Maize production provides employment for communities in rural area and improves the farmer's livelihood (Saïdou et al., 2018). Among the West African countries, maize production volume is low in countries such as Benin Republic, Côte d'Ivoire and Togo compared to that of Nigeria and Burkina Faso (FAOSTAT, 2020). At the same time, the yearly per capita consumption of maize is high in Benin Republic (87 kg), followed by Togo (70 kg) and Ghana (45 kg) (Badu-Apraku & Fakorede, 2017). The actual maize grain yield is between 0.8 ton and 1.2 ton/ha which is far below the potential yield of 3 to 4t/ha. According to the DSA (2021) the maize grain yields in Benin during 2017, 2018, 2019, 2020 production season were respectively 1.29 ton/ha, 1.32 ton/ha, 1.07 ton/ha, 1.27 ton/ha. This reported low yield is caused, by the soil degradation due to the increasing of the fertilizers amount, by the soil fertility degradation, and by the climate change effect (low annual rainfall, high temperature) (Tovihoudji et al., 2022). Considering the importance of maize and huge consumption by the population with the poor grain yield, it is urgent to develop strategies to increase maize yield.

Attempts have been made by Saïdou et al. (2018) who recommended the use of N-P-K rates at 80 Kg N /ha, 30 Kg P /ha and 25 Kg K /ha and 80 Kg N/ha, 15 Kg P/ha and 40 Kg K/ha (for Acrisols) and 80.5 Kg N/ha, 22.5 Kg P/ha, 20 Kg K/ha (for Ferric and Plintic Luvisols) in intensive maize grains production system in the Southern and Center parts of Benin. According to Tovihoudji et al. (2022), the combination of microdose and drought tolerant varieties (especially 35 kg/ha of N and 8 kg/ha of P applied to TZE Y Pop STR QPM maize varieties), was suggested in the current context of declining soil fertility and climatic variability. In the context of increasing prices of fertilizers (Ali & Azaroual, 2022), of climate change, soil fertility declines along with consumers tendency to consume safe and quality product, there is an urgent need to develop eco-friendly practices (agro-ecological practices) respecting consumers attributes and farmers health.

Many researches have been conducted to develop agro ecological practices in maize production. Tovihoudji and al. (2019) found that microdose fertilization alone increased maize grain yields up to 1.145 ton/ha compared to the unfertilized land (1.096 ton/ha) in northern Benin. The same authors also reported that combining microdose fertilization with farmyard manure increased yields from 1.834 to 4.475 ton/ha with microdose + farm yard manure compared by 0.420 to 1.687 ton/ha. Akplo et al. (2019) found that the highest growth rate (2.38 cm/day), leaf area (65.70 cm^2), collar diameter (1.39 cm), grain yield (4.148 ton DM/ha), straw yield (5.077 ton DM/ha) and harvested index (40%) were obtained with the combination of plowing and mulch. Amogou et al. (2021) showed that the inoculation of maize of seeds with *Pseudomonas syringae* + 50% NPK + urea led to an increase of yield by 30.64 to 32.25%. All these technologies, although proven by research, are not accessible to farmers. Therefore, there is a need to develop and rethink other agronomic practices promoting the reduction of urea while increasing maize grain yield and with high potential to be adopted by maize grains farmers.

In India, Gudge et al. (2019) found that the application of Neem Oil Coated Urea (NOCU) increased the cob length, the cob width, the numbers of cobs per hectare and 1000 seed weight in maize plants compared with simple urea application (uncoated urea). Ashraf et al. (2019) found that the application of NOCU delayed the nitrification up to 30 days and increased the plant available N pool compared to uncoated urea. The apparent N recovery ranged from 61-84% between coated urea treatments than ordinary urea. The relative growth rate increased by 11-89% and 30-70% in all natural nitrification inhibitors coated urea. Fagodiya et al. (2019) found that the NO_2-N emission decreased by 16% in NOCU with higher maize grain yield as compared to the uncoated urea application. The same authors also reported that the greenhouse gas intensity was reduced by 6% in NOCU. So far, no scientific report has been found dealing with NOCU in maize production in Benin Republic. Therefore, this study aims at developing eco-friendly practices based on NOCU application in maize production in Benin. Specific objectives were to (i) evaluate the effect of the NOCU on the different maize varieties yield and physiological parameters and (ii) determine the economical rate of NOCU giving a relatively high grain yield.

MATERIALS AND METHODS

Experimental sites and maize varieties used

The experiment was conducted from April 2023 to August 2023in the southern Benin (Guinean zone phytogeographical zone) at Zè municipality. The climate is characterized by a tropical type with a bimodal rainfall with two rainy seasons (March to July and September to October) and two dry seasons: (August and November to February). Geographically, the site was in latitude of 6°36' 36"N and longitude of 2°13' 46"E. The variation of the annual rainfall in southern Benin is between 1200 mm and 1300 mm (Adigoun et al., 2022). The average annual temperature is around 25 °C and the maximum is 34.5 °C.

Four maize varieties were used, three local varieties and one hybrid. The local varieties are those that are well appreciated by the farmers and mostly produced in southern Benin. These varieties are: DMR ESR-W, EVDT 97 STR W and 2000 SYN EE-W (Adigoun et al., 2022).

Experimental design and treatments
In each experimental site a Split-plot design with two factors was used. The first factor was the ''**Variety**'' with 4 modalities: **V1**: DMR ESR-W; **V2**: EVDT 97 STR W; **V3**: 2000 SYN EE-W; **V4**: ABONTEM, The second factor was the "**Rate of NOCU**": For maize cultivation in the Republic of Benin, the NPK 10-20-20 fertilizer is applied at 200 Kg/ha 21 days after sowing (DAS) and urea is applied at 100Kg/ha between 30 and 45 DAS depending on the varieties (Salami et al. 2020). According to Ashraf et al. (2019), 100g of granular urea is coated with 1mL of neem oil. To prepare the NOCU, 75% of the dose of 100 Kg/ha of urea (2.4g per plant) was mixed with the neem oil at the rate of 1ml/100g of urea. The NOCU was applied at different doses; 1%, 3% and 6%. The NOCU at 1% was prepared by a mixture of 100g of granular urea and 1ml of neem oil. The NOCU at 3% was prepared by a mixture of 100g of granular urea and 3ml of neem oil and the NOCU at 6% was prepared by a mixture of 100g of granular urea and 6ml of neem oil. Based on these data, five modalities were identified: (i) The control (T0: 0 Kg/ha of NPK and 0 Kg/ha of urea); (ii) Urea (T1: 200 Kg/ha of NPK and 100 Kg/ha of PU); (iii) NOCU at 1% (T2: 200 Kg/ha of NPK and NOCU at 1% (75 Kg/ha PU + 1ml of neem oil)); (iv) NOCU at 3% (T3: 200 Kg/ha of NPK and NOCU at 3% (75 Kg/ha PU + 3ml of neem oil) and (v) NOCU at 6% (T4:200 Kg/ha of NPK and NOCU at 6% (75 Kg/ha PU + 6ml of neem oil).

The experiment was composed by four replications (4 blocks) with 20 experimental units (5 × 4 from treatments combination with a total of 80 experimental units per experiment) per block. The plots size was 3 m × 5.5 m (16.5 m²) and contained 24 maize plants. The block size was 132 m × 4 m (528 m²). The maize seeds were sown at the density of 62,500 plants/hectare (0.80 m × 0.40 m) with 2 seeds per hole.

Collected data and data analysis
Yield data was collected at harvesting. Data were analyzed with R.4.3.1 software (2023) using ANOVA model. The hierarchization of the means were obtained using "Student-Newman-Keuls" (SNK), and boxplot function was used to make the boxplot.

RESULTS AND DISCUSSION

Results showed main effects of varieties and Treatments (NOCU) (Table 1). Regarding the varieties, similar yields were obtained for V1 and V3 and V2 and V4 (Figure 1). All treatments with NOCU have high yield compared to the farmer's practice. Although the interaction between variety and treatment was not significant, results indicated that:

- For the variety V2, the highest maize grain yield (5 ton/ha) was obtained on the plots which received the treatment T4 and the lowest (4,03 ton/ha) was obtained on the plots which did not receive any treatment.
- For the variety V3, the highest maize grain yield (4,07 ton/ha) was obtained on the plots which receive the treatment T4 and the lowest (1,99 ton/ha) on the plot which did not receive any treatment.

- For the variety V4, the highest maize grain yield (4,71 ton/ha) was obtained on the plots which receive the treatment T3 and the lowest (2,76 ton/ha) on the plants which did not receive any treatment.

Table 1. P-value of the effect of NOCU application on the maize grain yield

Factors	Grain yield
Variety (V)	0.000***
Treatment NOCU (T)	0.002**
V*T	0.675

: Statistically significant at 0.01 > $P \geq 0.001$; *: Statistically significant at $P < 0.001$

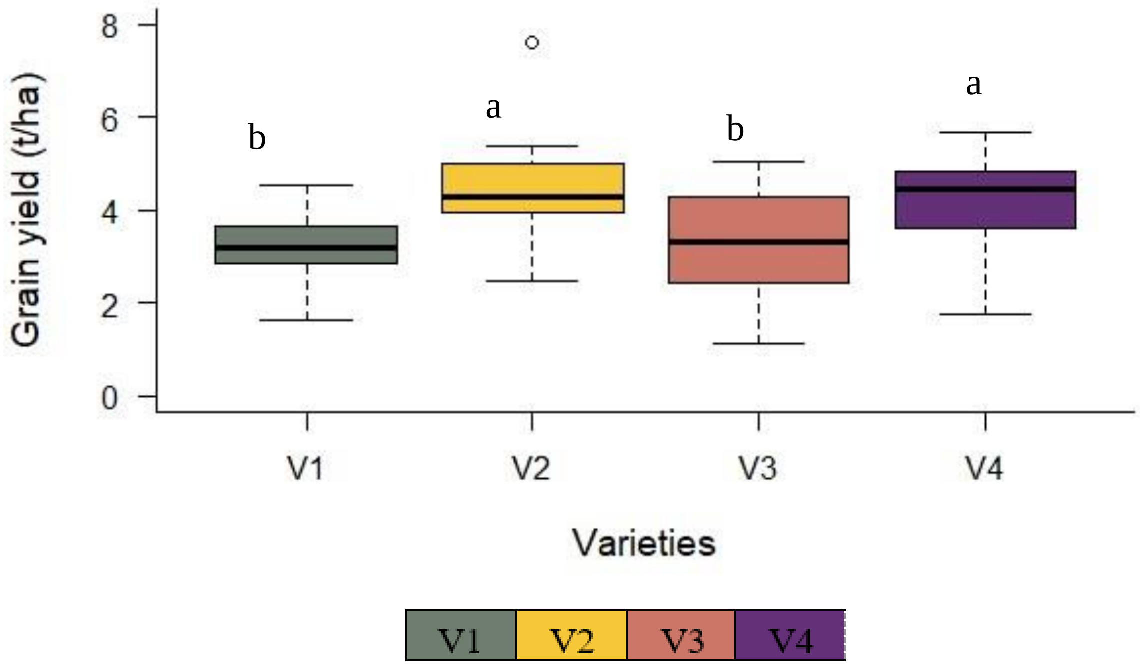


Figure 1. Effect of NOCU application on maize grain yield per variety

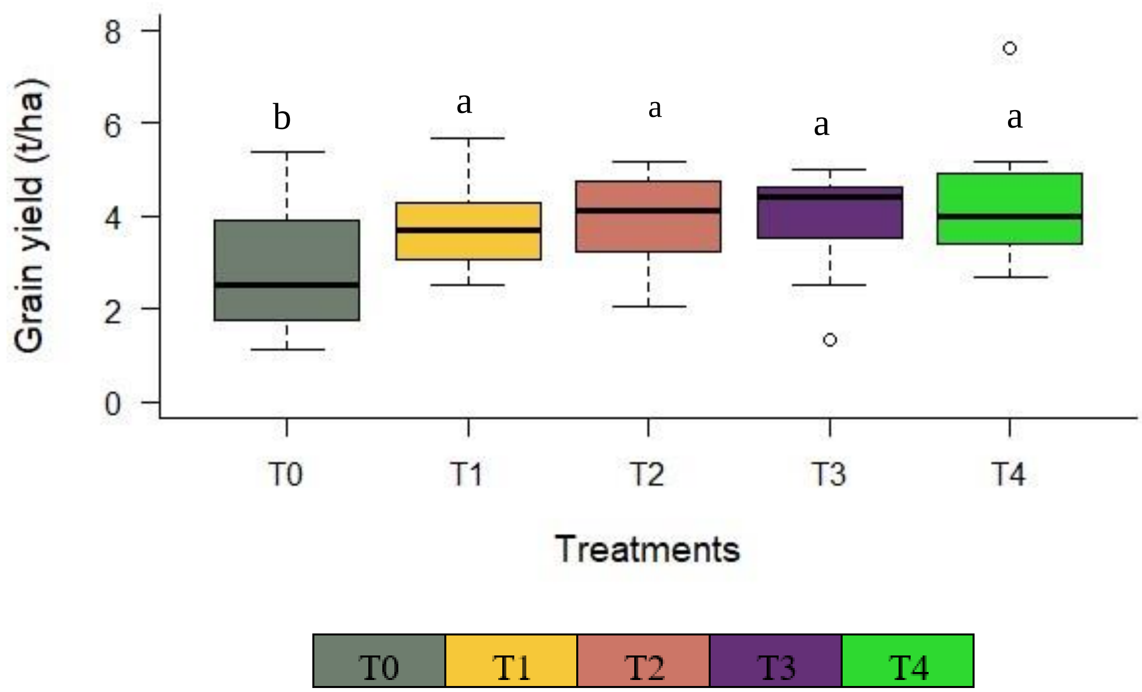


Figure 2. Effect of NOCU application on maize grain yield

These previous results can be explained by the fact that the NOCU at 3% and 6% allow the nitrification inhibition for a long period of time (Ali et al., 2020). This nitrification inhibition increases the nitrogen content in the soil and in the plant by the decreasing of the NH_4^+ losses. The maize grain yield is increased because the nitrogen availability increases the stem girth which lead to the better nutrient and water uptake by the plants (Ashraf et al., 2019; Nasar et al., 2021). It is also due by the increasing of the ear length and diameter which increase the number of grains rows and the numbers of grains per row (Mu & Chen, 2021). In fact, the maize grain dry weight is influenced by the main component of the grain which is the starch (Liu et al., 2021). Physiologically, the maize grain formation is closely related with the starch synthesis in the grain by the starch enzymes. The starch synthesis enzymes such as ADP-glucose pyrophosphorylase (AGPase) ($C_{16}H_{25}N_5O_{15}P_2$), granule bound starch synthetase (GBSS), soluble starch synthase (SSS) and starch branching enzyme (SBE) have an crucial role in starch accumulation and grain weight (Liu et al., 2021). According to the same authors, when the nitrogen supply is high it has a strong positive effect on this starch enzymes activities which increase the starch synthesis and by this way the grain weight.

CONCLUSION

Maize grain yield in Benin can be increased by improving the nitrogen use efficiency of the plants. To allow this it is essential to avoid the ammonium losses in the soil by the coating of the nitrogen fertilizer with the natural nitrification inhibitors such as neem oil. The NOCU application increased the maize leaves chlorophyll content, the maize leaves area index, the maize plants height and stem girth. The different maize varieties used showed different trends after the application of the treatment. The aim of this study which is to find an eco-friendly practice to enhance the maize grain yield in Benin by the reducing of the urea amount is reached. In this study we used 75% of the recommended dose and obtained good results. We suggest conducting a second trial to be sure about the results obtained

REFERENCES

Adigoun RFR, Houdegbe AC, Fassinou Hotegni NV, Segnon AC, N'Danikou S, Adjé CAO, Adadja RPM and Achigan-Dako EG (2022). Enabling effective maize seed system in low-income countries of West Africa: Insights from Benin. Front. Sustain. Food Syst. 6:1045629. doi: 10.3389/fsufs.2022.1045629

Akplo, T. M., Kouelo, A. F., Azontonde, H. A., & Houngnandan, P. (2019). Effect of tillage and mulching on agronomics performances of maize and soil chemical properties in Linsinlin Watershed of Centre of Benin. African Journal of Agricultural Research, 14(31), 1421-1431. https://doi.org/10.5897/AJAR2019.13952

Ali, P. A. A., & Azaroual, F. (2022). Les répercussions économiques de la guerre en Ukraine pour l'Afrique et le Maroc.

Amogou, O., Noumavo, A. P., Agbodjato, N., & SINA, H. (2021). Rhizobacterial inoculation in combination with mineral fertilizer improves maize growth and yield in poor ferruginous soil in central Benin. Journal of Biotechnology, Computational Biology and Bionanotechnology, 102(2), 141-155. https://doi.org/10.5114/bta.2021.106520

Ashraf, M., Aziz, T., Maqsood, M., Bilal, H., Raza, S., Zia, M., Mustafa, A., Xu, M., Wang, Y., Ashraf, M. N., Aziz, T., Maqsood, M., Bilal, H., Raza, S., Zia, M., Mustafa, A., Xu, M., & Wang, Y. (2019). Evaluating Organic Materials Coating on Urea as Potential Nitrification Inhibitors for Enhanced Nitrogen Recovery and Growth of Maize (Zea mays L.). International Journal of Agriculture and Biology, 22(5). https://doi.org/10.17957/IJAB/15.1175

Badu-Apraku, B., & Fakorede, M. A. B. (2017). Maize in Sub-Saharan Africa : Importance and Production Constraints. In B. Badu-Apraku & M. A. B. Fakorede, Advances in Genetic Enhancement of Early and Extra-Early Maize for Sub-Saharan Africa (p. 3-10). Springer International Publishing. https://doi.org/10.1007/978-3-319-64852-1_1

DSA. (2021). Direction des Statistiques Agricoles. https://dsa.agriculture.gouv.bj/

Fagodiya, R. K., Pathak, H., Bhatia, A., Jain, N., Gupta, D. K., Kumar, A., Malyan, S. K., Dubey, R., Radhakrishanan, S., & Tomer, R. (2019). Nitrous oxide emission and mitigation from maize–wheat rotation in the upper Indo-Gangetic Plains. Carbon Management, 10(5), 489-499. https://doi.org/10.1080/17583004.2019.1650579

FAOSTAT. (2020). Classement des États d'Afrique par production de maïs. https://atlasocio.com/classements/economie/agriculture/classement-etats-par-production-mais-afrique.php

Gudge, A., Rawat, G., JAT, S., & Tiwari, S. (2019). Impact of conservation agriculture and nitrogen management on growth and productivity of maize (Zea mays L.). Journal of Pharmacognosy and Phytochemistry, 8(4), 2260-2264.

Liu, X., Gu, W., Li, C., Li, J., & Wei, S. (2021). Effects of nitrogen fertilizer and chemical regulation on spring maize lodging characteristics, grain filling and yield formation under high planting density in Heilongjiang Province, China. Journal of Integrative Agriculture, 20(2), 511-526. https://doi.org/10.1016/S2095-3119(20)63403-7

Mu, X., & Chen, Y. (2021). The physiological response of photosynthesis to nitrogen deficiency. Plant Physiology and Biochemistry, 158, 76-82. https://doi.org/10.1016/j.plaphy.2020.11.019

Nasar, J., Khan, W., Khan, M. Z., Gitari, H. I., Gbolayori, J. F., Moussa, A. A., Mandozai, A., Rizwan, N., Anwari, G., & Maroof, S. M. (2021). Photosynthetic Activities and Photosynthetic Nitrogen Use Efficiency of Maize Crop Under Different Planting Patterns and Nitrogen Fertilization. Journal of Soil Science and Plant Nutrition, 21(3), 2274-2284. https://doi.org/10.1007/s42729-021-00520-1

Saïdou, A., Balogoun, I., Ahoton, E. L., Igué, A. M., Youl, S., Ezui, G., & Mando, A. (2018). Fertilizer Recommendations for Maize Production in the South Sudan and Sudano-Guinean Zones of Benin. In A. Bationo, D. Ngaradoum, S. Youl, F. Lompo, & J. O. Fening (Éds.), Improving the Profitability, Sustainability and Efficiency of Nutrients Through Site Specific Fertilizer Recommendations in West Africa Agro-Ecosystems (p. 215-234). Springer International Publishing. https://doi.org/10.1007/978-3-319-58792-9_13

Tovihoudji, P. G., Akponikpè, P. B. I., Agbossou, E. K., & Bielders, C. L. (2019). Variability in maize yield and profitability following hill-placement of reduced mineral fertilizer and manure rates under smallholder farm conditions in northern Benin. Field Crops Research, 230, 139-150. https://doi.org/10.1016/j.fcr.2018.10.018

Tovihoudji, P. G., Bagri, B. M., Batamoussi Hermann, M., Tonnang, Z. E. H., & Akponikpè, P. B. I. (2022). Interactive Effects of Drought-Tolerant Varieties and Fertilizer Microdosing on Maize Yield, Nutrients Use Efficiency, and Profitability in the Sub-Humid Region of Benin. Frontiers in Agronomy, 3. https://www.frontiersin.org/articles/10.3389/fagro.2021.763430

GEOSPATIAL DATA AND MAPPING

TOWARD PRECISION AGRICULTURE BY ASSESSING FAO SOIL DATA ACCURACY WITH LOCALISED SOIL MAPPING IN MID-WESTERN UGANDA

#11669

[1*]Emmanuel Ojambo; [1]L. Abasize, [1]P. Tamale, [1]T. Matila, [1]B. Kiconco, 1E. Opolot, [2]S. Kusiima, [1]P. Ebanyat, [3]J. Mutegi, [3]T. Oberthur, [1]P. Musinguzi
[1]School of Agricultural Sciences, Makerere University, Kampala, Uganda
[2]Local Government, Kikuube District
[3]African Plant Nutrition Institute, Benguérir, Morrocco
[*]e-mail: ojamboemman@gmail.com

ABSTRACT

Proper soil mapping remains a major input for efforts that aim at developing context specific soil and crop management. Soil maps often enable policy makers and other agricultural extension programs to establish the suitability of land for various production systems. Currently, most soil maps have been developed basing in the FAO soil databases at a scale of 1:50,000 yet farmers and other local land users require fine scales to guide decision in the use of fertilizers and selection of suitable crop enterprises. A study was conducted in midwestern Uganda in Kikuube town council to establish the accuracy of FAO Soil maps for improving soil information for precision agriculture. The methodology involved use of ARCGIS 10.8, Google Earth Pro and SAGA GIS creating local mapping units, which are areas relatively homogeneous in soil composition. The mapping units were defined using a combination of slope percentage, topographic wetness index, remote sensing data and land cover. Field morphology surveys were conducted and soil samples collected basing on WRB guidelines in selected soil profiles along soil mapping units. Soil classification by harmonisation was conducted. A near-tool analysis in GIS was used to overlay the new soil profile data on mapped units basing on their proximity to sampled points. Findings from ground truthing and soil mapping activity indicate that Ferralsols, Plinthisols, and Gleysols cover 44.84%, 37.45%, and 17.71% of the aredca, respectively. The existing FAO classification identified four soil types: Dystric Regosols, Gleysols, Acric Ferralsols, and Histosols, covering 80.51%, 12.75%, 6.72%, and 1.78% of the area, respectively. The soil types under FAO-Database were somewhat different from soil types obtained in the re-mapping activity in Kikuube town council. Overall, local soil mapping is essential for farmers to accurately identify soil types to aid proper use of fertilizers. The study highlighted discrepancies between the FAO soil classification and field soil mapping activity, underscoring the importance of ground-truthing and re-doing soil morphology for accurate soil maps to guide precision agriculture.

INTRODUCTION

Uganda is in the East region of Africa with a population of about 45.9 million people as per UBOS 2024 census. More than 75% of its population is employed in the agricultural sector mainly composed of peasant farmers (Okonya, 2014). Uganda was historically known for its fertile soils in the past decades, but now the fertility is decreasing from low to medium due to land degradation, soil erosion and population increasing leading to over utilization of land (Apanovich et al., 2018). Farmers are adopting to the use of fertilizers to boost their yields to cope with soil infertilities as noted by Rapsomaniki in 2015, though many smallholder farmers are reluctant to purchase fertilizer to increase crop yields, despite the evidence that fertilizer use increases yield that in turn increases income (Larson.2016). Efficient application of fertilizers requires knowing the type and composition of soils for optimal use of fertilizers (Singh et al., 2015). Proper soil mapping remains a major input for efforts that aim at developing context specific soil and crop management (Chen et al., 2022). Soil maps often enable policy makers and other agricultural extension programs to establish the suitability of land for various production systems (Apokti et al., 2019). Currently, most soil maps have been developed basing in the FAO soil databases at a scale of 1:50,000 yet farmers and other local land users require fine scales to guide decision in the use of fertilizers and selection of suitable crop enterprises (Campbell, 2018). This calls for farmers to map and analysis the soils before making selecting crops and making fertilizer use decisions.

METHODS AND MATERIALS

Study Area

The study was conducted in Kikuube town council that is in western Uganda in Bunyoro kingdom in Kikuube district. The district covers an area of about 2,097 Km^2, with Lake Albert covering 905.9 Km^2 (43.2%) according to Uganda Investment Authority (UIA) in 2021. The district has five sub-counties namely, Kiziranfumbi, Kabwoya, Buhimba, Bugambe and Kyangwali and two town councils, Kikuube and Buhimba. The district had a population estimation of 410,000 people in 2019 with 110, 000 refugees (UIA, 2021). The district’s climate varies with altitude, featuring a bimodal rainfall pattern ranging from 800 mm in the Rift Valley floor to 1,500 mm in the escarpment. The soils are mainly ferralitic and acidic, with good organic matter in lower slopes and valleys and varying soil productivity, with some areas having fair to low productivity according to Kikuube district local government. Agriculture is the main source of livelihood for 90% of Kikuube's residents, who cultivate key food crops such as maize, rice, cassava, bananas, and beans. Important cash crops include tobacco, tea, and sugarcane. Livestock farming, including poultry and piggery, also contributes to the local economy. Fishing on Lake Albert boost the economy of the locals. Recent developments include oil and gas exploration in the Albertine Rift Valley (Nuwagaba, 2021), specifically in Kyangwali and Kabwoya Sub-Counties expected to have a major impact on Uganda's GDP and public revenue (Ddamulira, 2021).

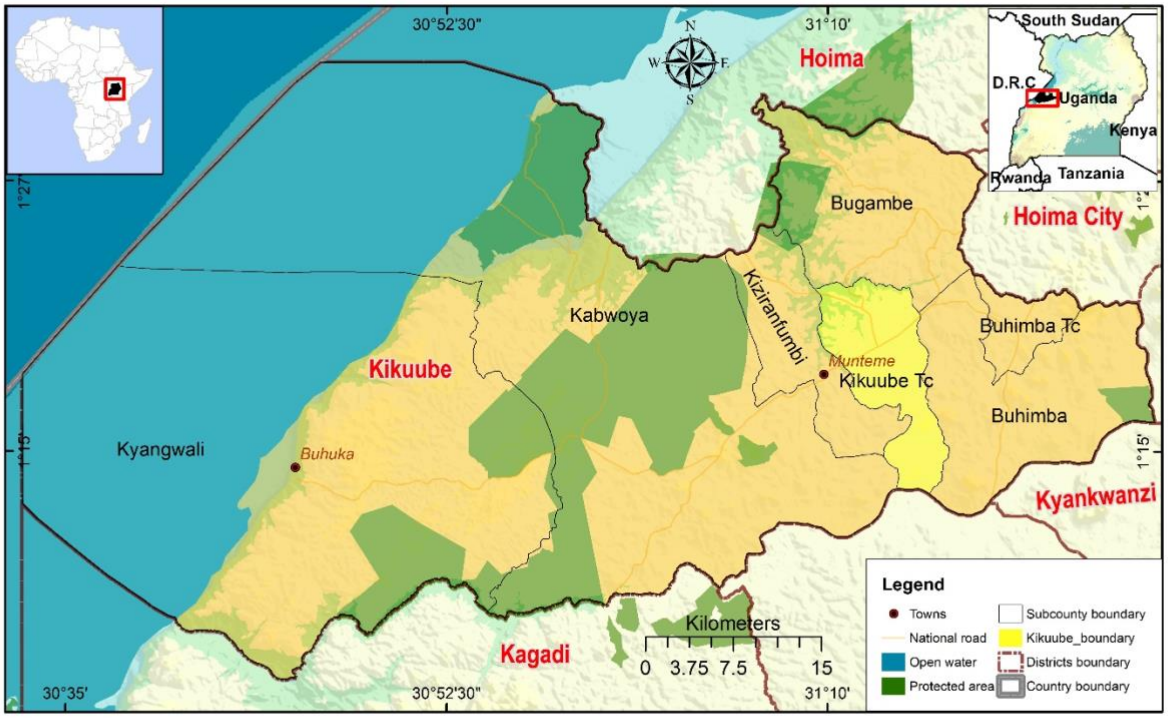


Figure 3. Location of Kikuube district

Data Collection and Analysis

The methodology involved using ARCGIS 10.8, Google Earth Pro, and SAGA GIS to create local mapping units. Local mapping units were composed of slope percentage derived from digital elevation model, topographic wetness index derived from digital elevation model in SAGA GIS, FAO Soil maps, and land use/cover obtained from land use classification of satellite images. The datasets were then overlaid and soil mapping units created based on homogeneity. Map units were then used in field morphology soil surveys, and soil samples were collected based on the World Reference Base guidelines from selected soil profiles (IUSS, 2022). The collected soil samples were analyzed in the laboratory and results tabulated based on Fao classification (Fao, 2015) visa vie the sampled mapping units and soil types generated. The laboratory results were then used to classify the generated mapping units visa vie the Near-tool analysis in GIS used to overlay the new soil profile data on mapped units, considering their proximity to sampled points.

Ferrallsols	Gleysols	Plinthisols

Figure 4. Field Soil Type Mapping.

RESULTS AND DISCUSSION

FAO Soil mapping comprised of four soil types namel;-Acric Ferralsols, Dystric Regosols, Gleysols and Histosols covering 6.72%, 80.51%, 12.75% and 0.02% respectively. Whereas the Field Soil Mapping comprised of Ferralsols, Gleysols and Plinthisols covering 44.84%, 17.71% and 37.45%. An overlay of FAO soil map and Field mapping Soil map show FAO Soil Mapping Classification was generic, and it was noted that each Fao soil type comprised of the three field mapping soil types except the Histosols that were 100% Classified as Gleysols as shown in Table 1.

Comparison of Soil Classification Area

The FAO maps indicated Dystric Regosols as dominant soil types covering more than three quarters of the soil types of which 44.47% were Ferralsols, 15.78% were Gleysol and 39.75 were Plinthisols (Table 2). The Local Field Mapping identified Ferralsols as the most commom soil type covering 44.84% of the soils in the study area. More than half of the Fao Classified Ferralsols were on a local precise scale classified as Plinthisol. This was also noted in the Fao Gleysols classification, that locally on a precise scale comprised of a mixture of three locally mapped soil types dominated by Ferralsols. The generalization of Fao Soils on a scale of 1:50,000 which on ground represents several mapping units underscores the importance of ground-truthing and re-evaluating soil morphology to produce accurate soil maps.

Table 3. Results from FAO and Field Soil Classification

FAO Soil Map			**Field Soil Mapping**		
Soil Type	Area (ha)	Area (%)	Soil Type	Area (ha)	Area (%)
Acric Ferralsols	695.93	6.72	Ferralsol	4,645.11	44.84
Dystric Regosols	8,341.54	80.51	Gleysol	1,834.86	17.71
Gleysols	1,321.14	12.75	Plinthisol	3,880.42	37.45
Histosols	1.78	0.02	Total	10,360.39	100
Total	10,360.39	100			

Table 4. Soils Comparison

Soil Classification		Area (ha)	Area (%)
Fao Dataset	Field Mapping		
Acric Ferralsols	Ferralsol	296.19	42.56
	Gleysol	18.80	2.70
	Plinthisol	380.95	54.74
Dystric Regosols	Ferralsol	3,709.77	44.47
	Gleysol	316.32	15.78
	Plinthisol	3,315.45	39.75
Gleysols	Ferralsol	639.15	48.38
	Gleysol	497.96	37.69
	Plinthisol	184.02	13.93
Histosols	Gleysol	1.78	100.00

Therefore, accurate soil mapping is essential for farmers to make informed decisions about fertilizer use and crop selection. The study's findings suggest that localized soil mapping provides a more accurate representation of soil types, which is crucial for precision agriculture. By identifying the correct soil types, farmers can optimize their agricultural practices, improve crop yields, and ensure sustainable land management.

REFERENCES

Akpoti, K., Kabo-bah, A. T., & Zwart, S. J. (2019). Agricultural land suitability analysis: State-of-the-art and outlooks for integration of climate change analysis. Agricultural systems, 173, 172-208.

Apanovich, N., & Mazur, R. E. (2018). Determinants of seasonal food security among smallholder farmers in south-central Uganda. Agriculture and Food Security, 7(1). https://doi.org/10.1186/s40066-018-0237-6

Campbell, G., Corstanje, R., Hannam, J. A., Black, H. I. J., & Lilly, A. (2018). The Application Of Digital Soil Mapping To Improve The Resolution Of National Soil Properties Across Great Britain School Of Water, Energy And Environment (Swee).

Chen, S., Arrouays, D., Mulder, V. L., Poggio, L., Minasny, B., Roudier, P., & Walter, C. (2022). Digital mapping of GlobalSoilMap soil properties at a broad scale: A review. Geoderma, 409, 115567.

Ddamulira, R. (2021). The co-existence of sustainable forest management amidst oil development analyzing resource policy options for uganda-east africa.

FAO. (2015). World reference base for soil resources 2014: International soil classification system for naming soils and creating legends for soil maps. Food and Agriculture Organization of the United Nations.

IUSS Working Group WRB. 2022. World Reference Base for Soil Resources. International soil classification system for naming soils and creating legends for soil maps. 4th edition. International Union of Soil Sciences (IUSS), Vienna, Austria.

Kikuube District Local Government. (n.d) Retrieved August 31, 2024, from https://kikuube.go.ug/

Larson, D. F., Savastano, S., Murray, S., & Palacios-López, A. (2016). On the Determinants of Low Productivity in Maize Farming in Uganda: The Role of Markets, Fertilizer Use and Gender. In In Pursuit of an African Green Revolution (pp. 165–182). Springer Japan. https://doi.org/10.1007/978-4-431-55693-0_8

Nuwagaba, I., & Tshombe, L. M. (2021). African Renaissance. https://journals.co.za/doi/pdf/10.31920/2516-5305/v2021sin1a10

Okonya, J. S., & Kroschel, J. (2014). Gender differences in access and use of selected productive resources among sweet potato farmers in Uganda. Agriculture & Food Security, 3, 1-10.

Rapsomanikis, G. (2015). Food and Agriculture Organization of the United Nations Rome. www.fao.org/publications.

Singh, B., & Ryan, J. (2015). Managing fertilizers to enhance soil health. International Fertilizer Industry Association, Paris, France, 1.

UBOS. (2024). National-Population-and-Housing-Census-2024-Preliminary-Report. Retrieved August 30, 2024, from https://www.ubos.org/wp-content/uploads/publications/National-Population-and-Housing-Census-2024-Preliminary-Report.pdf

Uganda Investment Authority. (2021). Kikuube District Investment Profile Brief District Profile. https://www.ugandainvest.go.ug/wp-content/uploads/2021/08/Kikuube-2021.pdf

ASSESSING OF SOIL NUTRIENTS USING LABORATORY AND REMOTE SENSING METHODS IN NORTHERN GUINEA SAVANNAH

#11640

[1]A.R. Garba, [2]A.M. Yamusa, [1]C.K. Daudu, [2]S.L. Yau, [3]M.I., Gaya, [2]A. Abdulkadir
1. National Agricultural Extension and Research Liaison Services (NAERLS), Ahmadu Bello University (ABU) Zaria
2. Department of Soil Science, Institute of Agricultural Research (IAR)/ABU, Zaria
3. Samaru College of Agriculture, Division of Agricultural Colleges, Ahmadu Bello University, Zaria, Nigeria
e-mail: abbariruwai@gmail.com; +2348035457216

ABSTRACT

To understand soil properties and how they might be used sustainably, mapping of soil attributes is a crucial activity. The study was carried out in four local government area of Kaduna State of Nigeria to map out some soil properties and assess their variability within the area. From the study area, a total of 16 soil samples (0–20 cm) were collected from different cropping patterns. A portable global positioning system (GPS) was used to collect the coordinates of each sampling site. Then, the soil properties, that is, soil organic carbon (SOC), total nitrogen (Total N), soil organic matter (SOM), and soil available nutrients (P and K) were measured in the laboratory. Correlation analysis between laboratory and remote sensing data showed positive relationships for carbon (r=0.23), total nitrogen (r=0.14), and organic matter (r=0.68), but negative correlations for available phosphorus (r=-0.48) and potassium (r=-0.42). These variable results highlight the greater reliability of remote sensing for assessing total carbon and organic matter versus limitations in quantifying phosphorus and potassium availability. Interactive effects of climate variables on soil nutrients were not directly assessed but remain a critical area for further research.

Keywords: Remote sensing, Laboratory analysis and Soil nutrients

INTRODUCTION

Soil is a complex material that is extremely variable in its physical and chemical composition. The influence of soil and crop management practices such as fertilization, cropping systems, and land-use change exert considerable changes to such soil compositions over time. Over the years, routine analysis of such chemical and physical changes remains the only way to access and maintain the fertility of soil. The importance of the soil analysis cannot be over-emphasised since low nutrient values limit plant growth and excessive rainfall may result in loss of nutrients from the soil, causing soil fertility degradation and water pollution (Chi, *et al.*, 2019). Therefore, soil analysis is the basic frame for providing the nutrient requirements of every crop.

Comparative assessment of soil nutrients under different cropping systems and changing climate conditions requires a combination of ground-based soil sensing and laboratory analytical methods along with remote sensing technologies. Ground-based sensors like portable X-ray fluorescence (pXRF) analyzers allow rapid in-situ quantification of major and trace nutrients in soils (Towett *et. al.* 2015). Laboratory methods using combustion analysis, titrations, and spectroscopic techniques offer accurate and precise measurements of total and plant-available nutrient pools (Robertson *et. al.* 1999). Satellite and aerial remote sensing provide spatial data on vegetation characteristics and soil properties related to soil fertility at broader scales (Mulder *et al.* 2011). Together, these approaches can provide a comprehensive assessment of soil nutrient dynamics across landscapes. This study synthesizes research utilizing integrated soil laboratory, ground-based sensing, and remote sensing methods to evaluate the impacts of climate and agricultural land use on soil nutrients. The focus is on comparative studies across different cropping systems under current and projected future climate scenarios, concentrating on research conducted in sub-Saharan Africa.

Monitoring agriculture from remote sensing is a vast subject that has been widely addressed from multiple viewpoints, sometimes based on specific applications (e.g. precision farming, yield prediction, irrigation, weed detection), on specific remote sensing platforms (e.g. satellites, Unmanned Aerial Vehicles - UAV, Unmanned Ground Vehicles - UGV) or sensors (e.g. active or passive sensing, wavelength domain, spatial sampling) or specific locations and climatic contexts (e.g. country or continent, wetlands or dry lands).

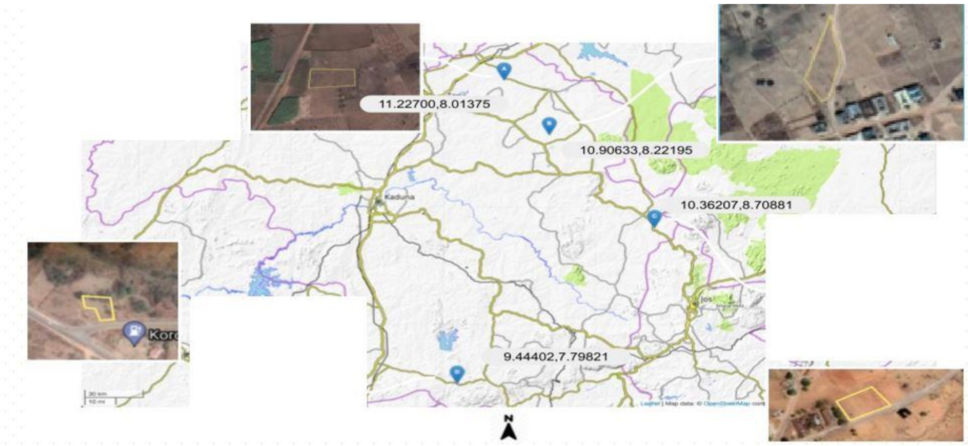
In recent years, digital soil mapping has been identified as a low-cost and efficient method for predicting the spatial distribution of soil nutrients. Most digital soil mapping methods are based on soil-landscape models, which establish mathematical or statistical relationships between soil properties and related environmental variables (Zhang *et. al.*, 2019) by predicting soil characteristics and fertility status with the help of remote sensing data. Remote sensing in itself is the process of detecting and monitoring the physical characteristics of a particular soil by measuring its reflected and emitted radiation at a distance. The nature and working principle of remote sensing give it the advantages of being an extensive, non-invasive, timeliness, and flexible method of soil analysis, and it has the potential to increase the availability of high-resolution remote sensing data by providing a new opportunity for predicting soil characteristics with acceptable accuracy.

MATERIALS AND METHODS

Study Area Description

This study was conducted in the northern and southern Guinea savannahs of Kaduna State. The locations in the northern savannah were Kubau and Makarfi while the southern Guinea savannah was Kagarko and Lere LGAs.

Nigeria's climatic zone encompasses the tropical humid forest in the south and the savannah in the north. Nigeria's climatic zone encompasses the tropical humid forest in the south and the savannah in the north. The derived savannah is a transition zone between the rainforest and savannah biomes caused by forest clearance as stated by Ofomata (1975). The study was carried out in Kaduna state (Longitude/Latitude 9°26' to 11°13' N and 7°47 to 8°42' E) respectively, which is in the Northwest of Nigeria (Fig.1). The climate belt of the area is tropical Guinea Savanna, with an annual average temperature of 25.2℃ and an annual average rainfall of 1,323mm (Akinbode *et. al.*, 2008).



Location of area(s) of interest in Kaduna state (Kubau, Makarfi, Lere, and Kagarko Local Government Areas) and distribution of samples.

Soil Laboratory Analysis

The chemical properties of the soils were determined at the Soil Science Laboratory, Faculty of Agriculture, Ahmadu Bello University, Zaria, Nigeria.

The soil samples were determined by using the following methods: The organic carbon was analyzed by the wet oxidation method of Walkley and Black as modified by (Nelson and Sommers, 1982). Total nitrogen by the micro-kjeldahl distillation procedure according to (Bremmer, 1996), available phosphorus was determined by the Bray No. 1 acid fluoride method (Nelson and Sommers, 1982).

Field Sampling and Spatial Analysis

The remote sensing samples were collected in the same 4 LGAs of Kaduna state distributed evenly between the northern and southern parts of the state; and for each farm, a sample was collected for each 4 points at 0-20cm depth. This is because most satellite data for soil properties are within the top-soil range (Hengl *et al.*, 2015). Therefore, restricting the ground-based sampling in this study to 0-20 cm aligns with the typically sensed depth ranges from satellite platforms. The remote sensing samples were collected same time during the soil sample collection on the field. A data streaming pipeline is used to query and download multispectral data from the Sentinel-2 repository which is then processed using a proprietary algorithm. The result from the satellite image and how it correlates with those from chemical analysis is the subject and primary objective of this study.

Correlation Analysis

Python programming language version 3.11.4 was used as the correlation analysis tool using Pearson to compare the laboratory analysis and remote sensing results (Virtanen *et al.*, 2020). Scatter plots allow visualization of the relationship between two variables, while correlation analysis provides a quantitative measure of the strength and direction of the relationship (Graham, 2023). Python was selected due to its extensive libraries for statistical analysis and data visualization along with the flexibility to handle diverse data types from both laboratory and satellite sources (Qiusheng *et al.*, 2009). Utilizing the Python environment for integrated analysis of remote sensing imagery and laboratory soil analytics follows established best practices for digital soil mapping and precision agriculture applications (Padarian *et al.*, 2019).

Python provides a flexible open-source platform for handling diverse datasets and performing correlation analysis (Hengl *et al.* 2022). Two datasets were employed, one from remote sensing and the other from the laboratory, each containing 16 instances of soil chemical properties across 12 columns. These datasets were collected from four distinct communities in Kaduna State: Gubuchi, Kuli, Krosha, and Kubacha, each located in different Local Government Areas.

RESULTS AND DISCUSSIONS

Correlation Analysis

Correlation between the remote sensing nitrogen and the lab nitrogen result

The result of correlation between total nitrogen of remote sensing data and laboratory analysis is presented in Figure 1. From the result, there was a weak positive correlation between the determined parameters, and this indicates an existing relation between nitrogen levels assessed through the remote sensing and the laboratory analysis. The weak positive correlation (r=0.14) found between the laboratory and remote sensing soil nitrogen could be associated with the high mobility and volatilization nature of nitrogen that may encourage leaching, run-off and other nitrogen losses from the soil, hence very difficult to measure. Towett *et al.* (2015) found a weak correlation (r=0.19) between laboratory and portable X-ray Fluorescent sensor nitrogen measurements in Kenyan soils due to difficulties estimating subsurface nitrogen indirectly from the spectral response. The low correlation highlights challenges in using remote sensing alone to accurately predict soil nitrogen across agricultural landscapes. The need for further ground-based sensing ground-truthing of satellite data to improve nitrogen prediction aligns with Piikki *et al.* (2013), who used on-ground sensors to calibrate satellite imagery for soil clay mapping. Vågen and Winowiecki (2019) also emphasized multi-scale calibration of remote sensing using soil analytical lab data for accurate digital soil mapping.

The finding that neither remote sensing nor laboratory methods fully capture soil nitrogen complexity agrees with Hengl *et al.* (2017), who concluded that integrated approaches are essential given the intricacies of nitrogen biogeochemistry. The variability between sites also reflects Towett *et al.* (2015), who found location-specific differences in remote sensing accuracy for soil nutrients. Further coordinated research and data integration will help improve soil nitrogen assessment and enhance remote sensing capabilities for nutrient management.

Correlation between the remote sensing organic matter and the lab organic matter result

The statistical analysis indicates a significant positive correlation between the remote sensing-derived organic matter data and the laboratory organic matter data. The strong positive correlation (r=0.68) between remote sensing and laboratory soil organic matter data is consistent with findings from other studies. Shepherd and Walsh (2002) reported R-values from 0.76 to 0.89 between lab and field spectroscopy organic matter measurements across diverse African agricultural soils. Towett *et al.* (2015) found the highest correlation (r=0.86) between laboratory and portable XRF sensor organic carbon content compared to other nutrients in Kenyan soils. The reliability of remote sensing for organic matter mapping aligns with Vågen and Winowiecki (2019), who used MODIS satellite data to map soil organic carbon across Sub-Saharan Africa with reasonable accuracy compared to ground-based sensing. The robust relationship between spectral response and organic matter is attributed to the direct impacts of surface organic content on crop growth patterns detectable through remote imaging (Hengl *et al.* 2017). However, some researchers note challenges in relating surface organic matter to total profile carbon stocks using remote sensing alone (Piikki *et al.* 2013). Integrated approaches incorporating soil sampling, terrain analysis, and digital soil mapping techniques may further improve organic matter quantification across landscapes (Hengl *et al.* 2017). Still, the strong positive correlation demonstrates the potential of remote sensing for cost-effective wide-area mapping of this important indicator of soil quality and health.

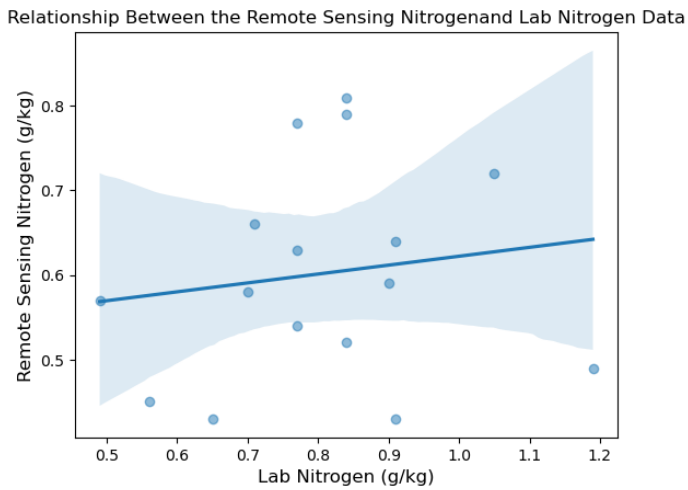


Figure 1. Correlation between the Remote Sensing Nitrogen and the Lab Nitrogen result.

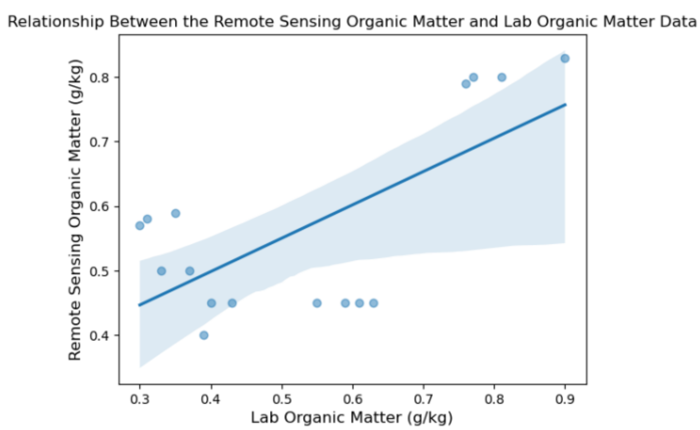


Figure 2. Correlation between the remote sensing organic matter and the lab organic matter result.

Correlation between the remote sensing potassium and the lab potassium result

A negative correlation was observed between the remote sensing-derived potassium data and the laboratory potassium data, with a correlation value of -0.42 The negative correlation (r=-0.42) between remote sensing and laboratory soil potassium aligns with other studies showing the complexity in using spectral data to estimate plant-available potassium. Piikki and Söderström (2019) found poor correlation (r=0.38) between remote sensing vegetation indices and exchangeable potassium measured in topsoils across agricultural fields in Sweden. They attributed this to the dependence of spectral response on multiple soil factors like mineral composition influencing potassium availability. Mulder *et al.* (2011) noted challenges in relating leaf potassium absorption to total soil potassium pools given intricacies of potassium chemistry and soil interactions. Vågen and Winowiecki (2019) were unable to map exchangeable potassium at sufficient accuracy using solely MODIS (moderate resolution imaging spectroradiometer) satellite data for Sub-Saharan African soils. This could indicate that the remote sensing data might not accurately capture the true potassium levels in the soil or that there are other factors affecting the results. The finding highlights the need for integrated approaches combining spectral data with soil chemistry analysis, geologic surveys, and crop modeling to improve potassium prediction noted by both Piikki and Söderström (2019) and Vågen and Winowiecki (2019).

While it shows promise for assessing organic matter, it may have limitations in accurately estimating potassium levels. Understanding these correlations is vital for the appropriate interpretation of remote sensing data in agricultural and environmental applications. Further research and validation may be needed to better understand the factors contributing to these correlations and improve the accuracy of remote sensing techniques for soil property assessments.

Correlation between the remote sensing carbon and the lab carbon data

Based on figure 4 below, it shows that a weak positive correlation of 0.23 was observed between the remote sensing-derived carbon data and the laboratory carbon data. The weak positive correlation (r=0.23) between remote sensing and laboratory soil carbon aligns with other studies showing the limitations of using vegetation indices alone to estimate total soil organic carbon. Mulder *et al.* (2011) found poor correlations between satellite data and measured soil carbon, as remote sensors only detect surface carbon versus total profile stores. Piikki *et al.* (2013) reported underestimation of soil carbon by 40-60% using solely remote sensing due to difficulties assessing subsurface carbon. Hengl *et al.* (2017) concluded that integrated approaches are needed to improve carbon mapping, given uncertainties in relating land cover to soil carbon balances and the importance of environmental covariates like climate, topography and parent material. The potential reasons for the weak correlation noted here are supported by the literature, including mismatches between surface and profile carbon and the indirect nature of spectral indicators relying on biomass proxies (Vågen and Winowiecki 2019). Recommendations for further analysis align with emphasis on multi-source data integration and digital soil mapping advancements to strengthen carbon prediction (Towett *et al.* 2015).

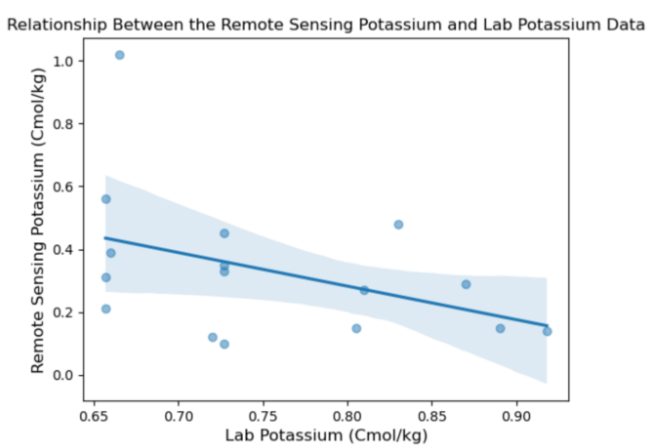


Figure 3. Correlation between the remote sensing organic matter and the lab organic matter result.

Lastly, the carbon correlation analysis reflects consistent findings in the literature on the benefits and limitations of remote sensing for soil carbon assessment, highlighting the particular importance of integrating spectral data with soil analytics, terrain attributes, land use data and process-based models to support carbon monitoring and management.

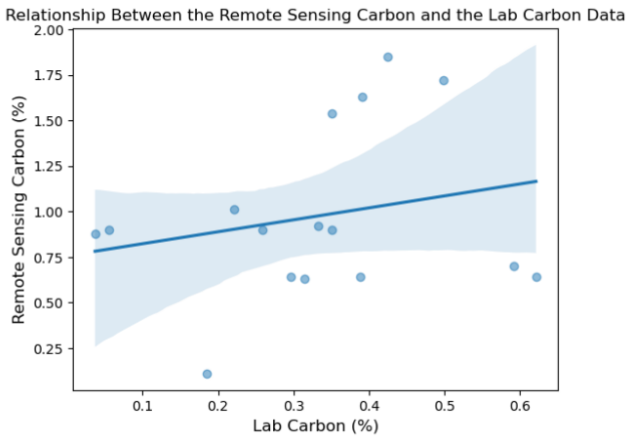


Figure 4. Correlation between the remote sensing organic matter and the lab organic matter result.

Correlation between the remote sensing phosphorus and the lab phosphorus data

Figure 5 revealed a significant negative correlation of -0.48 between the remote-sensing phosphorus data and the laboratory phosphorus data. The moderate negative correlation (r=-0.48) between remote sensing and laboratory soil phosphorus aligns with other studies demonstrating challenges in using spectral vegetation indices to estimate plant-available phosphorus.

Mulder *et. al.* (2011) found a poor correlation between remote sensing data and soil test phosphorus due to difficulties detecting complex soil phosphorus chemistry from leaf reflectance. Piikki and Söderström (2019) reported an underestimation of Mehlich-3 extractable phosphorus by 80% using solely remote sensing across agricultural fields in Sweden.

Hengl *et. al.* (2017) concluded that machine learning approaches combining remote sensing with soil data, terrain attributes, geology maps, and land use improved the prediction of plant-available phosphorus compared to spectral data alone. The negative correlation suggests reliance on indirect plant phosphorus proxies from remote sensing is insufficient to capture dynamics of sorption, precipitation, and labile phosphorus forms in the soil (Vågen and Winowiecki 2019). Integrating targeted soil sampling and digital soil mapping techniques could potentially strengthen phosphorus assessment noted by Towett *et al.* (2015).

The finding calls for further investigation to ascertain the fundamental reasons for the negative correlation. It may indicate limitations in the accuracy of remote sensing techniques for assessing phosphorus levels, or it could be influenced by other factors affecting the data. Understanding and addressing the reasons for this negative correlation are essential for improving the reliability of remote sensing-based assessments of phosphorus in soil.

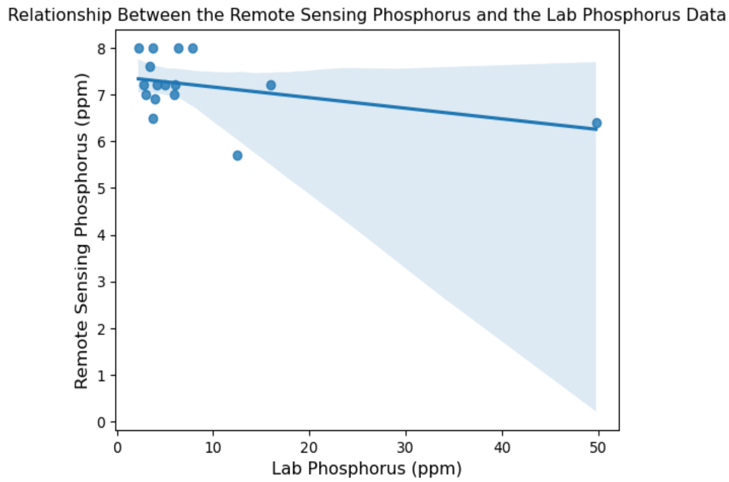


Figure 5. Correlation between the remote sensing organic matter and the lab organic matter result.

Heat-map representation of the correlations among all the variables

A heat map is a powerful visual tool for representing the correlations among variables which is also known as the "R" value table. The heat map visualization provides a clear overview of the variable relationships between soil properties measured through remote sensing and laboratory methods, as noted in other studies. The positive correlations for nitrogen, carbon, and organic matter reflect the reliability of remote sensing for total concentrations of these parameters found by Towett *et. al.* (2015) and Hengl *et. al.* (2017) in African agricultural soils.

In contrast, the negative correlations for phosphorus and potassium align with the literature on the challenges of using spectral vegetation indices to estimate plant-available nutrient pools given complex sorption dynamics (Mulder *et al.* 2011; Piikki and Söderström 2019).

Vågen and Winowiecki (2019) effectively used similar heat map matrices to represent validation results between ground-based sensing and laboratory measurement of soil organic carbon and texture fractions. The visualization format allows clear interpretation of correlations and discrepancies essential for selecting appropriate remote sensing approaches for different soil nutrients (Towett *et al.* 2015).

By summarizing multiple correlation analyses in one figure, the heat map enables the identification of strengths and limitations across soil parameters to guide integrated data collection and analysis strategies (Hengl *et al.* 2017). Conversely, a negative correlation is observed in the Phosphorus (P) and Potassium (K) data. A negative correlation implies that as one variable increases, the other tends to decrease. In essence, it means that there is a discrepancy or difference between the measurements obtained through remote sensing and lab analysis for Phosphorus and Potassium. This negative correlation could be indicative of some level of inaccuracy in the remote sensing data for these specific soil properties or perhaps differences in how these properties are measured using the two methods.

In practical terms, the positive correlations for Nitrogen, Carbon, and Organic Matter suggest that remote sensing can be a valuable tool for assessing these soil properties, offering a time and cost-effective alternative to laboratory analysis. However, for Phosphorus and Potassium, the negative correlations highlight the need for further investigation into the reasons behind the discrepancies and whether adjustments are necessary in the remote sensing methodology or calibration.

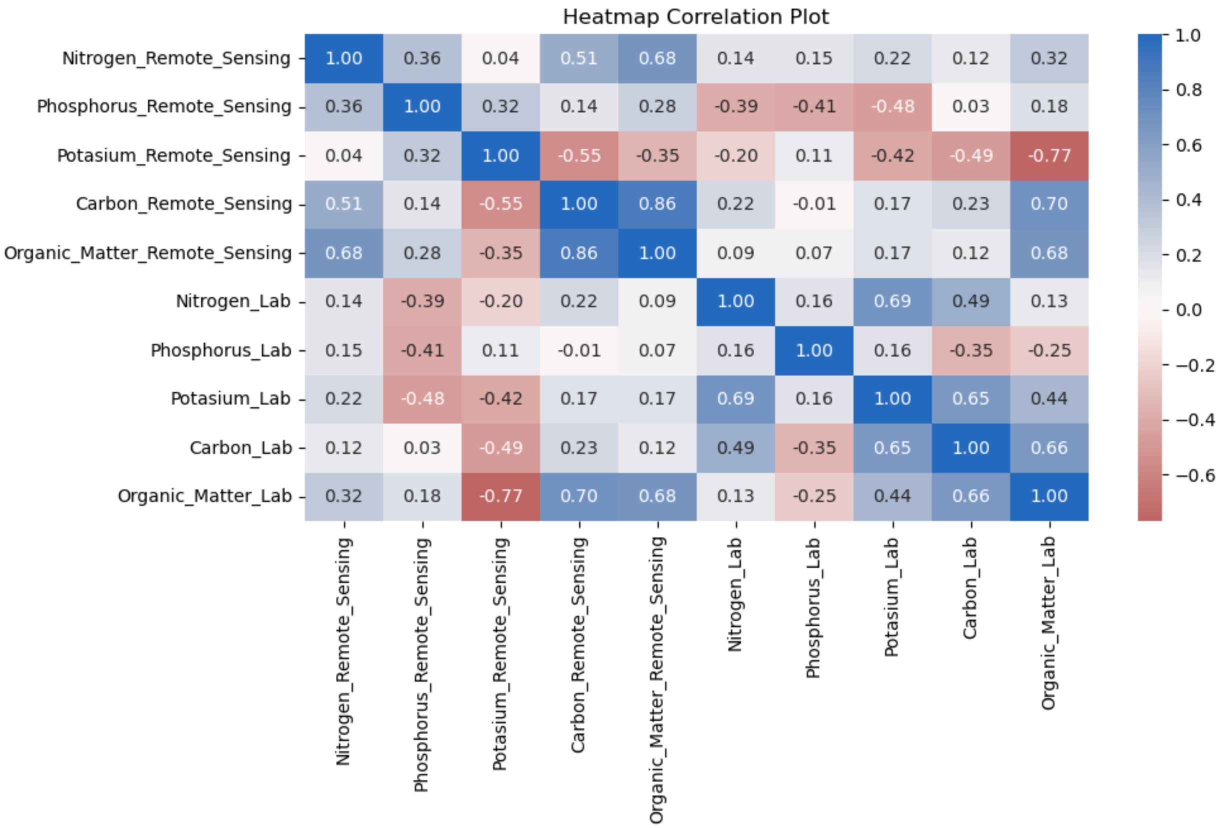


Figure 6. Correlations among all the variables.

CONCLUSION

This study demonstrated the potential of integrated laboratory and remote sensing techniques for the comparative assessment of soil nutrients.

1. Laboratory and remote sensing techniques showed varying degrees of correlation and accuracy for different soil properties. Strong positive correlations were found for carbon and organic matter having r=0.23 and r=0.68. Weak positive correlation was seen for total nitrogen having r=0.14. And poor negative correlations existed for phosphorus and potassium having r=0.48 and r=0.42 respectively.
2. Remote sensing provided useful climate and environmental data to characterize the cropping systems. But incorporation of additional climate variables could further improve biophysical crop-soil system characterization.

REFERENCES

A. K. Stum, Random forests applied as a soil spatial predictive model in arid Utah [M.S. thesis], Utah State University, 2010.

Bielders, C.L., Gérard, B. (2015). Millet response to microdose fertilization in south–western Niger: Effect of antecedent fertility management and environmental factors. Field Crops Research, 171, 165-175.

Black C.A. (1965) method of soil analysis Agronomy No 9-part 2 American society Agronomy

Bouyoucos G.J. (1951). Hydrometer method improved for marking particle size analysis of soils.

Brady, N.C. and Well, R.R. (2002). The nature and properties of soil, 13th edition. Prentice Hall,

Brady, N.C., and R.R. Weil. 2000. Elements of the nature and properties of soils. 12th ed. Prentice RaIl, New Jersey

Bray, R. H., and Kurtz, L.T. (1945). Determination of total organic and available phosphorus in soils. Soil Science, 59: 39-45.

Bremner, J. M. (1996). Nitrogen total. In: D. L. Sparks et al. (Ed.). Methods of soil analysis, Part 3.Chemical Methods. Soil Science Society of America Book series. 5. Soil Science Society of America and American Society of Agronomy. Madison, Wisconsin. p. 1085-1121.

Chi, Y.; Zhao, M.; Sun, J.; Xie, Z.; Wang, E. Mapping soil total nitrogen in an estuarine area with highland scape fragmentation using a multiple-scale approach. Geoderma 2019,339, 70–84.

Graham, A. (2023). Evaluating correlation in Excel, SPSS Statistics and R. Statistics How To.

G. R. Blake, “Bulk density,” in Methods of Soil Analysis Agron, C. A. Black, Ed., Part I, No. 9., pp. 374–399, American Society of Agronomy, Madison, Wis, USA, 1965.

Hengl, T. Heuvelink, G.B., Walsh, M.G. (2017). Soil nutrient maps of Sub-Saharan Africa: assessment of soil nutrient content at 250m spatial resolution using machine learning. Nutrient Cycle Agroecosystem, 109, 77–102.

Mulder, V.L., de Bruin, S., Schaepman, M.E. and Mayr, T.R. (2011). The use of remote sensing in soil and terrain mapping—A review. Geoderma, 162(1-2), 1-19.

Nelson, D. W., & Sommers, L. E. (1982). Total carbon, organic carbon, and organic matter. In A. L. Page (Ed.), Methods of soil analysis. Part 2. Chemical and microbiological properties (pp. 539-579). American Society of Agronomy, Soil Science Society of America.

Nelson, D.W., and L.E. Sommers. 1996. Total carbon, organic carbon, and organic matter. p. 961-1010 In J.M. Bartels et al. (ed.) Methods of soil analysis. Part 3 Chemical methods. SSSA Book Ser No.5. SSSA, Madison, WI. Nigeria. Geoderma, 48: 113-129.

Ofomata, G. E. K. (1987). Soil erosion in Nigeria: The views of a geomorphologist. University of Nigeria Inaugural Lecture Series.

Padarian, J., Minasny, B. and McBratney, A.B. Using machine learning to predict soil organic matter and particle size distribution from VIS-NIR spectra. Soil Tillage Res 195, 104400 (2019).

Piikki, K. and Söderström, M. (2019). Digital soil mapping of arable land in Sweden – Validation of performance at multiple scales. Geoderma, 352, 342-350.

Piikki, K., Söderström, M., and Stenberg, B. (2013). Sensor data fusion for topsoil clay mapping. Geoderma, 199, 106-116.

Qiusheng, W. (2009). What is Python and Why is it a Good Language Choice for Science and Scientific Computing.

Towett, E. K., Shepherd, K. D., Sila, A., Aynekulu, E., & Cadisch, G. (2015). Modelling of soil organic carbon stocks in the northern Rangelands of Kenya using remotely sensed covariates. Soil Use and Management, 31(1), 81-92.

Towett, E.K., Shepherd, K.D., Sila, A., Aynekulu, E., and Cadisch, G. (2015). Mid-infrared and total x-ray fluorescence spectroscopy complementarity for assessment of soil properties. Soil Science Society of America Journal, 79(5), 1375-1385.

Vågen, T. G., & Winowiecki, L. A. (2019). Predicting the spatial distribution and severity of soil degradation in East Africa. Applied Geography, 94, 130-142.

Vågen, T.G., Winowiecki, L.A., Tondoh, J.E., Desta, L.T. and Gumbricht, T. (2016). Mapping of soil properties and land degradation risk in Africa using MODIS reflectance. Geoderma, 263, 216-225.

Virtanen, P., Gommers, R., Oliphant, T.E. et al. SciPy 1.0: fundamental algorithms for scientific computing in Python. Nat Methods 17, 261–272 (2020).

Zhang, M.; Shi, W. Systematic comparison of five machine-learning methods in classification and interpolation of soil particle size fractions using different transformed data. Hydrol. Earth Syst. Sci. Discuss.2019,2019,1–39.

LAND SUITABILITY PREDICTION FOR MAIZE PRODUCTION IN SOUTHWEST NIGERIA USING GEOGRAPHICAL INFORMATION SYSTEM AND MOST-LIMITING SOIL NATIVE FERTILITY FACTORS

[1]Taiwo S. Olutoberu, [1]Mutiu A. Busari, [1]Olusegun Folorunso, [1]Muftau Adebayo, [1]Sodeeq O. Azeez, [1]Sarafadeen G. Hammed, [1]J.A. Oyedepo, [2]Oluwafolake Ojo, and [1]G.A. Ajiboye

[1]Federal University of Agriculture, Abeokuta, Nigeria
[2]Osun State University, Osogbo, Nigeria
e-mail: solutoberu@gmail.com; +234 8039658671

ABSTRACT

Maize yield per hectare in Southwest Nigeria has been found to be one of the lowest compared to other regions of the world. Digital land suitability assessment was carried out using indices of most-limiting soil native fertility and geographical information systems. We explored the combined use of continuous soil attributes modeling, and ordinal logistic regression through a two-stage mapping process to accomplish the land suitability assessment for maize production. Stepwise forward regression analysis of environmental covariates was conducted to reduce the number of predictors to only those having significant effects at 95% confidence interval. Most area from northern to southern part of the study area had organic carbon content less than 1%. Larger portion of the study area northern part had soil native total nitrogen below 0. 1 g/kg. Most portion of the study area had extractable phosphorus between 23 and 28 mg/kg while the northern part had extractable potassium between 0.29 and 0.33 g/kg. Only some area around southern part of the study area had pH less than or equal 5.5 while other parts had values above 5.5. According to FAO land suitability classification systems, 69.078% of the landmass is moderately suitable, 29.865% is unsuitable and only 1.056% is suitable for maize production. We recommend that policy should be enacted and implemented to regulate infrastructural development and protect agricultural land, non-regenerative agricultural practices should be discouraged, and government and private sectors should empower the agrarian communities with modern soil management training and subsidized farm inputs

INTRODUCTION

Youths in Southwest Nigeria are constrained by lack of access to scientific and technological information that could enhance maize production capacity (Olaniyi and Adewale, 2012). Although they are said to be the future farmers who are expected to carry on farming as a profession for sustainable food production in the Country. Fawole (2008) posited that clamor for adoption of innovation in agricultural development may not be justified without availability and dissemination of innovative information. Olaniyan also posited that increase in maize production in Nigeria has been achieved greatly by expansion in area cultivated rather than increase in yield. The author further stated that the area cultivated and harvested increased from 2.8 million hectares in 1986 to over 3 million hectares in 2000 and over 6 million in 2010. However, the average yield of maize in Nigeria is 1.68 tons/hectare while it is average 9.3 t/ha in the United States of America over the same period (ATA, 2011)

Previous studies on maize production in Southwest Nigeria have done justice to the socio-economic aspect of maize production but no study has investigated the spatial-temporal land suitability evaluation of Southwest Nigeria for maize production (otherwise known as digital soil assessment) to achieve optimum yield and hence maximum profitability and to give credence to the principle of comparative advantage.

According to Akinbode et al. (2024), the production of systematic digital soil fertility mapping in Nigeria is of urgent national emergency in this era of digital advancement and precision agriculture as such has not been previously conducted for the optimum utilization of farm resources towards improving farm productivity. Until now, the country has maintained its conventional soil maps. However, digital soil mapping provides *in-situ* real-time information about the soil in a given location. Hence, it assists farmers' decision-making and impacts positively on agricultural productivity. This study is therefore set up to investigate holistically temporal and spatial land suitability of Southwest Nigeria for maize production. We explored the combined use of continuous soil attributes modeling and ordinal logistic regression through a two-stage mapping process to accomplish the land suitability assessment for maize in the Southwest. This way all covariate factors necessary for the holistic evaluation such as soil, climate, organism, relief, parent materials, age, and spatial position have been included as predictors. The results of this study will have implications for the cultivation of land for maize production in Southwest Nigeria in line with the sustainable development goals 2 (zero hunger), 11(sustainable cities and communities), and 12 (responsible consumption and production) of the United Nations in Nigeria. This study answered the following research questions – 1) What is the soil's native fertility status in Southwest Nigeria in terms of composite soil nutrients? 2) What is the status of environmental covariates in the study area? And 3) Which region within Southwest Nigeria is best suited for maize production?

The null hypotheses of this study are:

$H1_0$: The native soil nutrients of any two randomly selected geographical locations within Southwest Nigeria are not significantly different from each other.

$H2_0$: Any two randomly selected geographical locations within Southwest Nigeria are not significantly different from each other in terms of suitability for optimum maize production.

$H3_0$: Soil native nutrients have no statistical association with maize production in Southwest Nigeria.

MATERIALS AND METHODS

The study was carried out in six states of Southwest Nigeria comprising Ekiti, Lagos, Ogun, Osun, Ondo, and Oyo States between latitude 5^o N and 9 ^{o} N of the Equator and longitudes 2.5 ^{o} and 6 ^{o} East of the Greenwich Meridian. It is bounded by the Atlantic Ocean in the South, Kwara, and Kogi states in the North, Anambra state in Eastern Nigeria, and the Republic of Benin in the West (Fig.1). The study area has a land area of about 114,271 km^2 representing about 12 percent of the country's total land area (Olaniyi and Adewale, 2012). The climate in southwestern Nigeria is predominantly humid with rainfall from 1500mm to 3000mm per annum. The mean monthly temperature ranges from 18 ^{o}C to 24 ^{o}C during the rainy season and 20 ^{o}C to 35 ^{o}C during the dry season (Sahib et al,1997).

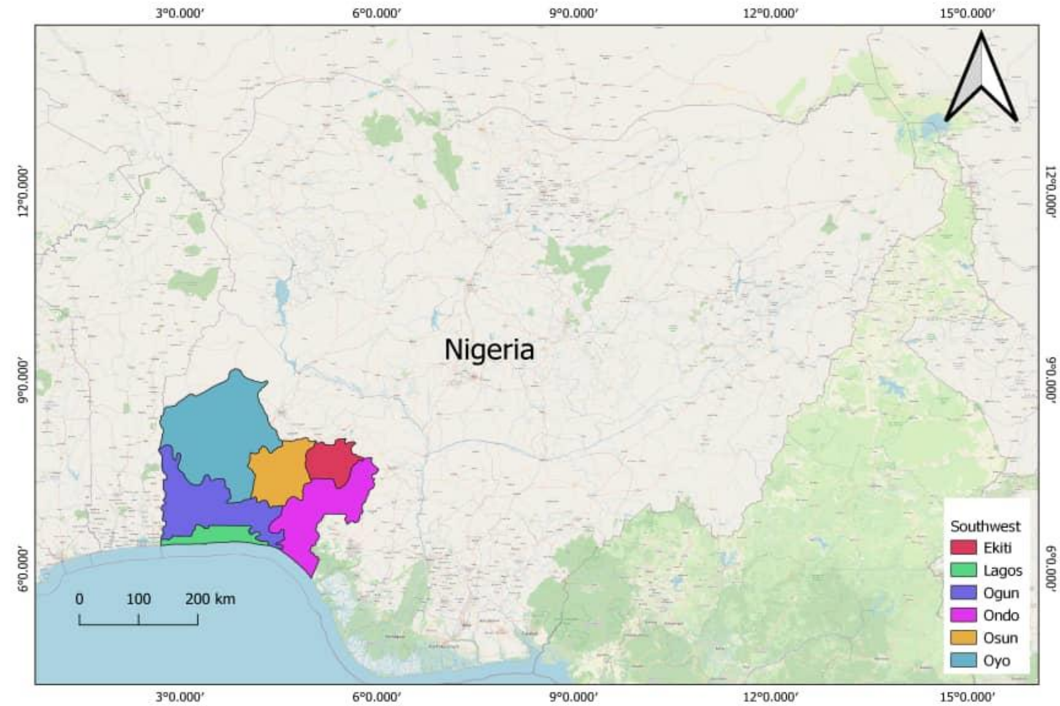


Figure 1. Maps of the study area. Source: Akinbode et al. (2024).

The 30 m resolution land use and land cover map of the study area from 1st January 2022 to 31st January 2023 was downloaded from USGS website and was classified by supervised learning using the maximum likelihood algorithm in Qgis version 3.26.3 (QGIS Development Team, 2021) (Fig. 2). Then stratified sampling method was adopted at 10 km sampling distance within each stratum like Wang et al (2022). However, some sampling points were shifted to nearby distances from their georeferenced points when they fell on watersheds, water bodies, built-up areas, or road networks. At every georeferenced point sampled, the quadrant method of sampling was adopted by taking 3 composite samples at 0 – 40 cm depths in each quadrant which were then thoroughly mixed and from which representative sample was taken into a black cellophane sample bag which was properly labeled with the location's unique number identifier. Environmental and biophysical covariates used as predictors include precipitation, annual temperature, elevation, hill shading, terrain wetness index (TWI), topography positioning index (TPI), altitude above channel network (AACN), gamma radiometric potassium (radK), normalized difference vegetation index (NDVI), Mid slope position, slope, light insolation, and terrain ruggedness index. Also, the multiresolution index for valley bottom flatness (MRVBF) and multiresolution index for terrain top flatness (MRTTF) were included in the predictor variables because many areas within Southwest Nigeria are characterized by undulating landscapes. Soil native nutrients such as soil total nitrogen, phosphorus, potassium, organic matter content, and pH were the target or dependent variables. Soil total N was determined using the micro Kjeldhal method (Brememer and Mulvancy, 1982). Available P was analyzed using Bray-1 P extractant and determined colorimetrically by the molybdenum blue procedure. Exchangeable cations were extracted using 1M Ammonium Acetate pH 7.0 and the potassium in the extract was determined by atomic absorption spectrophotometer (AAS). Continuous soil attribute modeling, regressions, and land suitability modeling were carried out using R statistical software version 4.3 (R Core Team, 2019)

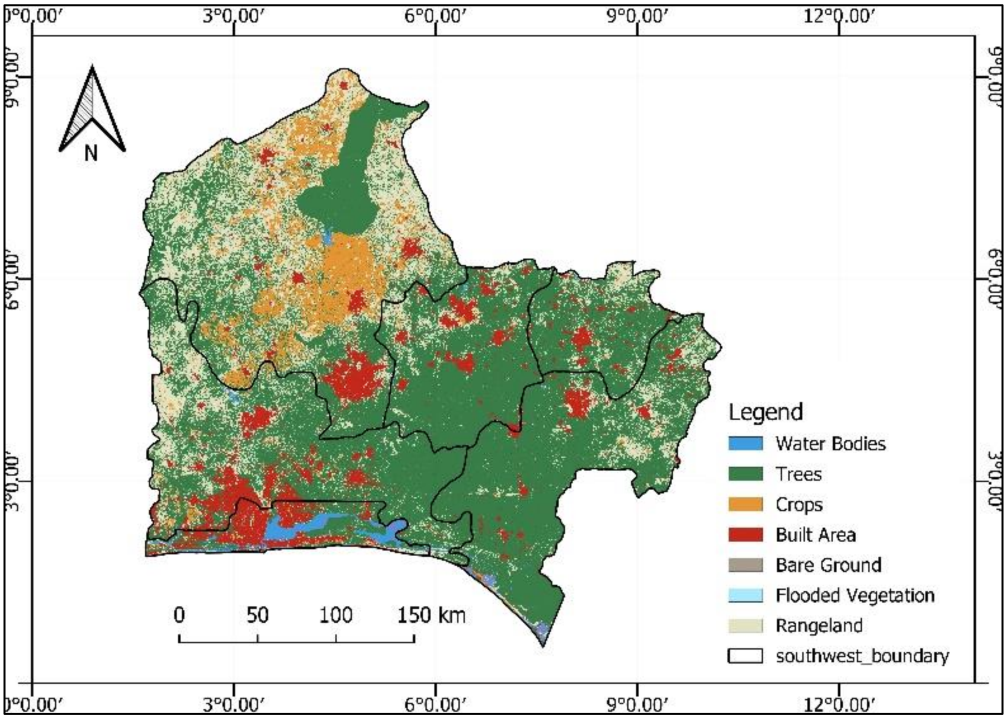


Figure 2. Southwest Nigeria land use and land cover.

RESULTS AND DISCUSSION

The translation of digital soil mapping outputs of soil native nutrients and climatic conditions, framed by the contextual expert-value system that addresses the optimum conditions for maize production, revealed that Southwest Nigerian soil fell only within 3 FAO land suitability categories (FAO, 1976) for maize production. These include Moderately suitable, suitable, and unsuitable (Fig. 3). The largest portion of Southwest Nigerian soil (69.078%) was within the moderately suitable category for maize production. This suitability category was found in all cardinal locations of the study area extending from north to south and east to west (Fig. 3). This agrees with the findings of Olaniyan who posited that an increase in maize production in Nigeria has been achieved greatly by expansion in area cultivated rather than increase in yield. The author further reiterated that Nigeria had to commit over 3 million hectares of land in 2000 which it later increased to 6 million hectares in 2010 to the production of maize as against 2.8 million it committed in 1986 to have higher quantitative yield. Such a huge land resource could have been allocated to more profitable crop enterprises if a land suitability assessment like this had been carried out. However, Olaniyan (2015) advocated that maize production in such areas could improve if fertilizer, land, and subsidized education could be provided by the government, private investors, and non-governmental organizations.

Larger percentage (29.865%) of the study area was unsuitable for maize production using the indices of soil native nutrients and climatic conditions fed into a computer algorithm that was guided by agronomist prescriptions. The unsuitable categorized soil was also found localized in different parts of the study area. (Fig.3)

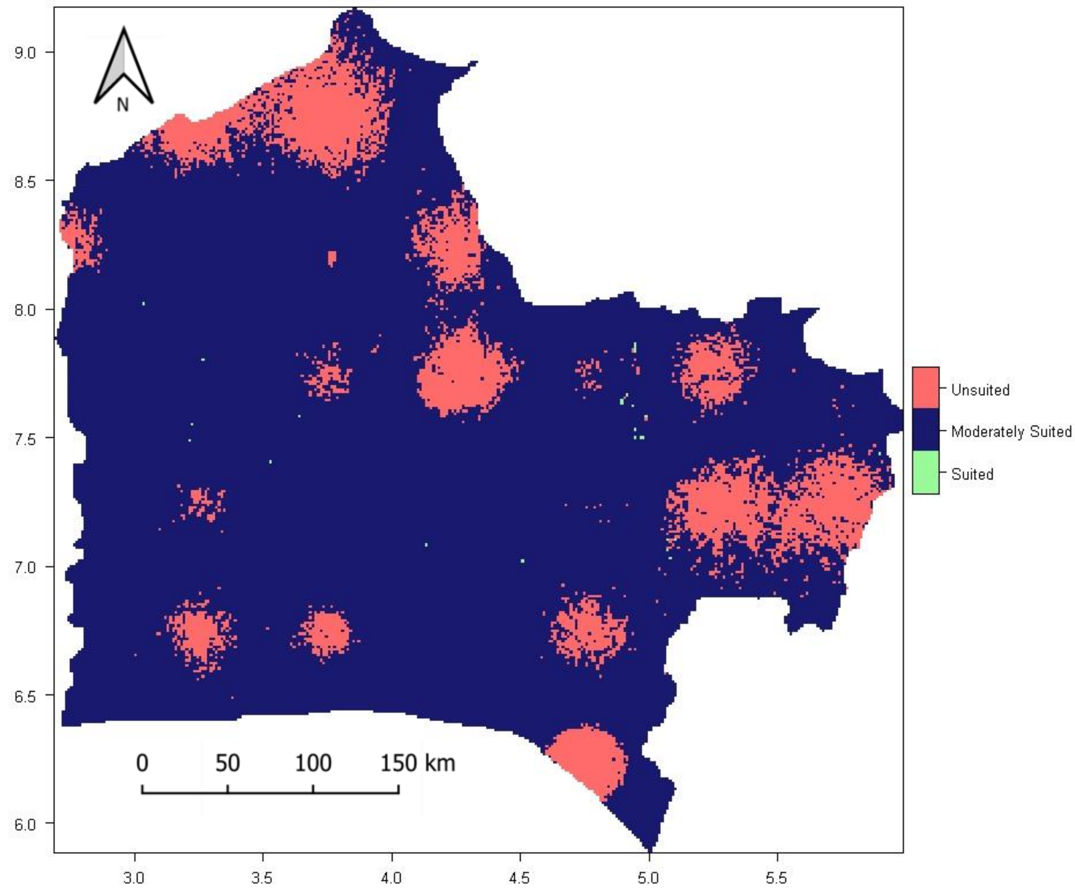


Figure 3. Land suitability map for maize (*Zea mays. Linn)* production in Southwest Nigeria using geographical information system and most-limiting soil nutrients.

The superimposition of land suitability prediction maps (Fig. 3) on initial land use and land cover maps revealed that the bulk of this unsuitable land fell in built-up areas, flooded vegetation, and heavily tree canopy-covered areas while some also fell within heavily crop-cultivated regions (Fig. 2). This revelation that some FAO classified unsuitable areas fell within built-up areas attests to the fact that the quest for urbanization which takes up space for residential, road networks and industrial development could render some land unsuitable. In a study conducted to evaluate the impacts of urbanization in Nigeria Makurdi town, Yusuf et al. (2020) reported that 336 km^2 representing 32% of the total landmass of the study area was taken up by built-up area while 200 km^2 representing 19% of the agricultural land was lost to urbanization.

Observation also revealed that only a few regions of the study area (1.056%) were suitable for maize production using the indices of soil native nutrients and climatic conditions. The suitable regions appeared as spots scattered at different parts of the study area. Most of the suitable land was observed as a cluster at the boundary of Osun State with Ekiti State while others were found as fragments of land in other regions.

CONCLUSIONS

The findings of this study revealed that the largest part of Southwest Nigeria is moderately suitable for maize production while the larger part is unsuitable. However, a few regions of the study area are suitable using the indices of native soil nutrients and climatic conditions. Some of the unsuitable regions were found in built-up areas suggesting indiscriminate and legitimate activities of man competing for agricultural land. Government can control this by putting regulations in place to prevent indiscriminate development and protect Agricultural land. Also, provision of modern soil management training and supply of farm input like organic fertilizer could encourage agrarian communities in regenerative agricultural practices that can improve the nutrient status of moderately suitable lands.

Moreover, digital land suitability assessment like this should be encouraged in other regions of the Country not only to produce maize but also for other crops to ensure adequate allocations of land resources for optimum yield and to comply with sustainable development goals of zero hunger, sustainable cities and communities, responsible consumption and production of United Nations. This study advocates for more research in digital land evaluation for sustainable agricultural production while acknowledging that both the resolution of data and methodology of this research could be improved upon in future studies

REFERENCES

Agricultural Transmission Agenda (ATA) (2011). Maize-Soybean Transmission Action Plan. Federal Ministry of Agriculture and Rural Development, Abuja, Nigeria.

Akinbode, S.O., Folorunso, O., Olutoberu, T.S., Olowokere, F.A., Adebayo, M., Azeez, S.O., Hammed, S.G., and Busari, M.A. (2024). Farmers' Perception and Practice of Soil Fertility Management and Conservation in the Era of Digital Soil Information Systems in Southwest Nigeria. Agriculture. MDPI. 14, 1182. https://doi.org/10.3390/ agriculture14071182

Bremmer, J.M.; Mulvaney, C.S. (1982). Nitrogen-Total. Methods of soil analysis. Part 2. In: Chemical and Biological Properties; Page, A.L., Miller, R.H., Keeney, D.R., Eds.; American Society of Agronomy, Soil Science Society of America: Madison, WI, USA, pp. 526–595.

Fawole, O.P. (2008). Pineapple farmers' information sources and usage in Nigeria. Bulgarian Journal of Agricultural Sciences, 14(4): 381 – 389.

Food and Agriculture Organization (1976). A framework for land evaluation. Soils Bulletin, vol 32. Food and Agriculture Organisation of the United Nations, Rome

Olaniyan, A. B. 2015. Maize: Panacea for hunger in Nigeria. African Journal of Plant Science, 9 (3). Pp 155 -174. Doi: 10.5897//AJPS2014.1203

Olaniyi, O. A. and Adewale, J. G. (2012). Information on maize production among rural youth: A solution for sustainable food security in Nigeria. Library Philosophy and Practice, ISSN 1522-0222. Doi: http://unllib.unl.edu/LPP/

R Core Team, (2019). R: A Language and Environment for Statistical Computing. URL. R Foundation for Statistical Computing, Vienna, Austria. https://www.R-project.org/

QGIS Development Team (2021). QGIS Geographic Information System. Open Source GeoDPatial Foundation Project. http://qgis.osgeo.org.

Wang W, Duan M, Zhang X, Song X, Liu X, Cui D. (2022). Determining Optimal Sampling Numbers to Investigate the Soil Organic Matter in a Typical County of the Yellow River Delta, China. Applied Sciences. 12(12):6062. https://doi.org/10.3390/app12126062

Yusuf Mohammed Bakoji, Elijah Elizabeth, Anita Humshe Philip, Mohammed Salim Isa, Umar Jauro Abba. (2020). Urbanization and its Impact on Agricultural Lands in Growing Cities in Developing Countries: A Case Study of Makurdi, Benue State Nigeria. International Journal of Economy, Energy and Environment. Vol. 5, No. 4, 2020, pp. 41-46. doi: 10.11648/j.ijeee.20200504.11

ON-FARM EXPERIMENTATION

ON-FARM EXPERIMENTATION PROCESS TRIGGERS FARMERS' ZEAL TO TEST TECHNOLOGIES IN MAIZE SYSTEMS OF EMBU COUNTY, KENYA

#11665

[1*]Onesmus Kitonyo, Evans Chimoita, Timothy Kamanu, Felister Nzuve, Esther Muindi, Alfred Micheni, James Muthomi, Vincent Kathumo, Grace Mureithi, George Chemining'wa
[2]Department of Plant Science and Crop Protection, University of Nairobi, Nairobi, Kenya; [2]Department of Agricultural Economics, University of Nairobi, Nairobi, Kenya; [3]Department of Mathematics, University of Nairobi, Nairobi, Kenya; [4]Department of Crop Sciences, Pwani University, Kilifi, Kenya; [5]Kenya Agricultural and Livestock Research Organization, Embu, Kenya. [6]Mount Kenya University, Thika, Kenya; [7]BRITS Agribusiness & Farmers Call Centre, Nairobi, Kenya.
[*]e-mail: kitonyo@uonbi.ac.ke; +254721434412

ABSTRACT

Using on-farm experimentation (OFE) approach, this study was carried out to validate a package of soil moisture and fertilizer nitrogen management practices, and to track farmer adoption of better agronomic practices in maize systems of Embu County, Kenya. Crop residue mulch in combination with calcium ammonium nitrate fertilizer, and a soil conditioner (hydrogels) coupled with slow-release urea were validated against farmer practices. Both management practices increased maize grain yield compared with farmers' practice. Stakeholders observed that these practices improved plant density and vigour, increased grain yield, reduced weed and pest pressure. The OFE process facilitated quick adoption and testing of technologies by farmers. At the onset of the third experimentation season, farmers began to experiment on a range of practices, especially mulching and optimal plant density.

INTRODUCTION

Despite enormous investment in research to improve the productivity of maize systems of Embu County, farmers hardly adopt high yielding agronomic practices. Low adoption could partly be attributed to approaches used in the research process. Researchers have traditionally used on-farm experiments to generate data but without the involvement of the farmer, either at design of experiments, data collection or interpretation of the results (Kummer et al., 2017). To improve bridge the gap in knowledge generation and transfer, and promote innovation by both researchers and farmers, and other stakeholders, it is important to rethink the way experiments are conducted (Richardson et al., 2021). Besides the large pool of stakeholders in co-creation of knowledge, OFE creates value proposition that distinguishes it from other participatory approaches in research. Often, this value arises from farmers being able to access information they can trust (Lacoste et al., 2022). To accelerate farmer experimentation and innovation, this study co-designed experiments with farmers and stakeholders to validate water and nitrogen management practices in maize systems of Embu County, Kenya.

METHODS

On-farm experiments (OFE) were carried out in two environments in the maize growing region of Embu County, in eastern Kenya. The OFE sites were in the upper midland (UM) zones UM3 and UM4, and lower midland (LM) zones LM3 and LM4. Prior to the establishment of experiments, farmers engaged in focus group discussions with researchers to identify relevant management practices for improved productivity of maize. In a bottom-up consultation process, farmers prioritized fertilizer and soil moisture management as the most pressing issues. Subsequently, farmers and researchers co-designed treatment combinations that could address the identified problems. Due to the large pool of treatments, management packages were designed in two distinct plots. The highest best management package (BMP1) comprised the use of soil conditioners (hydrogels) and a slow-release nitrogen (N) source of 'KynoPlus S®' while the next highest management package (BMP2) consisted of the application of 3 t/ha crop residue as mulch and calcium ammonium nitrate (CAN) as N source. The two researcher-managed plots were compared with farmers' business as usual plots. However, it was agreed that practices would change from season to season depending on experiences gathered. In this case, based on learning from the first experimental cycle, treatments were amended during the second season to include a uniform application of 5 t/ha of manure in both BMP1 and BMP2, and the farmer continued business as usual operations but with integration of knowledge from the OFE process.

While plot sizes varied from farm to farm, BMP1 and BMP2 were each allocated at least 900 m2, a size that is comparable with farmers' plots. Data were collected in researcher-managed (BMP1 and BMP 2) and farmer business as usual plots. Prior to harvesting, experiment host farmers, neighbours and other stakeholders were invited to evaluate the performance of the experiments. Farmers were asked to select preferred treatment plots based on their own criteria. The farmers were given three categories of choice per treatment plot, either poor performance, average performance or best performing treatment. The selection exercise was followed by a dialogue to document the criteria applied and farmer perception about the demonstrated management practices.

RESULTS

Yield and farmer selections

Figure 1 presents results from farmer evaluation of experimental plots. Overall, farmers' plots were least preferred by the respondents.

These selections were a true reflection of crop yield performance. Generally, plots applied with hydrogels outperformed those treated with applied with crop residue. However, in UM3/4 sites, differences in grain yield between hydrogel and mulched plots were small, and sometimes not significant. However, in the drier LM3/4 sites, hydrogel plots consistently and largely out-performed mulched plots.

Learning and evolution of farmer practice

Figure 2 shows the evolution of farmer learning from business-as-usual operations to the implementation of better management practices for improved water and nitrogen management. Farmers provided diverse feedback on their learning and presented a range of practices they were willing to test and implement in their plots in the ensuing seasons. At the on-set of the third experimentation season (2023 short rains), majority farmers implemented at least one practice learnt from the engagement with the project. Although farmer perception was not measured, farmers demonstrated confidence with the experimentation process and trusted the results. Indeed, more farmers were enthusiastic to either join the project or test technologies in their farms.

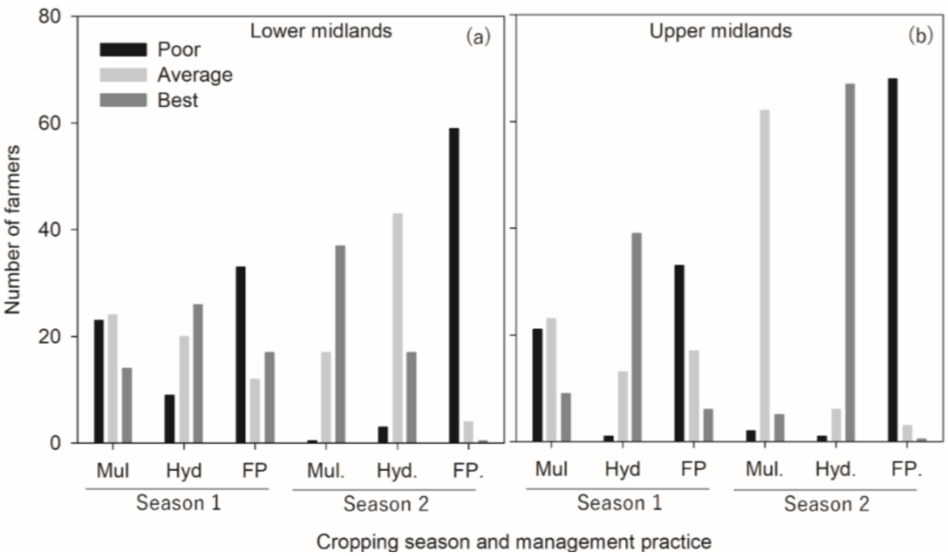


Figure 1. Farmers' selection of management practices during 2022 short rains (season 1) and 2023 long rains (season 2) in lower midland zones (a) and the upper midland zones (b). 'Mul' denotes mulched plots, 'hyd' indicates plots with hydrogels and 'FP' is farmer's practice.

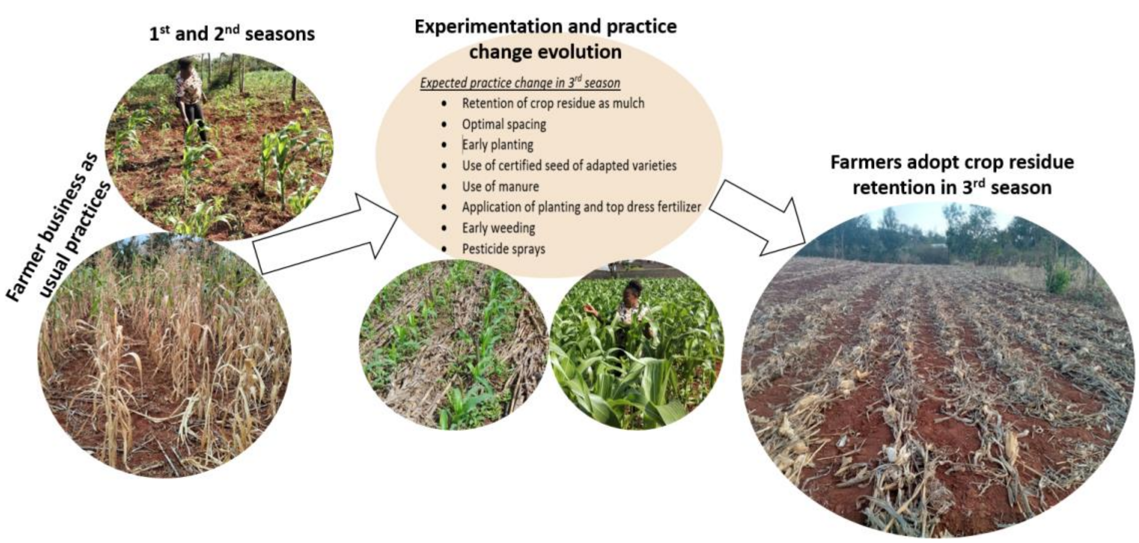


Figure 2. Evolution of farmer management practices as the project entered the third season.

DISCUSSION

The two researcher-managed plots optimized crop management practices unlike in the farmer plots where there were delays in weeding, fertilizer application and pest control. However, the study did not measure significant differences between the two plots. This implies that both hydrogels and mulch potentially conserved soil moisture at similar efficiency. Similarly, the application of calcium ammonium nitrate or the slow-release nitrogen fertilizer formulation did not show differences in maize yield. However, based on the unit price of nitrogen in each formulation, gross margin analyses (not shown) pointed to significantly higher returns per unit area with the use of slow-release fertilizer compared with calcium ammonium nitrate. Nonetheless, either of the fertilizer formulation ought to be applied at an optimal rate, at the right crop stage and placed near the root zone to maximize plant uptake (Bruulsema, 2021).

Adoption of residue retention among smallholder farmers, and especially those in mixed crop-livestock systems of Embu is constrained by the competing uses of crop residue (Jaleta et al., 2012; Baudron et. Al., 2014). In Embu, crop residues are primarily used as animal feed or sold improve household incomes. Through the OFE project farmers evaluated the benefits of mulch in improving maize yield, an outcome that fundamentally changed the farmers' mindset in the allocation of more crop residue to conserve moisture. Improved moisture conservation would open a window for better utilization of nutrients and reduce drought stress. In addition, farmers learnt the importance of better agronomic practices to improve maize yield. Key among the practices, farmers are willing to experiment are early planting, optimal plant density, early weeding, optimal fertilization based on the weather outlook, and use of manure.

In this study, the OFE approach accelerated knowledge transfer and practice change. This was demonstrated in the ability of farmers to take only two seasons of experimentation to start to adopt and test weather-resilient management practices such as mulching of soils with crop residue. This was a significant shift from the status quo where farmers remove crop residue for livestock feed or sale.

REFERENCES

Baudron, F., Jaleta, M., Okitoi, O., & Tegegn, A. (2014). Conservation agriculture in African mixed crop-livestock systems: expanding the niche. Agriculture, Ecosystems & Environment, 187, 171-182. https://doi.org/10.1016/j.agee.2013.08.020

Bruulsema, T. (2022). Nutrient stewardship: Taking 4R further. Crops & Soils, 55(1), 34-40. https://doi.org/10.1002/crso.20165

Jaleta, M., Kassie, M., & Shiferaw, B. (2013). Tradeoffs in crop residue utilization in mixed crop–livestock systems and implications for conservation agriculture. Agricultural Systems, 121, 96-105. https://doi.org/10.1016/j.agsy.2013.05.006

Kummer, S., Leitgeb, F., & Vogl, C. R. (2017). Farmers' own research: Organic farmers' experiments in Austria and implications for agricultural innovation systems. Sustainable Agriculture Research, 6(526-2017-2663). https://dx.doi.org/10.5539/sar.v6n1p103

Lacoste, M., Cook, S., McNee, M., Gale, D., Ingram, J., Bellon-Maurel, V., ... & Hall, A. (2022). On-Farm Experimentation to transform global agriculture. Nature Food, 3(1), 11-18. https://doi.org/10.1038/s43016-021-00424-4

Laub, M., Corbeels, M., Ndungu, S. M., Mucheru-Muna, M. W., Mugendi, D., Necpalova, M., ... & Six, J. (2023). Combining manure with mineral N fertilizer maintains maize yields: Evidence from four long-term experiments in Kenya. Field Crops Research, 291, 108788. https://doi.org/10.1016/j.fcr.2022.108788

Mwaura, G. G., Kiboi, M. N., Bett, E. K., Mugwe, J. N., Muriuki, A., Nicolay, G., & Ngetich, F. K. (2021). Adoption intensity of selected organic-based soil fertility management technologies in the Central Highlands of Kenya. Frontiers in Sustainable Food Systems, 4, 570190. https://doi.org/10.3389/fsufs.2020.570190

Richardson, M., Coe, R., Descheemaeker, K., Haussmann, B., Wellard, K., Moore, M., ... & Nelson, R. (2022). Farmer research networks in principle and practice. International Journal of Agricultural Sustainability, 20(3), 247-264. https://doi.org/10.1080/14735903.2021.1930954

Toffolini, Q. & Jeuffroy, M. (2022). On-farm experimentation practices and associated farmer-researcher relationships: a systematic literature review. Agronomy for Sustainable Development, 42 (144), 1-16. https://doi.org/10.1007/s13593-022-00845-w

THE VALUE AND POTENTIAL OF ON-FARM EXPERIMENTATION TO CATALYZE AGRICULTURAL TRANSFORMATION

#11253

[1*]Ivan S. Adolwa, [2]Eileen Nchanji, [1]Joses Muthamia, [2]Cosmas Lutomia, [3]Simon Cook
[1]African Plant Nutrition Institute (APNI), Nairobi
[2]Bioversity International & CIAT, Nairobi
[3]Murdoch University, Murdoch, Australia
[*]e-mail: i.adolwa@apni.net; +254799657652

ABSTRACT

On-farm experimentation (OFE), which inculcates farmers' agency in knowledge discovery, has the potential to support and accelerate transformative agronomy at scale. The OFE process within the Nutrient-Catalyzed Agricultural Transformation in Africa (NUTCAT) project, encompasses farmer engagements, set-up of simple, easy-to-understand treatment designs, and contextual analysis of the data to enhance the relevance of the results to farmers. Ultimately, it is envisaged that this process will unpack the potential of precision nutrient management (PNM) to improve cereal system production. In this study we focus on the value propositions of OFE for maize-mixed systems of Kenya. To understand the value of OFE we applied the value proposition canvas (VPC) tool on three customer segment categories: Farmers, Service providers and Researchers. We also sought to understand how OFE could be embedded in existing agricultural innovation systems and contexts in which farmers operate. To this end, a survey was implemented to socioeconomically characterize Kenyan maize-mixed farming systems. In terms of the value of OFE, we find that maize farmers are the customer segment that stands to benefit most from the NUTCAT OFE. Farmers derive functional value in terms of high yields and income obtained, but also personal value which is realized through learning and internalization of agronomic concepts. It was observed that farmers value change processes that are holistic with targeted interventions across the value chain. This implies that for OFE to effectively take root in current innovation systems there is a need to explore several entry points beyond plant nutrition interventions. Analysis of the survey data shows that farmers operate under less-than-ideal conditions where fertilizers are costly and supporting institutional structures tend to be ineffective. For instance, although there have been efforts to provide subsidized inputs only a small share of farmers is accessing them. Nevertheless, at least a third of farmers seek and test for relevant solutions to overcome some of the obstacles they face in their farm enterprises. This goes to show that OFE can play a role in strengthening farmer agency to lead the innovation process and transform agricultural landscapes.

Keywords: Value proposition, on-farm experimentation, precision nutrient management

INTRODUCTION

The innovation system in Africa is still characterized by top-down or linear approaches that largely have stifled farmer agency thus contributing to agricultural stagnation. There has been an overt focus by Agricultural Research for Development (AR4D) organizations to prescribe blanket nutrient management recommendations to beneficiary farmers (Zingore at al. 2022). A substantial amount of participatory work has been done with farmers to understand underlying driving factors to their decision-making, but this is yet to bear fruits in terms of increasing their innovative capacity. On-farm experimentation (OFE) is disruptive to this counter-productive process as it brings agricultural stakeholders together around mutually beneficial experimentation to support farmers' own management decisions (Lacoste et al. 2022). Given that OFE is farmer-centric, farmers are not only passive recipients of technologies but are also experimenters, hence are central to the innovation processes. The experiments are conducted at scales that include effects of variations and mimic local conditions as far as possible (Cook et al. 2018). In addition, OFE is characterized by evidence-driven (standardized data protocols), expert-enabled (added value through scientific engagement), co-design (of experiments), and scaling by co-learning (sharing of data, insights, or ideas) principles (Lacoste et al. 2022).

An introspection of the relevant literature ascribes value of agricultural technologies in terms of productivity and household income. There is evidence that technologies such as fertilizers and improved seeds have contributed significantly to increased productivity or incomes of smallholder farmers (Khonje et al. 2015). Nevertheless, the supposed benefits of these technologies have still not been adequate to support their widespread adoption. An interesting perspective is drawn from the re-definition of 'value' by Christensen et al. (2016). They define the value of a product or service as the ability to accomplish the intended task of the beneficiary at a specific point in time. Instead of focusing on the attributes of the beneficiary or 'customer', it is more crucial to concentrate efforts in establishing what the 'customer' hopes to accomplish. Hence, borrowing from this definition we define 'value' as the ability of OFE to enable farmers (or other beneficiaries) to complete 'jobs to be done'. This paper explores the value propositions of OFE for maize-mixed systems of Kenya to understand the value of OFE to different customer segments (farmers, service providers and researchers) and how it could be embedded in existing agricultural innovation systems.

MATERIALS AND METHODS

The value proposition canvas (VPC) was used to garner data on the value of the OFE process from the perspective of the farmers, service providers and researchers (Osterwalder et al. 2015). The value proposition (VP) concept and set of tools is aimed at creating products and services that customers want. In our case the 'customers' were i) farmers who participated in the OFE process and those that were not a part of the process; ii) service providers, mainly the extension agents, non-governmental organizations and any other actors involved in sharing information and knowledge; and iii) researchers drawn from academia and international organizations. The VP is a useful methodology and approach that furnishes tools to help in creating value for the customers, helps us to learn what customers want, trains focus on customers rather than on technologies, products and features, and helps one work with clear processes and tools. Hence, the VPC consists of the customer profile ('understanding your customer') and the value map ('how to create value for the customer'). Finally, you try to see where the two parts fit.

A one-day workshop was organized in September 2023 that brought together different 'customer' segments to ascertain the value they derived from the OFE process. The participants were taken through the tool so that could effectively partipate in the exercise. This was followed by interactive sessions with participants in the late morning and early afternoon sessions where the customer profile was defined, the value map described and finally the value proposition for OFE determined and reviewed (Figure 1). The forty-one attendees included 15 farmers with the rest drawn from 9 organisations including OCP-Africa, APNI, Kenya Agricultural Livestock Research Organization (KALRO), Tupande by One Acre Fund, Cereal Growers Association (CGA), University of Nairobi, Pwani University, County Government extension, and the Alliance of Bioversity and CIAT.

RESULTS AND DISCUSSION

The beneficiaries or customer segments of NUTCAT OFE were categorized into four: i. NUTCAT farmers ii. Non-NUTCAT farmers iii. Service providers iv. Researchers. On application of the VPC tool, it was clear that farmers were the main beneficiaries, but with service providers and researchers benefiting as well albeit to a smaller extent.

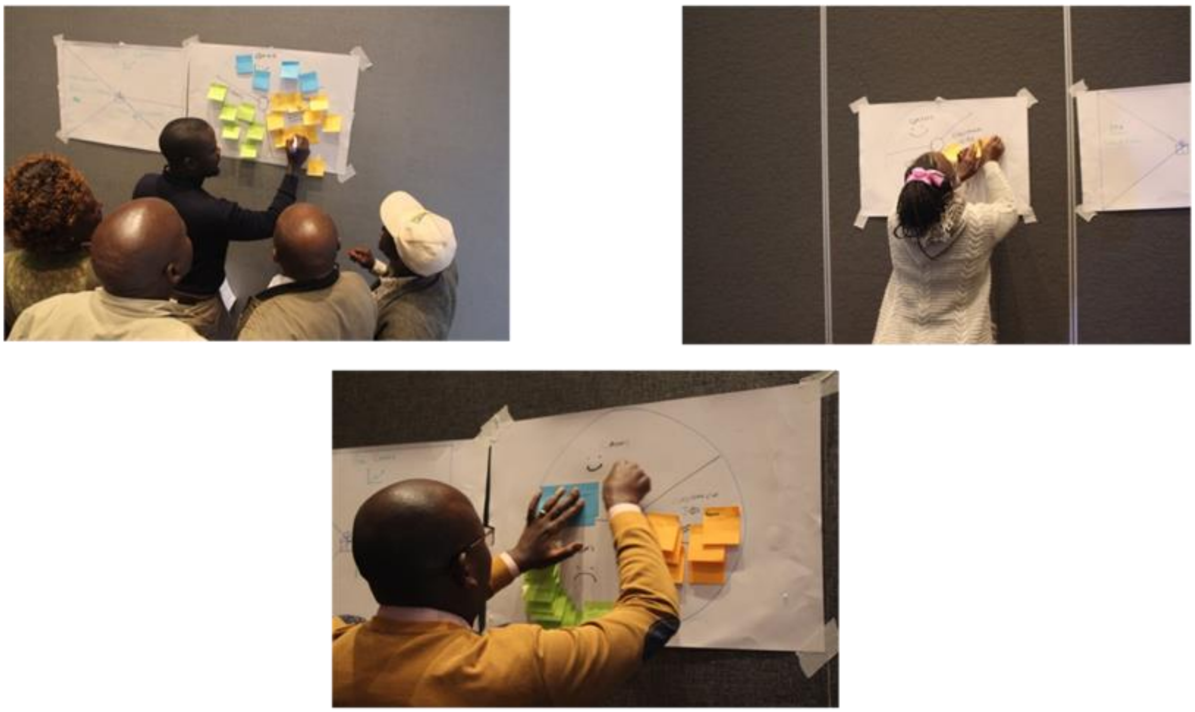


Figure 5. Interactive session to define customer profiles of service providers (top left), farmers (top left) and researchers.

In terms of gains, for farmers functional gains were the most important. Farmers learned from the OFE process on best management practices e.g., crop density, proper use of fertilizer. Farmers valued the higher income earned because of increased productivity. They were well motivated to continue their farming enterprise due to anticipated yield increases. For instance, one NUTCAT farmer reported getting a revenue of US$ 1500 from maize sales. Farmers derived personal value from NUTCAT OFE given that they were able to learn and internalize new agronomic concepts ultimately building their human capital. This is important as it improves the management skills of farmers enabling them to be more adept at innovating. Also, personal value was derived when there was an improvement in social status. Farmers, for instance, indicated that one gain from the OFE process was an increase in social standing in the community as they were able to pay their children's school fees or go to good hospitals.

In terms of inputs and treatments, the inputs OFE works with included fertilizers (DAP, CAN, MoP, Urea, Urea-S, Urea-S Zn), hybrid seeds (Pannar, Duma, DK8033, DK8031), farmyard manure, herbicides, and pesticides. The treatment OFE works with was precision nutrient management (PNM), which emphasizes the efficient and appropriate use of fertilizers. It ialso focuses on site specific nutrient management considering spatial (and temporal) variability. There is also the aspect of sustainable intensification that includes elements of soil and water conservation e.g., use of furrows, and integrated soil fertility management (ISFM). The intent of the OFE process was to increase efficiency of applied inputs through the application of PNM, which in this case is undergirded by 4R Nutrient Stewardship principles i.e., using the right fertilizer source, planting at the right time, right rate, and using the right application method. Substitution took place as well with farmers having stopped using recycled seeds and now using certified, high vigour ones. There was also the intent to redesign the farming system using soil and water conservation technologies to help conserve soil moisture. From a science standpoint, the OFE process entailed the collection of agronomic data (mainly crop cuts). Agronomic principles are adhered to especially where the input of the scientist was prominent. This would entail use of hybrid seed varieties, recommended spacing (crop density), gapping, weed control, and pest control. These agronomic practices were documented for both the scientist-led (OT) and the farmer-led (FP) treatments. All the sampling points (9-36 per field) for the crop-cuts were georeferenced. This was important for garnering spectral data that could be used to generate imageries and yield maps and be correlated analytically with measured yields.

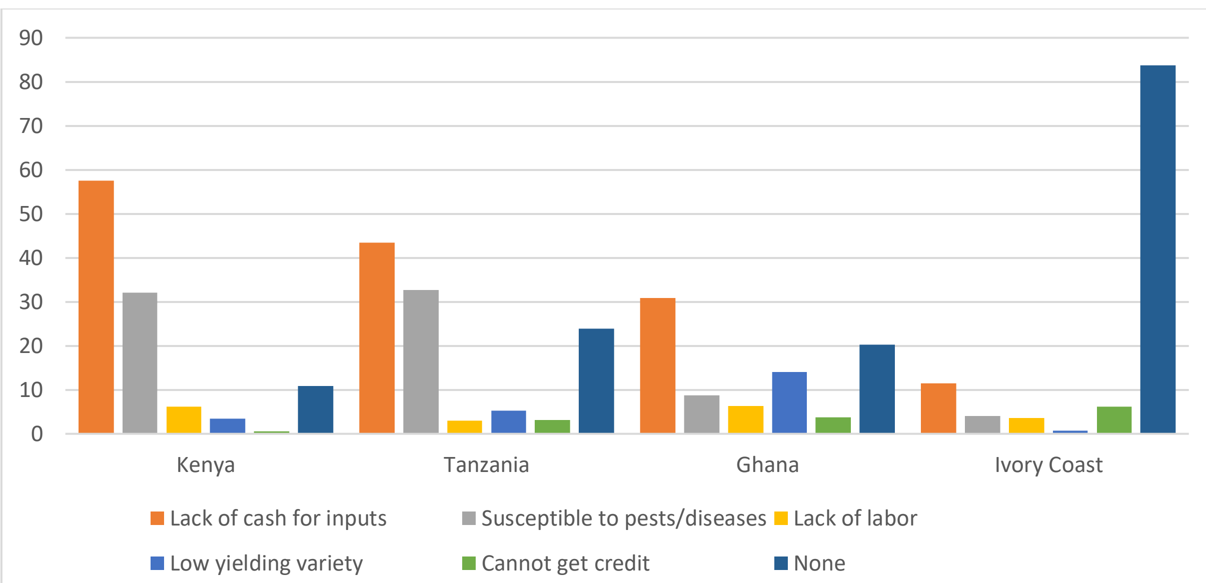


Figure 6. Major farm constraints across countries.

Social or qualitative data is collected at engagement events with farmers and other stakeholders e.g., post-harvest dialogue meetings. Focus group discussion check lists and interviews are applied. Monitoring is done throughout the season to track farmer learning and uptake of innovations. Detailed surveys were also conducted to unravel the socio-economic context in more depth. Key survey results show that farmers operate under less-than-ideal conditions where fertilizers are costly and supporting institutional structures tend to be ineffective (Figure 2). Despite efforts to provide subsidized inputs only a small share of farmers are accessing them. Nevertheless, at least a third of sampled farmers are experimenting with various options to overcome some of the obstacles they face in their farm enterprises (Table 1).

Table 5. Level of farmer-led experimentation and knowledge generation in Kenya.

Experimentation	
Farmer experimenting /testing solutions (%)	28.10%
Farmers have sought for solutions (%)	33.10%

CONCLUSIONS

The OFE process in principle portends substantive value for farmers. Nevertheless, OFE has not addressed financial literacy and record keeping needs of farmers. This is important if they are to derive maximum value from the process as they need to know if their farming enterprise is profitable. There other issues related to translational uncertainties e.g., access to good, certified seeds that need to be addressed to further unlock OFE. There is need to strengthen extension given the high farmer to extension ratio. Gender streamlining, which is important for service providers and researchers, may have a positive spillover on the OFE process. Government support is crucial for researchers to derive benefits from an OFE process and to alleviate some of the infrastructural constraints that generally hinder the change process.

REFERENCES

Christensen, C.M., Hall, T., Dillon, K. and Duncan, D.S., 2016. Know your customers' jobs to be done. Harvard business review, 94(9), 54-62.

Cook, S., Lacoste, M., Evans, F., Ridout, M., Gibberd, M., and Oberthür, T. 2018. An On-Farm Experimental Philosophy for Farmer-centric Digital Innovation. Proceedings of the 14th International Conference on Precision Agriculture.

Lacoste, M., Cook, S., McNee, M., Gale, D., Ingram, J., Bellon-Maurel, V., MacMillan, T., Sylvester-Bradley, R., Kindred, D., Bramley, R., Tremblay, N., Longchamps, L., Thompson, L., Ruiz, J., García, F. O., Maxwell, B., Griffin, T., Oberthur, T., Huyghe, C., … Hall, A. 2022. On-Farm Experimentation to transform global agriculture. Nature Food, 3(1), 11–18. https://doi.org/10.1038/s43016-021-00424-4

Khonje, M., Manda, J., Alene, A.D., and Kassie, M., 2015. Analysis of adoption and impacts of improved maize varieties in eastern Zambia. World Dev. 66, 695–706.

Osterwalder, A., Pigneur, Y., Bernarda, G. and Smith, A., 2015. Value proposition design: How to create products and services customers want. John Wiley & Sons.

Zingore, S., Adolwa, I.S., Njoroge, S., Johnson, J.-M., Saito, K., Phillips, S., Kihara, J., Mutegi, J., Murrell, S., Dutta, S., Chivenge, P., Amouzou, K., Oberthür, T., Chakraborty, S., and Sileshi, G.W. 2022. Novel insights into factors associated with yield response and nutrient use efficiency of maize and rice in sub-Saharan Africa. A review. Agronomy for Sustainable Development, 42, 82.

PRECISION LIVESTOCK MANAGEMENT

MONITORING GRAZING GOATS' BEHAVIOR USING SENSORS AND SATELLITE REMOTE SENSING

#11267

[1]Y. Chebli, [1]S. El Otmani, [2]F. Elame, [3]J.F. Cabaraux, [4]A. Keli 4, [1]M. Chentouf
[1]Regional Center of Agricultural Research of Tangier, INRA, Morocco; [2]Regional Center of Agricultural Research of Agadir, INRA, Morocco; [3]Faculty of Veterinary Medicine, University of Liège, Belgium; [4]National School of Agriculture, Meknes, Morocco
e-mail: youssef.chebli@inra.ma

ABSTRACT

The recent development of new methods for remotely observing animal behavior using electronic sensors such as global positioning systems (GPS) and three-axis accelerometers to monitor and record behavior at different spatial and temporal scales presents real opportunities to better understanding and interpreting behaviors of grazing animal. The goal of this study was to distinguish different behavioral categories of grazing goats by combining GPS collars, accelerometers, and satellite remote sensing. It was conducted in the mountainous forest rangeland of Beni Arouss (Northern Morocco) from an extensive local goat's farm. Eight experimental goats were fitted with GPS collars and leg sensors to monitor their seasonal grazing activities. A calibration study and classification tree analysis were used to predict the grazing activities of goats. According to the results, goats spent most of their time searching for forage in the spring and autumn. Goats prolonged their resting time in summer ($p<0.001$) at the expense of grazing time. The number of steps was numerically similar and significantly higher in both seasons of summer and autumn ($p<0.001$). Goats spent 48% of their feeding time grazing (foraging) during the spring season, in contrast to the summer (27%) and autumn (31%). Analysis of GPS collar data showed a significant effect of the season on the measured parameters ($p<0.001$). Monitoring grazing activities by using GPS collars and sensors provides useful and accurate information, which could be used to manage grazing strategies and optimize animal performance

INTRODUCTION

In Northern Morocco, forest rangelands ensure abundant and free fodder production for grazing animals. Livestock in this region is concerned with grazing goats in forest pastures, guaranteeing free animal feed all year round (Chebli et al., 2023). Grazing in mountainous forest rangelands generates additional physical activities for the vertical locomotion of goats (Chebli et al., 2022). These altitudinal motions increase the time and energy required to travel a given distance. This information is difficult to obtain only through direct observation because observers cannot accurately measure individual animal behavior, such as movement and activity patterns. Data on an animal's behavioral activities are critical to understand feeding behavior and interactions with the environment, and to identify optimal management intervention strategies. The recent developments in Global Positioning Systems (GPS) and the increasing number of accelerometers used to monitor and record behavioral activities offer real opportunities to expand databases and understand animal grazing behavior. Previous studies using sensors and GPS technology to track animal grazing activities have focused on grazing cattle and sheep (Barbari et al., 2006; González-Pech et al., 2015; Ungar et al., 2018). The aim of this research is to ensure the sustainability of goat farming in extensive production systems using GPS collars, sensors, and remote sensing to better understand the grazing behaviour of goats to make targeted decisions for management and grazing strategies.

MATERIALS AND METHODS

This work was carried out in the forest pasture of Beni Arouss in Northern Morocco. Eight experimental local meat goats of the Beni Arouss breed (local goat, 30 ± 2.6 kg live weight (BW) and 36 ± 6 months of age) were chosen to conduct this study, during the three-grazing seasons (spring, summer, and autumn). Goats spend most of their day in the studied forest pasture. At the end of the grazing day, the animals are confined to a closed and semi-open shed inside the farm. In winter, access to forest rangelands is very limited and corresponds to the calving period. To ensure that goats are fed during winter season, herders delimb the branches of evergreen trees in the forest as fodder and bring them to the goat farm (Chebli et al., 2023). Each experimental goat was fitted with a GPS collar and an IceTag sensor on the left hind leg for three days during each studied season. Several days before the actual experimentation, these goats were fitted with GPS collars and IceTag sensors to accustom them to the devices attached to their bodies. GPS data was used to estimate location, speed, and horizontal and vertical traveled distances. The data were analyzed by the GPS3000 Host software. Coordinates were converted from UTM WGS84 to Moroccan Transverse Mercator using ArcGIS 10.X. Coordinates (x and y) in meters were calculated for each fixed record using ArcMap. The vertical distance (VD) was derived from the altitude difference between successive positions 1 (z1) and 2 (z2). IceTag data was analyzed by IceManager software. The variables provided are the goat is lying (sitting to rest or ruminating), standing (standing without eating and ruminating), number of steps, and movement index (a proprietary metric of overall leg activity measured in three dimensions).

Data analyzes were performed using SAS software. The grazing activity data were analyzed according to the SAS PROCMIXED procedure. Parameters were compared across seasons (i.e., spring, summer, and autumn). For all analyzes, the level of significance was declared at $p < 0.05$. In case of significance, means were compared using Tukey test.

RESULTS AND DISCUSSION

Figures 1 and 2 represent the seasonal variation of grazing goat activities. Goats spent most of their time searching for palatable species in the spring and autumn. Goats prolonged their resting time in summer ($p<0.001$) to the detriment of resting time. The number of steps was numerically similar and significantly higher in both seasons of summer and autumn ($p<0.001$).

Analysis of GPS collar data showed a significant effect of the season on the measured parameters ($p<0.001$). During the summer, the forage availability is very limited, which obliges the goats' herder to move during this season and to settle in another forest pasture in the region (Figure 2). The horizontal distance traveled by goats was similar and significantly higher in autumn and summer. A similar trend was observed for the vertical distance. Conversely, goat speed was significantly higher in spring compared to other seasons ($p<0.001$). Foraging day length (time spent grazing) was prolonged ($p<0.001$) in summer compared to autumn and spring. According to CART (Classification and Regression Tree) analysis, the time spent grazing (eating) was longer in spring and similar in summer and autumn ($p<0.001$). Standing rest was similar between seasons ($p = 0.191$). Time spent walking without grazing (eating) is classified as fall > summer > spring. The findings of this study correlate with seasonal variations in grazing behavior of goats in similar forest pastures (Chebli et al., 2022). In other regions of Africa, Safari et al. (2011) reported that goats in the semi-arid zone of Tanzania increased their grazing (eating) time (57–68%) and decreased their resting time (6.8–1.4%) between rains and late summer, while their time spent walking was similar (27%). In a similar region of Zimbabwe, goats spent most of their time eating during the rainy season (52–75%) in contrast to the summer (29–50%) (9. Nyamangara et al., 1995). Like the current results, goats spent 48% of their feeding time grazing (eating) during the green season, in contrast to the summer (27%) and autumn (31%) seasons [2]. This result could be explained by the high abundance of preferred shrubs (*Cistus spp*. and *Lavandula stoechas*) and herbaceous plants during the spring season. In the semi-arid zone of Tanzania, Safari et al. (2011) reported that goats extended the length of their grazing day in the summer compared to the rainy season to meet their intake requirements.

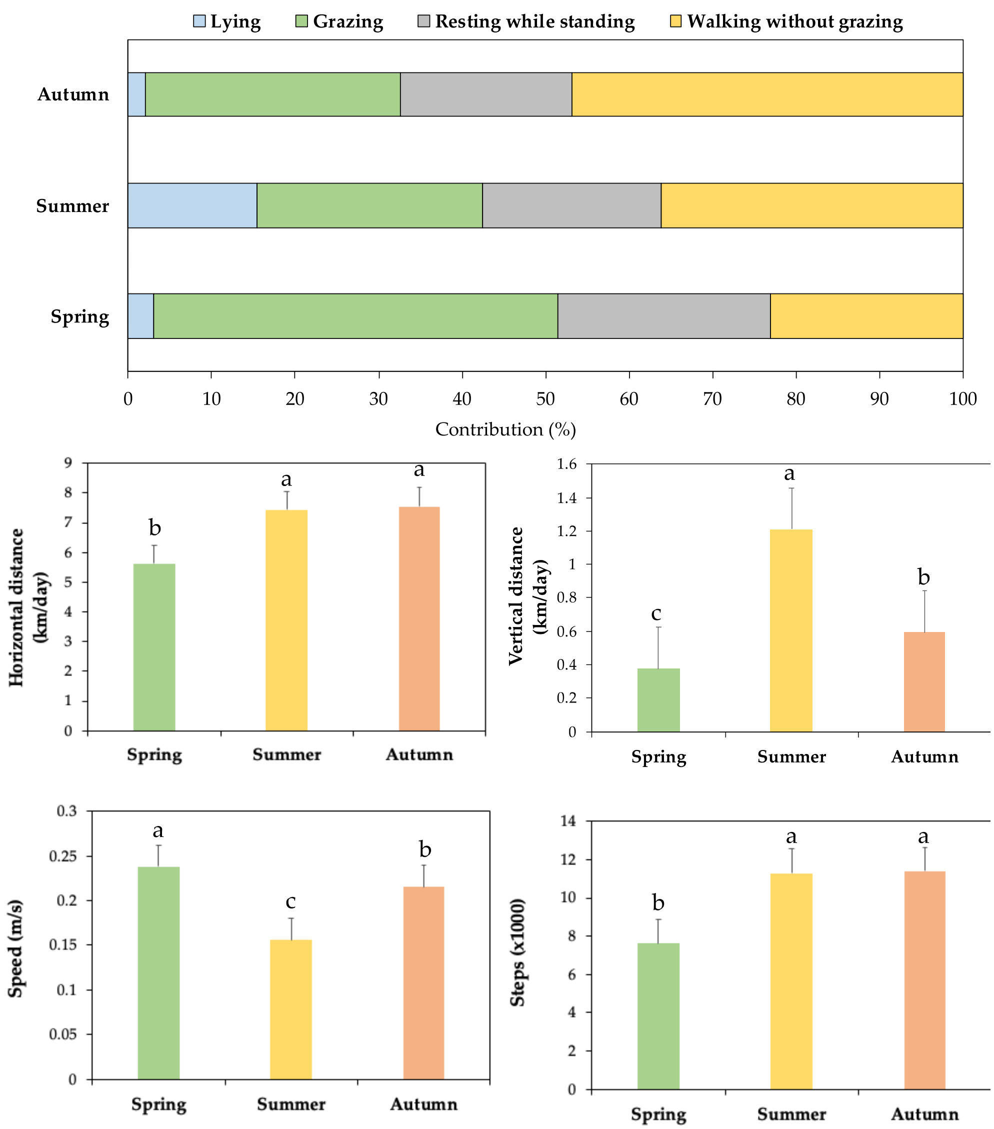


Figure 1. Seasonal variation in grazing activities of experimental local goats browsing in Beni Arouss pasture (Northern Morocco).

CONCLUSIONS

The combination of GPS collar, accelerometer, and remote sensing to monitor and record the grazing activities of goats has provided useful data for understanding the grazing behavior of goats in a complex forest rangeland of Northern Morocco.

Data on individual animal behavior, such as movement and activity patterns, are often important for their management on pasture. It would be more interesting to extend this type of study to other livestock systems and other types of animals to develop a guide on the use of forest pastures in Morocco.

REFERENCES

Chebli Y., Chentouf M., Cabaraux J.F., and El Otmani S. 2023. Floristic Composition, Diversity, Palatability, and Forage Availability of Forest Rangelands in the Southern Mediterranean Region of Northern Morocco. Land, 12: 215.

Chebli Y., El Otmani S., Hornick J.L., Bindelle J., Cabaraux J.F., Chentouf M. 2022. Estimation of grazing activity of dairy goats using accelerometers and global positioning system. Sensors, 22: 5629.

Barbari M., Conti L., Koostra B.K., Masi G., Guerri F.S., Workman S.R. 2006. The use of global positioning and geographical information systems in the management of extensive cattle grazing. Biosyst. Eng. 95: 271–280.

González-Pech P.G., Torres-Acosta J.F.D.J., Sandoval-Castro C.A., Tun-Garrido J., de Jesús Torres-Acosta J.F., Sando-val-Castro C.A., Tun-Garrido J. 2015. Feeding behavior of sheep and goats in a deciduous tropical forest during the dry season: The same menu consumed differently. Small Rumin. Res. 133: 128–134.

Ungar E.D., Nevo Y., Baram H., Arieli A. 2018. Evaluation of the IceTag leg sensor and its derivative models to predict be-haviour, using beef cattle on rangeland. J. Neurosci. Methods. 15: 127–137.

Safari J., Mushi D.E., Kifaro G.C., Mtenga L.A., Eik L.O. 2011. Seasonal variation in chemical composition of native forages, grazing behaviour and some blood metabolites of Small East African goats in a semi-arid area of Tanzania. Anim. Feed Sci. Technol. 164: 62–70.

Nyamangara M.E., Ndlovu L.R. 1995. Feeding behaviour, feed intake, chemical and botanical composition of the diet of indigenous goats raised on natural vegetation in a semi-arid region of Zimbabwe. J. Agric. Sci. 124: 455–461.

ADVANCEMENTS IN PRECISION AGRICULTURE: CUTTING-EDGE SOLUTIONS FOR COCCIDIOSIS DISEASE USING SMART DIAGNOSTIC SYSTEMS

[1*]F.O. Bamigboye, [2]O. Bello, [2]O.A. Osaikhuwuomwan, [2]P.C. Anakua
[1] Department of Agricultural Sciences, College of Sciences, Afe Babalola University Ado-Ekiti, Ekiti State; [2]Department of Computer Science, College of Sciences, Afe Babalola University Ado-Ekiti, Ekiti State
e-mail: bamigboyefo@abuad.edu.ng

ABSTRACT

The poultry industry in Nigeria faces critical challenges from diseases like Coccidiosis, which severely hinder productivity. Traditional farming methods, limited access to veterinary services, and unreliable diagnostic information exacerbate this issue. To address these challenges, this study harnesses artificial intelligence (AI) and machine learning (ML) to develop a smart diagnostic solution for poultry diseases. Using Google Teachable Machine and a dataset of 4,880 faecal images sourced from an open-access Zenodo repository, this study applied advanced image augmentation, pre-processing, and segmentation techniques to enhance diagnostic accuracy. The dataset was split into 85% for training and 15% for testing, achieving an impressive 99% accuracy. The classification model was integrated into a mobile application built with Flutter and Python, enabling farmers to easily access diagnostic tools for proactive disease management. This innovation bridges the gap in veterinary services, providing an efficient and cost-effective solution for identifying and managing Coccidiosis in poultry. Future work will explore extending the application to other poultry diseases and validating its impact through real-world field trials. This study marks a significant advancement towards sustainable poultry farming in Nigeria, fostering economic growth and improved food security.

Keywords: Machine Learning, Precision Agriculture, Poultry Disease Diagnostics, Mobile Applications, Image Classification

INTRODUCTION

Nigeria is noted as having the second largest chicken population in Africa, with a standing stock of about 180 million birds producing more than 14 billion eggs and 454,000 tonnes of meat annually. The Nigerian poultry industry contributes approximately 25% to agricultural GDP (Makasi *et al*., 2020). However, poultry production has not kept pace with the rapid increase in domestic consumption because it is greatly affected by poultry diseases. Coccidiosis is a poultry disease ranked as one of the leading causes of death in poultry with *Eimeria tenella* among the most pathogenic parasite (Abbas *et al*., 2019; Williams, 2005). Without timely detection and intervention, outbreaks of coccidiosis can lead to substantial economic losses in the livestock sector.

The present and most common diagnostic techniques for coccidiosis rely on clinical indicators, such as determining if the diarrhoea is bloody or brown, counting the number of oocytes in the stool, and assessing the intestinal tract to get the lesion score. In addition to taking days to complete, all of these procedures are costly and time-consuming since by the time a diagnosis is obtained, the disease may have progressed, or a high death rate may have occurred.

Recent studies highlight how smart diagnostic systems—powered by sensors, machine learning, and data analytics—can offer real-time monitoring and early detection of coccidiosis in livestock, enabling farmers to implement timely interventions and reduce reliance on antibiotics (Ahmad *et al*., 2020; Su *et al*., 2018). These systems utilize data-driven insights to provide continuous health assessments, helping farmers address disease outbreaks efficiently while supporting sustainable livestock production practices. Hence, the present study explored the possibilities of cutting-edge solutions for Coccidiosis disease using Smart Diagnostic Systems in poultry production.

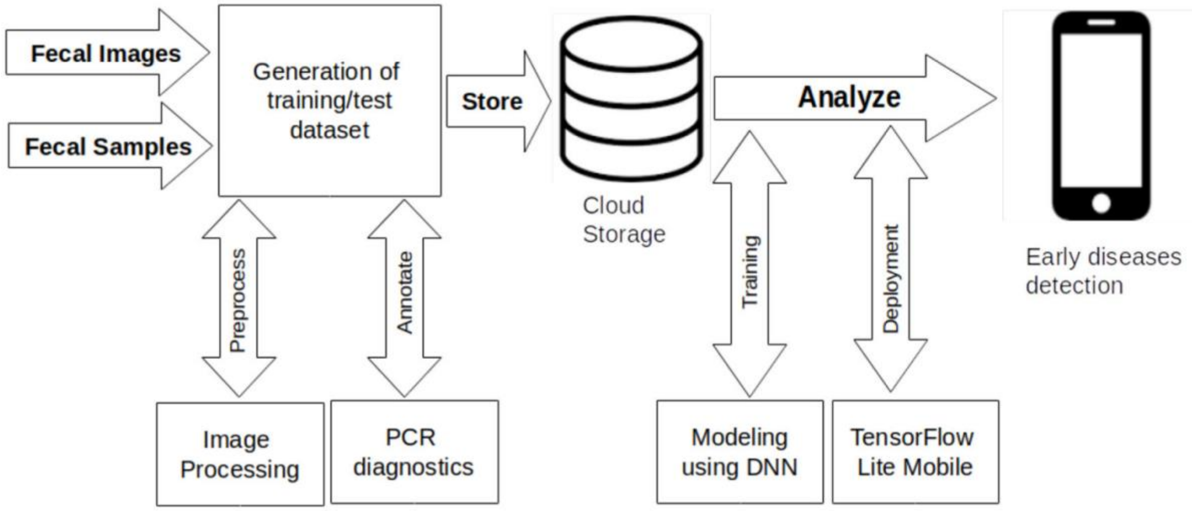
MATERIALS AND METHODS

The study utilized a comprehensive dataset of poultry faecal images, sourced from a Zenodo repository published by Machuve *et al.* (2021). The images, collected between February 2020 and February 2021 from farms in Tanzania, represented two categories: chickens affected by coccidiosis and healthy chickens. A total of 720 laboratory-labelled images were processed using Polymerase Chain Reaction (PCR) for disease confirmation, while 4160 farm-labelled images were annotated by veterinarians and field officers based on visual features like color and shape.

To prepare the data, the images were resized to uniform dimensions (224x224 or 512x512 pixels) and categorized into training (85.2%), validation (15%), and testing (14.8%) sets. Pre-processing involved manual labeling and data augmentation techniques, such as image flipping, cropping, padding, and saturation adjustments, to enhance the training set and prevent overfitting.

Model training was conducted using Google Teachable Machine, employing pre-trained deep neural networks. Key parameters included a learning rate of 0.001, 50 training epochs, and a batch size of 16. Performance was evaluated by monitoring training and validation accuracy and loss across epochs. Once trained, the model was exported as a TensorFlow Lite file for mobile application deployment.

The final system integrated the AI model with a Flutter-based mobile application, enabling efficient and portable diagnostics for chicken diseases. This framework provided farmers with an accessible tool to detect coccidiosis on-site using a lightweight, high-performing classification model.



Automated coccidiosis disease diagnostics research work-flow

RESULTS AND IMPLEMENTATION

The study evaluated the performance of a deep-learning model trained to diagnose coccidiosis in poultry using a dataset of 4880 labelled faecal images. The dataset included 2476 images of chickens affected by coccidiosis and 2404 images of healthy chickens. The model, trained using Google Teachable Machine, demonstrated exceptional accuracy, achieving 99% for the coccidiosis class and 100% for the healthy class. Performance metrics, including the confusion matrix, accuracy trends, and loss per epoch over 50 training iterations, confirmed the model's reliability and effectiveness in classification tasks.

For practical implementation, the trained model was converted into TensorFlow Lite format to optimize it for mobile devices. This lightweight format ensured compatibility with devices having limited computing resources while maintaining the model's high accuracy. The conversion process included loading the model, preprocessing input images, running predictions, and postprocessing the output to generate class labels and their probabilities.

The integrated system was deployed as a mobile application developed with Flutter, providing a user-friendly interface for poultry farmers. The app allows users to capture or upload images of chicken faeces, which are classified in real-time using the embedded AI model. Results, including the predicted class (Coccidiosis or Healthy) and prediction accuracy, are displayed alongside expert-verified treatment recommendations. Treatment options, such as herbal and chemical remedies, are stored in a centralized database and accessed dynamically within the app.

CONCLUSION AND RECOMMENDATION

The mobile application developed for the detection of coccidiosis in poultry demonstrates the potential of leveraging artificial intelligence to support early disease diagnosis in agricultural settings. The integration of a highly accurate deep-learning model (achieving 99% and 100% accuracy for coccidiosis and healthy classes, respectively) with a user-friendly interface ensures a practical, scalable tool for poultry farmers. By enabling real-time analysis of faecal images and offering reliable treatment recommendations, the system addresses a critical challenge in poultry farming—minimizing disease-related losses. Its deployment as a lightweight mobile application ensures accessibility even for small-scale farmers with limited resources.

It is therefore recommended that efforts should focus on promoting the app's adoption through training programs and awareness campaigns to educate farmers about its benefits. Regular updates to the AI model are essential to enhance its robustness, ensuring accuracy across diverse regions and poultry breeds. Expanding the app's diagnostic capabilities to include other poultry diseases would further increase its value as a comprehensive tool for farmers.

To improve accessibility, offline functionality should be developed, to enable farmers in remote areas with limited internet access to use the app effectively. Additionally, integrating the app with veterinary services could provide users with expert guidance for advanced diagnosis and treatment. Data privacy measures must be prioritized to safeguard user information and ensure compliance with security standards. Finally, conducting economic evaluations to quantify the app's financial benefits—such as reduced disease-related losses and improved productivity—will highlight its value and encourage wider adoption.

REFERENCES

Abbas, R. Z., Colwell, D. D., & Gilleard, J. (2019). Advances in the diagnosis of coccidiosis in poultry. Veterinary Parasitology, 268, 3-11.

Ahmad, T., Awais, M. M., Akhtar, S., & Saleem, M. (2020). Smart farming: real-time diagnostic approaches in livestock disease management. Journal of Animal and Plant Sciences, 30(5), 1093-1105.

Machuve, Dina, Nwankwo, Ezinne, Lyimo, Emmanuel, Maguo, Evarist, & Munisi, Charles (2022). Machine Learning Dataset for Poultry Diseases Diagnostics - PCR annotated (Version 3) [Data set]. Zenodo. https://doi.org/10.5281/zenodo.5801834

Masaki, M.N., Lee, I., Duns, H., Toromade, F. and Ayo, O. (2020). Poultry Sector Study in Nigeria. By Netherlands Enterprise Agency (NABC, 2020).

Su, W., Li, Y., & Yang, Y. (2018). Application of big data and artificial intelligence in intelligent farming of animals. Engineering, 4(5), 560-565.

Williams, R. B. (2005). Intercurrent coccidiosis and necrotic enteritis of chickens: Rational, integrated disease management by maintenance of gut integrity. Avian Pathology, 34(3), 159-180.

PRECISION NUTRIENT MANAGEMENT

ASSESSMENT OF NITROGEN FERTILIZATION IN TUNISIAN WHEAT PRODUCTION USING PROXIMAL AND REMOTE SENSING
#11255

[1*]M. Mechri, O. Alshihabi, H. Angar, I. Nouiri, M.H. Landolsi, M. Söderström, K. Persson, S. Phillips
[1]National Institute of Field Crops (INGC/Tunisia)
[*]e-mail: mounassol.mm@gmail.com; 00216 5010712

ABSTRACT

The study aims to develop an approach and a workflow to optimize the in-season nitrogen (N) application in wheat cultivation in Tunisia, using the remote and proximal sensing techniques. Two types of trials, N response trials on small plots and large-scale trials, were carried out for two seasons (2023-2024) in the different climatic zones in the country. Data were collected for several parameters (e.g. N content, vegetation indices 'VIs', yield) and statistically analyzed. The preliminary results showed wide variations of data around the means and no significant differences, for the different parameters, between the N rates in the N response trials, even in the zero plot (no N added). The VIs were quickly saturated at early Growth stage (GS≈31-39), only the first measurement in February showed slight differences between the measurements of the different N treatments. The correlation between the N content and the VIs for the first date was weak ($r2=0.2$).

INTRODUCTION

Tunisia faces water scarcity, and the agricultural sector declines due to climate change, with projected decreases in rainfall, changes in rainfall pattern and increases in temperature (Ouessar et al., 2021; Mechri et al., 2023). Tunisian farmers face challenges in effective land management and optimal N fertilisation due to the crucial role of agriculture in Tunisia's economy and food security (FAO, 2023). N is one of the key nutrients that limit the crop growth of cereals in many production systems and is a key factor in achieving the optimum grain yield (Wang et al, 2023). The importance of N fertilization in increasing wheat production has been well recognized but still difficult to determine the quantities to apply under water deficit conditions (Kedir, 2020). The cereal sector in Tunisia covers wide areas in the country from sub-humid to semi-arid zones; where most of the fields are rainfed (Sadok et al., 2019). The Nutrients availability in the soil are induced elements in the soil, water shortage is tightly correlated to water management policy in the country that prioritizes allocating surface water to domestic uses rather than to irrigation. On the other hand, irrigation using groundwater (e.g. in Kairouan) continues to overuse the water table with an average drawdown of 5 m year-1. These conditions lead to a low N use efficiency, low national wheat (Triticum durum L.) average yield – estimated to 1.4 t ha-1, in addition to groundwater pollution (de Oliveira et al 2020). In Sweden, the zero plot technique to assess the initial soil N supply is widely used by farmers, often in combination with proximal sensing based digital tools for variable rate application (VRA) of N (Alshihabi et al., 2020). The risk of nutrients leaching is high during the after-harvest rainfall, in Sweden catch crops, is a measure commonly used to uptake the residual nutrients in between growing seasons, which is not applicable in Tunisia due to lack of rainfall during the summer season. In this study an experimental program was implemented in Tunisia to assess the N uptake using proximal and remote sensing for better N fertilizing practices.

MATERIALS AND METHODS

The present project (2023-2024), is a collaboration between the Swedish university of agricultural sciences (SLU) and two institutions in Tunisia (the National Institute of Field Crops ‘INGC’, and the National Agronomic Institute of Tunisia ‘INAT’), it aims to develop basic knowledge, methods, calibration models and workflows for proximal and remote sensing in wheat production in Tunisia, to be used as the basis for a DSS for optimizing N recommendations to the wheat farmers. The project collaborates with a wider project on N application management (NUTCAT) covering several African countries. The joint research program in Tunisia covers all the climatic zones of cereal cultivation, the rainfed production in the sub-humid (e.g. Beja) and the semi-arid (e.g. Manouba and Siliana) areas, while irrigation is applied in the arid area in Kairouan. In each climatic zone, two types of trials were implemented in farmers’ fields: N response trial on small plots (3×12m), and 2-3 larger trials (1 ha). The N response trials cover 15 different rates of N application (T1-15), which vary from 0 kg ha-1 for the zero plot in all areas, and for the fertilized plots varies from 20-80 kg ha-1 in the semi-arid area, 50-190 kg ha-1 in the sub-humid area to 70-280 kg ha-1 in the aridIrrigated area. The fertilization was carried on in 1, 2 or 3 doses (D1 pre-plant, D2 at growth stage 25 and D3 at GS 30). Although, the amount of added N varies from region to another, but it follows same strategy:

- _T1, for zero plots (no N added)
- _T2-5, only D1 varies increasingly from T2 to T5
- _T6-8, D1 same amount and D2 varies increasingly from T6 to T8
- _T9-11, D1 same amount, no D2 and D3 varies increasingly from T9 to T11
- _T12-15, D1 same amount, D2 same amount and D3 varies increasingly from T9 to T11

The large-scale trials are split into two parts (1 ha each), one for the optimal practices (OT) designed by INGC, and the second part is the farmer practices (FP). Data on soil properties, in season crop status, yield and grain quality, georeferenced vegetation indices (VIs) using simple radiometer proximal sensors (RapidScan CS-45, Holland Scientific, USA and Green Seeker handheld, Trimble, USA) and the chlorophyll meter (SPAD-502, Konica Minolta, Japan) were collected. The satellite images, mainly from Sentinel-2, were downloaded and correlated with the ground truth measurements and the proximal data in the OT and FP experiments. The approach and the workflow aim at developing two correlations, one between the ground truth N uptake and the VIs from the proximal sensors measured in the N response trials, the second is a correlation between the VIs measured from the proximal sensors in the large trials and those calculated from the satellite images. The data analysis is still ongoing, in this study only the statistical analysis, the ANOVA test (at 95% confidence level) results of the yield and the VIs in the different N response trials for the two seasons 2023-2024 and the correlation between the VIs and the N content for the year 2023 will be presented.

RESULTS AND DISCUSSION

The results showed a wide range of variations in the yield between treatments in the two years in all the climatic areas. The year 2024 was worse, in general, in term of yield except for the semi-arid area. The range of StDev was very high in the semi-arid area when compared to the means (70% of the mean in 2024, 90% in 2023), while it was below 50% for the sub-humid and arid irrigated areas (see Table 1). This can be explained by the severe shortage of water, where the variations are less when water is more available (the case for sub-humid and arid irrigated areas). The maximum obtained yield in the sub-humid and semi-arid didn't exceed 4 t ha-1, while the minimum values were very low (e.g. 0.14 kg h-1 in the semi-arid in 2023). In the Arid Irrigated area, the maximum yield reached 6.55 t ha-1, and the minimum obtained yield was 1.26 in 2023, the maximum yield in the year 2024 was lower than the maximum in 2023 but the lower yield was noticeably higher (3.1 t ha-1) as shown in table 1. The highness and the stability of the yield in this area, compared to the sub-humid and semi-arid areas, is attributed to the high N rate application and the irrigation.

Table 1. Descriptive statistic for the yield in the three regions for the two years.

Region	Year	Mean	StDev	Min.	Max
Sub-humid	2023	1.99 – 2.88	0.10 – 1.23	0.57 – 2.25	2.25 – 3.96
	2024	1.49 –2 .45	0.18 – 1.24	1.03 – 2.05	1.35 – 3.62
Semi-arid	2023	0.27 – 1.63	0.03 – 1.46	0.14 – 0.56	0.44 – 3.32
	2024	0.61 – 2.15	0.09 – 1.48	0.20 – 1.03	1.11 – 3.52
Arid (Irrigated)	2023	2.75 – 6.21	0.10 – 2.21	1.26 – 4.61	3.81 – 6.55
	2024	3.64 – 5.24	0.25 – 1.31	3.10 – 4.73	4.10 – 5.66

The zero plots (T1) showed comparable yield values to the other treatments in the two years at the three zones (this was obvious in the field visits at the different growth stages). Adding the total amount of the fertilizer at the pre-plant stage (T2-5) was slightly beneficial to the crop in term of final yield comparing to the other treatments (T6-15), no clear trend was noticed between the different N rates among T2-5 (Figure 1). Adding N at different amounts (2 or 3 doses) did not improve the yield in the different climatic zones for the two studying years. The ANOVA test showed no significance at confidence level 95% between the different treatments, including the zero plot (T1-15), for the different N rates and application strategy. This likely means that something other than N supply was more limiting for crop growth and development. In the non-irrigated trials, it may have been water (small crop N demand). In the irrigated trials, it may instead be due to a large soil N supply (large soil N supply). This shows that, in a farming situation, small on-farm trials, like zero N plots, may be useful for the farmer to understand the balance between soil N supply and crop N demand, and how much is the need for supplemental N fertilization. If the zero plot cannot be distinguished from the surrounding field, the local soil N supply is large enough for the current crop and one may consider saving on supplemental N fertilization (which would mean avoided cost and reduced risk of N leaching to the environment). If, on the other hand, the zero-plot shows symptoms of N deficiency, one may consider supplemental N fertilization, considering whether one expects otherwise favorable conditions such that the crop can use the additional N.

The statistical analysis gave the same result (no significance at 95% confidence level from ANOVA test between the different treatments T1-15) for the VIs (NDVI, NDRE) measured using the proximal sensors, the chlorophyll concertation measured using SPAD and the N concentration from the laboratory analysis. The VIs were saturated (reached maximum values NDVI≈0.93, NDRE≈0.43) in end of February (GS≈31-39). The crop growth goes very fast in the month of

February and varies between the climatic zones. The VIs values were lower in March because of the progress to the heading growth stages (GS≈50-58). The correlation between the N content and the VIs for the measurements taken in 24th February 2023 was weak (r2=0.2), the correlation was not studied for the later measurements because of the saturation in VIs' values.

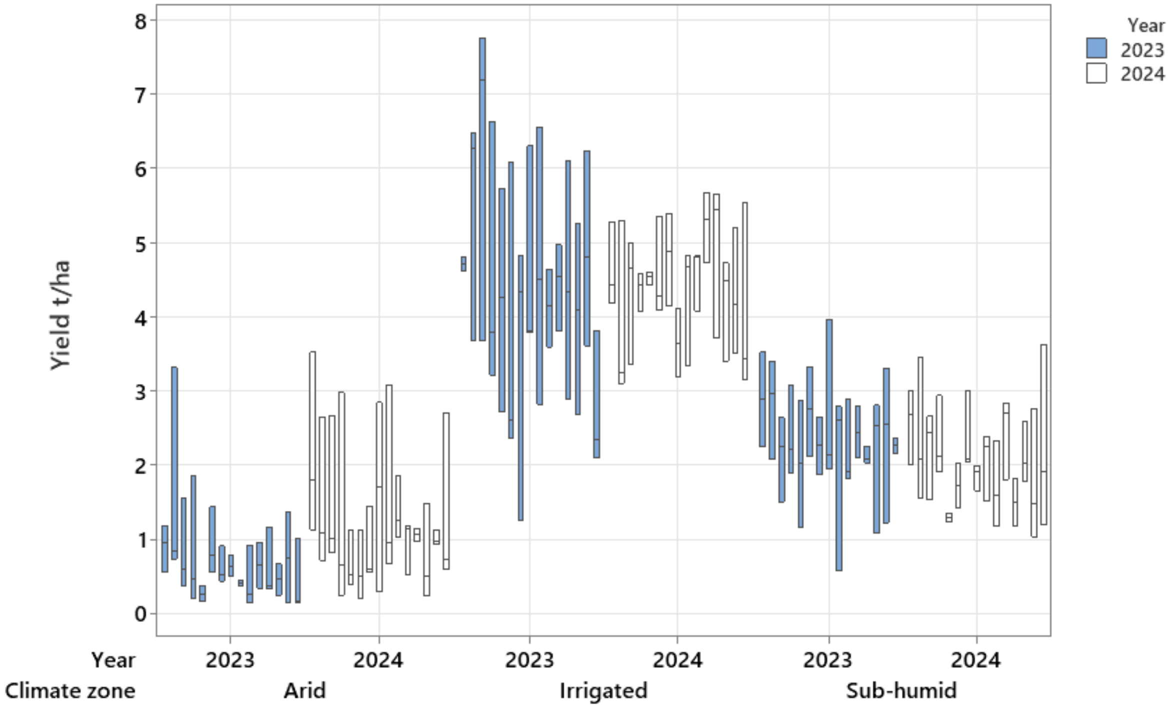


Figure 1. Yield in t ha-1 (2023,2024), N response trials by climate zone, T1-15 from 0 N kg ha-1 (T1, the one on the left of each group) to 80-280 N kg ha-1 (T15, the one to the right of each group).

The preliminary obtained results in this project showed, for the three climate zones and the two successive years, there is a need to assess the soil N supply from the previous season as a vital measure to optimize the N management in term of amount and timing. Simple technics can be adopted in the farmers' fields, like the zero plot, to detect the plant-available N storage in the soil, the technique is easy enough, that the farmer can apply several zero plots in his field to detect the within field variations for precision agriculture practices.

REFERENCES

Alshihabi, O., Nouiri, I., Mechri, M., Angar, A., Piikk, K., Martinsson, J., Söderström, S., 2020. CropSAT – opportunities for applications in precision agriculture in Africa. First African Conference on Precision Agriculture. 1st AfCPA. 8-10 December.

de Oliveira Silva, A.; Ciampitti, I.A.; Slafer, G.A.; Lollato, R.P., 2020. Nitrogen utilization efficiency in wheat: A global perspective. Eur. J. Agron. 114, 126008. Nitrogen utilization efficiency in wheat: A global perspective - ScienceDirect

FAO, 2023. Bulletin de la FAO sur l'offre et la demande de céréales. 8 septembre.

USE OF "FERTIEDGE" APPLICATION FOR OPTIMIZING WHEAT FERTILIZATION

#11646

[1]I. Sbai, [2]M. Hmimou, [1]A. Bouslimi, [1]M. Hannachi, [2]H. Baroudi, [2]F. Sehbaoui, [1]A. Bousselmi, [1]S Arfaoui

[1]National Institute of Field Crops; [2] AgriEdge SA, Benguerir, Morocco

e-mail: sbaibtihel@gmail.com; 0021628332795

ABSTRACT

Wheat is a crop of global importance, and effective fertilization is crucial to maximize yield and quality. Traditional methods of fertilization often result in under- or over-application of nutrients, resulting in environmental problems and suboptimal crop yields. FertiEdge is a digital application that provides accurate fertilization recommendations based on real-time data, it's an innovative tool designed to enhance the efficiency of wheat fertilization. This study evaluates its impact on optimizing nutrient management, improving crop yield, and promoting sustainable agricultural practices. The study included a comparative analysis of wheat fields managed with and without the FertiEdge application. Key metrics measured included soil nutrient levels, fertilizer application rates, and final yield. Plots using the 'FertiEdge' application showed a 22 % and 20.6 % increase in yield compared to those managed with the conventional method respectively for Site 1 and Site 2 in the North of Tunisia. In addition, the application has allowed to reduce the quantities of nitrogen fertilizer applied by 56 kg/ha and 113.7 kg/ha compared to those managed with the conventional method respectively for site 1 and site 2. The use of 'FertiEdge' significantly enhances the precision of wheat fertilization, leading to better resource use efficiency and higher yields. The application's ability to integrate diverse data sources and provide real-time recommendations is a key advantage over traditional methods. Furthermore, the reduction in excessive fertilizer use contributes to environmental sustainability by minimizing nutrient leaching and greenhouse gas emissions. FertiEdge is a valuable tool for farmers looking to optimize wheat fertilization. Its application leads to higher yields, better resource management, and sustainable farming practices. These results remain preliminary and must be proven by repeating the same experiment two more agricultural years.

INTRODUCTION

Wheat is one of the most widely cultivated cereal crops globally, serving as a staple food source for billions of people. The efficient management of nitrogen fertilization is critical to maximizing wheat yields and ensuring food security. Nitrogen is a vital nutrient for plant growth, influencing not only the productivity of wheat but also the quality of the grain. However, the application of nitrogen fertilizers must be carefully managed to avoid environmental degradation, such as nitrogen leaching, greenhouse gas emissions, and soil acidification, which can result from over-application or improper timing.

In recent years, precision farming technologies have emerged as transformative tools in agricultural practices, offering the potential to enhance nitrogen management in wheat cultivation. These technologies, including satellite imagery, soil sensors, and variable rate application systems, enable farmers to apply fertilizers more accurately, ensuring that nitrogen is supplied according to the specific needs of the crop and the variability of the field. By integrating precision farming techniques, it is possible to optimize nitrogen use efficiency, reduce input costs, and minimize environmental impacts, ultimately leading to more sustainable and productive wheat farming systems.

At a firsthand, this paper reviews the critical role of nitrogen fertilization management in wheat production and examines the added value of precision farming technologies in enhancing nitrogen use efficiency. Secondly, this paper includes a comparative analysis of wheat fields managed with and without the FertiEdge application which is a precision farming technology developed by AgriEdge to enhance nitrogen fertilization management. The KPIs metrics measured included soil nutrient levels, fertilizer application rates, and final yield.

Importance of Nitrogen Fertilization Management

Nitrogen fertilization is a critical component in the management of wheat cultivation, directly influencing crop yield, quality, and environmental impact. The advancement of precision farming technologies has significantly enhanced the efficiency and effectiveness of nitrogen management in wheat farming, leading to substantial benefits for both agricultural productivity and sustainability.

Nitrogen is a vital nutrient for wheat, essential for protein synthesis and overall plant growth. Proper nitrogen management is crucial in optimizing wheat yield, improving grain quality, and minimizing environmental impacts such as nitrogen leaching and greenhouse gas emissions. Recent studies have emphasized the importance of precise nitrogen management strategies. For instance, long-term studies have shown that increased nitrogen application can significantly improve wheat yield and soil properties, particularly in systems combining nitrogen fertilization with organic practices such as straw return (Jaćimović et al., 2023).

Moreover, studies on winter wheat cultivation under waterlogged conditions have demonstrated that optimizing nitrogen fertilization rates can enhance plant growth and productivity, even in challenging environmental conditions (He et al., 2024). Similarly, optimal fertilization strategies, as observed in North China, have shown that tailored nitrogen management can significantly increase wheat yield and improve environmental sustainability (Jiang et al., 2023).

Added Value of Precision Farming Technologies

Precision farming technologies have revolutionized nitrogen management by allowing site-specific application, which tailors fertilization to the specific needs of different areas within a field. This approach not only optimizes nitrogen use efficiency but also reduces the overall amount of nitrogen required, thereby minimizing environmental impacts.

One of the key advancements in precision farming is the use of Variable Rate Technology (VRT). This technology incorporates soil property maps and management zones to apply nitrogen more accurately. Studies have shown that VRT can lead to a 25% reduction in nitrogen fertilizer usage in wheat cultivation while maintaining or even improving yield and quality characteristics such as grain protein and gluten content (Denora et al., 2022).

The potential of management zones and geospatial technologies to enhance wheat production by optimizing site-specific fertilization has been demonstrated in various studies (Haroon et al., 2023).

Remote sensing technologies, such as Sentinel-2 NDVI and hyperspectral imagery, have proven effective in monitoring crop nitrogen status and adjusting fertilization practices accordingly, further supporting sustainable intensification in wheat production (Santaga et al., 2021; Song et al., 2007). Additionally, integrating precision farming technologies with traditional farming practices, such as utilizing farmyard manure in conjunction with mineral nitrogen rates, has shown significant improvements in nitrogen use efficiency and crop productivity (Salama et al., 2021).

Summary table of the relevant references.

Study	Main Focus	Key Findings
Jaćimović et al., 2023	Long-term straw return and nitrogen fertilization	Enhanced wheat yield and soil properties with combined practices.
He et al., 2024	Nitrogen management under waterlogged conditions	Improved plant growth and productivity with optimized nitrogen rates.
Jiang et al., 2023	Optimal fertilization strategies in North China	Increased yield and sustainability with tailored nitrogen management.
Denora et al., 2022	Variable Rate Technology (VRT)	25% reduction in nitrogen use while maintaining yield and quality.
Haroon et al., 2023	Geospatial technologies and management zones	Enhanced wheat production with site-specific fertilization.
Santaga et al., 2021	Sentinel-2 NDVI in nitrogen management	Improved nitrogen use efficiency and sustainable wheat production.
Song et al., 2007	Hyperspectral imagery in nitrogen management	Optimization of fertilization strategies with precision technologies.
Salama et al., 2021	Integration of precision and traditional farming practices	Significant improvements in nitrogen use efficiency and productivity.

The integration of precision farming technologies into nitrogen fertilization management offers substantial benefits in terms of efficiency, sustainability, and crop productivity. These technologies enable more precise application of fertilizers, reduce environmental impacts, and support higher yields and better quality in wheat production. The ongoing advancements in this field suggest a promising future for sustainable agriculture, where precision management will play a pivotal role in addressing the challenges of food security and environmental conservation.

MATERIALS AND METHODS

Physical Environment

The experiment was conducted at two experimental stations of the National Institute of Major Crops (INGC) in Bousalem (Site 1), which has a superior semi-arid climate, and in Béjà (Site 2), which has a humid climate. Both sites are in the northwest of Tunisia with a rainfall regime.

Plant Material
The study focused on two varieties of durum wheat: the Inrat100 variety for Site 1 and the Maali variety for Site 2.

Experimental Design
For each site, the trial was conducted on a 1-hectare plot divided into two sections, each representing a different nitrogen fertilization treatment. Nitrogen was applied as ammonium nitrate (33.5%) in three fractions (at the 3-5 leaf stage, the tillering stage, and the booting stage) according to the recommendations of the FertiEdge application (Plot 1). The control (Plot 2) followed the recommendations of the balance method (Plot 2).

By the end of the season, at each plot for the two treatments, the actual yield was measured using a combine harvester.

RESULTS AND DISCUSSION

Nitrogen optimization
The results (Table 1) show that the nitrogen fertilization approach recommended by the FertiEdge application reduced the amounts of applied nitrogen fertilizers by 56 kg/ha and 113.7 kg/ha compared to those managed with the conventional method, respectively for site 1 and site 2.

Reducing the amount of nitrogen fertilizer helps lower production costs and mitigate the risk of pollution.

Table 1. Quantity of ammonium nitrate supplied.

	Site1		Site 2	
	Plot 1	**Plot 2**	**Plot 1**	**Plot 2**
Quantity of ammonium nitrate supplied (Kg/ha)	234	290	156.3	270

***** For Site 2, the first nitrogen application was missed due to the lack of rain.

Yield Enhancement
The results obtained (Table 2) show that plots using the 'FertiEdge' application experienced a yield increase of 22% and 20.6% compared to those managed with the conventional method, respectively for sites 1 and 2. This underscores the importance of precision fertilization, which ensures that crops receive the right amount of fertilizer at the right time and in the right place.

Table 2. Grain yield.

	Site1		Site 2	
	Plot 1	**Plot 2**	**Plot 1**	**Plot 2**
Grain Yield (qx/ha)	39.34	32.31	45.83	38

REFERENCES

Denora, M., Amato, M., Brunetti, G., De Mastro, F., & Perniola, M. (2022). Geophysical field zoning for nitrogen fertilization in durum wheat (Triticum durum Desf.). PLOS ONE, 17*(4)*, e0267219. https://dx.doi.org/10.1371/journal.pone.0267219

Haroon, Z., Cheema, M. J. M., Saleem, S., Amin, M., Anjum, M. N., Tahir, M., Hussain, S., Zahid, U., & Khan, F. (2023). Potential of precise fertilization through adoption of management zones strategy to enhance wheat production. Land, 12(3), 540. https://dx.doi.org/10.3390/land12030540

He, P., Yu, S., Ding, J., Ma, T., Li, J., Dai, Y., Chen, K., Peng, S., Zeng, G., & Guo, S. (2024). Multi-objective optimization of farmland water level and nitrogen fertilization management for winter wheat cultivation under waterlogging conditions based on TOPSIS-Entropy. Agricultural Water Management, 300, *108840*. https://dx.doi.org/10.1016/j.agwat.2024.108840

Jaćimović, G., Aćin, V., Mirosavljević, M., Brbaklić, L., Vujić, S., Dunđerski, D., & Šeremešić, S. (2023). Effects of Combined Long-Term Straw Return and Nitrogen Fertilization on Wheat Productivity and Soil Properties in the Wheat-Maize-Soybean Rotation System in the Pannonian Plain. Agronomy, 13(6), 1529. https://dx.doi.org/10.3390/agronomy13061529

Jiang, X., Li, J., An, Z., Liang, J.-M., Tian, X., Chen, Y., Sun, Y., & Li, Y. (2023). Optimal Fertilization Strategies for Winter Wheat Based on Yield Increase and Nitrogen Reduction on the North China Plain. Sustainability, 15(5), 4199. https://dx.doi.org/10.3390/su15054199

Salama, H. S. A., Nawar, A., Khalil, H., & Shaalan, A. (2021). Improvement of Maize Productivity and N Use Efficiency in a No-Tillage Irrigated Farming System: Effect of Cropping Sequence and Fertilization Management. Plants, 10(7), 1459. https://dx.doi.org/10.3390/plants10071459

Santaga, F., Benincasa, P., Toscano, P., Antognelli, S., Ranieri, E., & Vizzari, M. (2021). Simplified and Advanced Sentinel-2-Based Precision Nitrogen Management of Wheat. Agronomy, 11(6), 1156. https://dx.doi.org/10.3390/AGRONOMY11061156

Song, X., Yan, G., Wang, J., Liu, L., Xue, X., Li, C., & Huang, W. (2007). Use of airborne hyperspectral imagery to investigate the influence of soil nitrogen supplies and variable-rate fertilization to winter wheat growth. Proceedings of SPIE, 6752, 67521Q. https://dx.doi.org/10.1117/12.736116

COMPARATIVE STUDY ON PRECISION NITROGEN MANAGEMENT FOR WHEAT USING GREENSEEKER, CHLOROPHYLL METER AND LEAF COLOR CHART BASED ON SPECTRAL CHARACTERISTICS OF LEAVES

#11641

[1]Abdou A. Soaud, [1]A. El-Metwally, [2]M. Ali, [1]Radwa K. Sayed
[1]Faculty of Agriculture, Cairo University, Giza, Egypt; [2] Desert Research Centre, Cairo, Egypt
e-mail: a2soaud@yahoo.com; 00201007507791

ABSTRACT

Collecting results on nitrogen (N) uptake throughout the growing season using tools such as GreenSeeker optical sensor, chlorophyll meter and Leaf Color Chart (LCC) holds great promise for optimizing N fertilizer management in cereal crops. To investigate this further, field experiments were conducted over two consecutive winter seasons (2017/2018 and 2018/2019) on wheat at the Experimental Farm of the Faculty of Agriculture, Cairo University, located in Giza Governorate, Egypt. The primary objective of these experiments was to develop effective strategies for managing N fertilizer in wheat during the growing season using GreenSeeker optical sensor, chlorophyll meter or LCC. The goal was to enhance N-use efficiency, reduce the N fertilizer input and achieve optimal results. In the first season, various rates of N fertilizer were applied to create diversity in the readings obtained from the three tools: GreenSeeker optical sensor, chlorophyll meter and LCC. Based on the findings from the first season, a strategy was proposed for refining the application of N fertilizer during the jointing growth stage of wheat. This strategy was guided by the readings obtained from the three tools and implemented in the second season. For the GreenSeeker optical sensor, chlorophyll meter and LCC, an initial application of prescriptive N fertilizer (100 kg N ha^{-1} in two splits) was recommended, followed by corrective doses based on the guidance provided by the three tools. The results of this study were remarkable. The N recovery efficiency that correlated with higher yield values achieved using the GreenSeeker optical sensor, chlorophyll meter, and LCC was 74.1%, 67.4%, and 55.4%, respectively, compared to only 50.5% with the general recommendation treatment. Also, the rate of nitrogen application decreased to 160, 180, 190 Kg N ha^{-1} with the use of GreenSecker, chlorophyll meter and LCC, compared to 240 Kg N ha^{-1} with the treatment of general recommendations without affecting grain yield. These findings clearly demonstrate that the utilization of tools such as the GreenSeeker optical sensor, chlorophyll meter, and LCC can significantly improve the N-use efficiency and decrease N application rate without compromising grain yields.

INTRODUCTION

The application of nitrogen (N) fertilizer is widely recognized as a crucial factor in promoting the growth, yield, and quality of crops. Nitrogen plays a vital role in the formation of various compounds necessary for plant development, including chlorophyll and enzymes. Nitrogen fertilizer management in wheat production in Egypt is typically based on a general recommendation that is applied across large areas. However, to achieve high yields, farmers often exceed the recommended N application rates. This practice is influenced by the temporal and spatial variability of N requirements, which leads to either over or under-application of fertilizer, ultimately reducing its efficiency. It is worth noting that the global nitrogen recovery efficiency in cereals is estimated to be around 35% (Omara et al., 2019). This indicates that a significant portion of the N fertilizer applied is susceptible to losses from the soil-plant system. Consequently, substantial amounts of N fertilizer are lost from the soil, leading to both environmental degradation and increased costs. The low recovery efficiency of N fertilizer not only contributes to environmental concerns but also imposes financial burdens (Bijay and Yadvinder, 2003; Fageria and Baligar, 2005 and Ali and Habib, 2022). Therefore, it is crucial to address this issue to enhance both the sustainability and profitability of wheat production in Egypt. Advanced technologies such as GrS, ChM and LCC have emerged as promising tools for efficient N management (Ali et al., 2020; Singh et al., 2022 and Ram et al., 2022). These cutting-edge tools offer farmers real-time, non-destructive measurements of plant health, empowering them to apply N with precision according to the specific needs of their crops. By utilizing these technologies, farmers gain the ability to closely monitor the temporal and spatial variations of N levels across their fields. This invaluable insight allows for the optimization of fertilizer usage, minimizing the risk of nutrient losses that could harm the environment. In essence, these advanced tools not only provide farmers with accurate and timely information about their plants' N requirements, but also enable them to make informed decisions that promote sustainable farming practices. By harnessing the power of technology, farmers can enhance their productivity while minimizing the environmental impact of their operations.

The primary objective of this study was to develop effective strategies for managing N fertilizer in wheat during the growing season using GreenSeeker, chlorophyll meter, or LCC. The goal was to enhance N-use efficiency, reduce the N fertilizer input and achieve optimal wheat yield.

MATERIALS AND METHODS

The experimental site

In two successive winter seasons (2017/2018 and 2018/2019), field experiments were carried out on wheat (Triticum aestivum L.) variety Giza 171 at the Experimental Farm of the Faculty of Agriculture, Cairo University, Giza Governorate, Egypt, latitude 30.0861N, and longitude 31.2122E. Initial soil samples were taken from the experimental site and analyzed using the procedures outlined by Page et al. (1982) for some physical and chemical properties. Soil texture was clay loam, pH in soil saturation past was 7.91, EC in soil saturation past was 4.53, organic matter was 2.3% and available N, P and K were 100.9, 18.5 and 354.0 mg kg^{-1}, respectively.

Experimental design and treatments

The soil has been ploughed and levelled prior to sowing. In both seasons, in mid-November, wheat (Triticum aestivum L.) of the variety Giza 171 grains was mechanically sown in rows 15 cm apart and divided into 15 m^2 parcels. N fertilizer levels of 0, 40, 80, 120, 160, 200, 240, 280 and 320 kg N ha^{-1} were added in three equal split doses in the first season as ammonium sulphate. This range was used to determine plots with great variability in the wheat uptake and yield of N. The second season was developed to validate the effectiveness of the GreenSeeker optical sensor, chlorophyll meter, and LCC for the application of N fine-tuning fertilizer. The treatment consisted of setting various prescriptive N application scenarios at the early growth stage, followed by a corrective dose at the joint growth stage, as directed by GreenSeeker optical sensor, chlorophyll meter or LCC. The experiments were performed with three replications in a randomized complete block design. Following the general recommendation, phosphorus (as a single superphosphate) was applied for sowing. Potassium fertilizer was avoided because enough available K (354 mg kg^{-1}) were present in the soil.

Plant measurements

The greenness of plant was measured by portable GreenSeeker optical sensor, chlorophyll meter, and LCC. The GreenSeeker accurately detected spectral reflectance and presented it as NDVI (Normalized Difference Vegetation Index). The sensor unit was positioned approximately 1 meter above the plant canopy during the measurement procedure. To ensure precision, the sensor recorded NDVI measurements at a rate of 10 per second while moving at a slow walking pace. The chlorophyll meter measured transmittance at wavelengths of 660 and 940 nm. The procedure entailed inserting the central section of the most fully developed leaf into the aperture of the meter. From each plot, three plants were randomly selected, and their measurements were collected and averaged for subsequent analysis. The LCC with six green shades the greenness of plants. The topmost fully expanded leaf was placed on the LCC and the color of the middle part of the leaf was matched with greenness of the panels on the LCC.

Plant sampling and analysis

At the joint growth stage, over ground plant samples from an area of 1 m^2 were collected from each plot immediately after obtaining the tools' readings. The wheat production was manually collected from a net area of 6 m^2 at maturity from the center of each plot. Grain and straw samples were dried in a hot air oven set at 70º C until they reached a constant weight. Dried samples were digested in a mixture of H_2SO_4-H_2O_2, and total N was determined using the micro-Kjeldahl method (Kalra, 1997).

Calculations and statistical analysis

Using Microsoft excel program (a component in Microsoft Office 2016), regression models were mounted. Variance analysis (ANOVA) has been used to evaluate the effect of N treatments on the data collected. As described by Gomez and Gomez (1984), Duncan's multiple range test (DMRT) at probability value < 0.05 was used to examine the difference between means. As described by Cassman et al. (1998), the recovery efficiency of N (RE_N) was computed as:

$$RE_N(\%) = \frac{Total\ N\ uptake\ in\ fertilized\ plot - Total\ N\ uptake\ in\ zero\ N\ plot}{Quantity\ of\ applied\ N\ fertilizer}$$

RESULTS AND DISCUSSION

Effect of N fertilizer application rate on grain yield of wheat

The relationship between increasing N fertilizer rate and grain yields of wheat collected from the first season exhibited a second-degree response function ($y = - 0.1064\ x^2 + 45.922\ x + 3926.2$). Function derivation analysis showed that the highest grain yield of 8881 kg ha^{-1} was achieved by applying N fertilizer rate of 215.8 kg N ha^{-1}. Approximately 155 kg N ha^{-1} was calculated as the N fertilizer rate required for economic grain yield (8437 kg ha^{-1}, 95% of maximum yield). The widely adopted general N fertilizer recommendation for wheat in the area is 180-240 kg N ha^{-1}. These results suggest that there is a need to establish site-specific management strategies in the season that can adjust the rate of application of N fertilizer according to the actual need for the crop.

Prediction of N uptake at jointing growth stage

Rapid acquisition of N uptake information where plants can respond to N inputs prior to harvesting is essential for the development of a successful N fertilizer management plan for precision N management. Variation in N uptake at the joint growth stage of wheat was created by the increasing rate of N fertilizer applied in the first season experiment. This variability has been reflected in grain yield increases. The data derived from the relationship between grain yield and N wheat uptake were as follow: the estimated maximum uptake was 373 kg N ha^{-1}, the estimated maximum yield was 7981 kg grain ha^{-1}, the optimum grain yield (95% of the maximum grain yield) was 7582 kg grain ha^{-1} and the optimum N uptake = 275 kg N ha^{-1}.

a. Sufficiency index approach for managing N fertilizer using GreenSeeker

By many varietal groups, seasons or regions, leaves greenness may vary. Consequently, one GreenSeeker fixed threshold value may not work effectively. The strategy to the sufficiency index (calculated as the ratio of NDVI reading of the evaluated plot and that of a reference N-rich plot) allows dynamic values instead of a fixed threshold value to be used for precision N management. According to the variability of soil properties and seasons, this strategy has the potential to be self-calibrating. The sufficiency index can be calculated as follow:

SI= NDVI of the meausred treatment / NDVI of the reference treatment

The SI was used to calculate the corrective N fertilizer dose in the second season at jointing stage (Feekes 6) of wheat, as steered by the GreenSeeker algorithm created in first season as follow:

$$\textbf{N fertilizer dose (kg N ha}^{-1}\textbf{)} = \frac{\mathbf{275 - 291.47} \times \boldsymbol{SI\ NDVI}^{\mathbf{1.686}}}{\mathbf{0.65}}$$

b. Sufficiency index approach for managing N fertilizer using chlorophyll meter

To determine the N nutrition index and sufficiency index of the chlorophyll meter, a calculation was conducted by dividing the N uptake and chlorophyll meter readings in the tested plot by reference values. These reference values were established using boxplot diagrams, specifically identifying the upper interquartile values. The resulting reference values for the N nutrition index and sufficiency index were determined to be 63 and 54.5 kg N ha^{-1}, respectively. Upon analyzing the relationship between both indexes, a highly significant linear correlation (R^2= 0.6) was obtained. This correlation strongly suggests that the sufficiency index, derived from the chlorophyll meter, effectively captures variations in the N nutrition index. Based on this finding, a strategy was developed to optimize the application of N during the jointing stage of wheat in the second season. This strategy is based on recommended amounts of N fertilizer that should be applied based on the value of sufficiency index of the chlorophyll meter as follow: if the sufficiency index: >0.95, 0.95 – 0.85, 0.85 – 0.75 and < 0.75, the corrective N dose will be 0, 80, 120, 160, respectively.

c. Establishment of fertilizer N management strategies using LCC

The utilization of different N fertilizer rates has led to significant variations in measurements of LCC, grain yield, and total nitrogen uptake. A box-and-whisker diagram was constructed to display the LCC readings at Feekes 6, revealing a threshold score of 4. However, as the leaf greenness approaches an LCC score below 4, a higher amount of N (120 kg N ha^{-1}) is necessary to achieve optimal yield levels. It is recommended to apply a moderate dose of N fertilizer (90 kg N ha^{-1})

within the range of scores 4-4.5. Additionally, when the leaf greenness corresponds to an LCC score of 4.5 or more, fertilizer nitrogen application may be omitted (0 kg N ha^{-1}).

Validation of GreenSeeker, chlorophyll meter and Leaf Color Chart in managing N fertilizer

The experiment performed during the second season has been used to assess the GreenSeeker sensor, Chlorophyll meter and LCC performance as proposed in this study. Various doses and timings of N fertilizer were added prior to applying the corrective dose as steered by each one of the three tools to make growth variance in biomass and N uptake in wheat.

The data presented in table (1) show that the wheat grain yields obtained from Treatment 3 with the GreenSeeker, chlorophyll meter, and LCC, they were recorded at 7989, 8141, and 7971 kg ha^{-1}, respectively, with statistically equivalent values. However, there was a significant variance in the corrective dosage recommendations. While the GreenSeeker proposed a corrective dosage of 60 kg N ha^{-1}, the Chlorophyll meter and LCC advocated for 80 and 90 kg N ha^{-1}, respectively.

The utilization of the Green Seeker sensor, chlorophyll meter, and LCC has yielded N efficiencies of 74.1%, 67.4%, and 55.4%, respectively, in comparison to the general recommendation's modest 50.5%. These findings underscore the superior performance and reliability of these advanced tools in optimizing N fertilizer utilization for enhanced crop productivity. This discrepancy indicates the superiority of the GreenSeeker, as it necessitated the least nitrogen input for the same yield, thereby positively impacting nitrogen recovery efficiency. This outcome could be attributed to the GreenSeeker's utilization of red and near-infrared rays to compute the Normalized Difference Vegetation Index (NDVI), along with its capability to average readings across the entire plot. This feature renders it a more dependable indicator compared to the Chlorophyll meter and Leaf Color Chart, contributing to enhanced precision in nitrogen fertilizer management practices.

CONCLUSIONS

The standard recommendation for applying a fixed rate of fertilizer N over large areas is not optimal for achieving high N use efficiency in wheat grown in diverse soils in Egypt. Field experiments were conducted to investigate the use of tools such as Green Seeker optical sensor, chlorophyll meter and LCC for managing N fertilizer in wheat crops. The results showed that the N recovery efficiency achieved using the tools were higher compared to the general recommendation, with the GreenSeeker optical sensor achieving the highest efficiency. This study demonstrates that using these tools can significantly improve N-use efficiency without affecting grain yields.

The Green Seeker sensor, chlorophyll meter, and LCC have been validated as dependable tools for accurately predicting N uptake in wheat and effectively guiding N fertilizer applications. The strategies proposed in this study have demonstrated exceptional proficiency in N fertilizer management, resulting in remarkable yield levels and substantial savings in N fertilizer usage.

Furthermore, the utilization of these advanced tools not only improves N efficiencies but also contributes to sustainable agriculture practices. By accurately measuring the crop's nitrogen status, farmers can apply fertilizers more precisely, reducing unnecessary nitrogen application and minimizing environmental pollution.

Table 1. Wheat grain yields, total N uptake, and N use efficiencies as influenced by different N fertilizer treatments as guided by GreenSeeker sensor, chlorophyll meter and LCC.
‘

Treatment	N fertilizer rate at 0 DAS*	N fertilizer rate at 30 DAS	Tools' Sufficiency index	Corrective dose kg N ha^{-1} at feekes 6**	Total amount of N fertilizer kg N ha^{-1}	Grain yield kg ha^{-1}	Total N uptake kg ha^{-1}	RE_N*** %
N fertilizer treatments as guided by GreenSeeker sensor								
T1 (zero-N)	0	0	-	0	0	3118 d	109.6 c	-
T2 (general recommendation)	80	80	0.75	80 (fixed)	240	8023 a	233.4 a	51.5 c
T3	40	60	0.74	60.9	160.9	7989 a	228.9 a	74.1 a
T4	100	0	0.72	77.3	177.3	7373 b	238.7 a	72.8 a
T5	0	100	0.71	85.3	185.3	7742 a	243.2 a	72.1 a
T6	0	0	0.68	109.1	109.1	6114 c	183.5 b	67.7 b
T7	100	100	0.80	10.1	210.1	7871 a	224.6 a	54.7 c
N fertilizer treatments as guided by chlorophyll meter								
T1 (zero-N)	0	0	-	0	0	3208 d	96.6 c	-
T 2 (general recommendation)	80	80	-	80 (fixed)	240	8172 a	225.1 a	53.5 c
T3	40	60	0.91	80	180	8141 a	218.6 a	67.4 a
T4	100	0	0.82	120	220	7413 b	230.1 a	60.6 b
T5	0	100	0.87	80	180	7642 b	215.2 a	65.7 a
T6	0	0	0.73	160	160	6215 c	177.3 b	50.4 c
T7	100	100	0.96	0	200	7613 b	199.4 b	51.4 c
N fertilizer treatments as guided by LCC								
T1 (zero-N)	0	0	-	0	0	3118 e	105.2 c	-
T 2 (general recommendation)	80	80	4.5	80 (fixed)	240	7942 a	217.1 a	46.6 d
T3	40	60	4.5	90	190	7971 a	210.5 a	55.4 c
T4	100	0	4.5	90	190	7283 c	222.4 a	61.7 b
T5	0	100	4.5	90	190	7452 c	235.1 a	68.4 a
T6	0	0	4	120	120	6015 d	179.3 b	61.8 b
T7	100	100	5	200	200	7671 b	198.5 b	46.7 d

* DAS = days after sowing. ** Feekes 6 = around 50-60 days after sowing

*** RE_N = Recovery efficiency of nitrogen fertilizer

Means followed by the same letter within the same column are not significantly different at the 0.05 level of probability by Duncan's multiple range test (DMRT)

REFERENCES

Ali, A.M. and Habib, A.A. (2022). Estimation of the economic optimum rates of nitrogen fertilizer for maize grown in a calcareous soil in combination with organic manure applications. Communications in Soil Science and Plant Analysis, 53(18):2484-2496.

Ali, A.M.; Ibrahim, S.M. and Bijay, S. (2020). Wheat grain yield and nitrogen uptake prediction using atLEAF and Green Seeker portable optical sensors at jointing growth stage. Information Processing in Agriculture, 7(3):375-383.

Bijay, S. and Yadvinder, S. (2003). Environmental implications of nutrient use and crop management in rice-based ecosystems. In: Rice Science: Innovations and Impact for Livelihood (Eds. Mew, T.W.; Brar, D.S.; Peng, S.; Dawe, D. and Hardy, B.), IRRI, Los Banos, Philippines. pp.463-477.

Fageria, N.K. and Baligar, V.C. (2005). Enhancing nitrogen use efficiency in crop plants. Adv. Agron., 88:97-185.

Gomez, K.A. and Gomez, A.A., 1984. Statistical procedures for agricultural research. John Wiley & Sons.

Page, A.L. and Page, A.L., 1982. Methods of soil analysis: chemical and microbiological proerpteis. Amen Society of Agronomy.

Omara, P.; Aula, L.; Oyebiyi, F. and Raun, W.R. (2019). World cereal nitrogen use efficiency trends: review and current knowledge. Agrosystems, Geosciences & Environment, 2(1):1-8.

Ram, H.; Kaur, H. and Sikka, R. (2022). Need-based nitrogen management of wheat through the use of green seeker and leaf color chart for enhancing grain yield and quality. J. Plant Nutr., 45(17):2655-2671

Singh, V.; Singh, M. and Singh, B. (2022). Spectral indices measured with proximal sensing using canopy reflectance sensor, chlorophyll meter and leaf color chart for in-season grain yield prediction of basmati rice. Pedosphere, 32(6):812-822.

OPTIMIZING DURUM WHEAT NITROGEN NUTRITION INDEX (NNI) PREDICTION THROUGH SENTINEL-2 VEGETATION INDICES INTEGRATIONS
#11335

[1]N.H Boughattas, [1,2]M. Kadri, [2]M. Zekri, [3]S. Ayadi, [4]S. Arraouadi, [5]H. Hajlaoui, [3]Y. Trifa, [2]I. Hbiri

[1] University of Sousse, Higher Institute of agronomy of chott-Meriem (ISA-CM), Sousse, Tunisia; [2] Robocare, Sfax, Tunisia; [3] National Agronomic Institute of Tunisia (INAT), Tunis, Tunisia; [4] Regional Center of Agriculture Research of Sidi Bouzid (CRRA), Sidi Bouzid, Tunisia; [5] Faculty of Sciences and Technology of Sidi Bouzid, Tunisia.

e-mail: nourelhoudaboughattas@yahoo.fr; 00216 2921361

ABSTRACT

Nitrogen is crucial for durum wheat growth and productivity, but excess or insufficient levels can harm both the environment and farmers' finances. Remote sensing offers rapid, cost-effective, and nondestructive ways to assess crop nutrition, with vegetation indices (VIs) indicating plant health. This study aims to enhance the accuracy of durum wheat nitrogen status prediction by investigating modified formulations of Nitrogen Nutrition Index (NNI) coupled with various VIs, such as NDVI Sentinel-2, NDVI by GreenSeeker, GNDVI, NDRE, NRI, RESAVI, REDVI, and MCARI. Two experimental plots of durum wheat were selected, one in the Medjez El Bab region in the Beja governorate (Z30) and the other in the Sadaguia region in the Sidi Bouzid governorate (Z60). A nitrogen dilution curve (Nc) was established for each plot at a specific growth stage to determine the NNI index. Statistical analysis was performed using RStudio software to obtain a predictive model for NNI and the VIs extracted by CropCare application established by Robocare. The performance of this model was evaluated using the coefficient of determination, R^2. The correlation analysis allowed us to identify a significant correlation between NNI and VIs. The GNDVI index proved to be the best indicator for estimating NNI (R^2=0.972), while the NDVI was excluded (R^2=0.221). In summary, this study underscores the effectiveness of integrating modified NNI formulations with diverse VIs from remote sensing, offering improved precision in fertilizer management for precision agriculture.

INTRODUCTION

Nitrogen is a fundamental nutrient for plant growth, playing a pivotal role in photosynthesis, protein synthesis, and overall crop productivity (Nino et al., 2024). In the case of durum wheat (Triticum durum), a staple in many agricultural systems, nitrogen management is critical for achieving optimal yields and grain quality. However, the delicate balance between sufficient and excessive nitrogen application poses a challenge (P. Chen, 2015) (C. Chen et al., 2023). Over-application can lead to environmental issues such as nitrate leaching and greenhouse gas emissions, while under-application can result in reduced yields and economic losses for farmers (Denora et al., 2023). Traditionally, nitrogen management has relied on soil tests and fixed fertilizer application rates, which often fail to account for spatial and temporal variability in crop nitrogen needs (Diacono et al., 2012). This has driven the development of more precise, dynamic approaches, among which remote sensing has emerged as a powerful tool (Piikki et al., 2022). Remote sensing technologies offer the ability to monitor crop nutrition over large areas with high spatial and temporal resolution (Yu et al., 2023). By analyzing specific spectral bands, VIs can be derived to assess plant stress levels, and nutrient status (Xue & Su, 2017) (Fabbri et al., 2020). The Nitrogen Nutrition Index (NNI) is a widely used indicator for assessing the nitrogen status of crops, providing insights into whether a crop is experiencing nitrogen deficiency or sufficiency (Gée et al., 2023). However, the accuracy of NNI predictions can vary depending on the methods and indices used. Recent advancements in remote sensing, particularly with the availability of high-resolution satellite data like Sentinel-2, have opened new avenues for enhancing NNI prediction accuracy (Zha et al., 2020) (Gée et al., 2023) (Yu et al., 2023) (Nino et al., 2024). This study explores the integration of various VIs, including those derived from Sentinel-2, to optimize the prediction of NNI in durum wheat. By analyzing the performance of different VIs and their relationship with NNI, this research aims to refine nitrogen management practices, ultimately contributing to more sustainable and efficient agriculture.

MATERIALS AND METHODS

Site descriptions

During the 2023-2024 durum wheat growing season, this study was conducted at two experimental sites in Tunisia (Fig.1a), chosen to represent different agro-climatic zones and key phenological stages Z30 and Z60, per the Zadoks scale (Zadoks et al., 1974). Both sites followed actual field practices, reflecting the methods and techniques used by farmers in their daily agricultural activities. The first site, a 47 ha field located in Medjez El Bab, Beja Governorate (Fig.1b), typically receives 550-600 mm of annual rainfall. However, during the 2023 hydrological year, the region faced significant challenges due to adverse climatic conditions. From September 2022 to June 2023, the area experienced severe drought, with only 80 mm of rainfall.

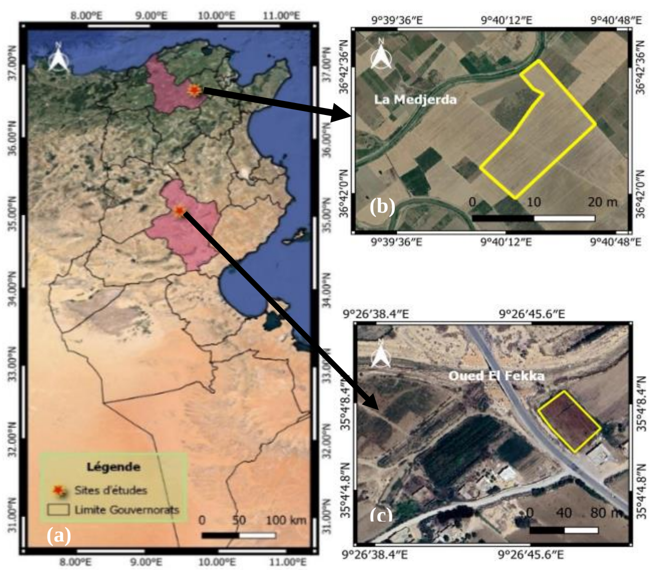


Figure 7. (a) Location of study plots in Tunisia. (b) Delineation of the study plot in Medjez el Bab. (c) Delineation of the study plot in Sadaguia, Sidi Bouzid.

The second site is in the Sadaguia region, Sidi Bouzid Governorate (Fig.3c), with an area of 0.278 ha. This site, cultivating Maali durum wheat, is situated in a semi-arid climate characterized by lower annual rainfall, averaging between 200 and 300 mm. The site features sandy loam soils, which pose specific challenges for water retention and nutrient management.

Experimentation

Sample collection points were chosen using the CropCare application, based on NDVI VI maps. In the field, one-square-meter plots were sampled to determine fresh weight. Chlorophyll content was measured with a SPAD 502Plus (SPAD), and NDVI values were recorded using a GreenSeeker (NDVI Green). In the laboratory, samples were dried at 60°C for 48 hours, then ground and analyzed for total nitrogen (%N measured) using the Kjeldahl method. Critical nitrogen levels (%Nc) were derived from dry matter values, and the NNI was calculated as the ratio of actual nitrogen absorption to critical nitrogen absorption.

Data collection and analysis

Sentinel-2 spectral bands were used to derive those traditional VIs commonly used in the literature (Tab.1) (Hatfield et al., 2019). These indices were computed over plant sample locations and at two phenological stages Z30 and Z60 using the CropCare application established by Robocare (Robocare, 2024). Measured variables (SPAD, NDVI Green, %N measured, %Nc, NNI) and VIs (Table 1)) were analyzed using descriptive statistics, correlation analysis, and multiple linear regression to determine NNI based on other parameters, all performed with R 4.4.1 statistical software.

Table 1. Vegetation Index extracted from Sentinel-2 images.

VIs	Definition	Formula	Application	References
NDVI	Normalized Difference Vegetation Index	$(NIR - Red)/(NIR + Red)$	Chlorophyll content	(Rouse et al., 1974)
NRI	Nitrogen Reflectance Index	$(Green - red)/(Green + Red)$	N content	(Diker & Bausch, 2003)
NDRE	Normalized Difference Red Edge	$(NIR - Red_{edge})/(NIR + Red_{edge})$	N content	(Barnes et al., 2000)
RESAVI	Red Edge Soil Adjusted Vegetation Index	$1{,}5\ x((NIR - Red_{edge})/NIR + Red_{edge} - 0.5))$	NNI	(Cao et al., 2013)
REDVI	Red Edge Difference Vegetation Index	$(2xNRI + 1)^2 - 8x(NRI - Red_{edge})$	NNI	
GNDVI	Green Normalized Difference Vegetation Index	$(NIR - Green)/(NIR + Green$	NNI	(Gitelson et al., 1996)
MCARI	Modified Chlorophyll Absorption Ratio Index	$(Red_{edge} - Red)/(Red_{edge} + Red)$	NNI	(Daughtry et al., 2000)

RESULTS AND DISCUSSION

Descriptive Statistical Analysis

The descriptive statistical analysis revealed notable differences between the Z30 and Z60 growth stages, particularly in key VIs and measured variables. The t-test results indicated significant variations in NDVI, SAVI, and NDVI Green, with higher values generally observed at the Z60 stage, reflecting more advanced plant development and increased biomass. Additionally, SPAD values, which measure chlorophyll content, showed a marked increase at Z60, aligning with the period of peak nitrogen demand. The %N measured and %Nc also differed significantly between stages, with higher nitrogen content observed at Z60. The NNI index was significantly higher at Z60, indicating better nitrogen status. These findings align with recent studies showing that these indicators increase with plant development and peak nitrogen demand, supporting their use for optimizing nitrogen management in durum wheat (Yu et al., 2023) (Al-Shammari et al., 2024) (Nino et al., 2024).

Correlation Analysis

The correlation analysis between various VIs and measured variables at the Z30 and Z60 stages for the Medjez El Bab and Sidi Bouzid plots revealed several key relationships. At Z30, strong positive correlations were observed between NDVI and GNDVI, NDVI and NDRE, and NDVI and RESAVI, indicating a close relationship between these indices. Additionally, NDVI Green showed strong correlations with SPAD, %N mesuré, and %Nc, while %Nc exhibited negative correlations with these variables. In contrast, the Z60 stage showed different correlation patterns, with NDRE strongly correlating with NDVI and RESAVI, while GNDVI and NRI also showed high positive correlations. Notably, the correlation between NDVI and GNDVI was positive at Z30 but negative at Z60, indicating a shift in their relationship across stages. Overall, these results highlight the varying strength and direction of correlations between VIs and N related variables at different phenological stages, underscoring the complexity of crop-nutrient interactions over time (Nino et al., 2024) (Yu et al., 2023). The shift in correlation patterns between NDVI and GNDVI across growth stages reflects similar trends reported in studies of crop development and nutrient uptake (Zha et al., 2020).

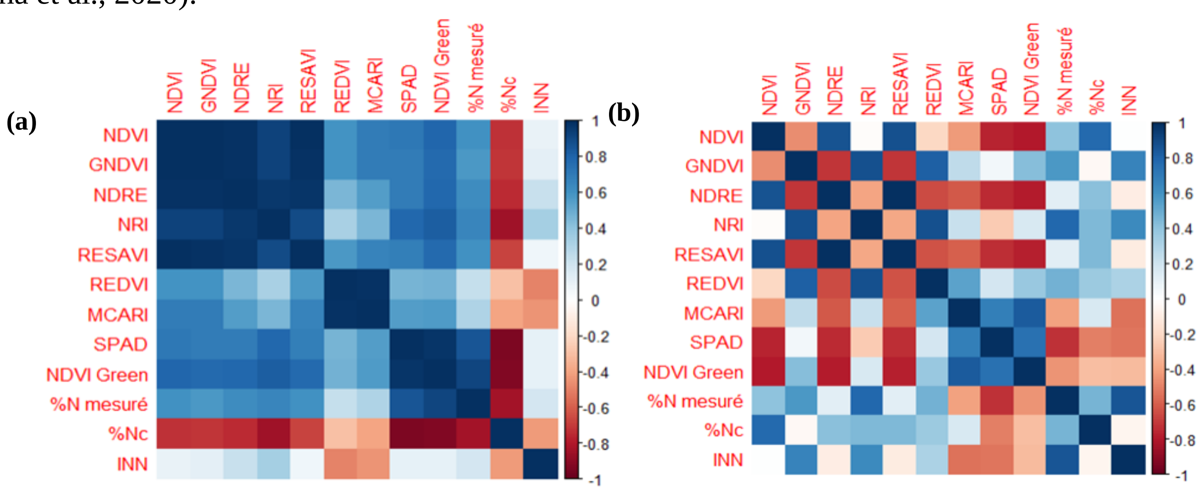


Figure 8. Correlation Matrix Between Different Variables, (a) of the Medjez El Bab Site (Z30), (b) of the Sidi Bouzid Site (Z30).

Relationship between NNI and VIs, Multiple Linear Regression Analysis

The multiple linear regression analysis focused on predicting the NNI Index using various VIs derived from the CropCare application. The model (Eq.1) achieved a high R^2 value of 0.975, explaining 97.5% of the variation in NNI. This indicates a strong predictive capability, with most

VIs contributing significantly to the model. The residuals were randomly distributed around zero, suggesting that the model accurately captured the relationships between the VIs and NNI.

$$INN = 220.60\ \mathrm{NDVI} - 19.10\ \mathrm{GNDVI} - 160\ \mathrm{NDRE} + 6.27\ \mathrm{NRI} - 48.19\ \mathrm{RESAVI} + 0.0376\ \mathrm{REDVI} - 0.0001456\ \mathrm{MCARI} - 8.16 \quad \textbf{Eq.1}$$

CONCLUSION

This study demonstrates the effectiveness of VIs and regression models in optimizing nitrogen management for durum wheat. Statistical analysis revealed significant differences in VIs between stages Z30 and Z60, along with strong correlations among the indices. The linear regression model accounted for 97.5% of the variability in the NNI at stage Z30. Future research should focus on incorporating additional data sources to improve model accuracy. Additionally, conducting field validation trials to evaluate practical applicability and developing new VIs could further enhance nitrogen management strategies.

REFERENCES

Al-Shammari, D., Fuentes, I., Whelan, B. M., Wang, C., Filippi, P., & Bishop, T. F. A. 2024. Combining Sentinel 1, Sentinel 2 and MODIS data for major winter crop type classification over the Murray Darling Basin in Australia. Remote Sensing Applications: Society and Environment, 34, 101200. https://doi.org/10.1016/j.rsase.2024.101200

Barnes, E., Clarke, T. R., Richards, S. E., Colaizzi, P., Haberland, J., Kostrzewski, M., Waller, P., Choi, C., Riley, E., & Thompson, T. L. 2000. Coincident detection of crop water stress, nitrogen status, and canopy density using ground based multispectral data.

Cao, Q., Miao, Y., Wang, H., Huang, S., Cheng, S., Khosla, R., & Jiang, R. 2013. Non-destructive estimation of rice plant nitrogen status with Crop Circle multispectral active canopy sensor. Field Crops Research, 154, 133-144. https://doi.org/10.1016/j.fcr.2013.08.005

Chen, C., Zhou, S., Afshar, R. K., Franck, W., & Zhou, Y. 2023. Durum wheat yield and protein influenced by nitrogen management and cropping rotation. Journal of Plant Nutrition. https://www.tandfonline.com/doi/abs/10.1080/01904167.2022.2068432

Chen, P. 2015. A Comparison of Two Approaches for Estimating the Wheat Nitrogen Nutrition Index Using Remote Sensing. Remote Sensing, 7(4), Art. 4. https://doi.org/10.3390/rs70404527

Daughtry, C. S. T., Walthall, C. L., Kim, M. S., de Colstoun, E. B., & McMurtrey, J. E. 2000. Estimating Corn Leaf Chlorophyll Concentration from Leaf and Canopy Reflectance. Remote Sensing of Environment, 74(2), 229-239. https://doi.org/10.1016/S0034-4257(00)00113-9

Denora, M., Candido, V., D'Antonio, P., Perniola, M., & Mehmeti, A. 2023. Precision nitrogen management in rainfed durum wheat cultivation: Exploring synergies and trade-offs via energy analysis, life cycle assessment, and monetization. Precision Agriculture, 24(6), 2566-2591. https://doi.org/10.1007/s11119-023-10053-5

Diacono, M., Rubino, P., & Montemurro, F. 2012. Precision nitrogen management of wheat. A review. Agronomy for Sustainable Development, 33(1), 219-241. https://doi.org/10.1007/s13593-012-0111-z

Diker, K., & Bausch, W. C. 2003. Potential Use of Nitrogen Reflectance Index to estimate Plant Parameters and Yield of Maize. Biosystems Engineering, 85(4), 437-447. https://doi.org/10.1016/S1537-5110(03)00097-7

Fabbri, C., Mancini, M., dalla Marta, A., Orlandini, S., & Napoli, M. 2020. Integrating satellite data with a Nitrogen Nutrition Curve for precision top-dress fertilization of durum wheat. European Journal of Agronomy, 120, 126148. https://doi.org/10.1016/j.eja.2020.126148

Gée, C., Denimal, E., de Yparraguirre, M., Dujourdy, L., & Voisin, A.-S. 2023. Assessment of Nitrogen Nutrition Index of Winter Wheat Canopy from Visible Images for a Dynamic Monitoring of N Requirements. Remote Sensing, 15(10), Art. 10. https://doi.org/10.3390/rs15102510

Gitelson, A. A., Kaufman, Y. J., & Merzlyak, M. N. 1996. Use of a green channel in remote sensing of global vegetation from EOS-MODIS. Remote Sensing of Environment, 58(3), 289-298. https://doi.org/10.1016/S0034-4257(96)00072-7

Hatfield, J. L., Prueger, J. H., Sauer, T. J., Dold, C., O'Brien, P., & Wacha, K. 2019. Applications of Vegetative Indices from Remote Sensing to Agriculture : Past and Future. Inventions, 4(4), Art. 4. https://doi.org/10.3390/inventions4040071

Nino, P., D'Urso, G., Vanino, S., Di Bene, C., Farina, R., Falanga Bolognesi, S., De Michele, C., & Napoli, R. 2024. Nitrogen status of durum wheat derived from Sentinel-2 satellite data in central Italy. Remote Sensing Applications: Society and Environment, 36, 101323. https://doi.org/10.1016/j.rsase.2024.101323

Piikki, K., Söderström, M., & Stadig, H. 2022. Remote sensing and on-farm experiments for determining in-season nitrogen rates in winter wheat – Options for implementation, model accuracy and remaining challenges. Field Crops Research, 289, 108742. https://doi.org/10.1016/j.fcr.2022.108742

Robocare. 2024. RoboCare—We Tech-Care Of your Land. RoboCare - We Tech-Care Of your Land. https://robocare.tn/

Rouse, J. W., Haas, R. H., Schell, J. A., & Deering. 1974. Monitoring Vegetation Systems in the Great Plains with ERTS. Third ERTS-1 Symposium NASA, 309-317.

Xue, J., & Su, B. 2017. Significant Remote Sensing Vegetation Indices: A Review of Developments and Applications. Journal of Sensors, 2017, 1-17. https://doi.org/10.1155/2017/1353691

Yu, F., Bai, J., Jin, Z., Zhang, H., Yang, J., & Xu, T. 2023. Estimating the rice nitrogen nutrition index based on hyperspectral transform technology. Frontiers in Plant Science, 14. https://doi.org/10.3389/fpls.2023.1118098

Zadoks, J. C., Chang, T. T., & Konzak, C. F. 1974. A decimal code for the growth stages of cereals. Weed Research, 14(6), 415-421. https://doi.org/10.1111/j.1365-3180.1974.tb01084.x

Zha, H., Miao, Y., Wang, T., Li, Y., Zhang, J., Sun, W., Feng, Z., & Kusnierek, K. 2020. Improving Unmanned Aerial Vehicle Remote Sensing-Based Rice Nitrogen Nutrition Index Prediction with Machine Learning. Remote Sensing, 12(2), Art. 2. https://doi.org/10.3390/rs12020215

PRECISION PLANTING/HARVESTING

MODELING OF THE OPTIMAL PARAMETERS, IMPROVEMENT AND PERFORMANCE EVALUATION OF MARC ENGINE DRIVEN COMMON BEAN (PHASEOLUS Vulgaris L.) THRESHER IN ETHIOPIA

#11221

[1*]Biniam Zewdie, [2]Adesoji M. Olaniyan, [1]Amana Wako, [3]Dereje Alemu, [3]Tamrat Lema
[1*]School of Mechanical, Chemical, and Materials Engineering, Departments of Agricultural Machinery Engineering, Adama Science and Technology University, P.O. Box 1888, Adama, Ethiopia; [2]Department of Agricultural and Bioresources Engineering, Faculty of Engineering, Federal University Oye-Ekiti, Ikole-Ekiti Campus, Post Code 370001, Ikole-Ekiti, Nigeria; [3]Ethiopian Institute of Agricultural Research; Agricultural Engineering Research, Melkassa Agricultural Research Center, P.O. Box 436, Adama, Ethiopia
[*]e-mail: nzg2001nzg@gmail.com

ABSTRACT

This executive summary provides an overview of the research study conducted on modeling the optimal parameters, improvement, and performance evaluation of the engine-driven bean thresher developed by the Melkassa Agricultural Research Center (MARC) in Ethiopia. The study aimed to enhance the efficiency and productivity of the bean thresher, contribute to sustainable agricultural practices, promote technology adoption, and support the economic development of the agricultural sector. The research study employed a comprehensive approach involving data collection, modeling, experimentation, and performance evaluation. **Key steps** undertaken during the study included: **Literature Review**: A thorough review of existing literature related to bean threshing, agricultural machinery, and optimization techniques was conducted to establish a knowledge base and identify research gaps. **Data Collection:** Field surveys, interviews, and observations will be conducted to gather data on the existing bean thresher's performance, challenges faced by farmers, and specific requirements for improvement. **Modeling and Optimization**: Mathematical modeling and simulation techniques will be employed to identify the optimal parameters for the bean thresher. Parameters such as cylinder speed, concave clearance, and fan speed will be analyzed to determine their impact on threshing efficiency and grain quality. **Experimental Design**: Field experiments will be designed and conducted to evaluate the performance of the optimized parameters. The experiments involved comparing the modified thresher with the existing version, measuring key performance indicators, and assessing grain loss, power consumption, and processing efficiency. **Performance Evaluation**: The data collected from the experiments will be analyzed to evaluate the performance of the optimized bean thresher. The evaluation included metrics such as grain damage, threshing efficiency, fuel consumption, and processing capacity. The findings of the research study demonstrate the significance and potential impact of the modeled optimal parameters and improved bean thresher. The key **outcomes and recommendations** will include the following: **Improved Thresher Performance**: The optimized parameters resulted in a significant improvement in the thresher's performance. Threshing efficiency increased, grain damage was reduced, and fuel consumption was reduced. These improvements contribute to enhanced productivity and reduced post-harvest losses. **Sustainable Agriculture**: The optimized bean thresher exhibited improved resource efficiency, reducing fuel and energy consumption. This promotes sustainable agricultural practices and reduces the environmental impact of bean processing. **Economic Benefits**: The improved thresher reduces labor requirements, processing

time, and operational costs. Farmers can achieve cost savings of approximately, leading to increased profitability and economic benefits for bean producers. **Technology Adoption**: The research study provides evidence-based recommendations for the adoption of the improved bean thresher. Farmers, agricultural extension workers, and policymakers are encouraged to promote the use of this technology to enhance agricultural productivity and modernize farming practices. **Policy Implications**: The study's findings will have policy implications for the agricultural sector. Policymakers are advised to consider incorporating support mechanisms and incentives for the adoption of improved agricultural machinery, fostering local manufacturing, and promoting sustainable agricultural practices.

Keywords: RSM, Thresher, Threshing efficiency, Germination, and Grain Damage

INTRODUCTION

The common bean (*Phaseolus vulgaris L.),* according to (Joshi et al., 2022), is one of the main nourishments for both humans and livestock in Africa and the third most consumed legume worldwide. Its seed is high in carbohydrates and protein, and animal feed originates from the seed and its pod (Uebersax *et al*., 2023). With 560,191 hectares of cultivated land and 208,913 tons of beans produced in 2019, Ethiopia is the world's most significant producer of edible legumes. Among the most significant legumes are common beans (Bento *et al*., 2022).

After being harvested by hand, the common bean crop is threshed by a machine. The thresher uses impact force and pressure to remove grain from pod and stalk (Que *et al*., 2024). Grains sustain significant damage from the crop migrating between the thresher unit's stirring components and from inadequate clearance among static as well as moving portions (Lee et al., 2023). Grain that has been damaged has the lowest shelf life and is less resilient to pests and diseases (Adewoyin, 2023). Grain grading is the primary factor that determines its marketability; fragmented seeds result in a lower grain grade (Parker et al., 2022). In addition, damaged grains prevent seeds from germinating (Chandra et al., 2024).

The most qualitative parameters to determine the efficiency of a thresher operation consist of mixed chaff with the grain, loss from threshing, and damage to the grain. According to Ghebrekidan et al. (2024) analysis of a thresher apparatus's design features, the threshing performance was significantly influenced by the rate at which materials were fed into the device as well as technological factors including drum speed and concave-to-drum clearance. Additionally, Juraev *et al.* (2023) observed that the threshing process was influenced by the crop cultivar, moisture content, and biometrical indices.

Grain damage, loss from threshing, and mingled the most prestigious are the particles with the grain metrics to assess a thresher's performance (Strecker *et al*., 2022). The velocity of material feeding into the device, along with technological aspects like drum acceleration and convex-to-drum aperture, had a substantial impact on the shredding performance, as per Ghebrekidan et al. (2024) analysis of the design elements of a thresher apparatus. The biometrical parameters, moisture level, and crop genotype were also found to have an impact on the threshing process by Jan et al. (2021).

Loss of grains, grain impairment, level of separation, as well as size of the pod decrease were all the parameters that Ejara et al. (2018) differentiated into standard bean threshing quality indices in an unusual investigation. In the process of threshing common beans, two important factors were identified to be the aperture along with the wire loop type drum and the convex, as well as drum peripheral velocity. Ghebrekidan et al. (2024) investigated the parameters of the typical mechanism used for separating beans. It was shown that the distance between the cylinder and the concaves and peripheral speed were the main parameters affecting crop quality. The findings of their experiment using the tangential threshing mechanism indicated that the rate of grain breakage improved from 3.8 to 6.01% when the cylinder perimeter speed was enhanced from 9.4 to 21.4 ms^{-1}.

Numerous threshing units were used by Umbataliyev *et al.* (2023) for common bean seeds. Using a multitude of sorts of drums, rates, as well as rate of feed, they assessed the thresher's performance in terms of throughput capacity, threshing effectiveness, damage to the grain, losses of the grain, differentiation, energy the threshold, as well as specific utilization of energy. They discovered that the apparent damage to the grain increased along acceleration as well as flow rate. Kidney bean threshers were examined by Wang and Cichy (2024) using variables such seed moisture level, clearance rates, and cylinder rpm. The outcomes demonstrated that moisture level, cyl speed, and convex level all had a major impact on the germination of threshed seeds.

Huertas et al. (2023) found that the feed rate, moisture content, and threshing drum beat all had a substantial impact on the success rate of threshing, output capacity, and grain damage and losses of a longitudinal flow barrier used in common beans. The impact of the moisture level, pod size, with the pace of the drum in a rasp-bean thresher were investigated in relation to the proportion of damaged grains and threshed pods (Lisciani et al., 2024). The findings showed that the pod size had the biggest impact on damage intensity, while the drum speed had the least. It was further suggested that the optimal circumstances for common bean threshing would be a water content ranging from 12 to 15% and a drum speed of 9.5 ms^{-1}. Although several studies have been conducted on the threshing of different agricultural crops, none have examined the response surface methodology's potential for optimizing the threshing of common beans with relation to machine-crop factors. To enhance technological parameters including cylinder acceleration, convex clearance levels, rate of feed, and level of moisture, the response surface approach is utilized, the principal aim of this investigation was to enhance threshing efficiency, minimize grain damage, and maximize seed germination when threshing common beans.

MATERIALS AND METHODS

Selected improved varieties of common beans from the Oromia regional State in Ethiopia were provided by the Awash Melkassa Research Center. A digital vernier caliper (TA, M5 0–300 mm, China) was used to measure the three primary axial dimensions of the beans: With an accuracy of 0.01 mm, the measurements are dimension (L, mm), (W, mm), and (T, mm). The experimental findings indicated that the average mean values for thickness (4.962 ± 0.50 mm), width (6.316 ± 0.502 mm), and length (9.848 ± 0.802 mm) were, accordingly. After common beans were harvested by hand, the threshing procedure was carried out using a laboratory wire loop/rasp type drum thresher. The assembled thresher and a collaborative assessment of it are depicted in Figure 1. With 33 teeth spaced 100 mm apart along each of the device's four axes, the drum measured 730 mm in length. The concave was made from 720 mm long steel sheets that had been rolled and perforated.

Experimental design

Based on the multifactorial experiment principle with three independent replications, the experiment utilized a split-split plot design. The main plot was assigned to the two varieties of crops levels, the sub plot was assigned to the three threshing drum speed levels, and the sub-sub plot was assigned to the three feeding levels, each with three replications (Table 1). The Response Surface Method was utilized to maximize the threshing performance, and statistical R-studio software was utilized to analyze all the data gathered during the laboratory and field performance evaluations.

Figure 1. MARC-Bean thresher schematic diagram and participatory evaluation assessment.

Response surface method (RSM)

Four independent parameters were considered for optimization: moisture content (5, 10, and 15% wb), convex aperture (25, 35, 45 mm), speed of cylinder (7.5, 9.17, 10.83 ms^{-1}), and rate of feeding (550, 650, 750 kgh^{-1}). Germination of seeds percentage, threshing efficiency, and damage to grain were the three dependent variables in the experimental method of optimization. To fit the experimental results, a polynomial equation of second order was thus developed using the method of response surfaces and central composite experiment design.

According to the findings of earlier research and the limitations of the manufactured thresher (Que *et al.*, 2024) the levels of convex aperture, moisture level, and chamber rate were chosen (Savic *et al*. 2019). In the end, 54 experiments were conducted utilizing triplets of implementation for the independent variables in a CCD-type experimental design, as shown in Table 1. In a random order, the trials were carried out. In the latter half of the parameters with encode, three replications were conducted to determine the relationship model describing the two main parameters' sum of square errors and lack of fitness (Güvercin and Yıldız, 2018). Design-Expert 12 was used to optimize the several responses simultaneously.

Table 1. Randomization layout.

R1			R2			R3		
$S_1F_1M_1$	$S_2F_2M_2$	$S_3F_3M_3$	$S_1F_1M_3$	$S_2F_2M_1$	$S_3F_3M_2$	$S_1F_1M_2$	$S_2F_3M_3$	$S_1F_1M_1$
$S_3F_2M_1$	$S_1F_2M_2$	$S_2F_1M_3$	$S_3F_2M_3$	$S_1F_2M_1$	$S_2F_1M_2$	$S_2F_2M_2$	$S_1F_2M_3$	$S_2F_2M_1$
$S_2F_3M_1$	$S_3F_1M_2$	$S_1F_3M_3$	$S_3F_1M_3$	$S_2F_1M_1$	$S_2F_2M_2$	$S_3F_3M_2$	$S_3F_1M_3$	$S_3F_3M_1$
$S_3F_3M_1$	$S_2F_3M_2$	$S_1F_1M_3$	$S_3F_3M_3$	$S_2F_3M_1$	$S_1F_1M_2$	$S_3F_1M_2$	$S_2F_1M_3$	$S_3F_1M_1$
$S_2F_1M_1$	$S_1F_3M_2$	$S_2F_3M_3$	$S_2F_1M_3$	$S_3F_1M_1$	$S_2F_3M_2$	$S_3F_2M_2$	$S_3F_3M_3$	$S_2F_3M_1$
$S_1F_2M_1$	$S_3F_2M_2$	$S_3F_2M_3$	$S_1F_2M_3$	$S_1F_3M_1$	$S_3F_2M_2$	$S_1F_2M_2$	$S_1F_3M_3$	$S_1F_2M_1$
$S_1F_3M_1$	$S_2F_1M_2$	$S_3F_1M_3$	$S_1F_3M_3$	$S_3F_2M_1$	$S_3F_1M_2$	$S_1F_3M_2$	$S_2F_2M_3$	$S_1F_3M_1$
$S_2F_2M_1$	$S_3F_3M_2$	$S_1F_2M_3$	$S_2F_3M_3$	$S_3F_3M_1$	$S_1F_2M_2$	$S_2F_1M_2$	$S_3F_2M_3$	$S_3F_2M_1$
$S_3F_1M_1$	$S_1F_1M_2$	$S_2F_2M_3$	$S_2F_2M_3$	$S_1F_1M_1$	$S_1F_3M_2$	$S_2F_3M_2$	$S_1F_1M_3$	$S_2F_1M_1$

S = drum speed, F = feed rate, M =moisture content, & R = replications

Evaluation procedure

The chamber rate, flow rate, Level of moisture, and convex aperture width of the thresher were evaluated at three different levels on a firm surface after installation and adjustments. With regards to the trial, the consequence of their separate parameters on sprouting, threshing efficiency and grain damage was considered. Samples were randomly prepared and put into the thresher once it was turned on to obtain the thresher performance indices. According to Wang and Cichy (2024), the effectiveness of threshing (TE), the aptitude for threshing (TC), effective cleaning (CE), and proportional of losses were determined using the following relationships to assess the threshing machine's effectiveness.

RESULTS AND DISCUSSION

Threshing Efficiency

The figures 2a–c were prepared using optimal feeding amounts of 672 kg/h, 37.4cm concave clearance, and 8.25 ms^{-1} drum speed. Threshing efficiency improved together with concave geometry clearance and rate of feed, as Figure 2a presented. Threshing efficiency attained a highest of 98.7% at an average feed rate of 672 kg/h and a convex clearance of 37.4 cm. Figure 2b illustrates how increasing the rate of feed and speed of the drum led to an enhancement to the effectiveness of threshing. The most significant threshing efficiency (99.7%) was ascertained with an intake rate of 672 kg/h and a drum with a speed of 8.25 ms^{-1}. In contrast, the efficiency of threshing climbed in tandem with the drum speed improved and convex clearance dropped. The drum speed at which the highest efficiency (99%) was achieved was 8.25ms^{-1} and a concave clearance of 37.4mm (Fig. 2c). Threshing efficiency improved when the rubbing force between the bean and the canvas concave increased, corresponding with a decrease in convex clearance between the concave strip and the concave bar. As perimeter rate climbed, so did momentum and thrust of impact on the trembling, which in turn boosted threshing efficiency as drum speed climbed. When it came to bean threshers, Umbataliyev et al. (2023) discovered similar patterns.

The experimental findings are illustrated in Figures 2-d to -f. throughout the range of input components examined, the threshing efficiency varied between 95.1 and 99%. At the 1% confidence level, Table 2 illustrates that threshing efficiency was significantly impacted through the rate of feed, cylinder speed, level of moisture, and convex clearance. The impact of the chamber frequency on common bean effectiveness of threshing is illustrated in Figure 2-d. When cylinder speed was increased from 7.5 to 9.17 ms^{-1}, threshing efficiency climbed from 96.81 to 99.21% with a moisture level of 11.6%. Furthermore, as anticipated, the highest cylinder speed (10.83 ms^{-1}) produced the highest threshing efficiency rating (99.69%).

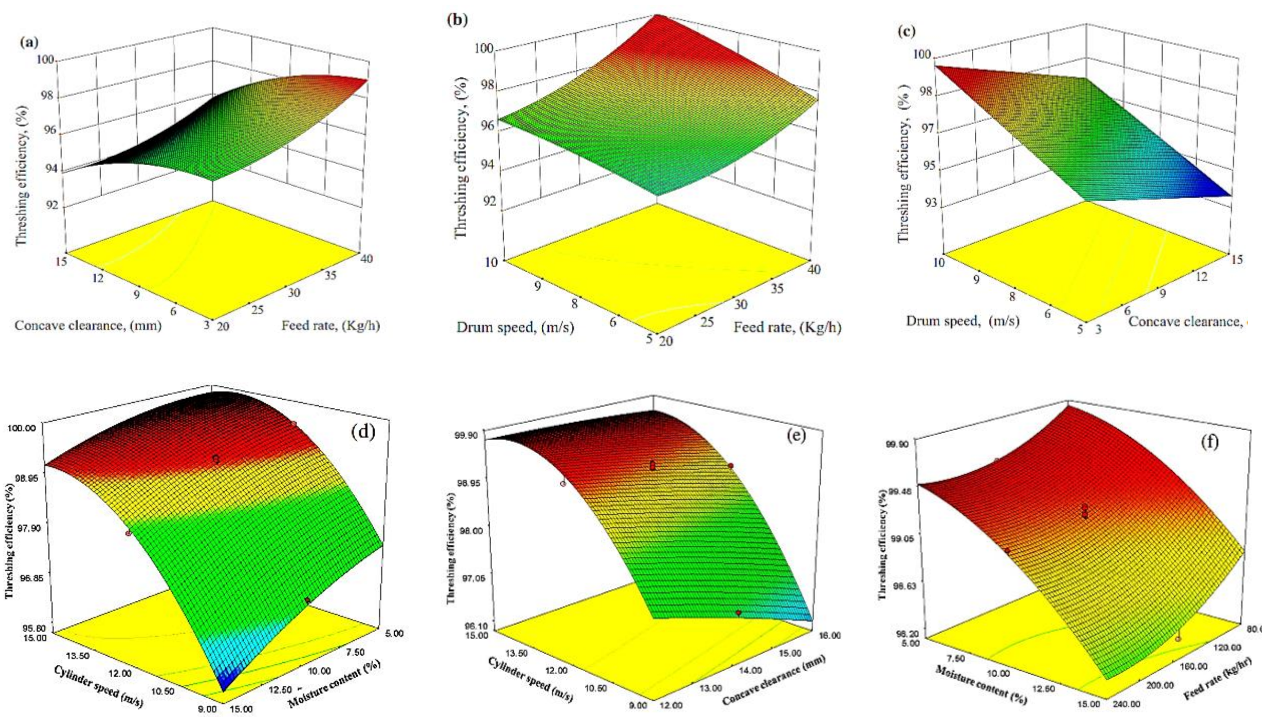


Figure 2. The implications of those parameters on the threshing efficiency: (a) feed rate and concave clearance; (b) drum speed and feed rate; (c) drum speed and concave clearance; (d) cylinder speed and moisture content; (e) cylinder speed and concave clearance; and (f) moisture content and feed rate.

As concave aperture increased, threshing efficiency decreased, as Figure 2-e illustrates. Considering improvements in convex aperture from 35 to 45 mm, the threshing efficacy reduced from 97.45 to 96.16% at 7.5 ms^{-1} with the chamber's frequency. Convex space did not significantly influence performances at speed of drum exceeding 9.17 ms^{-1}. The higher cylinder speed resulted in refined threshing efficiency because of an increased impact force. The rationale for lowest threshing efficiency at the highest concave clearance was the insufficient force exerted on the pods, which caused them to fall out without separating the seeds. At the 1% confidence level, the concave clearance and cylinder speed influences on the threshing efficiency interacted significantly. There was a negative correlation between the feed rate and threshing efficiency.

As the feed consumption rate went up from 550 to 750kgh^{-1}, the average threshing efficiency reduced from 99.52 to 99.09% in (Figure 2f). Outcomes of the investigation indicated that the detrimental impact of cylinder speed on crop threshing was mitigated as the rate of feed escalated due to an increase in the width of the trim slice between the cylinder and concave. For every drum speed level, Huertas et al. (2023) found that as feed rate climbed the effectiveness of threshing decreased.

The efficiency of threshing dramatically dropped as the input material's level of moisture escalated, shown in Figure 2-f. There was a correlation between the highest (99.52%) and minimum (98.31%) effectiveness of threshing and the amounts of water of 5% and 15%, within that sequence. At increasing levels of water content, there was a greater impact of moisture content on threshing efficiency. Que *et al*. (2024) also reported a similar outcome. Pods and seeds are more easily split because there is less tension holding the pod together and the pods are more brittle due to reduced seed moisture concentrations. Threshing efficiency dropped because of increased pod cohesion brought on by the plant materials' increased flexibility at higher moisture contents.

The ANOVA illustrated in Table 2 ($p<0.001$) implies that the predicted value of F (19.81) is high, indicating that a model with quadratic parameters could be a good fit for the outcomes of the experiment. Table 2 illustrates the F-values that demonstrate the significant impact of the rate of feed, convex clearance, and speed of drum in terms of linear regression on the effectiveness of shredding at the 1% significance level. In a similar manner at the 5% significance level, the interaction terms between the drum speed x convex clearances and the drum speed a quadratic term exhibited an important impact on the threshing effectiveness. The remaining interactive and graphs had no discernible effect on the threshing effectiveness while not even at the 10% threshold of significance.

Detects the proportion of noise to signal with adequate precision; A value more than four is preferred. In this case, the ratio changed to 16.577, indicating a strong pulse. Savic and Savic-Gajic (2021) assert that this framework can be used for maneuvering within the realm of design. This model's predicted R^2 (0.81) and adjusted R^2 (0.89) agreed. Using polynomial form fitting, the regression model illustrating the threshing efficiency change with regard to the independent parameters ($feed\ rate, F_r$), ($drum\ speed, v_s$) and ($concave\ clearance, C_c$) was produced. The simplified polynomial model was obtained by removing terms from the quadrilateral model that are not significant (Savic *et al*. 2019)

Grain Damage

The variation among the investigation's outcomes illustrated that the convex aperture, chamber rate, rate of feeding, and levels of water content are all exhibited a significant impact on the amount of grain damage (Table 2). The most significant factors were determined to be the cylinder speed, which was followed by rate of feeding, moisture level, and convex aperture. First-order interactions were prioritized according to relevance: chamber frequency × level of moisture, feed rate × level of moisture, chamber frequency × convex aperture, and cylinder speed × cylinder speed. The implications of convex clearance and speed of cylinder on the percentage of grain damage are shown in Figure 3a. This figure illustrates how the rotational frequency at which the drum is threshed enhances the amount of grain impairment.

Damage of grains escalated from 4.98 to 47.97% at the convex of 35 mm when the drum speed increased from 7.5 to 10.83 ms^{-1}. When cylinder speed was raised from 7.5 to 10.83 ms^{-1}, Grain breakage escalated from 1.71 to 33.29% at a convex aperture of 35mm. During threshing, the common bean was subjected to higher impact levels, which increased damage. However, as concave clearance improved, grain damage drastically decreased.

Table 2. Response surface quadratic model-based analysis of variance for common bean threshing.

Source of variation	df[a]	Grain damage	Threshing efficiency
Model	54	164.62**	99.73**
Cys	1	1437.46**	930.83**
Fr	1	78.75**	21.01**
Cc	1	70.63**	60.35**
Mc	1	232.06**	144.55**
Cys× Fr	1	15.69**	13.34**
Cc ×Fr	1	0.83ns[b]	0.082ns
Fr ×Mc	1	1 5.46*	0.92ns
Cc ×Cys	1	1 24.03**	35.36**
Cc ×Mc	1	3.59ns	0.78ns
Cys× Mc	1	94.68**	21.16**
$(Mc)^2$	1	5.38*	2.51ns
$(Cys)^2$	1	93.47**	52.46**
$(Fr)^2$	1	0.46ns	1.60ns
$(Cc)^2$	1	1.45ns	0.090ns
Res.	15		
Pe	5		
Corr. total	69		

*Significant at the 5% level; **highly significant at the 1% level; [a] Degrees of freedom, [b] Non-significant, Fr = Feed rate, Cs = Drum speed, Cc = Convex aperture, Mc = Level of moisture, Res. = Residual, Pe = pure error, Corr. = Correlation total

Grain damage and rate of feeding interacted inversely with each other across independent variables. Since the crop was subjected to more intense contact at the lower feed rate, the reduction in grain damage was approximately 50% (Figure 3b) when the concave clearance of 37.4mm was attained while upgrading the intake rate from 550 to 750 kg/h. Additionally, according to Ghebrekidan et al. (2024)), grain damage increased as feed rate diminished.

When the amount of moisture escalated, the proportion of grain damage dropped dramatically, as shown in Figure 3c. On the other hand, grain loss went from 33.42 to 57.79% when the amount of moisture decreased at a speed of 10.83 m/s, from 15% to 5%. At lower cylinder speeds, the impact of moisture content on grain damage was minimal. When moisture content was reduced from 15% to 5%, grain damage increased from 5.52 to 10.51% at a cylinder speed of 7.5m/s. Grain elastic behavior increased with increasing moisture content; hence, more energy was needed to crack the grain. Moisture content has also been identified by several researchers as a significant factor influencing grain impairment (Huertas et al., 2023; Chandra et al., 2024).

A 672 kg/h rate for feeding, a concave clearance of 35cm, and a drum speed of 8.25m/s were the optimal parameters for preparing the Fig. 3g–i. As illustrated in Fig. 3g, the greatest damage to the grain appeared at 35–45 mm convex clearance at rates of feed varied from 650–750 kg/h. There was no evidence of damage to grains within the 35–38 mm convex clearance range at 650–675 kg/h amount of intake. The greatest amount of grain impairment has been observed to be 3.5% at 25 cm convex spacing and 750 kg/h amount of intake. Figure 3h showed the proportion of damaged grains emerged in tandem with raised rate of feed and drum rpm. With an amount of intake 750 kg/h and a drum rate of 10.83 m/s, the ultimate breakdown of grain was achieved, at 3.3%.

Likewise, there was an increase in damage to grains when the drum speed climbed, and the convex clearance diminished. At a chamber inclination of 10.83 m/s and a convex space of 25 mm, the highest possible 3.8% loss of grain was seen (Figure 3i). The reduction in convex clearance led to an increase in the contacting action between the grains and the covering stripe, degrading the grains. Moreover, it happened because there was more intimate interaction among the beans and the canvas strip and the segments of the chamber that convex. Significant forces from impacts were detected when the drum was moving faster. The maximum grain damage was caused by those maximal impact forces. At lower drum speeds, the maximum grain damage is caused by these maximum impact forces, and vice versa. Grain damage was found to be decreased at higher feed rates because maximum feed rates share the power of collision and contacting force produced by drums in rotation, whereas minimum feed rates handle the greatest the power of collision and contacting force, which results in highest degree of scratches. Similar findings with respect to the multi-threshing machine (Huertas et al., 2023; Chandra et al., 2024) published their findings. The greater feed that was shared by the impact and rubbing power of the revolving drum resulted in less degradation of grain when the degree of feeding escalated.

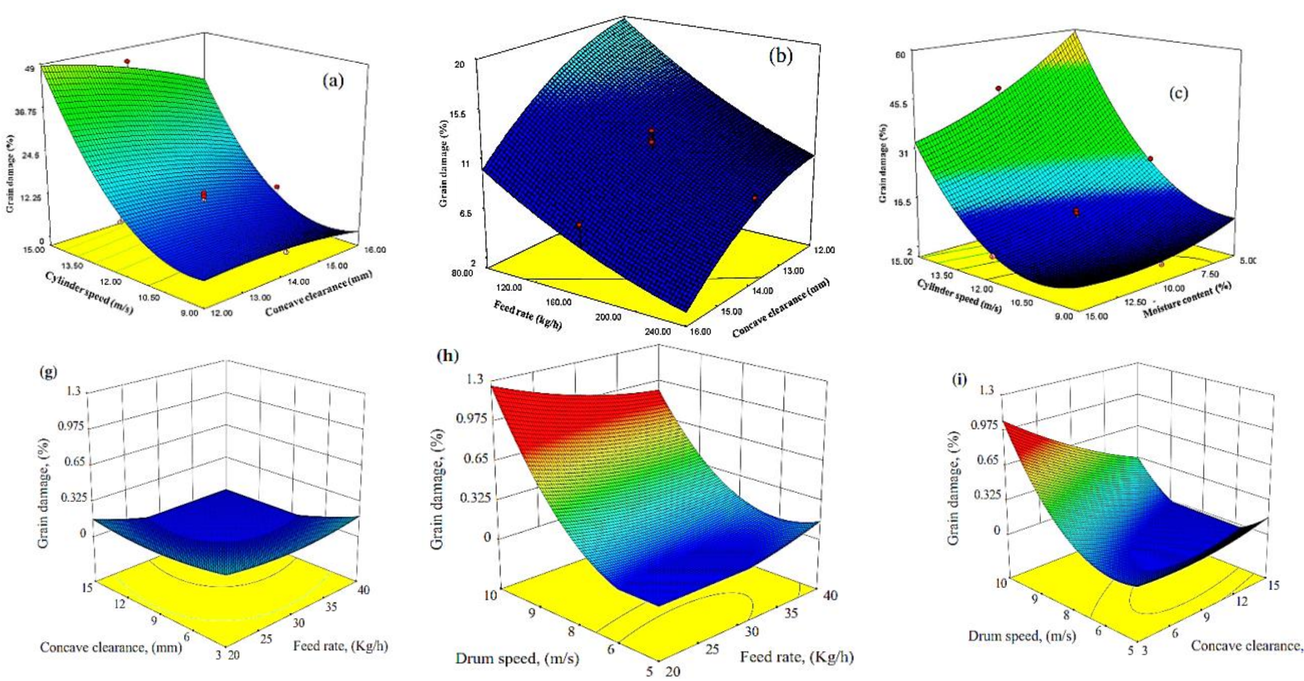


Figure 3. The implications on grain damage percentage of (a) cylinder speed and concave clearance, (b) feed rate and concave clearance, (c) cylinder speed and moisture content, (g) concave clearance and feed rate, (h) drum speed and feed rate, and (i) drum speed and concave clearance.

The influence of the rate of feeding (kg/h), speed of the drum (m/s), and convex clearance (mm) on common bean damage was investigated using the implementation of the ANOVA described in

Table 2. It is evident from emulate F's considerable value (44.34) ($p < 0.001$) that an equation with quadratic might correspond to the empirical information efficiently. The linear parameters of rate of feeding, drum speed, convex space, interaction coefficient curvature space x speed of drum, and nonlinear term convex clearance all had a significant impact on grains damage at the 1% level of significance, based on Table 2's F-values.

At the 5% significance level, the rate feed x drum speed interaction term also significantly influenced the degree of grain impairment. The damage to the beans was not significantly impacted by the relationship between the terms flow rate x concave aperture or the quadrilateral in relation to convex geometry and intake rate variables, irrespective of the significance threshold of 10% ($p < 0.1$).

Sufficient accuracy is used to measure the signal to noise proportion. Therefore, the ratio should be higher than four. In this instance, the ratio changed to 22.74, indicating a strong signal. To navigate the design space, one can apply this model (Savic *et al*. 2019; Savic and Savic-Gajic, 2021). This model's predicted R^2 (0.89) and adjusted R^2 (0.95) agreed. Polynomial form fitting was used to generate the regression equation that shows a variation of the percentage of grain damage (GD, %) with respect to the independent parameters ($feed\ rate, F_r$), ($drum\ speed, v_s$) and ($concave\ clearance, C_c$). The exponential model's insignificant terms had been eliminated to create the simplified multiplication framework (Savic *et al*. 2019)

Optimization of MARC bean thresher

The graphical optimization and optimal outcomes are shown in Figure 4. The machine's independent design parameters, which are connected to these outcomes, establish the optimal ranges of cleaning efficiency, threshing efficiency, and grain damage. The predicted percentages for cleaning efficiency, grain damage, and threshing efficiency were 85%, 0.086%, and 97.94%, respectively. By using graphical optimization, the optimal values of several variables were found, including concave clearances of 25 – 45mm with 87.94% efficiency of threshing, 85% cleaning effectiveness, and 0.086% fractures.

The marked region of Figure 4a–c displays the collective outcomes of this optimization. The same values were obtained by the numerical and graphical optimization techniques (Benaseer et al. 2018; Umbataliyev et al., 2023). These optimal features guided the development of the drum, which was then finished and its performance assessed to validate the chosen parameters. The findings indicated that the percentage of cleaning, detrimental to the grain and spinning was 86% compared to 85%, 99%, and 0.1%, respectively, compared to predictions of 97.94% and 0.086%. As a result, a cylinder speed of 8.25 ms^{-1}, convex aperture of 37.4mm, rate of feed 672kgh^{-1}, and level of moisture 11.6% were recommended for threshing common beans.

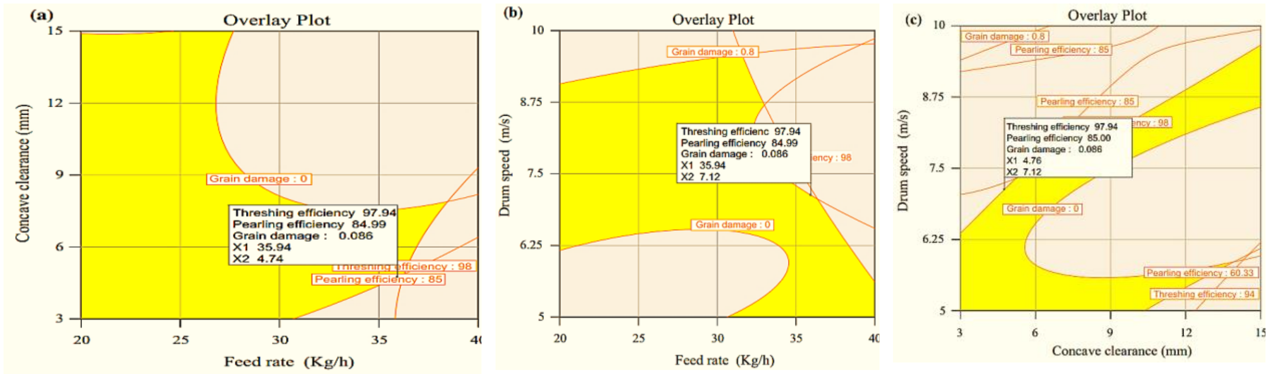


Figure 4. Graphical optimization of the operating parameters of the threshing drum; (a) Superimposed contours for threshing efficiency, pearling efficiency, and damage to bean at varying feed rates and concave clearance; (b) Superimposed contours for threshing efficiency, pearling efficiency, and speed of the drum at varying feed rates; and (c) Superimposed contours for threshing efficiency, drum speeds, and concave clearance at varying feed rates.

CONCLUSIONS

The threshing drum of the MARC bean thresher is one of its essential parts and its performance is depending on its operational parameters. Important variables influencing grain damage, threshing efficiency and cleaning efficiency in common bean threshed seed quality are rate of feed, moisture level, convex aperture, and drum speed. The most significant crop and machine measurement was cylinder speed, which was subsequently the moisture level. The percentage of damaged grain improved from 45.98 to 47.97% and the overall threshing efficiency elevated from 96.81 to 98.69% when the speed of drum was varied from 7.5 to 10.83 ms^{-1}. Increased moisture content was associated with increased grain damage, efficiency of threshing and rates of seed germination. The proportion of grain impairment, and threshing efficiency were all significantly ($P<0.01$) impacted by concave clearance. Within the 550–750 kg h^{-1} rate of feed range, there was variation in the average value of damage to grain (16.65–7.67%) and threshing efficiency (96.52-28.09%). As a result, a cylinder speed of 8.25 ms^{-1}, convex aperture of 37.4mm, rate of feed 672kgh^{-1}, and moisture level of 11.6% were recommended for threshing common beans.

REFERENCES

Adewoyin, O. B. (2023). Pre-Harvest and Postharvest Factors Affecting Quality and Shelf Life of Harvested Produce. In New Advances in Postharvest Technology. IntechOpen. 42, 28-420

Benaseer, S., Masilamani, P., Albert, V. A., Govindaraj, M., Selvaraju, P., & Bhaskaran, M. (2018). Impact of harvesting and threshing methods on seed quality: A review. Agricultural Reviews, 39(3), 183–192.

Bento, J. A. C., Gomes, M. J. C., Bassinello, P. Z., Martino, H. S. D., de Souza Neto, M. A., & Oomah, B. D. (2022). Benefits of Carioca Beans (Phaseolus vulgaris) Molecular Mechanisms to Human Health and Nutrition. Molecular Mechanisms of Functional Food, 112-141.

Chandra, R. J., Masilamani, P., Suthakar, B., Rajkumar, P., Sivakumar, S. D., & Manonmani, V. (2024). Effect of Moisture Content on Combine Harvested Seed Crop and its Quality. Journal of Experimental Agriculture International, 46(3), 114-138.

Ejara, E., Mohammed, W., & Amsalu, B. (2018). Genetic variability, heritability and expected genetic advance of yield and yield related traits in common bean genotypes (Phaseolus vulgaris L.) at Abaya and Yabello, Southern Ethiopia. African Journal of Biotechnology, 17(31), 973-980.

Ghebrekidan, B. Z., Olaniyan, A. M., Wako, A., Tadesse, A. G., Alemu, D., & Lema, T. (2024). Gravimetric characteristics and friction parameters of common bean (Phaseolus vulgaris L.). Turkish Journal of Agricultural Engineering Research, 5(1), 76-93.

Güvercin, S., & Yıldız, A. (2018). Optimization of cutting parameters using the response surface method. Sigma Journal of Engineering and Natural Sciences, 36(1), 113-121.

Huertas, R., Karpinska, B., Ngala, S., Mkandawire, B., Maling'a, J., Wajenkeche, E., & Foyer, C. H. (2023). Biofortification of common bean (Phaseolus vulgaris L.) with iron and zinc: Achievements and challenges. Food and Energy Security, 12(2),e406.

Jan, S., Rather, I. A., Sofi, P. A., Wani, M. A., Sheikh, F. A., Bhat, M. A., & Mir, R. R. (2021). Characterization of common bean (Phaseolus vulgaris L.) germplasm for morphological and seed nutrient traits from Western Himalayas. Legume Science, 3(2), e86.

Joshi-Saha, A., Sethy, S. K., Misra, G., Dixit, G. P., Srivastava, A. K., & Sarker, A. (2022). Biofortified legumes: Present scenario, possibilities and challenges. Field Crops Research, 279,108467

Juraev, D. T., Dilmurodov, S. D., Kayumov, N. S., Xujakulova, S. R., & Karshiyeva, U. S. (2023). Evaluating Genetic Variability and Biometric Indicators in Bread Wheat Varieties: Implications for Modern Selection Methods. Asian Journal of Agricultural and Horticultural Research, 10(4), 335-351.

Lee, G. H., Moon, B. E., Basak, J. K., Kim, N. E., Paudel, B., Jeon, S. W., ... & Kim, H. T. (2023). Assessment of Load on Threshing Bar During Soybean Pod Threshing. Journal of Biosystems Engineering, 48(4), 478-486.

Lisciani, S., Marconi, S., Le Donne, C., Camilli, E., Aguzzi, A., Gabrielli, P., & Ferrari, M. (2024). Legumes and common beans in sustainable diets: nutritional quality, environmental benefits, spread and use in food preparations. Frontiers in Nutrition, 11,1385232.

Parker, T. A., Gallegos, J. A., Beaver, J., Brick, M., Brown, J. K., Cichy, K., & Gepts, P. (2022). Genetic resources and breeding priorities in Phaseolus beans: Vulnerability, resilience, and future challenges. Plant breeding reviews, 46, 289-420.

Que, K., Tang, Z., Wang, T., Su, Z., & Ding, Z. (2024). Effects of Unbalanced Incentives on Threshing Drum Stability during Rice Threshing. Agriculture, 14(5),777.

Savic, I. M., & Savic Gajic, I. M. (2021). Optimization study on extraction of antioxidants from plum seeds (Prunus domestica L.). Optimization and Engineering, 22, 141-158.

Savic, I. M., Nikolic, I. L., Savic-Gajic, I. M., & Kundakovic, T. D. (2019). Modeling and optimization of bioactive compounds from chickpea seeds (Cicer arietinum L). Separation Science and Technology, 54(5), 837-846.

Strecker, K., Bitzer, V., & Kruijssen, F. (2022). Critical stages for post-harvest losses and nutrition outcomes in the value chains of bush beans and nightshade in Uganda. Food Security, 14(2), 411-426.

Uebersax, M. A., Cichy, K. A., Gomez, F. E., Porch, T. G., Heitholt, J., Osorno, J. M., ... & Bales, S. (2023). Dry beans (Phaseolus vulgaris L.) as a vital component of sustainable agriculture and food security—A review. Legume science, 5(1), e155.

Umbataliyev, N., Smailova, G., Toilybayev, M., Sansyzbayev, K., Koshanova, S., & Bekmukhanbetova, S. (2023). Optimization Of The Technological Process Of Threshing Combine Harvester. Eastern-European Journal of Enterprise Technologies, 124(1).

Wang, W., & Cichy, K. A. (2024). Genetic variability for susceptibility to seed coat mechanical damage and relationship to end-use quality in kidney beans. Crop Science, 64(1), 200-210.

REMOTE AND PROXIMAL SENSING

HIGH-RESOLUTION MAPPING OF LONG-TERM SOIL ORGANIC CARBON STOCKS AND CHANGES IN MOROCCO

#11287

[1*]Mohamed Bayad, [1]Bruno Gerard, [1]Abdellah Hamma, [2]Malcolm J. Hawkesford, [3]Eyal Ben-Dor, [4]Henry Wai Chau

[1]College of Sustainable Agriculture and Environmental Sciences, Mohammed VI Polytechnic University, Benguérir, Morocco; [2]Rothamsted Research, Harpenden AL5 2JQ, UK; [3]Remote Sensing Laboratory, Geography Department, Porter School of the Environment and Earth Sciences, Faculty of Exact Sciences, Tel Aviv University, Tel Aviv 699780, Israel; [4]Lethbridge Research and Development Centre, Agriculture and Agri-Food Canada, Lethbridge, Alberta, Canada

* Corresponding author at: College of Sustainable Agriculture and Environmental Sciences, Mohammed VI Polytechnic University, Benguérir, Morocco.

*e-mail: mohamed.bayad@um6p.ma

ABSTRACT

Soil organic carbon (SOC) is an important attribute for soil productivity and climate change mitigation. It stabilizes the soil structure and provides nutrients to the soil solution while playing a major role in carbon sequestration processes. Current regional SOC maps are not detailed enough and thus, do not support decision-making at farm and landscape and do not track long-term changes of carbon. Using large soil dataset, multispectral satellite data, climate data and machine learning approach, we created a topsoil (0-30 cm), 30m spatial resolution soil carbon stocks and temporal changes map of Morocco over the last 32 years. Our results show a total topsoil SOC stock of 3.57 Pg C, with a median SOC density of 4.98 kg C m^{-2}. The Moroccan biomes have acted as a net carbon sink in the last 32 years and absorbed an average 3.11 Mt C yr^{-1}, i.e., only 15.4% of the current anthropogenic annual carbon emissions of Morocco. However, high losses are estimated in niche areas such as the Acacia-Argania biosphere, parts of the coastal Mediterranean forest and large cropland-dominated areas due to anthropogenic pressure. The strength of sequestration is likely to diminish, if necessary, measures are not taken to protect these active carbon sinks. The present SOC mapping approach uses the largest soil C database ever recorded in North Africa and provides more accurate predictions compared to other regional studies. Our maps will help land managers and decision-makers improve climate mitigation actions and help understand trade-offs between soil carbon, biodiversity traits, and ecosystem management.

INTRODUCTION

Soil organic carbon (SOC) has received significant attention as a critical carbon pool of the terrestrial biosphere as well as a crucial soil property that governs soil health. Globally, about 2300–2500 Pg (1015g) C (60% organic and 40% inorganic) is sequestered in the top 2 m of soil, of which approximately 30% is stored in the 0-20 cm topsoil (Batjes, 1998; Paustian et al., 2016). Whilst the top 2m soil pool is hardly accessible to agroecosystem manipulation, the top 30 cm soil layer has promise as the most manipulatable layer through agroecosystem changes as it represents the root zone and the interface between the pedosphere and atmosphere. The global topsoil (0-30cm) organic carbon stocks (1500 Pg C) represent more than three times as much carbon as either the atmospheric CO_2 or the above-ground biomass. This makes the terrestrial biosphere a potential sink or source of atmospheric CO_2. Since the anthropogenic exploitation of terrestrial ecosystems can alter the SOC pool drastically (Deng et al., 2016), substantial efforts have been made to consolidate its potential role as a net sink of atmospheric CO_2. It has long been understood that ecosystem management and disturbance can affect the organic carbon stocks of the soil, and thus affect soil quality and atmospheric CO_2 emissions. Organic carbon plays a vital role in ecosystem sustainability and species occurrence and survival, which in turn control organic carbon inputs and cycling in the soil.

The dynamics of soil organic carbon are primarily influenced by the interplay of carbon inputs and residence time in the soil, which are influenced by various processes including net primary productivity, decomposition and factors such as fire and grazing, that can either facilitate or impede SOC loss or retention (Lal, 2004). At the regional scale, climatic factors and elevation play significant roles in determining soil C balance (Jobbágy & Jackson, 2000), whilst at farm and field levels, soil texture, mineralogy and topography interact with climate to shape SOC dynamics (Batjes, 1996; Bellamy et al., 2005). Temperature and precipitation regimes drive the occurrence of plant species with analogous functional traits within conspicuous areas forming biomes (Woodward et al., 2004). The species abundance, productivity, and functional traits are per se the main drivers of soil carbon inputs. Still, species interactions may also play a role in carbon dynamics (De Deyn, 2008).

Globally, there has been substantial interest in carbon sequestration in agricultural soils, not only to reach CO_2 mitigation targets, but also to enhance soil health (Frank et al., 2015; Lal, 63 2004). Carbon dioxide emissions caused by land use changes include deforestation, conversion from natural to farming ecosystems, biomass burning and drainage of wetlands for agriculture development (Lal, 2006). Some cultivated soils have lost 50-60% of the initial SOC stocks causing the release of up to 78 Pg C into the atmosphere. These losses are exacerbated by land misuse and poor soil management (Lal, 2004). Previous research showed that soil 68 organic C potential for CO_2 sequestration can be improved dramatically through ecosystem restoration strategies, smart cultivation, and improved management practices in agricultural lands. Lal (2004) recommended a range of improved management practices to enhance C stocks in agricultural soils.

Different climatic zones exhibit distinct patterns of SOC accumulation. Cold and wet climates tend to promote high primary productivity and low decomposition rates, resulting in the build-up of SOC (Batjes, 1996; Jobbágy and Jackson, 2000). Arid regions, on the other hand, typically have low SOC due to limited biomass production (Schlesinger, 1977). Tropical regions, however, display intermediate SOC levels due to their high rates of primary productivity, which offsets rapid decomposition (Houghton, 2007; Davidson et al., 2014). In temperate ecosystems, environmental and biological factors determine the persistence of SOC (Schmidt 79 et al., 2011). Houghton (2007) suggests that globally, high-latitude areas have the highest levels of SOC due to the slow decomposition caused by low temperatures and are still serving as a net sink for CO_2. The Atlas Mountains ecosystem might be potential carbon sink in North Africa as they were reported to have high SOC stocks (Sabir et al., 2020). Apart from climate, the characteristics of parent material and soil properties also influence SOC persistence. The association of SOC with minerals and the formation of soil aggregates play important roles in SOC retention (Chenu et al., 2000).

Multiple lines of evidence indicate that climate change is altering terrestrial SOC stocks, primarily by accelerating the decomposition rate. Despite large uncertainties related to the magnitude of the losses, climate-carbon cycle feedback has an undeniably significant impact on SOC (Walker et al., 2018). Terrestrial air temperature increased by 1.03°C on average between 1919 and 2018, which could have caused an average loss of 2.5 ± 5.5% of the agricultural topsoil (0-30 cm) SOC (Poeplau & Dechow, 2023). Moreover, climate change can alter soil carbon indirectly through increasing the occurrence of wildfires. The effect of wildfires on SOC depends on various factors such as fire severity, fire frequency, vegetation type, climate, and soil properties. The immediate effect of wildfires is the combustion of above-ground vegetation, which can lead to a substantial release of CO_2 into the atmosphere. The most intuitive impact soils undergo during a fire is the loss of organic matter. Subject to fire severity, organic carbon can be volatilized, charred, or completely mineralized. Up to 15% of the burned biomass is transformed to pyrogenic organic carbon (Santín et al., 2015), whose residence time lasts from decades to millennia. In the last decade, Morocco has lost nearly 77,000 ha of land to wildfire with 32,000 ha recorded in 2022 alone. However, the impact of wildfires on SOC stock in forest ecosystems in Morocco has not been studied. The recovery of SOC in burnt forests could occur rather quickly with the natural or artificial resettlement of vegetation, due to the high productivity attributed to secondary ecological successions (Certini, 2005). Baudena et al., (2020) suggested that recurring fires could transform Mediterranean forests into shrublands, hosting flammable biomass that regrows rapidly after fire. The authors theorized that this mechanism allegedly benefits shrubland persistence and may be enhanced in the future, with an eventual aridity increase (Baudena et al., 2020). Johnson & Curtis, (2001) revealed a post-fire time effect on soil organic carbon in forest ecosystems, using a meta-analysis of 48 different studies.

Given the high importance of organic carbon as a soil health indicator and a potential global carbon sink, accurate characterization is of utmost importance. A growing body of literature has shown complementarity between remote sensing and ecosystem modelling in studying organic carbon in the biosphere (Turner et al., 2004). Conventional approaches to soil organic carbon mapping include geostatistical methods that depend greatly on soil sampling (e.g., regression kriging (Somarathna et al., 2016)), or relate SOC status solely to land use and landcover (Minelli, 2018). These methods have a major limitation as they do not allow monitoring of soil carbon status over time, without recourse to new observations. Advances in cloud computing and remote sensing have opened new horizons for spatiotemporal assessment of soil organic carbon mapping from farm to global scale. Several studies have attempted machine learning, remote sensing, climate and biological predictors for high-resolution of SOC mapping at the country scale. For example, Venter et al., (2021) produced a low uncertainty prediction model of SOC stocks in South Africa's natural soils. The authors suggested a long-term carbon change map based on the high accuracy model.

In this study, we attempted the construction of a national long-term soil organic C stocks map for Morocco. We also aimed to improve the prediction accuracy of organic carbon using a large soil dataset, Landsat satellite imagery, climate and vegetation proxies in a machine-learning workflow. This method also permitted the estimation of 32 years of SOC stocks dynamics at 30 m spatial resolution mapping. These high-resolution maps are required to understand the national trends of soil carbon stocks from landscape to national scale. The resulting maps of soil carbon stocks and changes will inform future research on the drivers impacting potential active carbon sinks and will guide restoration efforts to reverse losses while preserving ecosystem vital functions.

MATERIALS AND METHODS

Study area

Morocco comprises eight ecoregions with contrasting north-south primary productivity and precipitation gradients. These ecoregions represent four different terrestrial biomes including 1) Mediterranean Forests, Woodlands and Scrub, 2) Temperate Coniferous Forests 3) Mediterranean Grasslands and Shrublands 4) Deserts and Xeric Shrublands. The Mediterranean woodlands and forest in the north are characterized by hot and dry summers and pleasant and humid winters. North Saharan Xeric Steppe and woodland and south Sahara Desert experience low rainfall (50-100mm) in the winter and high temperatures (40-45 °C) during summer. Mediterranean Acacia-Argania dry woodlands and succulent thickets cover the northwest of the country (Fig. 1).

Soil carbon data

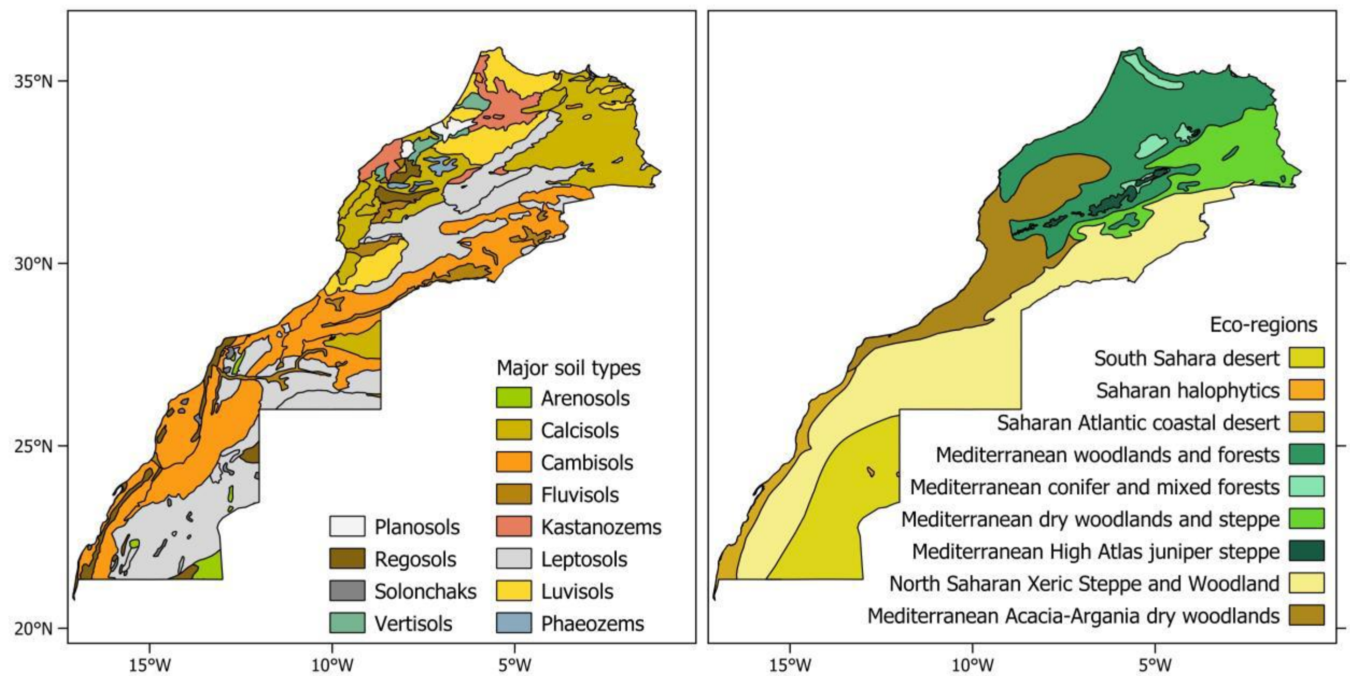


Figure 1. Major soil types (Dewitte et al., 2013) and eco-regions of Morocco (Dinerstein et al, 2017).

The complexity of the ecosystem resulted in diverse soil genesis that produced variable soil types. Moroccan soils are predominantly Calcisols, Luvisols, Cambisols, Leptosols and Kastanozems (Fig. 1). Other under-represented typologies include Vertisols, Regosols, Planosols and Fluvisols. The anthropogenic impact includes a wide range of land use going rom intensive cropping in plains and plateaux to complex agroecosystems including tree cultivation and grazing in high altitudes. Cultivated land represents around 12% of the total surface area of Morocco (8.7 M ha).

Over 52,000 soil samples were collected within Fertimap project the Al-Moutmir extension program backed by Mohammed VI Polytechnic University (UM6P) and OCP Morocco. The soil sampling campaigns occurred between 2011 and 2020. Topsoil (0-30cm) was sampled from agriculture and natural ecosystems and soil organic carbon content was analyzed using the Walkley-Black oxidation method (Walkley and Black, 1934). Soil stocks were estimated using 162 the following equation.

$SOC\ stock\ (kg\ C\ m{-}2) = SOC\ concentration\ (g\ kg{-}1) \times BD\ (g\ cm{-}3) \times d\ (cm)$

Prediction covariables and modelling

Where $SOCconcentration$ is organic carbon concentration and BD is bulk density that was not measured but estimated using a linear pedo-transfer function inferred from Ruehlmann & Körschens (2009). The coarse elements percentage was not considered because of the lack of this data.

The covariates used represent proxies for climate, surface biomass, and topography as determining factors of SOC stocks. In natural ecosystems, SOC is more likely to be controlled by environmental variables (e.g., climate, biomass, topography). In cultivated land, SOC dynamics are also strongly impacted by anthropogenic factors, which include tillage, cropping rotation, irrigation, residue management, etc. Temporal dynamics of Landsat data (e.g., NDVI) may inform on cropping intensity and even crop classification. Surface reflectance time series from Landsat 5, 7, and 8 were used from 1990 to 2022. Landsat surface reflectance (L2SR) data archives provided by USGS were atmospherically corrected by the Land Surface Reflectance Code. Clouds, cloud shadow and snow were masked using 'QA_PIXEL' band. Surface reflectance data from the tree sensors was harmonized using the cross-calibration method from Roy et al., (2016). Annual median and variance composites of NDVI and reflectance from all bands were calculated and tested as predictors.

The environmental covariates include mean climate water deficit, precipitation, Palmer Drought Severity Index, minimal temperature, and maximal temperature form the TerraClimate dataset provided by the University of California Merced (Abatzoglou et al., 2018). Topographic used predictors are data elevation, slope, and aspect are provided by NASA, USGS, and JPL-Caltech (Farr et al., 2007). Topographic diversity index derived from ALOS provided by Conservation Science Partners (Theobald et al., 2015). The Fraction of Absorbed Photosynthetically Active Radiation (FAPAR) and leaf area index (LAI) derived from the AVHRR sensor onboard the NOAA satellite (Claverie et al., 2014). Net primary productivity derived from MODIS and provided by NASA's Land Processes Distributed Active Archive Center (LP DAAC). Two- and 5-year median aggregates of all the predictors, prior sampling dates, were tested for predicting SOC stocks using a random forest algorithm. The used predictors are summarized in Table 1. After several iterations, the best model was adopted, and some variables were excluded because of their non-availability for the whole of the studied 32 years period and their low impact on model accuracy. All the predictors used for the final model extend from over the whole study period (1990-2022). The data processing and modelling workflow is summarized in Figure 3.

The random forest model hyperparameters *ntree* and *mtry* were set to 500 and the square root of the number of variables, respectively. A 30% sampling points subset was used for model validation. Models' prediction accuracy was evaluated using the coefficient of determination (R2) and root mean scare error (RMSE). The variables' importance of the random forest model is derived from the sum of decreases in the Gini impurity index, to see what predictors are more relevant in SOC stocks prediction.

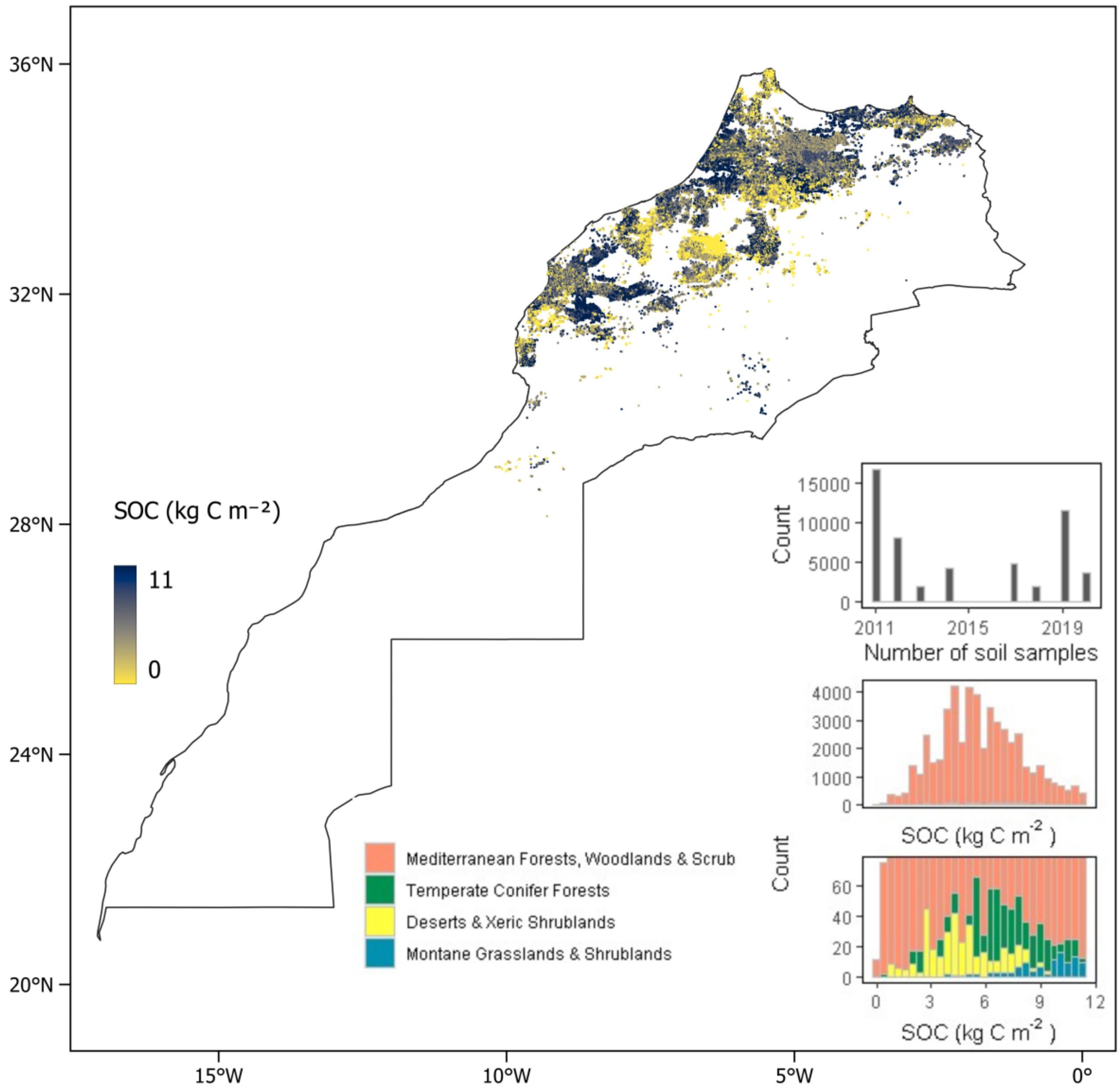


Figure 2. Distribution map of soil sampling across Morocco. Sampling points are colored by SOC values (kg C m^{-2}). Insert plots represent count of samples per years and distribution histograms of SOC (kg C m^{-2}) per biomes.

The validated random forest model was used to predict SOC stocks based on satellite and the environmental predictors from 1990 to 2022. The predictor variables were aggregated in 5-year median and used as inputs of random forest to predict annual SOC stocks (Fig. 3). The annual predictions served as basis for estimation of long-term average stocks and changes. The carbon stock changes were estimated using the Sen's slope (Sen, 1968) of the predicted stock time series at each pixel. This method has been used by Venter et., (2021) to estimate long-term SOC stocks temporal dynamics and the changes were estimated as:

ΔSOC (%) = s÷$SOCLTA$×100216

where s is the Sen's slope and $SOCLTA$ _is long-term average C stocks of the considered pixel.

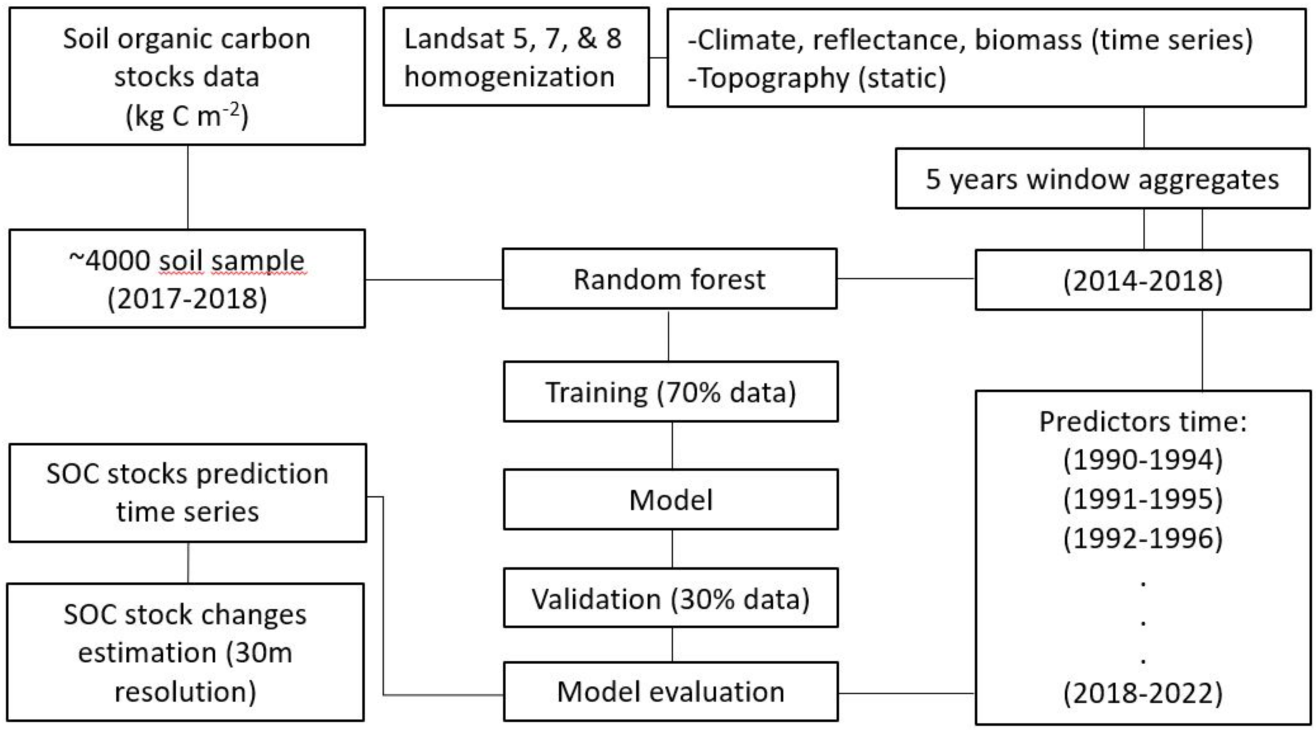


Figure 3. Workflow diagram that summarizes the data preparation and modelling framework.

RESULTS

Results indicate a total SOC stock of 3.57 Pg C in the years 2018 and a long-term 32-year average stock of 3.94 Pg C. This provides an estimate of the overall carbon storage capacity in the assessed area (~700,000 km^2) over all Moroccan biomes. The soil C stocks had an average 227 of 5.14 kg C m^{-2} and a median of 5.12 kg C m^{-2} (Table 2, and Table S1). This metric provides insights into the typical carbon content per unit area and helps in assessing the baseline SOC levels in Moroccan ecosystems.

This study reveals significant variations in SOC stocks distribution between northern-west and southern regions simulating the north-south climate gradient (Fig. 4 and Fig. S2). The northwestern and High Atlas areas exhibited higher carbon stocks, compared to the eastern and southern Saharan eco-regions. This highlights the strong impacts of climate and ecosystem characteristics in determining SOC stocks at the regional level.

The analysis demonstrates variations in long-term average SOC stocks across different biomes. The temperate conifer forest ecosystems show the highest SOC content per surface area, with a median of 6.06 kg C m^{-2}, followed by mountain grasslands and shrublands with 5.14 kg C m^{-2}, and Mediterranean forests woodlands & scrub areas with 5.31 kg C m^{-2}, while the deserts and xeric shrublands had the lowest SOC concentrations (4.76 kg C m^{-2}).

Table 1. Climate, biomass and topographic variables that were used to model SOC stock in Morocco.

Category	Spatial resolution (meter)	Predictors
Climate	4638	Mean annual precipitation
		Annual climate water deficit
		Palmer drought severity index
		Minimal temperature
		Maximal temperature
Biomass	5566	FAPAR Mean
		LAI Mean
	500	Net primary productivity
	30	Red band reflectance
		Green band reflectance
		Blue band reflectance
		Shortwave infrared band 1 reflectance
		Shortwave infrared band 2 reflectance
		NDVI median NDVI variance
		NDVI 10th percentile
		NDVI 90th percentile
Topographic	30	Elevation
		Slope
	270	Topographic diversity index

Using climate and remote sensing time series data allowed to derive historic estimates of the spatiotemporal dynamic changes of C stocks in Morocco. Model outputs indicated a 0.08% net increase in SOC stocks over 32 years (1990-2022). Whilst the findings suggest an overall slim increase in SOC stocks, the strongest changes were observed in the Mediterranean Forest, Woodlands and Scrub biome. Losses were observed in large parts of the Mediterranean Acacia-Argania dry woodlands and succulent thickets and Mediterranean woodlands and forests ecoregions (Fig. 5 and Fig. S3). While Desert and Xeric Shrublands experienced the smallest dynamics in SOC stocks, temperate conifer forest and montane grasslands and shrublands biomes showed the most important net increase in Morocco, indicating sequestration of 1.2×10^{-2} kg C m^{-2} and 1.1×10^{-2} kg C m^{-2}, respectively.

Table 2. Random Forest SOC stocks model analytical metrics including R2 and RMSE (kg C m^{-2}) and number of observations (n) used in the training and validation. The first model uses the predictors described in Table 1 (except green and blue bands) aggregated from 2017-2018. The second model uses the same predictors as the first model from the 2014-2018 period but excluded net primary productivity.

Model	Year	n	RMSE	R2	n	RMSE	R2
1	2017-2018	4473	1.086	0.734	2025	1.395	0.491
2	2014-2018	4478	1.035	0.729	2025	1.393	0.493

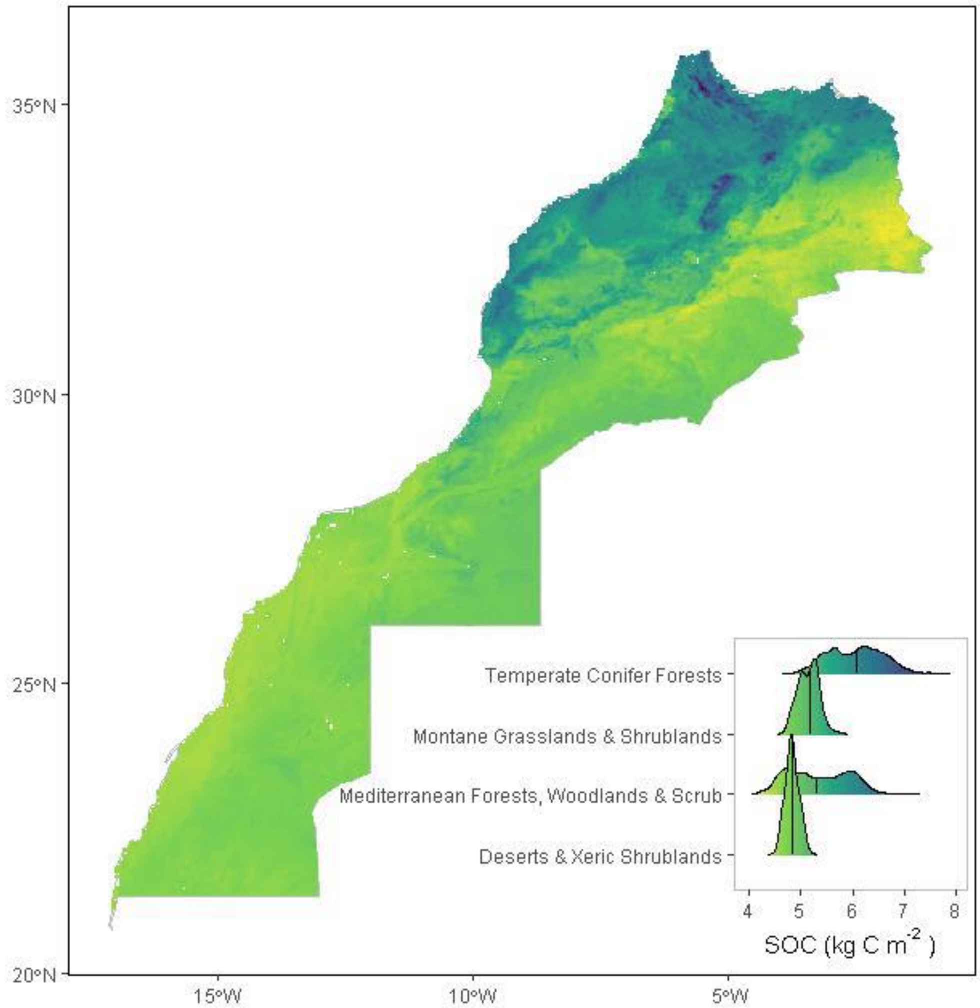


Figure 4. Long-term (1990-2022) average SOC stocks (kg C m^{-2}) map. Insert plot represent SOC stocks frequency distribution over biomes in Morocco.

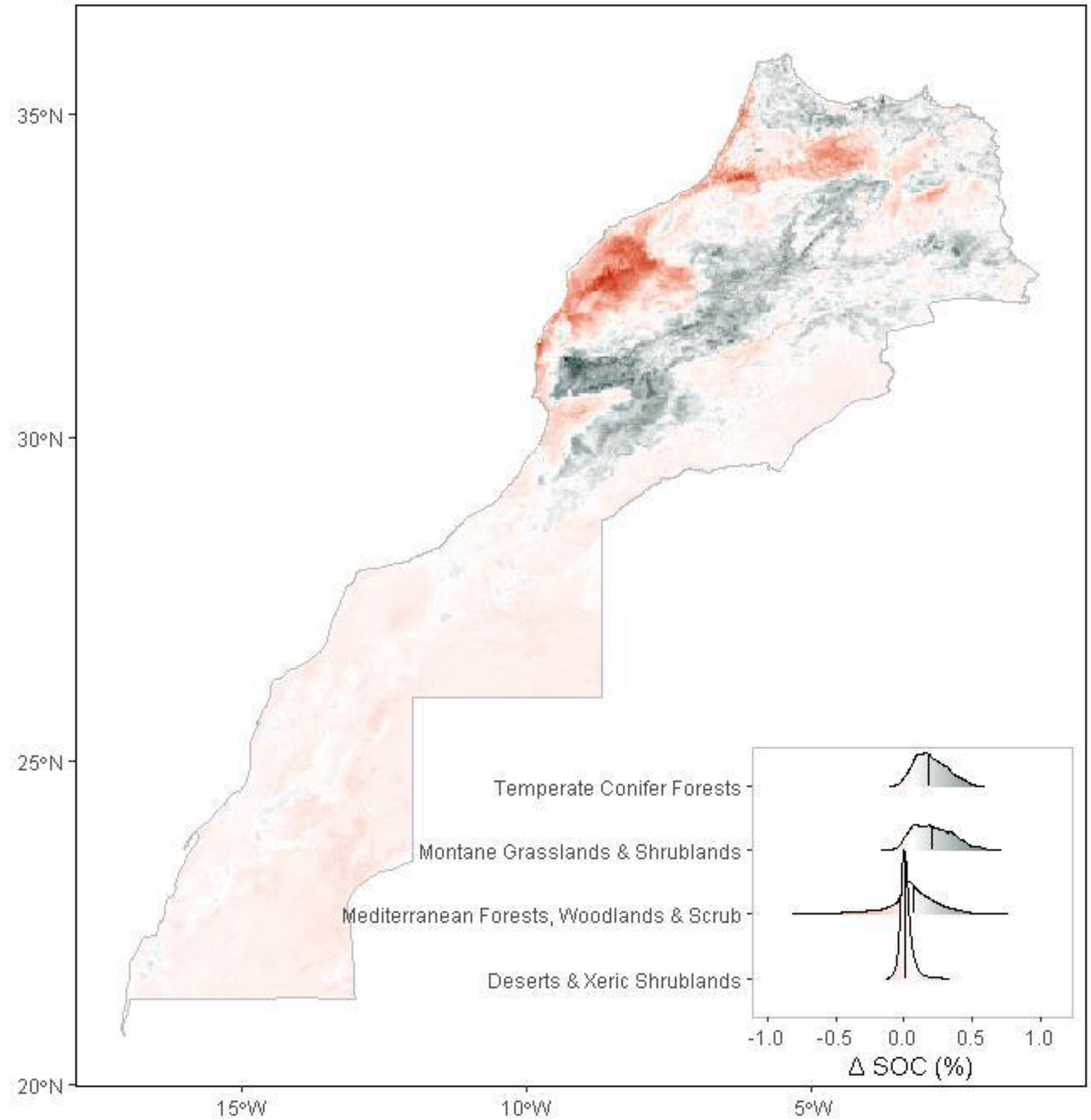


Figure 5. Long-term (1990-2022) average SOC changes (%) map. Insert panel shows SOC change frequency distribution in different biomes.

Model performance uncertainty

The variables importance values in the random forest prediction model showed that the drought severity index was the most influential in determining SOC, followed by temperature (Min, Max), elevation and primary productivity (Fig. 6 and Fig. S1). Vegetation dynamics captured by high-resolution NDVI contributed equally to the prediction compared to LAI and precipitation proxies (Fig. 6). The variables importance changed slightly when option for two instead of four-year aggregation period of the predictors (Fig. S1).

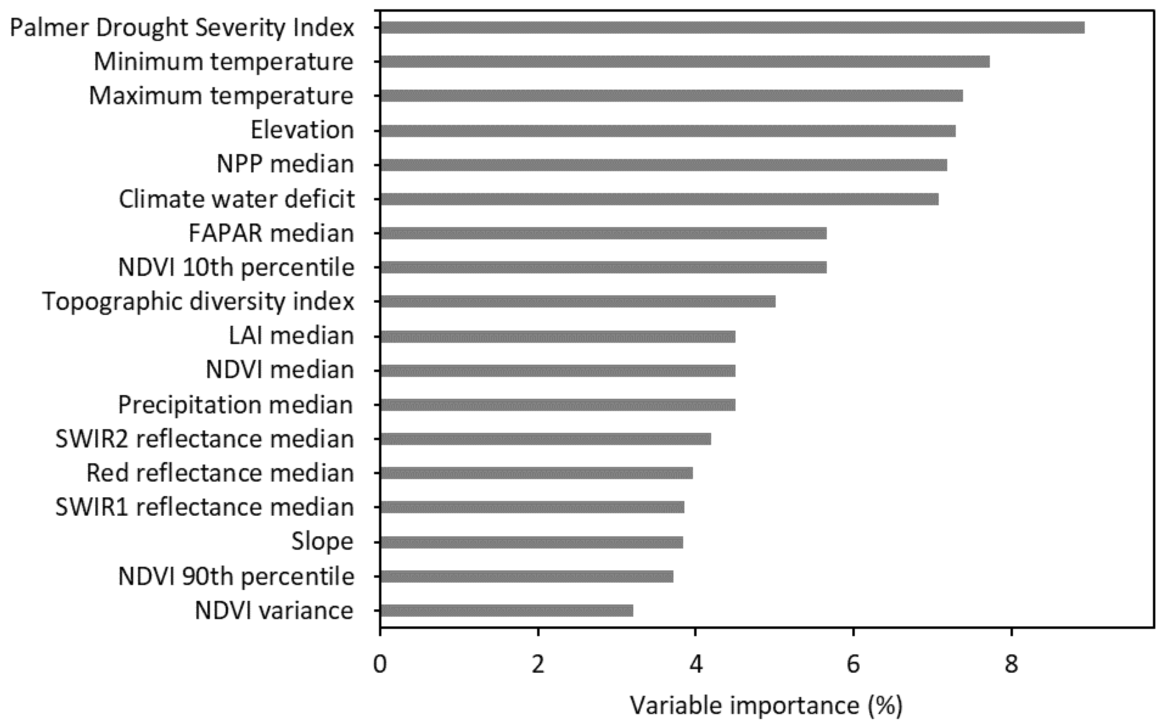


Figure 6. Random forest model variables importance (%) from the first model, derived from the sum of decrease in Gini impurity index.

SOC prediction performance was evaluated using the RMSE and R2 of the random forest model. The model validation had an R2 of 0.49 and RMSE 1.39 kg C m^{-2}. The model showed an R2 of 0.73 and RMSE 1.08 kg C m^{-2} with the training set (Table 2, Fig. 7). Long term change estimates were not validated because of the lack of repeated records in the same sampling locations. However, soil C stock times series estimates were compared with the measured values over 8 years (Fig. 8).

Although the model uncertainty was highly variable over space and time, in general, the error values showed unimodal distribution. When validated against measures from different years, the random forest model had a median absolute error 0.13 kg C m^{-2} (Q1=-1.32; Q2= 1.47). Model error was unevenly distributed over space, with the highest inaccuracy recorded in the montane grasslands and shrublands. The model underestimated SOC stocks in these biomes, which include the High Atlas and Mediterranean dry woodland and steppe eco-regions (Fig. 8). The model uncertainty varied between years, with the highest inaccuracies recorded in 2012, 2014, and 2020 (0.99, 0.95, and 0.88 kg C m-2, respectively) (Fig. 8 and Fig. S4). The lowest uncertainties were observed in 2013, 2017 and 2018, where median absolute error values were lower than 0.17 kg C m^{-2}.

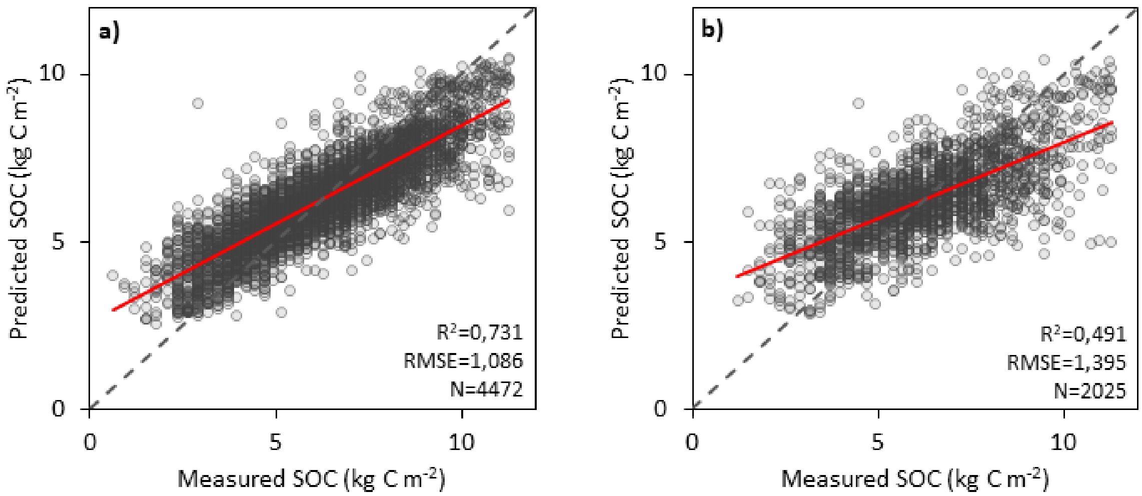


Figure 7. Scatter plots of predicted versus measured SOC stocks (kg C m^{-2}) with (a) training and (b) test datasets plot). Predictors include all variables shown in Fig. 6 aggregate from 2017-2018 time period.

Table 3. Long-term (32 year) mean and median SOC stocks and net change estimations by biomes in Morocco as estimated from the random forest model.

Biome	Mean SOC stocks (kg C m^{-2})	Median SOC stocks (kg C m^{-2})	SOC stock (Pg C)	Net change (%)	Net change (kg C m^{-2})
Deserts & Xeric Shrublands	4.77	4.76	1.91	0.012	5.7 10^{-4}
Temperate Conifer Forest	6.07	6.06	0.08	0.196	1.18 10^{-2}
Montane Grasslands & Shrublands	5.14	5.14	0.04	0.215	1.1 10^{-2}
Mediterranean Forests Woodlands & Scrub	5.19	5.17	1.91	0.056	2.9 10^{-3}
Total	5.14	5.12	3.94	0.079	4 10^{-3}

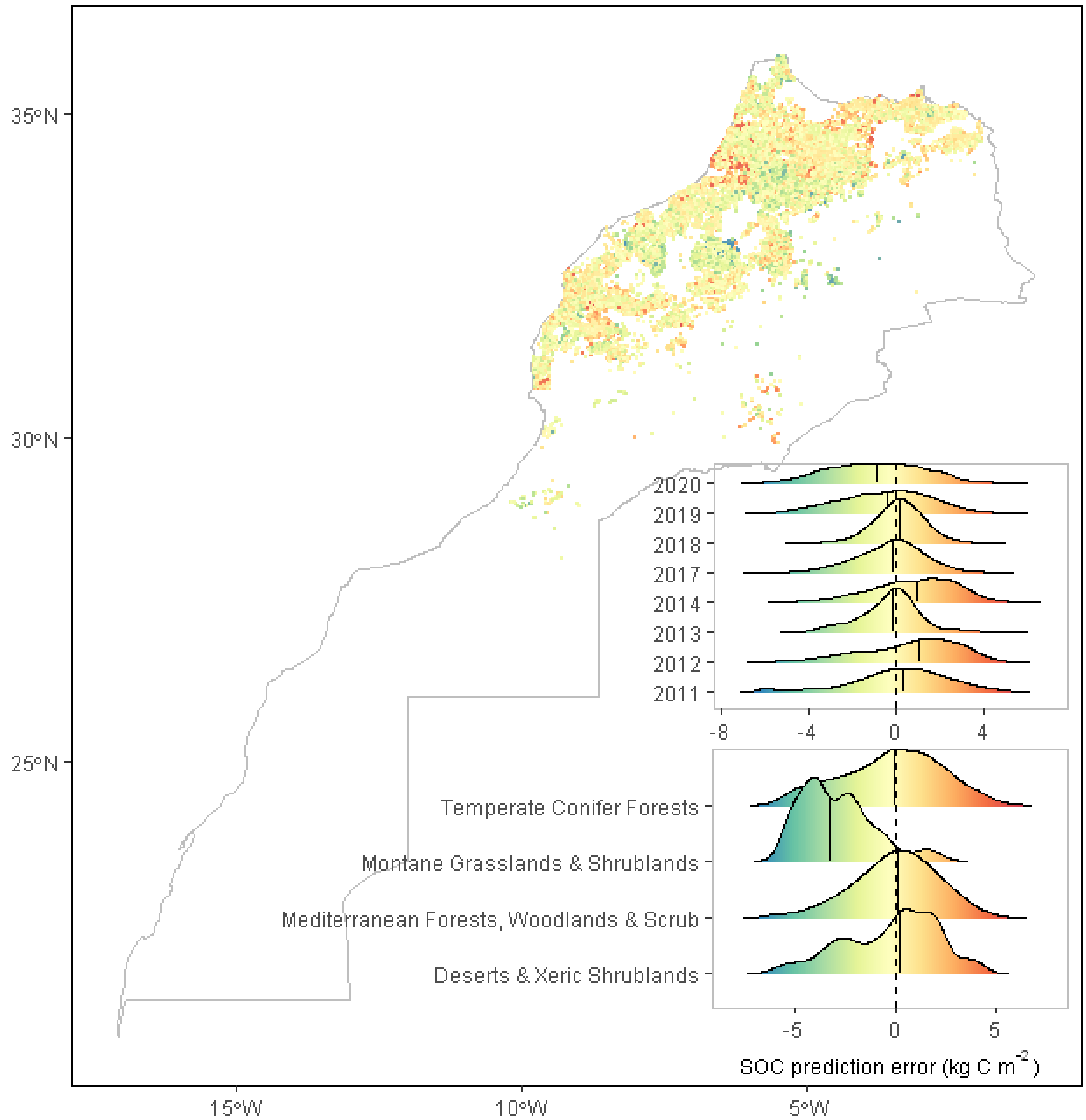


Figure 8. Spatial distribution map of the Random Forest error calculated as difference between predicted and measured SOC stocks (kg C m^{-2}).

Table 4. Long-term (32 year) mean and median SOC stocks estimations by eco-regions in Morocco as estimated from the random forest model.

Eco-region name	Biome name	Mean SOC (kg C m^{-2})	Median SOC (kg C m^{-2})	SOC stock (Pg C)
Saharan Atlantic coastal desert	Deserts & Xeric Shrublands	4.66	4.65	9.8 1013
South Sahara Desert	Deserts & Xeric Shrublands	4.82	4.82	5 1014
Mediterranean conifer and mixed forests	Temperate Conifer Forests	6.07	6.06	7.9 1013
Mediterranean High Atlas juniper steppe	Montane Grasslands & Shrublands	5.13	5.14	3.8 1013
Mediterranean Acacia-Argania dry woodlands and succulent thickets	Mediterranean Forests, Woodlands & Scrub	5.19	5.09	5.7 1014

DISCUSSION

Using climate and remote sensing predictors we estimated the soil C stock dynamics over a 32-year period in Morocco. Our mapping method uses a large soil database, 30 m resolution satellite data, climate and morphological data. This allowed the i) assessment of spatial dynamics of soil carbon from paddock to national scale, ii) estimation of the magnitude of topsoil stocks in Morocco at 0-30 cm, and iii) to step back on time to get historical estimates of soil C and thus, assess long-term C changes. Accessing this amount of detail is impossible with lower resolution maps, due to the substantial variability of soil properties from farm to pedon scale. While the SOC long term changes map was based solely on the spatial changes of the environmental proxies, it informs on change drivers, as well as potential increases in certain areas, as influenced by their inherent climate and edaphic features. This will give land managers a useful tool to detect and reverse losses using appropriate actions.

Previous attempts to estimate soil C magnitudes in different areas of Africa showed inaccuracies due to the low resolution of the maps employed and insufficient soil data. For example, the estimation of SOC stocks by Henry et al., 2009, who used DSMW, ISRIC and ETOPOS maps at a 1:5M scale, showed estimates of 2.87 and 2.23 Pg C (0-30cm) for South Africa and Morocco, respectively. However, Venter et al., 2001 quantified 5.59 Pg C in South Africa, using a large national soil database and a high-resolution mapping approach. The magnitude of our estimation of topsoil C stocks was at 3.94 Pg C in Morocco (711,000 km^2), which seems in accordance with other studies in the Mediterranean region–e.g., Spain (505,000 km^2), which is predominantly Mediterranean Forests, Woodlands, and Scrub, has a SOC stock of 3.3 Pg C (Calvo de Anta et al. 2020). These high variabilities and inaccuracies in regional studies, show the inadequacy of small-scale maps in quantifying the spatially highly dynamic soil carbon.

The level of accuracy of our model (RMSE = 1.36 kg C m^{-2}) is higher than some regional maps and national studies. Examples include subtropical maps such as South Africa (RMSE = 2.45 kg C m^{-2}, Venter et al.2021). Even when the model was tested against independent past data points, it still yielded low uncertainty for most past years, except for 2012, 2014, and 2020, when absolute errors were 0.99, 0.95, and 0.88 kg C m^{-2}, respectively (Fig. 8). Coupled with high-resolution multispectral data from Landsat, the large number of samples representing different ecosystems in Morocco clearly strengthened the accuracy of the model.

SOC stocks by biomes and ecozones

Sabir et al. (2020) attempted to quantify soil C in different agro-ecozones in Morocco and estimated high SOC levels in the Middle Atlas (mean of 4.55, min. 0.15, max. 9.81 kg C m^{-2}), followed by the Rif zone (mean of 4.13, min. 0.3, max. 7.71) that intersects with both Mediterranean conifer and mixed forest and Mediterranean woodlands and forest eco-regions. The authors estimated the lowest soil C concentrations in the Acacia-Argania dry woodlands (mean 2.14, min. 0.7, max. 3.93 kg C m^{-2}), and the Sahara Desert (mean of 0.18, min 0.15, max. 0.24 kg C m^{-2}). Boulmane et al., (2010) reported SOC stocks of 5.6-8 kg C m^{-2} in the forest green belt in the Middle Atlas Mountains. Sabir et al. 2004 also reported high C (10.5 kg C m^{-2}) values in the *Quercus suber L.* forest in northern Morocco. These values agree with the high median (6 kg C m^{-2}) found in the present study, in the Mediterranean conifer and mixed forests.

Changes in soil carbon stocks

It has long been appreciated that management and land-cover changes can alter the amount of organic carbon sequestered in the soil (Laganière et al., 2010), which subsequently affects both soil quality and atmospheric CO^2 fluxes (Powers et al., 2011). Land use change can cause a change in surface biomass and an associated disturbance in soil C stocks. Ecosystem changes can occur naturally or be the result of anthropogenic pressures. Each ecosystem has a potential carbon-carrying capacity and an equilibrium carbon status defined by inherent climate and edaphic characteristics. The soil carbon cycle is disturbed by land use changes until a new equilibrium is eventually attained in the ecosystem. Throughout this procedure, alterations in soil C stocks might have occurred, either as a sink or as a source of carbon. We estimated a 32-years average changes in soil carbon stocks at 0.08% (3.11 Mt C) in Moroccan topsoil. This average annual gain represents only 15.4% of the anthropogenic carbon emissions reported at 0.02 Pg C in 2021 in Morocco (Crippa et al., 2022). Nevertheless, the current annual anthropogenic carbon emissions represent only 5 per-mille (‰) of the topsoil stocks, indicating the substantial potential of the soil organic C pool to offset CO_2 emissions in Morocco. Over the 32-year period studied; Moroccan biomes constituted a net carbon sink. Soil carbon change magnitude at the regional scale is limited by climate and edaphic criteria. However, a net carbon sink is observed currently in the terrestrial biosphere of the northern hemisphere. De Vries et al., (2006) reported that for European forests, net carbon capture is in the range of 100 to 150 Mt C yr^{-1}. Similarly, Heath et al., (1993) suggested that temperate forest produces a net sink of 205 Mt C yr^{-1}. Our estimation shows the highest soil carbon increase in the Mediterranean conifer and mixed forests in the north and Mediterranean High Atlas juniper steppe (including Anti-Atlas) eco-regions. The highest losses we estimated were in the Acacia-Argania dry biosphere, the Gharb Forest in the northwest of Morocco and large parts of the Prerif Mediterranean woodland and forest. Losses in the Gharb Forest were estimated at 21% (3000 ha) in the last 20 years (Hansen et al., 2013). The Prerif areas have lost up to 8% of the forest in the last 20 years. Net losses observed in the Prerif areas (Taounate region) are likely related to climate and anthropogenic pressures. In the first decade of the century, more than half a million olive and carob trees were planted in this area. Still, these efforts are still not enough to reverse carbon losses.

For the Acacia-Argania woodlands, le Polain de Waroux et al., (2012) reported a net decrease of tree density of 44.5% between 1970 and 2007. Consequently, this area will continue to act as a carbon source until a new equilibrium is reached. Although this endemic species is well adapted to the Mediterranean dry climate in Morocco, anthropogenic pressure presented by overgrazing and use as fire fuel are the main causes of this decline (Le Potain de Waroux et al., 383 2012). Croplands around the world are losing massive soil carbon stocks depending on their initial state and a high-loss area was the cropland in the coastal plain in the Settate region. Similar net carbon sink patterns were also observed at the country scale (Janssens et al., 2005), where areas with a high prevalence of cultivated land tended to be a carbon source, whilst forest and grassland-dominated areas acted as net terrestrial carbon sinks (Janssen et al., 2005). In the future, the Northern Hemisphere will maintain a role as a carbon sink, although the upward trends are likely to be decreased (Canadell et al., 2007; Zaehle et al., 2007). Although our estimates of carbon changes are consistent with the theoretical dynamics of Soil C, given the land use changes and anthropogenic pressures, future work should validate the change trend map using repeated measurements from the current sampling locations.

CONCLUSION

The present work provides the first high-resolution dynamic map of topsoil carbon in Morocco. This national map provide accurate and valuable insights onto the soil carbon magnitudes in north African Biomes and an estimate of the C stock changes in the last 32 years. The map could be used as a soil carbon stock watch that will support CO_2 mitigation actions. Generally, Moroccan biomes are still acting as net carbon sink. However, high losses were estimated in ecological niches such as the dry Acacia-Argania ecoregion, which undergoes relentless anthropogenic pressure. Using this high-resolution map, different stakeholders should take an important leap forward in identifying carbon source areas and target appropriate remedial actions, whilst understanding trade-offs between ecosystems management, biodiversity, and soil carbon. The extensive database has the potential for future applications, including the modelling of how climate changes affect carbon sequestration in Morocco.

REFERENCES

Abatzoglou, J. T., Dobrowski, S. Z., Parks, S. A., & Hegewisch, K. C. (2018). TerraClimate, a high-resolution global dataset of monthly climate and climatic water balance from 1958–2015. Scientific Data, 5(1), Article 1. https://doi.org/10.1038/sdata.2017.191

Batjes, N. h. (1996). Total carbon and nitrogen in the soils of the world. European Journal of Soil Science, 47(2), 151–163. https://doi.org/10.1111/j.1365-2389.1996.tb01386.x

Batjes, N. H. (1998). Mitigation of atmospheric CO2 concentrations by increased carbon sequestration in the soil. Biology and Fertility of Soils, 27(3), 230–235. https://doi.org/10.1007/s003740050425

Baudena, M., Santana, V. M., Baeza, M. J., Bautista, S., Eppinga, M. B., Hemerik, L., Garcia Mayor, A., Rodriguez, F., Valdecantos, A., Vallejo, V. R., Vasques, A., & Rietkerk, M. (2020). Increased aridity drives post-fire recovery of Mediterranean forests towards open shrublands. New Phytologist, 225(4), 1500–1515. https://doi.org/10.1111/nph.16252

Bellamy, P. H., Loveland, P. J., Bradley, R. I., Lark, R. M., & Kirk, G. J. D. (2005). Carbon losses from all soils across England and Wales 1978–2003. Nature, 437(7056), Article 7056. https://doi.org/10.1038/nature04038 453

Boulmane, M., Makhloufi, M., Bouillet, J.-P., Saint-André, L., Satrani, B., Halim, M., & Elantry-Tazi, S. (2010). Estimation du stock de carbone organique dans la chênaie verte du Moyen Atlas marocain. Acta Botanica Gallica, 157(3), 451–467. https://doi.org/10.1080/12538078.2010.10516222

Dinerstein, E., Olson, D., Joshi, A., Vynne, C., Burgess, N. D., Wikramanayake, E., Hahn, N., Palminteri, S., Hedao, P., Noss, R., Hansen, M., Locke, H., Ellis, E. C., Jones, B., Barber, C. V., Hayes, R., Kormos, C., Martin, V., Crist, E., … Saleem, M. (2017). An Ecoregion-Based Approach to Protecting Half the Terrestrial Realm. BioScience, 67(6), 534-545.

Calvo de Anta, R., Luís, E., Febrero-Bande, M., Galiñanes, J., Macías, F., Ortíz, R., & Casás, F. (2020). Soil organic carbon in peninsular Spain: Influence of environmental factors and spatial distribution. Geoderma, 370, 114365. https://doi.org/10.1016/j.geoderma.2020.114365

Canadell, J. G., Kirschbaum, M. U. F., Kurz, W. A., Sanz, M.-J., Schlamadinger, B., & Yamagata, Y. (2007). Factoring out natural and indirect human effects on terrestrial carbon sources and sinks. Environmental Science & Policy, 10(4), 370–384. https://doi.org/10.1016/j.envsci.2007.01.009 469

Certini, G. (2005). Effects of fire on properties of forest soils: A review. Oecologia, 143(1), 1–10. https://doi.org/10.1007/s00442-004-1788-8

Chenu, C., Le Bissonnais, Y., & Arrouays, D. (2000). Organic Matter Influence on Clay Wettability and Soil Aggregate Stability. Soil Science Society of America Journal, 64(4), 1479–1486. https://doi.org/10.2136/sssaj2000.6441479x

Crippa, M., Guizzardi, D., Banja, M., Solazzo, E., Muntean, M., Schaaf, E., ... & Vignati, E. (2022). CO2 emissions of all world countries. JRC Science for Policy Report, European Commission, EUR, 31182. 477

Davidson, E. A., Savage, K. E., & Finzi, A. C. (2014). A big-microsite framework for soil carbon modeling. Global Change Biology, 20(12), 3610–3620. https://doi.org/10.1111/gcb.12718 480

De Deyn, G. B., Cornelissen, J. H., & Bardgett, R. D. (2008). Plant functional traits and soil carbon sequestration in contrasting biomes. Ecology letters, 11(5), 516-531.

De Vries, W., Reinds, G. J., Gundersen, P., & Sterba, H. (2006). The impact of nitrogen deposition on carbon sequestration in European forests and forest soils. Global Change Biology, 12(7), 1151–1173. https://doi.org/10.1111/j.1365-485 2486.2006.01151.x

Deng, L., Zhu, G., Tang, Z., & Shangguan, Z. (2016). Global patterns of the effects of land-use changes on soil carbon stocks. Global Ecology and Conservation, 5, 127–138. https://doi.org/10.1016/j.gecco.2015.12.004

Dewitte, O., Jones, A., Spaargaren, O., Breuning-Madsen, H., Brossard, M., Dampha, A., Deckers, J., Gallali, T., Hallett, S., Jones, R., Kilasara, M., Le Roux, P., Michéli, E., Montanarella, L., Thiombiano, L., Van Ranst, E., Yemefack, M., & Zougmore, R. (2013). Harmonisation of the soil map of Africa at the continental scale. Geoderma, 211-212, 138-153. https://doi.org/10.1016/j.geoderma.2013.07.007

Farr, T. G., Rosen, P. A., Caro, E., Crippen, R., Duren, R., Hensley, S., Kobrick, M., Paller, M., Rodriguez, E., Roth, L., Seal, D., Shaffer, S., Shimada, J., Umland, J., Werner, M., Oskin, M., Burbank, D., & Alsdorf, D. (2007). The Shuttle Radar Topography Mission. Reviews of Geophysics, 45(2). https://doi.org/10.1029/2005RG000183

Frank, S., Schmid, E., Havlík, P., Schneider, U. A., Böttcher, H., Balkovič, J., & Obersteiner, M. (2015). The dynamic soil organic carbon mitigation potential of European cropland. Global Environmental Change, 35, 269–278. https://doi.org/10.1016/j.gloenvcha.2015.08.004

Hansen, M. C., Potapov, P. V., Moore, R., Hancher, M., Turubanova, S. A., Tyukavina, A., ... & Townshend, J. (2013). High-resolution global maps of 21st-century forest cover change. science, 342(6160), 850-853.

Heath, L. S., Kauppi, P. E., Burschel, P., Gregor, H.-D., Guderian, R., Kohlmaier, G. H., Lorenz, S., Overdieck, D., Scholz, F., Thomasius, H., & Weber, M. (1993). Contribution of temperate forests to the world's carbon budget. Water, Air, and Soil Pollution, 70(1), 55–69. https://doi.org/10.1007/BF01104988

Houghton, R. A. (2007). Balancing the Global Carbon Budget. Annual Review of Earth and Planetary Sciences, 35(1), 313–347. https://doi.org/10.1146/annurev.earth.35.031306.140057

Janssens, I. A., Freibauer, A., Schlamadinger, B., Ceulemans, R., Ciais, P., Dolman, A. J., Heimann, M., Nabuurs, G.-J., Smith, P., Valentini, R., & Schulze, E.-D. (2005). The carbon budget of terrestrial ecosystems at country-scale – a European case study. Biogeosciences, 2(1), 15–26. https://doi.org/10.5194/bg-2-15-2005

Jobbágy, E. G., & Jackson, R. B. (2000). The Vertical Distribution of Soil Organic Carbon and Its Relation to Climate and Vegetation. Ecological Applications, 10(2), 423–436. https://doi.org/10.1890/1051-0761(2000)010[0423:TVDOSO]2.0.CO;2

Johnson, D. W., & Curtis, P. S. (2001). Effects of forest management on soil C and N storage: Meta analysis. Forest Ecology and Management, 140(2), 227–238. https://doi.org/10.1016/S0378-1127(00)00282-6

Laganière, J., Angers, D. A., & Paré, D. (2010). Carbon accumulation in agricultural soils after afforestation: A meta-analysis. Global Change Biology, 16(1), 439–453. https://doi.org/10.1111/j.1365-2486.2009.01930.x

Lal, R. (2004). Soil carbon sequestration to mitigate climate change. Geoderma, 123(1), 1–22. https://doi.org/10.1016/j.geoderma.2004.01.032

Lal, R. (2006). Enhancing crop yields in the developing countries through restoration of the soil organic carbon pool in agricultural lands. Land Degradation & Development, 17(2), 197–209. https://doi.org/10.1002/ldr.696

le Polain de Waroux, Y., & Lambin, E. F. (2012). Monitoring degradation in arid and semi-arid forests and woodlands: The case of the argan woodlands (Morocco). Applied Geography, 32(2), 777–786. https://doi.org/10.1016/j.apgeog.2011.08.005

Minelli, S. (2018). Default data: Methods and interpretation - A guidance document for 2018 UNCCD. https://policycommons.net/artifacts/1983874/default-data/2735639/

Paustian, K., Lehmann, J., Ogle, S., Reay, D., Robertson, G. P., & Smith, P. (2016). Climate-smart soils. Nature, (7597), Article 7597. https://doi.org/10.1038/nature17174

Poeplau, C., & Dechow, R. (2023). The legacy of one hundred years of climate change for organic carbon stocks in global agricultural topsoils. Scientific Reports, 13(1), Article 1. https://doi.org/10.1038/s41598-023-34753-0

Powers, J. S., Corre, M. D., Twine, T. E., & Veldkamp, E. (2011). Geographic bias of field observations of soil carbon stocks with tropical land-use changes precludes spatial extrapolation. Proceedings of the National Academy of Sciences, 108(15), 6318–6322. https://doi.org/10.1073/pnas.1016774108

Ruehlmann, J., & Körschens, M. (2009). Calculating the Effect of Soil Organic Matter Concentration on Soil Bulk Density. Soil Science Society of America Journal, 73(3), 876–885. https://doi.org/10.2136/sssaj2007.0149

Sabir, M., Sagno, R., Tchintchin, Q., Zaher, H., & Benjelloun, H. (2020). Chapitre 3. Évaluation des stocks de carbone organique dans les sols au Maroc. In M. Brossard, L. Chapuis-Lardy, T. Chevallier, & T. M. Razafimbelo (Eds.), Carbone des sols en Afrique: Impacts des usages des sols et des pratiques agricoles (pp. 71–90). IRD Éditions. https://doi.org/10.4000/books.irdeditions.34902

Santín, C., Doerr, S. H., Preston, C. M., & González-Rodríguez, G. (2015). Pyrogenic organic matter production from wildfires: A missing sink in the global carbon cycle. Global Change Biology, 21(4), 1621–1633. https://doi.org/10.1111/gcb.12800

Schlesinger, W. H. (1977). Carbon Balance in Terrestrial Detritus. Annual Review of Ecology and Systematics, 8(1), 51–81. https://doi.org/10.1146/annurev.es.08.110177.000411

Somarathna, P. D. S. N., Malone, B. P., & Minasny, B. (2016). Mapping soil organic carbon content over New South Wales, Australia using local regression kriging. Geoderma Regional, 7(1), 38–48. https://doi.org/10.1016/j.geodrs.2015.12.002

Theobald, D. M., Harrison-Atlas, D., Monahan, W. B., & Albano, C. M. (2015). Ecologically-Relevant Maps of Landforms and Physiographic Diversity for Climate Adaptation Planning. PLOS ONE, 10(12), e0143619. https://doi.org/10.1371/journal.pone.0143619

Turner, D. P., Ollinger, S. V., & Kimball, J. S. (2004). Integrating remote sensing and ecosystem process models for landscape-to regional-scale analysis of the carbon cycle. BioScience, 54(6), 573–584.

Venter, Z. S., Hawkins, H.-J., Cramer, M. D., & Mills, A. J. (2021). Mapping soil organic carbon stocks and trends with satellite-driven high-resolution maps over South Africa. Science of The Total Environment, 771, 145384. https://doi.org/10.1016/j.scitotenv.2021.145384

Walker, T. W. N., Kaiser, C., Strasser, F., Herbold, C. W., Leblans, N. I. W., Woebken, D., Janssens, I. A., Sigurdsson, B. D., & Richter, A. (2018). Microbial temperature sensitivity and biomass change explain soil carbon loss with warming. Nature Climate Change, 8(10), Article 10. https://doi.org/10.1038/s41558-018-0259-x

Woodward, F. I., Lomas, M. R., & Kelly, C. K. (2004). Global climate and the distribution of plant biomes. Philosophical Transactions of the Royal Society of London. Series B: Biological Sciences, 359(1450), 1465-1476.

Zaehle, S., Bondeau, A., Carter, T. R., Cramer, W., Erhard, M., Prentice, I. C., Reginster, I., Rounsevell, M. D. A., Sitch, S., Smith, B., Smith, P. C., & Sykes, M. (2007). Projected Changes in Terrestrial Carbon Storage in Europe under Climate and Land-use Change, 1990–2100. Ecosystems, 10(3), 380–401. https://doi.org/10.1007/s10021-007-9028-582 9

EVALUATING SOIL PARAMETERS USING PROXIMAL SOIL SENSORS (EM38, MSP3)

#11090

[1,2*]H. Hajjaj, [1]K. Ibno Namr, [2]C. El khalif, [2]A. El-Aissaoui
[1]Laboratory of Geosciences and Environmental Techniques, Department of Geology, Faculty of Sciences, Chouaïb Doukkali University, BP.20, El Jadida 24000, Morocco
[2]Laboratory of Agricultural Engineering and Precision Agriculture, National Institute of Agronomic Research, CRRAS, PO 586, Settat,26000, Morocco
e-mail: hajjaj.hasna@ucd.ac.ma

INTRODUCTION

Site-specific farming requires an accurate information on soil spatial variability. In fact, by using digital mapping of physical, biological and chemical soil parameters, some indicators and pedotransfert functions can be developed for evaluating not only soil quality but also for monitoring performances of agricultural system, natural resource management, climate modelling and environmental science (Liu et al.2006; Robinson & Metternicht, 2006; Bhunia et al. 2018). Thus, adequate information on the status behaviour of soil parameters is required for spatiotemporal monitoring and assessment. However, direct measurements are precise but expensive, time-consuming and labour-intensive (Bhunia et al.2018). Otherwise, better planning and management of soil data cannot be systematically effective using interpolation at unsampled sites.

According to the technological progress, today's spatial data analysis methods and tools allow the monitoring of spatiotemporal changes in almost all soil attributes at various levels (Mabit and Bernard 2010; Dai et al. 2014; Bhunia et al. 2018). In fact, proximal soil sensing refers to the use of sensors in the field to obtain signals from the soil when the sensor detector is either in contact or close to soil matrix (Viscarra Rossel et al., 2011).

This paper aims to review the proximal soil sensing technologies mainly the **MSP3 and EM38 ECa meter** and to evaluate both technologies for their ability to predict soil parameters under arid conditions

On the go soil sensor (MSP3)

On-the-go soil sensors such as MSP3 (Fig 1), equipped with GPS, is designed to effectively delineate soil differences across fields, capturing data that other technologies might miss (Adamchuk et al., 2004). It utilizes dual wavelength optical sensors to measure organic matter and pH, along with coulter electrodes for direct electrical conductivity readings at depths of 0-12 inches and 0-36 inches. As the implement is pulled behind a tractor at speeds up to 6 mph, data is logged on GPS maps, which can inform fertility management decisions such as split fertilizer applications and variable rate seeding. The system records digital reflectance data and GNSS coordinates at a rate of 1 Hz, averaging 260 reflectance data points per hectare while ensuring effective sensing through self-cleaning optical module (Kweon & Maxton, 2013; Bönecke et al., 2020).

Figure 9. a) MSP3 sensor, b) pH,OM and EC coulters c) MSP3 prepared to map in the field d) MSP3 in the field (Veris Staff; Mackowiaket al., 2016).

Electromagnetic induction sensor (EM38 SENSOR)

Non-contact electrical conductivity sensors use electromagnetic induction and do not need to come into contact with the ground. These sensors measure the change in mutual impedance between the coils (McNeill, 1980). This measurement is then converted into an estimate of the EC known as the apparent EC (ECa). These units are capable of monitoring at greater depths than contact sensors.

The EM38 sensor (Fig 2), designed for versatile use on the ground, in the air, and in boreholes, is a hand-held instrument that can also be mounted and directed using GPS for automated data logging in a Geographic Information System (McDaniel et al., 2018) The standard EM38-MK2 model measures 1.05 m in length and weighs 3.5 kg, powered by a 9-volt battery with a life of up to 20 hours. It records soil electrical conductivity (EC_a) in both horizontal (H-mode) and vertical (V-mode) dipole modes, providing measurements at depths of 0.375 m and 0.75 m in H-mode, and 0.75 m and 1.5 m in V-mode. ((Kitchen et al., 2005; Geonics, 2012).

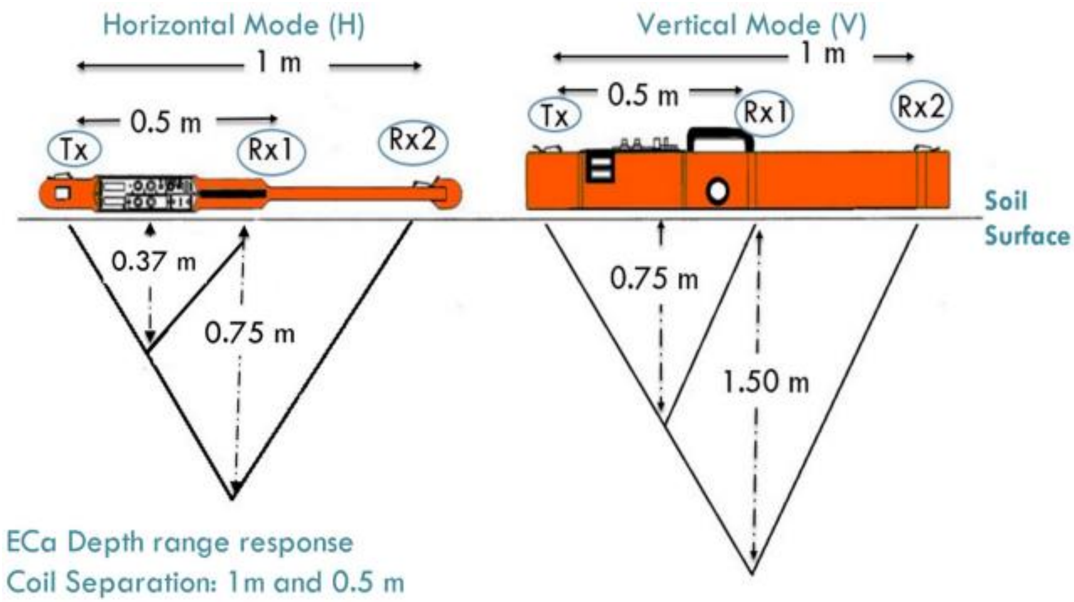


Figure 10. The EM38 sensor in horizontal (H) and vertical (V) mode with the effective depth range responses of ECa for coil separation of 1 m and 0.5 m when placed on the soil surface. (Petsetidi & Kargas, 2023).

EM38 AND MSP3 USE IN ARID LAND CONDITIONS

The MSP3 sensor has been used and proved its effectiveness in analysing soil properties in arid and semi-arid regions. Several studies (Kweon, 2012a, 2012b; Mackowiak et al., 2016; Novais et al., 2019) showed that this sensor could be effective to distinguish soil textures and organic matter variability, with moderate to strong correlations compared to laboratory results. Its potential use for precise soil management in challenging environments has been emphasized, particularly for detecting small-scale spatial variability and controlling variable rate inputs management with reference to established prescription maps.

Similarly, EM38 sensor has been used in arid lands to produce valuable data for assessing soil properties, particularly in understanding soil electrical conductivity (ECa) and its behaviour and relationship with the soil parameters according to the occurring soil water content. Several Studies (Rhoades et al., 1976,1989,1990,1997,1999; Corwin & Lesch, 2005b, 2013, 2017; Molinl et al,2005) indicated that ECa measurements could effectively differentiate between dry and saturated soils, which is crucial to approach soil parameters in arid regions having irregular soil water content due to intermittent rainfall.

Table 6. Some studies based on using MSP3 sensor in arid land context.

Study	Objective	Location	Key Findings	Recommendations
Novais et al. (2019)	Calibrate and validate the MSP3 in rainy conditions	Guanacaste, Costa Rica	Correlations established for soil texture and organic matter ($R^2 \geq 0.55$) at 0-30 cm; varied textures observed.	Alternative calibration methods needed for deeper measurements (30-90 cm).
Mackowiak et al. (2016)	Improve soil mapping for nutrient and water management using MSP3	Florida USA	Organic matter (OM) values help distinguish soil texture differences; dark colors correlated with higher OM.	Use MSP3 to delineate differences for variable rate management rather than achieving specific OM or EC targets.
Kweon (2012a, 2012b)	Evaluate MSP3 performance across multiple fields in the Midwest USA	Midwest USA	Proximal sensor measurements correlated well with lab samples; detected small-scale variability not seen in traditional methods.	Multi-sensor approach increases chances of identifying soil property variations; improve CEC predictions through data integration.

Table 7. Studies based on using EM38 in arid land context.

Years	Objective	Study Area	Findings	Recommendations
(Rhoades et al., 1976; 1989a; 1990a; 1997; 1999a; 1999b)	Obtain empirical coefficients used in equations to predict ECa by depth intervals within the soil profile from EM readings taken above ground.	California, USA	The authors stated that electromagnetic measurements on soils with less than 10% water by weight are not a reliable indication of salinity, and for very sandy soils, the limiting value of moisture content is probably higher. Proximity to the water table also influences EM38 readings.	Predictions were found to be more accurate using the new coefficients rather than those previously available.
(Corwin & Lesch, 2005a, 2005b, 2013, 2017)	Applications of ECa measurements in agriculture, particularly site-specific crop management	Arizona, USA	It appeared to be a stronger than normal water content influence on the EM38 signal data, consistent with typical surveying conditions encountered because of the prevalence of lighter textured soils.	Evaluates site-specific management from a holistic perspective of environmental, crop productivity, and economic impacts.
Molinl et al 2005	to perform spatial monitoring of soil moisture in two different experimental fields over two consecutive years and evaluate the influence of moisture on soil ECa.	Brazil	demonstrated the potential of ECa sensors for understanding soil characteristics and their impact on crop yields, particularly in no-till fields.	ECa is a qualitative indicator in areas with high spatial variability in soil texture. In the field, where soil moisture range was lower, ECa was not associated to moisture levels.

CONCLUSION AND RECOMMENDATIONS

This paper outlines a comprehensive approach to assessing soil parameters using two proximal soil sensor tools, mainly the MSP3 and EM38 tools.

This review showed several studies highlighting importance of using the Veris MSP3 mapping tool in improving land management decisions. The MSP3's electrical conductivity (EC) package could effectively track nutrient variations, while its pH tool can show promise, though further calibration is required to confirm its accuracy. Challenges such as technical glitches with inexperienced operators and the underdevelopment of the organic matter (OM) tool emphasize the need for enhanced data support and interface improvements to facilitate research.

Additionally, while the EM38 performs well under conventional irrigation systems, it faces challenges with micro-irrigation due to localized salinity variations, highlighting the need for updated research protocols. The growing adoption of inverse modelling for soil salinity profiling is crucial for managing water resources in cash crops, especially in the context of climate change. (Corwin & Scudiero, 2016, 2019)

Ultimately, while the MSP3 excels in data integration and the creation of management zones, the EM38 remains valuable for rapid field assessments. The combined use of both tools could significantly enhance soil management practices.

REFERENCES

Bhunia, G.S., Shit, P.K., Maiti, R. 2018. Comparison of GIS-based interpolation methods for spatialdistribution of soil organic carbon (SOC). Journal of the Saudi Society of Agricultural Sciences, 17(2),114–126. DOI: 10.1016/j.jssas.2016.02.001 (PDF) Modelling and Mapping of Soil Organic Matter in Doukkala Plain Morrocan Semi-Arid Region.

Bönecke, E., Kling, C., Kramer, E., Lück, K., Philipp, G., Rühlmann, J., Schröter, I., & Gebbers, R. (2022). Direct prediction of site-specific lime requirement of arable fields using the base neutralizing capacity and a multi-sensor platform for on-the-go soil mapping. Precision Agriculture, 23(1), 127–149. https://doi.org/10.1007/s11119-021-09830-x

Corwin, D. L., & Lesch, S. M. (2005a). Apparent soil electrical conductivity measurements in agriculture. Computers and Electronics in Agriculture, 46, 11–43. https://doi.org/10.1016/j.compag.2004.10.005

Corwin, D. L., & Lesch, S. M. (2013). Protocols and Guidelines for Field-scale Measurement of Soil Salinity Distribution with EC a -Directed Soil Sampling . Journal of Environmental and Engineering Geophysics, 18(1), 1–25. https://doi.org/10.2113/jeeg18.1.1

Corwin, D. L., & Lesch, S. M. (2017). Validation of the ANOCOVA model for regional-scale ECa to ECe calibration. Soil Use and Management, 33(2), 178–190. https://doi.org/10.1111/sum.12262

Corwin, D. L., & Scudiero, E. (2016). Field-Scale Apparent Soil Electrical Conductivity. Methods of Soil Analysis, 1(1), 0. https://doi.org/10.2136/methods-soil.2015.0038

Corwin, D. L., & Scudiero, E. (2019). Review of soil salinity assessment for agriculture across multiple scales using proximal and/or remote sensors. In Advances in Agronomy (Vol. 158, pp. 1–130). Academic Press Inc. https://doi.org/10.1016/bs.agron.2019.07.001

Kweon, G. (2012a). Delineation of site-specific productivity zones using soil properties and topographic attributes with a fuzzy logic system. Biosystems Engineering, 112(4), 261–277. https://doi.org/10.1016/j.biosystemseng.2012.04.009

Kweon, G., Lund, E., & Maxton, C. (2013). Soil organic matter and cation-exchange capacity sensing with on-the-go electrical conductivity and optical sensors. Geoderma, 199, 80–89. https://doi.org/10.1016/j.geoderma.2012.11.001

Kitchen, N. R., Sudduth, K. A., Myers, D. B., Drummond, S. T., & Hong, S. Y. (2005). Delineating productivity zones on claypan soil fields using apparent soil electrical conductivity. Computers and Electronics in Agriculture, 46, 285–308. https://doi.org/10.1016/j.compag.2004.11.012

Mackowiak, C., Pi, L., & Wright, D. (2016). Soil Mapping Enhancements via Veris MSP3.

McDaniel, P., Ross, M., Jimenez, J., Strawn, D. G., Valerio, M., Kimsey, M. J., Campbell, S., & Falen, A. (2018). Pedogenic Pathways in Andic Soils of the Northern Rocky Mountains (USA). Soil Science Society of America Journal, 82(6), 1308–1318. https://doi.org/10.2136/SSSAJ2018.05.0186

McNeill, J. D. (1980). Electromagnetic Terrain Conductivity Measurement at Low Induction Numbers. In Technical note TN (Vol. 6, Issue TN--6, p. 13). http://www.geonics.com/pdfs/technicalnotes/tn6.pdf

Novais, W., Rodríguez-Mejías, J. C., Perret, J., Soto, C., Villalobos, J. E., Fuentes, C. L., & Abdalla, K. (2019). Calibration and validation of Veris MSP3 on two soils in Guanacaste, Costa Rica. Agronomia Mesoamericana, 30(2), 535–551. https://doi.org/10.15517/am.v30i2.33579

Petsetidi, P. A., & Kargas, G. (2023). Assessment and Mapping of Soil Salinity Using the EM38 and EM38MK2 Sensors: A Focus on the Modeling Approaches. In Land (Vol. 12, Issue 10). Multidisciplinary Digital Publishing Institute (MDPI). https://doi.org/10.3390/land12101932

Rhoades, C. C., Brosi, S. L., Dattilo, A. J., & Vincelli, P. (n.d.). Effect of soil compaction and moisture on incidence of phytophthora root rot on American chestnut (Castanea dentata) seedlings. https://doi.org/10.1016/S0378-1127(03)00147-6

Robinson, T. P., & Metternicht, G. (2006). Testing the performance of spatial interpolation techniques for mapping soil properties. Computers and Electronics in Agriculture, 50(2), 97–108. https://doi.org/10.1016/j.compag.2005.07.003

Veris Technologies Inc. (2016). Quantifying the Value of Precise Soil Mapping. 1–8.

Viscarra Rossel, R. A., A., K., & Schulze, P. (2011). Sensor Fusion for Precision Agriculture. *Sensor Fusion - Foundation and Applications*, *May 2014*. https://doi.org/10.5772/19983

SMALL HOLDERS AND PRECISION AGRICULTURE

THE USE OF UNMANNED AERIAL VEHICLE (UAV) REMOTELY SENSED DATA AND BIOPHYSICAL VARIABLES TO PREDICT MAIZE ABOVE-GROUND BIOMASS (AGB) IN SMALL-SCALE FARMING SYSTEMS

#11068

[1*]Celuxolo M Dlamini, [1]John Odindi, [1]Onisimo Mutanga, [2]Trylee N Matongera
[1]Discipline of Geography and Environmental Science, School of Agricultural Earth and Environmental Sciences, University of KwaZulu-Natal, Scottsville, Pietermaritzburg 3209, South Africa; [2]Centre for Transformative Agricultural and Food Systems, School of Agricultural, Earth and Environmental Sciences, University of KwaZulu-Natal, Scottsville, Pietermaritzburg 3209, South Africa
*e-mail: 219003508@stu.ukzn.ac.za/celuxolomichal09@gmail.com; +27780632013

ABSTRACT

Considering the current and projected increase in human population, approaches to optimize crop productivity to meet the rising demand are paramount. Timely and accurate maize Above Ground Biomass (AGB) measurements allow for development of models that can precisely predict yield prior to harvesting, useful for food production management and sustenance. The development of Unmanned Aerial Vehicles (UAVs) as a new generation of robust remote sensing platforms, mounted with high-resolution sensors has allowed timely and accurate prediction of maize AGB in pursuit of sustaining food security. This study aimed to predict maize crop AGB in small-scale farming systems using UAV-remotely sensed data and landscape biophysical variables. The DJI Matrice 300 UAV mounted with a MicaSense multispectral camera was used to acquire high-resolution images at four phenological stages that covered the vegetative (V8 &V12) and reproductive stages (R2 & R5). Furthermore, in-situ plant biophysical measurements and landscape variables were acquired and combined with UAV-remote sensing derived vegetation indices to model maize AGB using a Deep Neural Network (DNN) model. Results showed that the V12 phenological stage yielded a better overall prediction accuracy (R2 = 0.74) than the V8 (R2 = 0.65), R2 (R2=0.71), and R5 (R2=0.67) phenological stages. The study concludes that the V12 and R2 phenological stages are optimum for estimating maize AGB. This study contributes to a better understanding of maize crop health and crop monitoring efforts for improved food security.

Keywords: UAV-Remote Sensing; Above-Ground Biomass; Maize; Smallholder Farming; Deep Neural Networks.

INTRODUCTION

Small-scale crop farming plays a critical role in the economies of developing countries and is crucial for sustaining food security. However, productivity in smallholdings is often adversely affected by unfavourable bioclimatic conditions, climate change, and lack of farming resources (Mgbenka et al., 2016). Maize (*Zea mays*) is ranked as one of the most extensively cultivated crops worldwide. In South Africa, maize is widely produced and consumed as a staple food by the majority population and also used for livestock fodder (Luo et al., 2019; Ngoune Tandzi & Mutengwa, 2019). Other uses of maize include the production of starch, ethanol, and fuels (Mgbenka et al., 2016). Although the demand for maize has significantly increased in South Africa, challenges related to production and yield remain prevalent (Haarhoff et al., 2020; Verschuur et al., 2021). Hence, it is imperative to adopt prompt and robust techniques such as crop yield prediction to accurately counteract these challenges.

Maize Above Ground Biomass (AGB) is an essential basis for crop yield formation as it indicates plant growth and productivity (Meiyan et al., 2022; Tang et al., 2023). A higher maize AGB signifies a superior crop performance in capturing and converting sunlight, nutrients, and water into energy for grain development and increased yield (Luo et al., 2019). A direct positive correlation between maize AGB and yield is well established in literature (Leroux et al., 2019; Tollenaar & Lee, 2002; Zhang et al., 2021). Hence, timely and accurate maize AGB measurements allow for development of models that can precisely predict yield prior to harvesting, useful for strategic evaluations, financial planning, efficient irrigation, and food production management (Yahui Guo et al., 2020). Furthermore, maize AGB serves as a crucial source of nutrition for livestock during periods of limited forage availability, such as the dry season (Palacios-Rojas et al., 2020). Therefore, the assessment of maize AGB to optimise yield, particularly in small-scale farming systems, is essential for optimising productivity and mitigating potential losses (Cheng et al., 2020).

Traditionally, quantifying maize AGB involves in-situ measurements of foliar weight, which is destructive and laborious, hence unsuitable for large spatial extents and repeated observations (Gerke, 2019; Han et al., 2019b). Recently, satellite remote sensing has been widely adopted to accurately monitor agricultural crops, with many studies showing a positive correlation between remotely sensed variables and AGB (Battude et al., 2016; Kayad et al., 2019; Leroux et al., 2019). For instance, Geng et al. (2021) estimated maize AGB using Moderate Resolution Imaging Spectroradiometer (MODIS) reflectance data and machine learning, achieving a coefficient of determination of 0.77 ($R^2 = 0.77$). However, despite these successes, the application of satellite remote sensing is limited by as among others cloud cover, which significantly restricts maize crop monitoring requirements for small-scale farming systems (Zhang et al., 2021). Furthermore, small-scale farming systems are characterized by small spatial extents of less than two hectares, hence higher spatial resolution sensors are necessary for effective capture of crops spectral information (Peter et al., 2020). In addition, the transition between phenological stages in maize crops occurs rapidly, necessitating the use of high-temporal-resolution sensors and on demand dataset to accurately monitor and capture the changes in AGB at each growth stage (B. Yang et al., 2022).

Recently, Unmanned Aerial Vehicles (UAVs), also known as drones, have demonstrated a remarkable capability to bridge the gap between satellite remote sensing and ground-based observations (Gargiulo et al., 2023). This is attributed to their ability to provide cloud-free, near-real-time data at ultra-high spatial resolution (Z. Li et al., 2022; Sharma et al., 2022). UAVs offer several benefits for agricultural crop monitoring that include the ability to hover over areas of interest and fly beneath cloud cover at flexible altitudes, allowing for high resolution imagery and precise monitoring of individual crops (Aasen et al., 2018). Additionally, their flexible flight mission make them ideal for capturing data during optimal periods, such as the short-window peak photosynthetic phase in maize crops (B. Yang et al., 2022). However, despite these advancements and capabilities, studies on the use of UAV technology on small holder farms, particularly in the global south, remain scarce. This underscores the need for studies that investigate the potential of UAVs, equipped with high resolution sensors, in predicting maize AGB in small-scale farming systems.

High resolution sensors mounted onto UAV platforms cover a wide range of the electromagnetic bands including the visible, near-infrared, and red-edge sections that are useful in predicting maize AGB and deriving vegetation indices to support yield estimations (Li et al., 2016). For instance, vegetation indices derived from the near-infrared and red-edge wavelengths such as the Normalized Difference Vegetation Index (NDVI), have demonstrated the ability to detect subtle changes in crops properties such as canopy structure, photosynthetic activity, and crop health (Che et al., 2022; Vélez et al., 2023). For example, Brewer et al. (2022) obtained satisfactory results by using various multispectral derived vegetation indices such as NDVI and Soil Adjusted Vegetation Index (SAVI) for estimating leaf chlorophyll content to determine crop health and vigour.

Typically, maize crops are characterised by variable stock height, density, and greenness, while canopy vegetation index remains unchanged (Adewopo et al., 2020). Hence, vegetation index-based empirical approaches alone cannot accurately estimate maize AGB. Consequently, to account for these variations, biophysical variables such as leaf chlorophyll content and leaf area index (LAI) can be combined with vegetation indices to accurately predict maize AGB (Meiyan et al., 2022). Leaf chlorophyll content and LAI have been identified as strong crop health indicators that positively correlate with maize AGB (Che et al., 2022; Liu et al., 2019; Luo et al., 2019). However, measuring the aforementioned biophysical variables is only ideal for small spatial extents (Liu et al., 2023). In addition, considering that most small-scale farmlands are often characterized by challenging terrain featuring steep topography, it is essential to assess the influence of landscape variability on maize AGB (Polzin & Hughes, 2023). Therefore, landscape and landscape related variables that directly and indirectly influence crop growth such as soil moisture, slope, aspect, and elevation can provide a precise maize AGB estimation (Fry & Guber, 2020; Goldenberg et al., 2022; Svedin et al., 2021). Consequently, integrating drone-derived multispectral bands, with optimal vegetation indices, and biophysical landscape variables can provide better and precise estimates of maize AGB in small-scale farming systems.

Numerous regression techniques have been proposed in literature for the prediction of crop properties (Ali et al., 2022; Khan et al., 2022; Tripathi et al., 2022). Machine learning algorithms, combined with spectral variables from remote sensing datasets have proven superior for data analysis than other statistical approaches (Altaweel et al., 2022). Deep learning algorithms, such as Deep Neural Networks (DNN), have particularly gained popularity over the past decades for their ability to learn and discover patterns from large and complex datasets and generate accurate predictions (X. Li et al., 2022; Muruganantham et al., 2022). DNN comprises a hierarchy of more than two hidden neural network layers and are subsequently called 'deep learning' (Odebiri et al., 2021a, 2021b). The primary limitation of this technique is its propensity to overfitting and requirement of large datasets for optimal performance (Cao et al., 2022). However, features such as regularization and dropout in neural networks can counteract these effects (Vojnov et al., 2022). Numerous studies have successfully adopted DNN to predict maize agronomic variables and obtained results surpassing other machine learning algorithms (Khaki & Wang, 2019; Lischeid et al., 2022). Despite its potential, deep learning is the least used approach in agricultural monitoring applications, particularly at small-scale extents due to small acquirable datasets. Therefore, there is need for further research to explore the full potential of UAV remotely sensed data combined with landscape and biophysical variables for estimating and mapping maize crop AGB using DNN machine learning techniques.

Studies have employed either plant biophysical, landscape variables or remotely sensed data to estimate maize AGB (Liu et al., 2019; Luo et al., 2019; Meiyan et al., 2022). Generally, studies have seldom integrated the two, with the landscape variables for precision agriculture. Therefore, this study sought to evaluate the utility of UAV remotely sensed data combined with landscape and biophysical variables in estimating maize AGB in small-scale farming systems using DNN machine learning techniques. The main objective of this study was to predict maize AGB using a combination of UAV remotely sensed data, landscape variables, and plant biophysical variables. Additionally, this study sought to determine the optimum phenological stage for timely and efficient maize AGB prediction in subsequent seasons. Finally, the study sought to assess the performance of DNN algorithm to identify an optimal model for predicting maize AGB using small spatial extent acquired dataset.

MATERIALS AND METHODS

Description of the study area

This study was conducted in Swayimane communal area (Latitude: -29.524444°, Longitude: 30.699846°) within the UMshwathi Municipality, in the KwaZulu-Natal province, South Africa (Fig.1). The experimental field is approximately 1.4 hectares and exhibits distinct variations in slope, aspect, and elevation. Average air temperature is 17 ℃, while the minimum and maximum temperatures are 11.8 ℃ and 24 ℃, respectively (Ndlovu et al., 2021) . Annual rainfall ranges from 600 mm to 1100 mm, with most rainfall received in summer. Swayimane is characterized by wet-hot summers and dry-cold winters. Since cropping activities in the study area are rain fed, crops are grown during the summer season. The area has excellent bioclimatic and physical conditions, that include loam soils with efficient nutrient and water holding capacity as well as optimum terrain for efficient sunlight capture, making it suitable for crop farming. Farmers in the area mainly rely on traditional farming methods such as use of kraal manure as fertilizers and animal draft implements for ploughing and weeding. However, with recent socio-economic improvements in the area, some farmers are adopting artificial fertilizers and mechanized farming, particularly in larger fields. In addition to maize, legumes, sweet potatoes, taro and small holding sugarcane are grown in the study area.

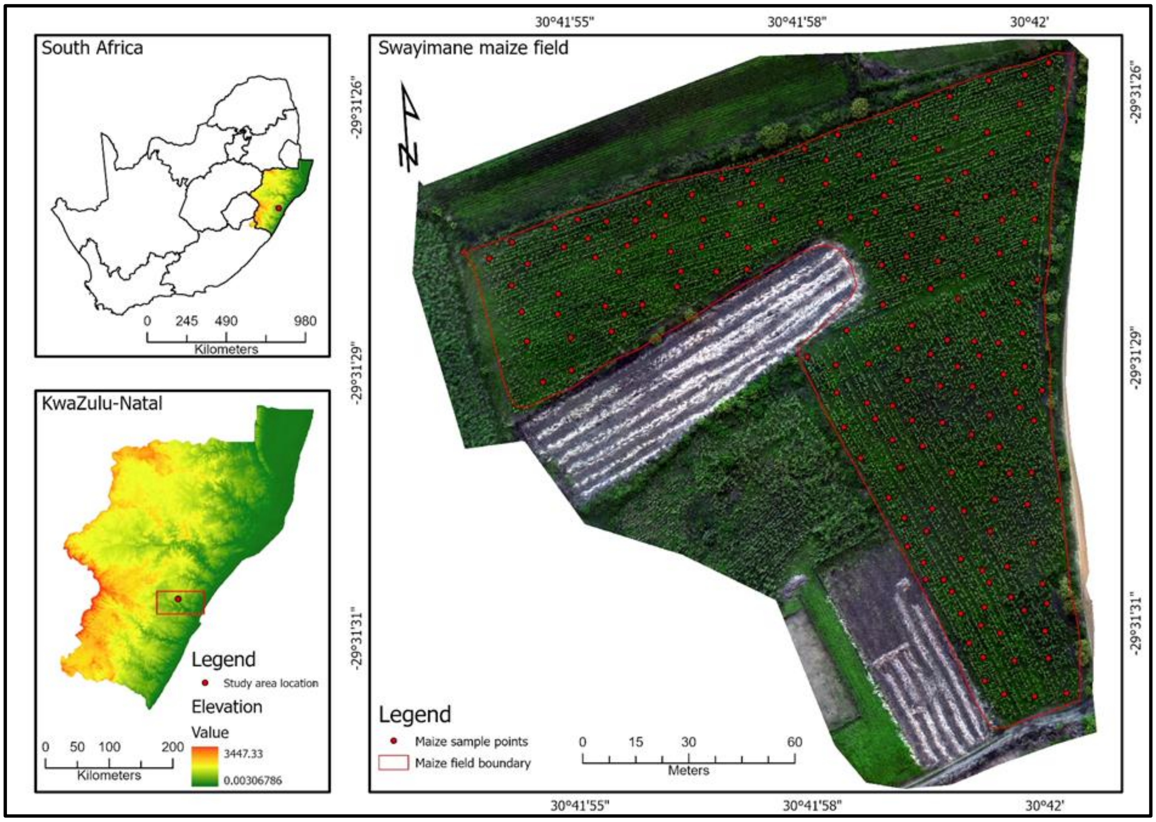


Figure 1. Location of the study site.

Maize phenotyping

The maize field was planted with the SC 701 hybrid (Pannar Seed Company, SA) on the 24th of February 2023, and harvested on the 7th of July 2023. The SC 701 seed type was chosen because of its high yield capacity estimated at more than 13 tons per hectare according to the seed producers. The SC 701 hybrid is late maturing (140-148 days) and known to be heat and drought tolerant. However, in such cases, irrigation is recommended for maximum yield. The maize was rain-fed throughout the growing season, and no drought and extreme temperatures were recorded. The maize was planted in rows perpendicular to the slope to minimize nutrient runoff and soil erosion during rainfall. The distance between the crops and rows was at least 20 cm and 70 cm, respectively, to avoid inter-competition within the crops and stunted growth. To eradicate weeds, an affordable water-soluble Basagran herbicide with a mixability of 480 g/l was applied when the maize was 30 days old, and a nitrogen-phosphorus-potassium [N: P: K (2:3:4=30)] fertilizers applied when the maize was 50 days old to enhance growth.

Data acquisition

Ground data collection

Data for the study was collected at four phenological stages ranging from the vegetative to reproductive growth phases i.e. V8 (32 days old), V12 (47 days old), R2 (96 days old) and R5 (123 days old) (Table 1). The vegetative stages were selected as they are characterized by fully developed leaves, which is essential for field measurements and light reflectance. The R2 is full canopy stage while R5 represents the end of mass gain in maize crop. Field measurements were conducted at four-week intervals to capture the above-mentioned stages of the growth cycle. Using a handheld Trimble Global Positioning System (GPS), 200 points were sampled using a stratified random approach within the experimental plot. The experimental plot was divided into sub strata based on slope, crop health, and crop size. Thereafter, random crops within the strata were sampled, ensuring variability capturing and a comprehensive and representative sample of the maize population. The approach was adopted to capture the size variability and representative crops for the whole maize field. Each sample point was marked with red tape and labelled for consistent monthly measurements. Field measurements were conducted on clear sunny days between 10 a.m. and 14:00 p.m. to capture data at peak photosynthetic activity and maximum reflectance.

Table 1. Maize phenological stages used in the study.

Growth Stage	**Vegetative Stages**	
	V8	V12
Day after sowing	32	47
Maize Crop		
Growth Stage	**Reproductive stages**	
	R2	R5
Day after sowing	96	123
Maize Crop		

At each sampling point, LAI was obtained using a LiCOR 2200C plant canopy analyser (LI-COR GmbH, Germany). The analyser uses 7°, 22°, 38°, 52°, and 68° zenith angles to measure light interception and transmittance below and above the plant canopy and ultimately estimates the LAI (Buthelezi et al., 2023). Soil moisture content was measured using HH2 moisture probe (Delta-T soil moisture sensors, United states) at each sample point. The HH2 soil moisture probe is inserted in the soil close to the root systems of the crop and records soil moisture volume with a 5% accuracy based on standard calibration (Cheng et al., 2022). Leaf chlorophyll content was measured using a Konica Minolta Soil Plant Analysis Development (SPAD) 502 chlorophyll meter (Minolta corporation, Ltd., Osaka, Japan). The SPAD measures a unit less chlorophyll reflectance in the leaf using the Red and Infrared portions of the electromagnetic spectrum (Brewer et al., 2022). Finally, at the R6 phenological stage, marking the end of the growing season, the designated maize crops underwent sampling, involving cutting the aboveground foliage, followed by weighing it using a mass balance to determine the fresh AGB values at each sampling point. No mass correction was performed on the maize crops, considering their crucial role in small-scale farming systems as a source of both livestock fodder and human consumption. The decision to retain moisture in the maize aligns with its practical use for easy swallowing, addressing the specific needs of both animals and humans during this stage of maturity.

UAV platform and remotely sensed data acquisition

The digital multispectral images were collected over four phenological stages using a DJI Matrice 300 series (M300) UAV platform (SZ DJI Technology Co., Ltd, China) mounted with a MicaSense Altum multispectral and thermal sensor (AgEagle Aerial Systems Inc, Kansas) (Fig.2a). The Altum sensor is equipped with six spectral bands [red (668 nm), green (560 nm), blue (475 nm), red edge (717 nm), near-infrared (840), and thermal band (8 to 14 nm)] (Fig.2c). The M300 is equipped with Internet of Things (IoT) technology, such as obstacle avoidance sensors and a locational GPS connected to the camera, making the drone safe to operate and capture automatically georectified images. The UAV flights were conducted simultaneously with field measurements. A flight path covering the experimental field was digitized from Google Earth Pro and imported into the drone controller (Fig.2b). Before and after each flight, a whiteboard calibration panel was used to calibrate the reflectance of the images (Fig.2d). The calibration panel was used to determine illumination and atmospheric conditions during the flight for accurate vegetation indices retrieval. The flights were conducted between 10:00 a.m. and 14:00 p.m. under open sky and suitable weather conditions for optimum sunlight reflectance. The drone was operated at 15 m/s speed and 100 m altitude with 80% forward and 70% side overlap. The images were collected at 6 cm per pixel spatial resolution, based on 8mm focal length and 8º x37º field of view (FOV) angle.

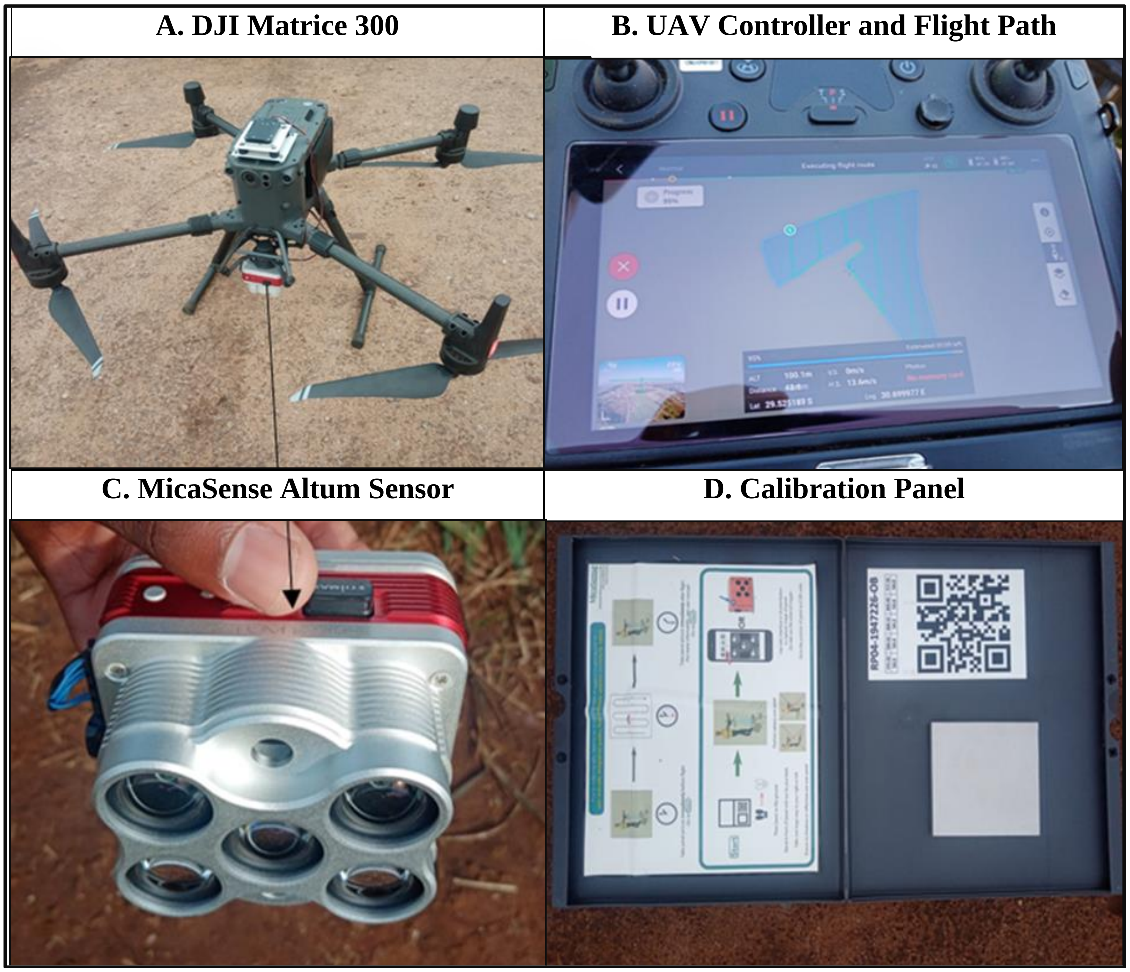


Figure 2. The UAV platform, controller with flight plan, image sensor, and calibration panel used for remotely sensed data acquisition in this study.

Image pre-processing and retrieval of vegetation indices

A total of 480 images were collected during each flight at each sampled growth stage. During the flights, the digital images were automatically georectified by the GPS payload mounted on the M300 UAV platform. Subsequently, the Pix4D 4.6 Fields photogrammetry software (Pix4D Inc. Denver, USA) was used to pre-process the images and generate an orthomosaic image and a digital elevation model (DEM). In addition, the index calculator of the Pix4D photogrammetry software was used to calculate optimal vegetation indices for estimating maize AGB (Table 2). The Pix4D index calculator uses mathematical equations from the Index Data Base (IDB) (https://www.indexdatabase.de/) to compute vegetation indices and provide a raster data showing their spatial distribution. The maize sample points, orthomosaic, and vegetation index raster images were imported into ArcGIS pro 10.7.1 software for data extraction using the 'extract multi-values to points' in the Arc Toolbox. The extracted band reflectance and vegetation indices for each sample point were then exported into Microsoft Excel for statistical analysis. Evidence from literature has proven the efficiency of vegetation indices in predicting maize AGB (Han et al., 2019b; Li et al., 2020; Li et al., 2016; Yue et al., 2023).

Table 2. Selected optimum vegetation indices for predicting maize AGB.

Vegetation Index	Formula	Reference
NDVI	$\frac{NIR - RED}{NIR + RED}$	(Shi & Xingguo, 2011)
CVI	$NIR\,(\frac{RED}{(GREEN)(GREEN)})$	(Hunt Jr et al., 2011)
BNDVI	$\frac{NIR - BLUE}{NIR + BLUE}$	(Wang et al., 2007)
NDVI_Rededge	$\frac{Rededge - RED}{Rededge + RED}$	(Ehammer et al., 2010)
RBNDVI	$\frac{NIR - (RED + BLUE)}{NIR + (RED + BLUE)}$	(Wang et al., 2007)
ENDVI	$\frac{((NIR + GREEN) - (2 * BLUE))}{((NIR + GREEN) + (2 * BLUE))}$	(Ahamed et al., 2011)
CI_Rededge	$\frac{NIR}{Red - edge} - 1$	(Hunt Jr et al., 2011)
GLI	$\frac{2(GREEN - RED - BLUE)}{2(GREEN + RED + BLUE)}$	(Baroni et al., 2004)
EVI	$2.5 * \frac{(NIR - RED)}{(NIR + 6RED - 7.5BLUE) + 1}$	(Glenn et al., 2010)
EVI2	$2.4 * \frac{NIR - RED}{NIR + RED + 1}$	(Miura et al., 2008)
IPVI	$\frac{NIR}{\frac{NIR + RED}{2}}(NDVI + 1)$	(Kooistra et al., 2003)
SAVI	$\frac{NIR - RED}{NIR + RED + 0.5}(1 + 0.5)$	(Heiskanen, 2006)
OSAVI	$(1 + 0.16)\frac{NIR - RED}{NIR + RED + 0.16}$	(Wu et al., 2008)
SR	$\frac{NIR}{RED}$	(Malthus et al., 1993)
CI_Green	$\frac{NIR}{GREEN} - 1$	(Ahamed et al., 2011)
GDVI	$NIR - GREEN$	(Tucker et al., 1979)

Where, NDVI= Normalized Difference Vegetation Index, CVI= Chlorophyll Vegetation Index, BNDVI= Blue Normalized Difference Vegetation Index, NDVI_Rededge =Normalized Difference Vegetation Index Red edge, RBNDVI= Red Blue Normalized Difference Vegetation Index, ENDVI= Enhanced Normalized difference Vegetation Index, CI_Rededge= Chlorophyll Index Red edge, GLI= Green Leaf Index, EVI= Enhanced Vegetation Index, IPVI= Infrared Percentage Vegetation Index, SAVI= Soil Adjusted Vegetation Index, OSAVI= Optimised Soil Adjusted Vegetation Index, SR= Simple Ratio, CI_Green= Chlorophyll Index Green, GDVI= Generalised Difference Vegetation Index

Retrieval of landscape variables

To complete the objective of this study, landscape variables that significantly influence maize growth such as slope and aspect were acquired from the System for Automated Geoscientific Analyses (SAGA) Geographic Information Systems (GIS) 7.8.2 software (University of Hamburg, Germany). The digitized experimental field boundary and maize sample points were then used to clip and extract the landscape variables to the extent of the study area using ArcGIS Pro. Even though soil moisture was measured in-field together with biophysical variables, it was categorized under landscape variables because it quantifies the amount of water held by the soil. In addition, the DEM generated by Pix4D software was used to extract elevation data to the maize sample points as a landscape variable. The UAV remotely sensed data was then combined with the extracted landscape variables and field-measured biophysical variables in an Excel file for statistical analysis (Table 3). The data was then split into training (70%), and testing (30%) datasets using randomisation, thereby ensuring non-bias splitting and ensuring representative subsets for model training and validation.

Table 3. Input variables**.**

Variable	Data type	Number of variables
Remotely sensed	Spectral bands Vegetation indices	21
Landscape variables	Aspect Elevation Slope Soil moisture	4
Biophysical variables	Leaf chlorophyll content LAI	2
Total	**8**	**27**

AGB prediction

Deep learning architecture

Jupyter notebook extended from Anaconda3 was used to build a fully connected DNN model featuring 17 inputs, three hidden, and one output layer using python programming environment for predicting maize AGB at four phenological stages (Fig.3). The combination of innovative computational tools and sophisticated DNN architecture facilitates precise AGB predictions, contributing to a deeper understanding of maize growth dynamics and potential applications in agriculture (Coulibaly et al., 2022; Fuentes et al., 2017). DNN models are powerful in capturing non-linear relationships by self-learning from large datasets and make precise predictions (Zhang et al., 2022). DNN models use multiple layers with fully connected neurons that are similar to human brain neurons and known to produce highly accurate results, surpassing human experts (Saranya et al., 2023; Z. Zeng et al., 2022). Therefore, DNN have the potential to improve prediction accuracy of maize AGB compared to other traditional machine learning and statistical methods.

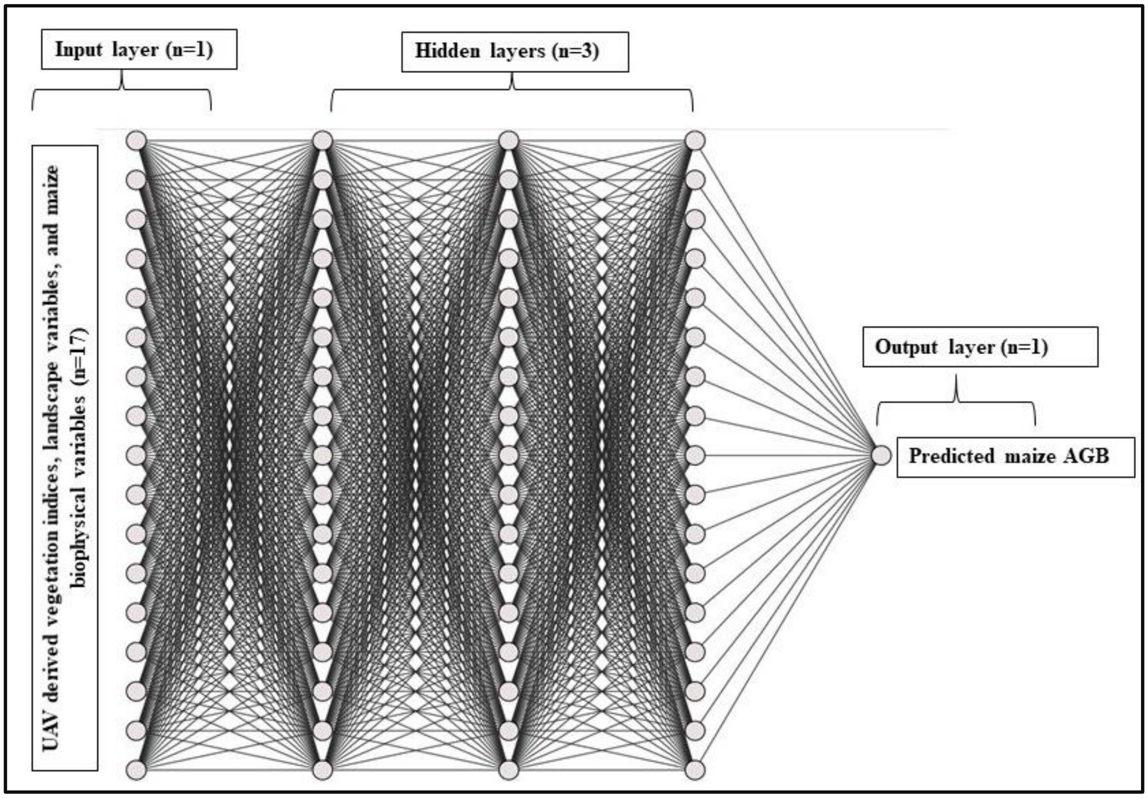


Figure 3. The diagrammatic illustration of the DNN model.

A good selection of hyperparameters based on the dataset is essential for building an optimum model (Dominguez-Olmedo, 2019). Therefore, the rectified linear unit (ReLu) was used in the input and hidden layers, respectively, to introduce non-linearity in the model. Linearity in DNN imply that all hidden layers have the same power in predicting the output (Kapočiūtė-Dzikienė et al., 2020). Due to the complexity and non-linearity within datasets, the hidden layers must have different magnitude of power in predicting the output (Tsai & Fang, 2021). Therefore, it is essential to introduce activation functions in the neural network to distinguish the hidden layers from each other for better detection and learning of the non-liner relationship between the input and predictor variables (Dubey et al., 2022; Jiang et al., 2022; X. Wang et al., 2022). The model was run over 500 epochs, implying that weights in the hidden layers were constantly adjusted five hundred times to minimize error and improve the maize AGB prediction accuracy. The input data is forwardly propagated to the hidden layers, where the weights and biases in the neurons predict the output by self-learning non-linear patterns from the input dataset. The loss functions quantify the deviation from the expected output and backwardly propagate the output to the hidden layers for adjustments in pursuit of minimising the prediction error (Dubey et al., 2022)

The output layer was fed with a SoftMax activation function and “Adam’ optimizer for model optimization and best results. Optimizers reduce the loss by selecting optimum weights in hidden layers to determine an optimum model for accurate prediction (Cho et al., 2020). Adam is known to surpass other optimizers such as stochastic gradient descent due to its ability of generalization and convergence speed within new datasets (Gaddam et al., 2022; Salem et al., 2022; Y. Wang et al., 2022). A batch size of 32 and normal initialization were also implemented in the model for best results. Neural network models are well known for overfitting, which is explained as when the training dataset yields significantly better results than the testing dataset (Frei et al., 2022). Such model cannot be generalized and cannot accurately predict from an unknown dataset. Therefore, the L2 regularization (0.001) and a dropout of 0.4 were implemented in the layers of the model to minimise overfitting. The dropout and regularization features in DNN minimize loss between the predicted output and observed input and nullify the contribution of "bad" neurons towards subsequent layers, hence a better prediction accuracy.

Accuracy assessment

The Root Mean Square Error (RMSE) and coefficient of determination (R^2) were used to evaluate the metrics. The RMSE is the difference between the predicted and the observed output, while the R^2 reflects the percentage of the AGB variance that is explained by the model. The best performing model is represented by a higher R^2 value and a lower RMSE. The variable importance in predicting maize AGB was evaluated using the SHapley Additive exPlanations (SHAP) approach. The SHAP uses a theoretic approach that selects the top twenty variables of high magnitude impact in the performance of the model (Ekanayake et al., 2022).

Data preparation, variables selection, and model validation

Data preparation and variables selection

The correlation coefficient (R) was calculated between the predictor variables using correlation heat maps to choose significantly low correlated values for best results (Fig.4). Thereafter, highly correlated variables within the dataset were identified and removed to ensure maximum prediction accuracy as such variables have technically the same magnitude impact in the performance of the model.

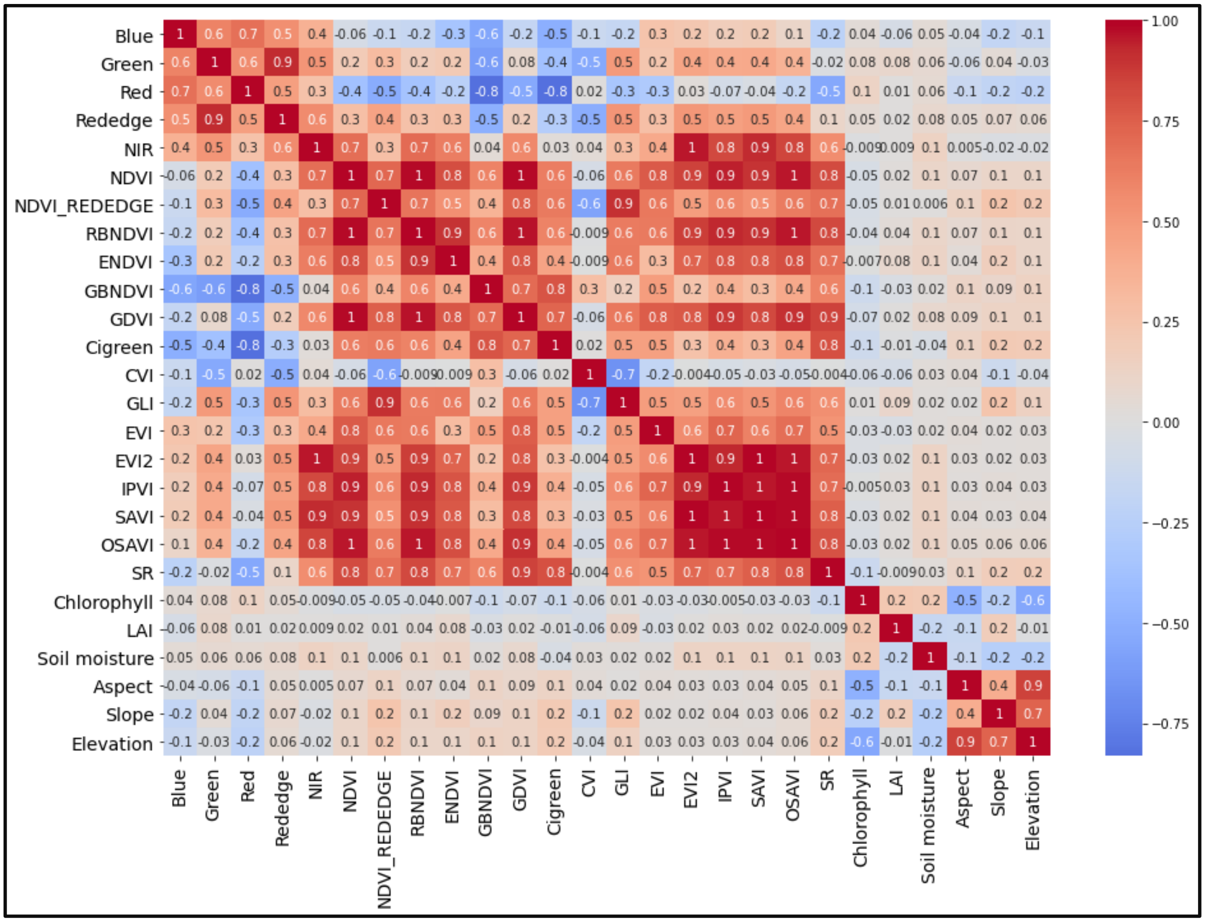


Figure 4. Pearson correlation (R) between the selected maize AGB predictor variables for all the phenological stages.

DNN model validation

Fig.5 shows loss curves during the validation of the DNN model using the training and test dataset over 500 epochs. Model validation is necessary for evaluating the performance of the DNN during self-learning from the dataset. The data was separated into 70% training and 30% testing dataset, and subsequently validated using the latter. The training and validation curves showed a uniform function, implying a gradual decrease in the maize AGB prediction error across all the phenological stages, hence the model was perfectly validated. An optimum model for predicting maize AGB was established and tested using the training dataset.

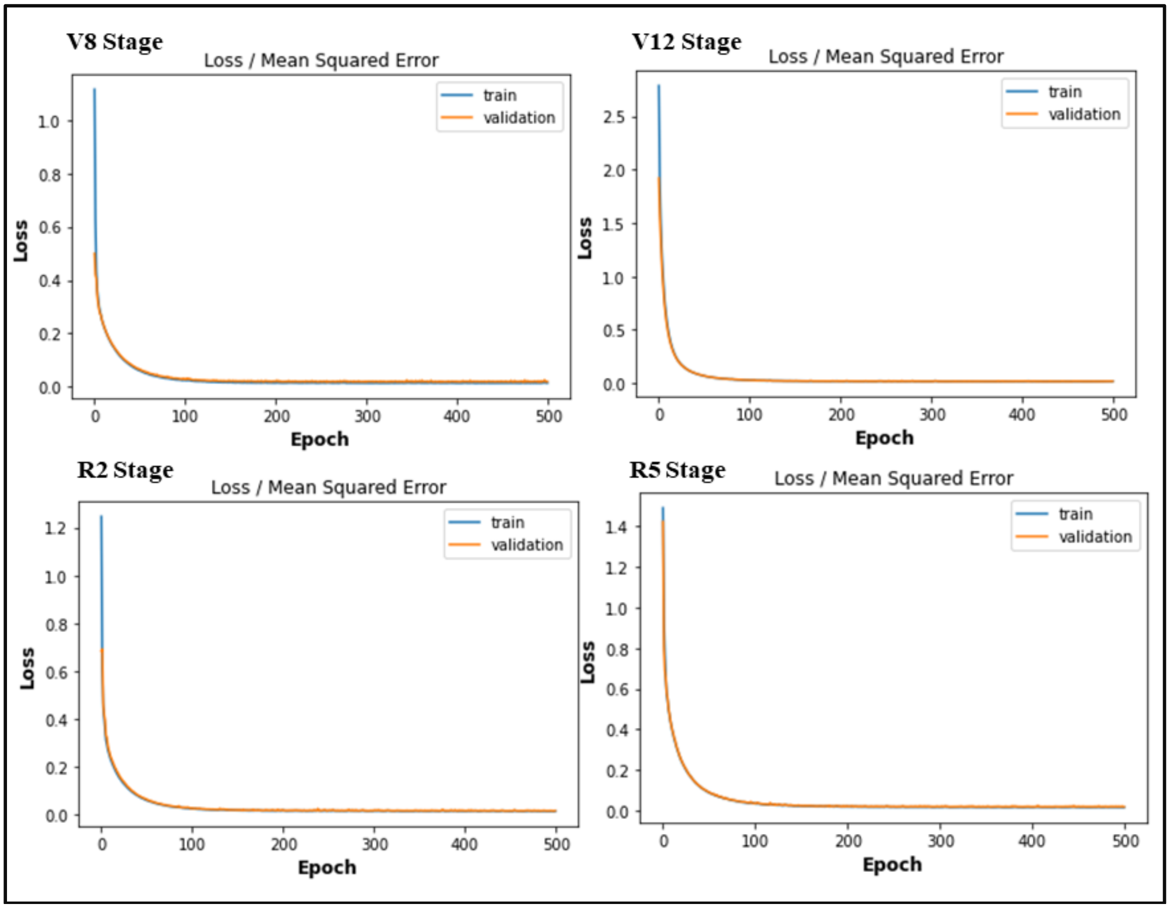


Figure 5. Loss graphs for model validation during all the phenological stages.

RESULTS

Descriptive statistics

The variations in field-measured biophysical and landscape variables of maize crops are shown in Table 4. On average, the recorded SPAD unit-less leaf chlorophyll content was 39.26, 37.38, 31.22, and 41.36 during the V8, V12, R2, and R5 phenological stages, respectively. The R5 phenological stage recorded the highest average chlorophyll content of 41.36. Soil moisture averages were 21.87%, 21.41%, 16.97%, and 19.1% during the V8, V12, R2, and R5 phenological stages, respectively. It was observed that soil moisture content decreased with growth from the V8-R5 phenological stages. The averages for LAI were 3.64, 2.78, 3.25, and 3.16 during the V8, V12, R2, and R5 phenological stages, respectively, with V8 recording the highest average.

Landscape variables are not subjected to rapid changes over a short time and were therefore assumed to be the same throughout the duration of the study. The average slope, elevation, and aspect were 9%, 856 m, and 2.73 degrees, respectively. The slope, elevation, and aspect ranged from 2% to 14%, 847m to 862m, and 2.20 degrees to 3.42 degrees, respectively. The recorded maize AGB was 1.19 kg/m^2 on average and ranged from 0.4 kg/m^2 to 1.81 kg/m^2, with 2.03 kg/m^2 and 2.11 kg/m^2 recorded as outliers. The outliers were due to measurement errors in the field and were therefore removed from the analysis for best results.

Table 4. Descriptive statistics of field measured biophysical and landscape variables across all phenological stages.

		Range (Min-Max)	Mean	Median	Std.
Field measured variables	**V8 Stage**				
	Chlorophyll	31.36-49.61	39.26	38.99	2.59
	LAI	13.99-27.01	21.87	22.16	2.21
	Soil Moisture (%)	2.48-4.64	3.64	3.64	0.25
	V12 Stage	**Range (Min-Max)**	**Mean**	**Median**	**Std.**
	Chlorophyll	29.70- 44.76	37.38	37.60	2.62
	LAI	15.67- 30.41	21.41	21.06	1.57
	Soil Moisture (%)	1.62- 4.58	2.78	2.74	0.23
	R2 Stage	**Range (Min-Max)**	**Mean**	**Median**	**Std.**
	Chlorophyll	21.36- 47.49	31.22	31.55	4.17
	LAI	13.52- 23.67	16.97	16.64	1.36
	Soil Moisture (%)	1.92- 7.75	3.25	3.38	0.49
	R5 Stage	**Range (Min-Max)**	**Mean**	**Median**	**Std.**
	Chlorophyll	21.6-59.4	41.36	41.7	6.27
	LAI	10.6-31.3	19.68	19.4	4.13
	Soil Moisture (%)	1.41-6.8	3.16	3.03	4.85
Landscape variables	**Across all stages**	**Range (Min-Max)**	**Mean**	**Median**	**Std.**
	Slope (%)	2-14	9	10	4
	Elevation (m)	847-862	856	857.6	4.02
	Aspect (degrees)	2.20-3.42	2.73	2.68	0.30

Deep Neural Network model evaluation in maize AGB prediction

Fig. 6 illustrates the maize AGB prediction results obtained when the most important and best performing variables were combined for all phenological stages. The V8 (R^2=0.65, RMSE= 0.1 kg/m^2, RMSE%=8.5%) and R5 (R^2=0.67, RMSE= 0.091 kg/m^2, RMSE%=7.6%) phenological stages had a relatively lower prediction accuracy. However, the prediction error was within the 10 % accepted range. The V12 (R^2=0.74, RMSE=0.07 kg/m^2, RMSE% =5.9%) and R2 (R^2=0.71, RMSE=0.086 kg/m^2, RMSE%=7.3%) phenological stages performed optimally, with relatively high prediction accuracy.

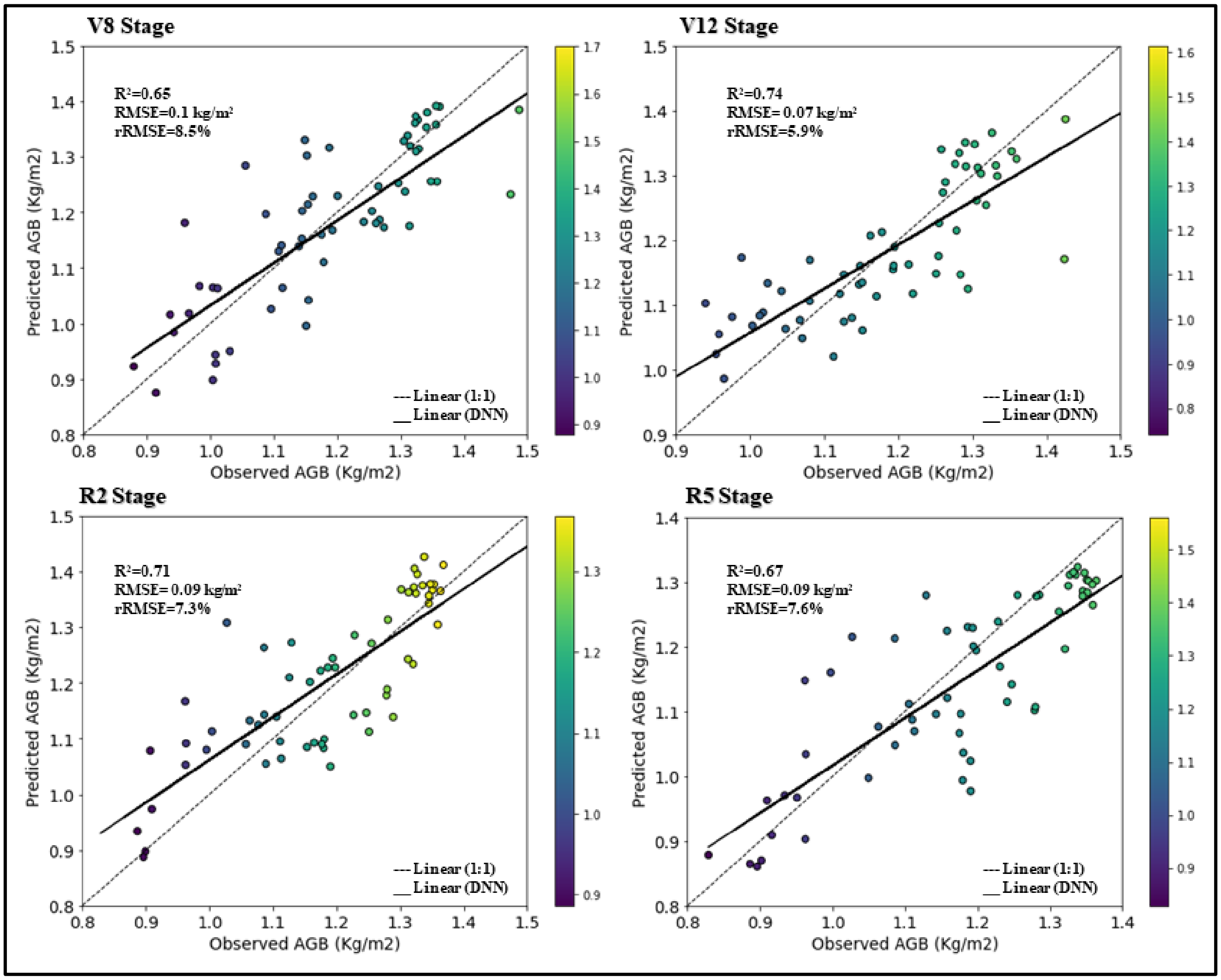


Figure 6. Predicted maize AGB using DNN model for the V8, V12, R2, and R5 phenological stages.

Variable importance assessment

Fig. 7 shows the most important variables in the prediction of maize AGB by the DNN model using the SHAP approach. The SR vegetation index was most important during the V8 and R2, while leaf chlorophyll content and elevation were most influential during the V12 and R5 phenological stages. The figure shows that all landscape variables were important in the prediction of maize AGB across all phenological stages. The biophysical variables (LAI and leaf chlorophyll content) were among the top six important variables during the V8, V12, and R5 phenological stages, while the Red spectral band was the least important variable in maize AGB prediction across all phenological stages. EVI had an extremely low importance in predicting maize AGB during the V12 and R5 phenological stages.

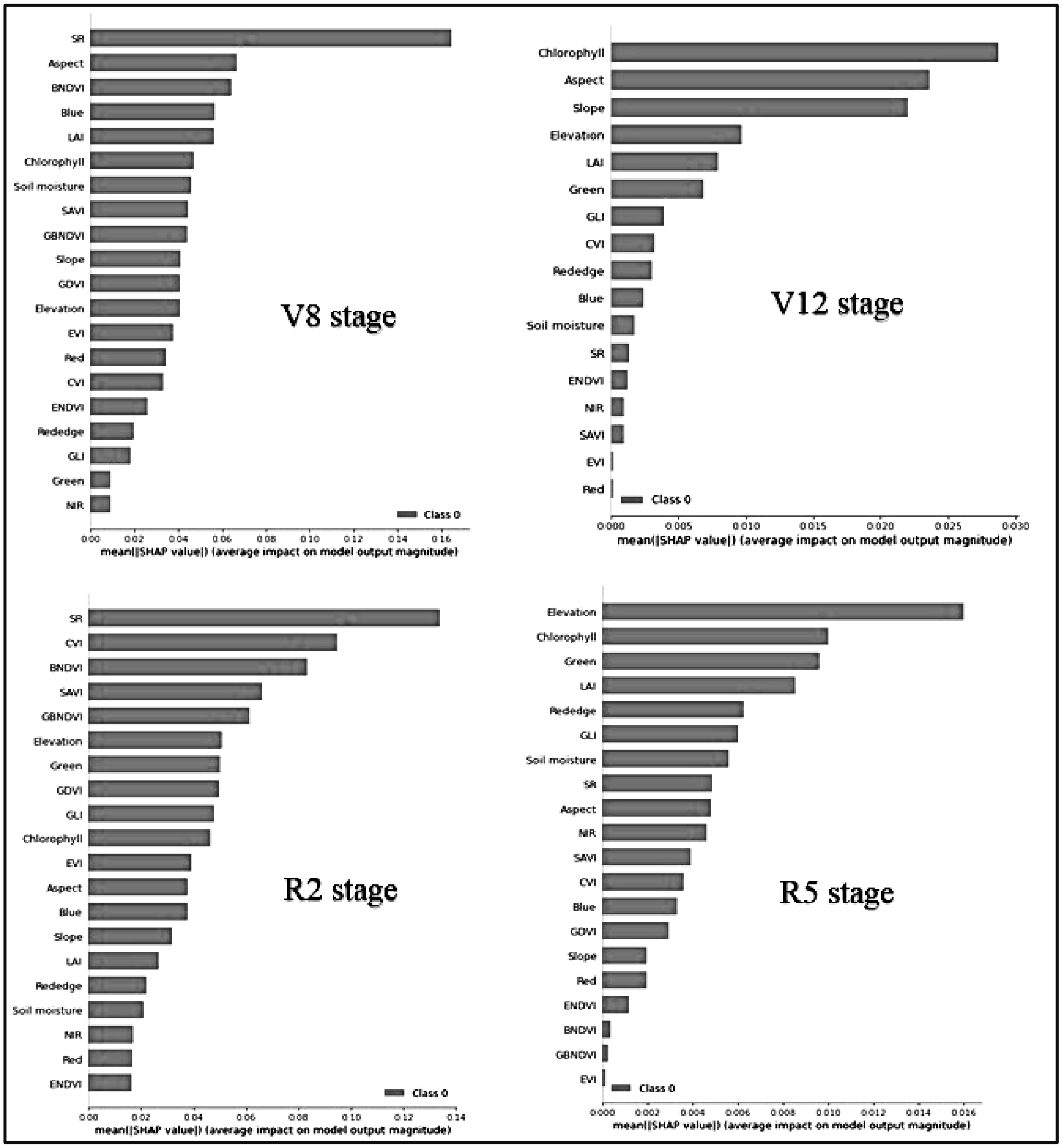


Figure 7. SHAP generated variable importance ranking of the model's input variables for all the phenological stages.

Mapping the spatial distribution of predicted AGB across the phenological stages

Fig.8 shows the spatial distribution of predicted maize AGB during all the phenological stages. The spatial distribution map was generated utilizing the important predictor variables (Fig.7) for maize AGB prediction and the equation of the line of best fit derived from scatter plots comparing predicted and observed AGB at each phenological stage. Typically, a raster file of the most important maize AGB predictor variable is generated using ArcMap, and the equation y=mx+c is applied, substituting x with the raster file. The generated distribution maps show an increase in maize AGB from the V8 to the R2 phenological stage. There was a slight decrease in the concentration of AGB during the R5 stage. This distribution is also shown by the prediction accuracy previously presented in Fig.6, which shows relatively higher prediction accuracy during the V8 and the R1, and lower during the R5 and V8 phenological stages. Similarly, the distribution maps show the same relationship in maize AGB concentration. During all phenological stages, high AGB concentration was observed towards the edges and the field's downslope. In addition, during all the phenological stages, low AGB was observed in a middle of the experimental field.

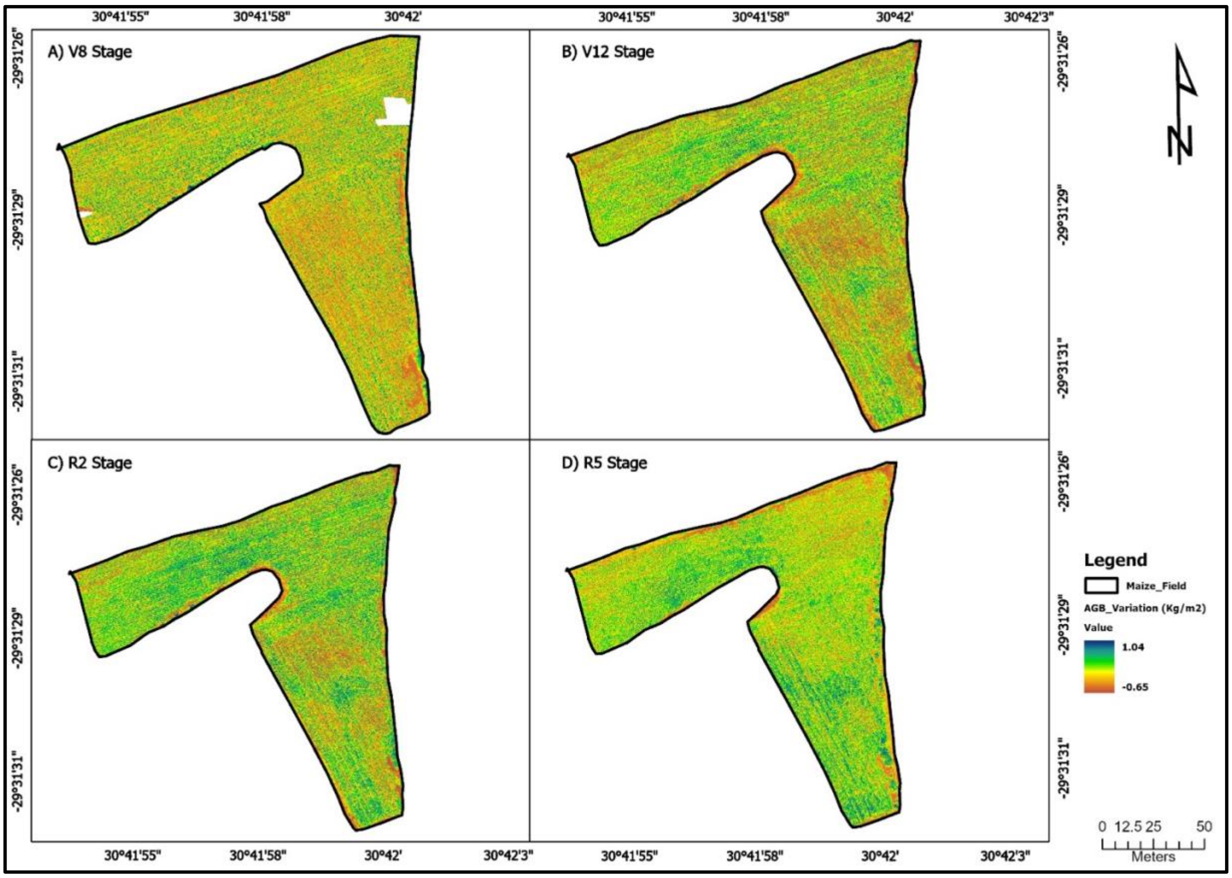


Figure 8. Spatial distribution of predicted maize AGB across all the phonological stage.

DISCUSSION

In developing countries, small-scale farming systems typically lack crop monitoring resources and knowledge on techniques to optimize yield (Onyango et al., 2021). Hence, this study bridged the gap by implementing an affordable crop monitoring resources such as the in-situ instruments, the UAV platform and sensor to accurately estimate maize AGB, which can serve as a proxy to yield. Specifically, this study aimed to develop a model that can accurately predict maize AGB and determine the optimal phenological stage for maize AGB estimation.

The potential of UAV-remotely sensed data in predicting maize AGB

Unmanned Aerial Vehicle-remotely sensed data offer a promising capability to effectively estimate maize AGB in small spatial extents. This is attributed to the remarkable ability of the platform mounted with sophisticated sensors to provide high spatial resolution dataset, enabling individual sensing and assessment of maize crops for accurate AGB estimation (Khun et al., 2021; Niu et al., 2019). Unmanned Aerial Vehicle-mounted cameras such as multispectral sensors offer a broad range of the electromagnetic bands including the visible, NIR, Red-edge, and thermal sections, allowing for efficient retrieval of vegetation indices capable of estimating maize AGB (Olson & Anderson, 2021). This study successfully predicted AGB at various maize phenological stages using UAV-remotely sensed data and deep learning approach. The results indicated that the V12 and R2 phenological stage reported relatively high accuracy in AGB predictions (R^2=0.74 and RMSE=0.07 kg/m^2) and (R^2=0.71 and RMSE= 0.086 kg/m^2), respectively. The V12-R2 phenological stages are the mid-stages of maize growth cycle and portray dark green leaves, symbolizing a high concentration of leaf chlorophyll content (Herrmann et al., 2010). Hence, the best results were obtained during the V12-R2 period due to optimum reflectance of maize leaves and minimal soil background noise. The findings of our study concur with B. Yang et al. (2022) who used multi-temporal and mono-temporal UAV-remotely sensed data and noted that R3 was the most suitable phenological stage for maize AGB prediction. Similarly, Amanullah et al. (2009) investigated maize yield using traditional methods, and established that the V12-R1 phenological stages had relatively higher yield compared to other phenological stages. Therefore, based on our results, we can deduce that V12-R2 is the optimum phenological stage for maize AGB estimation.

The V8 phenological stage and R5 phenological stages had lower maize AGB prediction accuracies, i.e., R^2 = 0.65 and R^2 = 0.67, respectively. This was because the maize canopy was not fully developed and soil background was more pronounced at V8 stage, hence, interfering with maize reflectance signatures (Y. Zeng et al., 2022). The spatial distribution map shows a high maize AGB downslope and some parts of the field where soils were thick and appeared rich in nutrients (Fig.8). Thin soils were also observed upslope and in some parts of the field; low maize AGB was observed in those areas. Considering that the study area is small, there was a significant variation in soil thickness, which is why the predicted concentration of maize AGB is not uniform across the experimental field. Thick soils have a better water retention and nutrient holding capacity for crop's use, hence higher maize AGB (Mu et al., 2018).

Brewer et al. (2022) noted that NIR derived vegetation indices can surpass variable background effects compared to conventional bands. The soil-adjusted vegetation indices were selected to eliminate soil background and accurately predict maize AGB. As expected, SAVI was among the significantly influential variables in the estimation of maize AGB during all the phenological stages, including the V8 where vegetation cover was minimal. The R5 phenological stage was characterized by dry-denting leaves and marked the end of mass gain. We speculate that the dry leaves significantly reduced the reflectance; hence remotely sensed variables were less important and lower maize AGB prediction accuracy was observed during this stage. While Red-edge-based vegetation indices were influential, they did not have a significant contribution to AGB prediction as compared to NIR-derived indices. The findings of this study are supported by Gao et al. (2017) who confirmed the efficacy of vegetation index-based biomass estimation in maize crops.

Plant biophysical variables in maize AGB prediction

The relationship between LAI, leaf chlorophyll content, and AGB is crucial in understanding the physiological and agronomic aspects of maize growth and productivity (Ban et al., 2019). LAI represents the total leaf area per unit ground area and is often indicates the canopy structure and the light interception capacity of maize crop (Liu et al., 2022). It is positively correlated with photosynthetic activity, as a higher LAI generally implies a larger surface area for light absorption, hence high productivity (Li et al., 2023). Leaf chlorophyll content is a key factor influencing photosynthesis, as chlorophyll is responsible for capturing light energy and transform it into chemical energy (Y. Guo et al., 2020). Higher chlorophyll content is generally associated with increased photosynthetic rates, contributing to greater biomass production (Meena et al., 2021). Hence, optimal LAI and chlorophyll content contribute to enhanced photosynthesis, leading to increased biomass accumulation in maize crops.

In this study, the recorded leaf chlorophyll content was higher in the early stage (V8) and the late reproductive stage (R5). This is supported by Brewer et al. (2022) who noted that high chlorophyll concentrations are associated with early vegetation and late reproduction stages when maize grows rapidly and kernelling, respectively. Similarly, leaf chlorophyll content in the early and late reproductive stages is associated with high LAI (H. Yang et al., 2022). As shown by the SHAP variable importance approach, leaf chlorophyll content had a relatively high impact on maize AGB prediction across all the phenological stages. Our results concur with Liu et al. (2019) who established a positive co-relationship between maize AGB and leaf chlorophyll content. In addition, LAI also had a relatively high impact on maize AGB prediction during the V8, V12, and R5 phenological stages. Contrary to our results, Tang et al. (2023) also established a strong relationship between LAI and maize yield after the R1 phenological stage in maize crops.

The potential of landscape variables on improving maize AGB prediction

Landscape variables significantly increased the maize AGB prediction accuracy and were all important during all the phenological stages (Fig.7). In addition, the landscape variables were less correlated to each other, hence the DNN model performed well with their inclusion. A study by Sun et al. (2023) successfully combined topographic variables and vegetation and texture indices to predict maize yield and obtained satisfactory results (R^2 = 0.81, RMSE = 0.297t/ha), which confirms the value of landscape variables in maize AGB prediction. Similarly, Behera et al. (2023) used elevation, slope, and aspect to model maize AGB, and obtained satisfactory results (R^2 = 0.72 and RMSE= 69.18 mg/ha). Salinas-Melgoza et al. (2018) modelled a relationship between landscape variables and noted that landscape variables explained 21% of AGB in reforested areas. Salinas-Melgoza et al. (2018) argued that human activities such as deforestation, land degradation, improper irrigation methods, changing land uses, and pollution have a significant impact on landscape alteration, while crops productivity heavily depend on landscape variables. These human activities facilitate soil erosion, urban expansion, and alterations of soil productivity which significantly affect the slope, aspect, elevation and soil water holding capacity (Mariye et al., 2022).

The performance of deep neural network model in maize AGB prediction

The deep learning approach in maize yield prediction was evaluated using UAV-remotely sensed data combined with biophysical and landscape variables. Furthermore, with DNN requirements for large datasets, the three variables used in this model were adequate to feed enough information to the model for accurate maize AGB prediction. The main objective of this study was to evaluate deep learning approach in maize AGB prediction, particularly with minimal dataset obtained from small spatial extent. To obtain a reliable statistical relationship, DNN require large sample size to effectively learn and discover patterns between the predictor and test variables (Zhang et al., 2021). Therefore, we sampled 200 points to generate an effective model. Based on the overall RMSE and RMSE% achieved in this study, our model had minimal prediction errors (< 10%) across all the phenological stages. In addition, combining three different sources of datasets improved the prediction accuracy of maize AGB. This was because DNN require a lot of complex and nonlinear datasets to perform effectively. Han et al. (2019a) successfully modelled maize AGB in commercial farming systems using DNN and other machine learning algorithms and achieved satisfactory results. However, this study argues that DNNs require significant repeat training, necessitating a lot of computational power to obtain an optimal model in minimal time.

Implications and recommendations

Unmanned Aerial Vehicle-mounted multispectral sensors provide high resolution dataset, allowing for detection of crop agronomical characteristics facilitating maize AGB estimation (Zhai et al., 2023). However, the spectral information of crops remains coarse due to multispectral wide bands portraying lower spectral resolution. Therefore, hyperspectral remote sensing for precise spectral information retrieval and effective maize AGB prediction is highly recommended. Additionally, the study concluded that landscape variables have a significant impact on maize AGB prediction. However, the analysis did not include an assessment of the magnitude of each landscape variable's influence on maize AGB prediction. Hence, it is recommended that forthcoming research endeavours explore the specific impact of individual landscape variables in the prediction of maize AGB. This will contribute to the improvement of validated data availability for further yield predictions. The DNN model requires extensive hyperparameters adjustments to obtain an optimal model. Consequently, its suitability for tasks demanding rapid turnaround times is not recommended. The acquired DNN model was trained using maize derived datasets, and validated using unknown maize dataset, thereby enhancing its applicability in other locations with variability in landscape variables. However, the performance of the acquired model remains limited to adequate dataset and applicable to maize AGB prediction only. Despite the success of the DNN model in adequately predicting maize AGB, more studies need to extensively explore the full potential of this approach, considering its promising potential to make accurate predictions. Despite the success of the DNN model in adequately predicting maize AGB, more studies need to extensively explore the full potential of this approach, considering its promising potential to make accurate predictions.

CONCLUSION

The study sought to assess the utility of landscape and biophysical variables combined with UAV-remotely sensed data in predicting maize AGB using the DNN algorithm at four phenological stages (V8, V12, R2, and R5). Based on the attained results, it can be concluded that:

- The V12-R1 phenological stages are optimal for maize AGB prediction when vegetation reflectance is at peak.
- Landscape variables improve the prediction accuracy of maize AGB and can therefore be used in maize AGB estimation.
- The Near infrared spectral bands were the most influential variables in predicting maize AGB prediction.
- Landscape variables, biophysical variables, and UAV-remotely sensed vegetation indices demonstrated significant importance in predicting maize AGB. Hence, the combination of these variables has demonstrated the ability to improve maize AGB prediction, underscoring the effectiveness achieved through their collaborative utilization in this study.
- Finally, the DNN algorithm yielded satisfactory results, attributable to the combined dynamic and non-linear datasets in pursuit of a good model.

The results of this study have a significant contribution to precision agriculture particularly in underprivileged small-scale farming systems. Furthermore, the findings of this study address gaps in the current literature, notably by introducing smart agriculture concepts to the global south for improved maize production and sustenance.

REFERENCES

Aasen, H., Honkavaara, E., Lucieer, A., & Zarco-Tejada, P. J. (2018). Quantitative remote sensing at ultra-high resolution with UAV spectroscopy: a review of sensor technology, measurement procedures, and data correction workflows. Remote sensing, 10(7), 1091.

Adewopo, J., Peter, H., Mohammed, I., Kamara, A., Craufurd, P., & Vanlauwe, B. (2020). Can a combination of uav-derived vegetation indices with biophysical variables improve yield variability assessment in smallholder farms? [Article]. Agronomy, 10(12), Article 1934. https://doi.org/10.3390/agronomy10121934

Ahamed, T., Tian, L., Zhang, Y., & Ting, K. (2011). A review of remote sensing methods for biomass feedstock production. Biomass and bioenergy, 35(7), 2455-2469.

Ali, A. M., Abouelghar, M., Belal, A., Saleh, N., Yones, M., Selim, A. I., Amin, M. E., Elwesemy, A., Kucher, D. E., & Maginan, S. (2022). Crop yield prediction using multi sensors remote sensing. The Egyptian Journal of Remote Sensing and Space Science, 25(3), 711-716.

Altaweel, M., Khelifi, A., Li, Z., Squitieri, A., Basmaji, T., & Ghazal, M. (2022). Automated archaeological feature detection using deep learning on optical UAV imagery: Preliminary results. Remote sensing, 14(3), 553.

Amanullah, Yasir, M., Khalil, S. K., Jan, M. T., & Khan, A. Z. (2009). Phenology, growth, and grain yield of maize as influenced by foliar applied urea at different growth stages. Journal of Plant Nutrition, 33(1), 71-79.

Ban, H.-Y., Ahn, J.-B., & Lee, B.-W. (2019). Assimilating MODIS data-derived minimum input data set and water stress factors into CERES-Maize model improves regional corn yield predictions. PLoS One, 14(2), e0211874.

Baroni, F., Boscagli, A., Di Lella, L., Protano, G., & Riccobono, F. (2004). Arsenic in soil and vegetation of contaminated areas in southern Tuscany (Italy). Journal of Geochemical Exploration, 81(1-3), 1-14.

Battude, M., Al Bitar, A., Morin, D., Cros, J., Huc, M., Sicre, C. M., Le Dantec, V., & Demarez, V. (2016). Estimating maize biomass and yield over large areas using high spatial and temporal resolution Sentinel-2 like remote sensing data. Remote Sensing of Environment, 184, 668-681.

Behera, D., Kumar, V. A., Rao, J. P., Padal, S., Ayyappan, N., & Reddy, C. S. (2023). Estimating Aboveground Biomass of a Regional Forest Landscape by Integrating Textural and Spectral Variables of Sentinel-2 Along with Ancillary Data. Journal of the Indian Society of Remote Sensing, 1-13.

Brewer, K., Clulow, A., Sibanda, M., Gokool, S., Naiken, V., & Mabhaudhi, T. (2022). Predicting the chlorophyll content of maize over phenotyping as a proxy for crop health in smallholder farming systems. Remote sensing, 14(3), 518.

Buthelezi, S., Mutanga, O., Sibanda, M., Odindi, J., Clulow, A. D., Chimonyo, V. G., & Mabhaudhi, T. (2023). Assessing the prospects of remote sensing maize leaf area index using UAV-derived multi-spectral data in smallholder farms across the growing season. Remote sensing, 15(6), 1597.

Cao, Y., Chen, Z., Belkin, M., & Gu, Q. (2022). Benign overfitting in two-layer convolutional neural networks. Advances in neural information processing systems, 35, 25237-25250.

Che, Y., Wang, Q., Zhou, L., Wang, X., Li, B., & Ma, Y. (2022). The effect of growth stage and plant counting accuracy of maize inbred lines on LAI and biomass prediction. Precision Agriculture, 23(6), 2159-2185.

Cheng, M., Jiao, X., Liu, Y., Shao, M., Yu, X., Bai, Y., Wang, Z., Wang, S., Tuohuti, N., & Liu, S. (2022). Estimation of soil moisture content under high maize canopy coverage from UAV multimodal data and machine learning. Agricultural Water Management, 264, 107530.

Cheng, Z., Meng, J., Ji, F., Wang, Y., Fang, H., & Yu, L. (2020). Aboveground biomass estimation of late-stage maize based on the WOFOST model and UAV observations [Article]. Yaogan Xuebao/Journal of Remote Sensing, 24(11), 1403-1418. https://doi.org/10.11834/jrs.20200069

Cho, H., Kim, Y., Lee, E., Choi, D., Lee, Y., & Rhee, W. (2020). Basic enhancement strategies when using Bayesian optimization for hyperparameter tuning of deep neural networks. IEEE access, 8, 52588-52608.

Coulibaly, S., Kamsu-Foguem, B., Kamissoko, D., & Traore, D. (2022). Deep learning for precision agriculture: A bibliometric analysis. Intelligent Systems with Applications, 16, 200102.

Dominguez-Olmedo, R. (2019). Sample-Efficient Deep Reinforcement Learning for On-The-Fly Thermal Process Control in Laser Powder Bed Fusion University of Sheffield].

Dubey, S. R., Singh, S. K., & Chaudhuri, B. B. (2022). Activation functions in deep learning: A comprehensive survey and benchmark. Neurocomputing.

Ehammer, A., Fritsch, S., Conrad, C., Lamers, J., & Dech, S. (2010). Statistical derivation of fPAR and LAI for irrigated cotton and rice in arid Uzbekistan by combining multi-temporal RapidEye data and ground measurements. Remote Sensing for Agriculture, Ecosystems, and Hydrology XII,

Ekanayake, I., Meddage, D., & Rathnayake, U. (2022). A novel approach to explain the black-box nature of machine learning in compressive strength predictions of concrete using Shapley additive explanations (SHAP). Case Studies in Construction Materials, 16, e01059.

Frei, S., Chatterji, N. S., & Bartlett, P. (2022). Benign overfitting without linearity: Neural network classifiers trained by gradient descent for noisy linear data. Conference on Learning Theory,

Fry, J. E., & Guber, A. K. (2020). Temporal stability of field-scale patterns in soil water content across topographically diverse agricultural landscapes. Journal of Hydrology, 580, 124260.

Fuentes, A., Yoon, S., Kim, S. C., & Park, D. S. (2017). A robust deep-learning-based detector for real-time tomato plant diseases and pests recognition. Sensors, 17(9), 2022.

Gaddam, D. K. R., Ansari, M. D., Vuppala, S., Gunjan, V. K., & Sati, M. M. (2022). A performance comparison of optimization algorithms on a generated dataset. ICDSMLA 2020: Proceedings of the 2nd International Conference on Data Science, Machine Learning and Applications,

Gao, Y., Gao, J., Wang, J., Wang, S., Li, Q., Zhai, S., & Zhou, Y. (2017). Estimating the biomass of unevenly distributed aquatic vegetation in a lake using the normalized water-adjusted vegetation index and scale transformation method. Science of the Total Environment, 601, 998-1007.

Gargiulo, J. I., Lyons, N. A., Masia, F., Beale, P., Insua, J. R., Correa-Luna, M., & Garcia, S. C. (2023). Comparison of Ground-Based, Unmanned Aerial Vehicles and Satellite Remote Sensing Technologies for Monitoring Pasture Biomass on Dairy Farms. Remote sensing, 15(11), 2752.

Geng, L., Che, T., Ma, M., Tan, J., & Wang, H. (2021). Corn biomass estimation by integrating remote sensing and long-term observation data based on machine learning techniques. Remote sensing, 13(12), 2352.

Gerke, D. (2019). An Evaluation of Unmanned Aerial Systems and Structure-From-Motion for Fluvial Large Wood Sensing and Risk Assessment.

Glenn, E. P., Nagler, P. L., & Huete, A. R. (2010). Vegetation index methods for estimating evapotranspiration by remote sensing. Surveys in Geophysics, 31, 531-555.

Goldenberg, M. G., Burian, A., Seppelt, R., Ossa, F. A. S., Bagnato, C. E., Satorre, E. H., Martini, G. D., & Garibaldi, L. A. (2022). Effects of natural habitat composition and configuration, environment and agricultural input on soybean and maize yields in Argentina. Agriculture, Ecosystems & Environment, 339, 108133.

Guo, Y., Wang, H., Wu, Z., Wang, S., Sun, H., Senthilnath, J., Wang, J., Bryant, C. R., & Fu, Y. (2020). Modified red blue vegetation index for chlorophyll estimation and yield prediction of maize from visible images captured by uav [Article]. Sensors (Switzerland), 20(18), 1-16, Article 5055. https://doi.org/10.3390/s20185055

Guo, Y., Wang, H., Wu, Z., Wang, S., Sun, H., Senthilnath, J., Wang, J., Robin Bryant, C., & Fu, Y. (2020). Modified red blue vegetation index for chlorophyll estimation and yield prediction of maize from visible images captured by UAV. Sensors, 20(18), 5055.

Haarhoff, S. J., Kotzé, T. N., & Swanepoel, P. A. (2020). A prospectus for sustainability of rainfed maize production systems in South Africa. Crop Science, 60(1), 14-28.

Han, L., Yang, G., Dai, H., Xu, B., Yang, H., Feng, H., Li, Z., & Yang, X. (2019a). Modeling maize above-ground biomass based on machine learning approaches using UAV remote-sensing data. Plant Methods, 15(1), 10. https://doi.org/10.1186/s13007-019-0394-z

Han, L., Yang, G., Dai, H., Xu, B., Yang, H., Feng, H., Li, Z., & Yang, X. (2019b). Modeling maize above-ground biomass based on machine learning approaches using UAV remote-sensing data. Plant methods, 15(1), 1-19.

Heiskanen, J. (2006). Estimating aboveground tree biomass and leaf area index in a mountain birch forest using ASTER satellite data. International Journal of Remote Sensing, 27(6), 1135-1158.

Herrmann, I., Karnieli, A., Bonfil, D., Cohen, Y., & Alchanatis, V. (2010). SWIR-based spectral indices for assessing nitrogen content in potato fields. International Journal of Remote Sensing, 31(19), 5127-5143.

Hunt Jr, E. R., Daughtry, C., Eitel, J. U., & Long, D. S. (2011). Remote sensing leaf chlorophyll content using a visible band index. Agronomy Journal, 103(4), 1090-1099.

Jiang, F., Sun, H., Ma, K., Fu, L., & Tang, J. (2022). Improving aboveground biomass estimation of natural forests on the Tibetan Plateau using spaceborne LiDAR and machine learning algorithms. Ecological Indicators, 143, 109365.

Kapočiūtė-Dzikienė, J., Balodis, K., & Skadiņš, R. (2020). Intent detection problem solving via automatic DNN hyperparameter optimization. Applied Sciences, 10(21), 7426.

Kayad, A., Sozzi, M., Gatto, S., Marinello, F., & Pirotti, F. (2019). Monitoring within-field variability of corn yield using Sentinel-2 and machine learning techniques. Remote sensing, 11(23), 2873.

Khaki, S., & Wang, L. (2019). Crop yield prediction using deep neural networks. Frontiers in plant science, 10, 621.

Khan, S. N., Li, D., & Maimaitijiang, M. (2022). A Geographically Weighted Random Forest Approach to Predict Corn Yield in the US Corn Belt. Remote sensing, 14(12), 2843.

Khun, K., Tremblay, N., Panneton, B., Vigneault, P., Lord, E., Cavayas, F., & Codjia, C. (2021). Use of oblique RGB imagery and apparent surface area of plants for early estimation of above-ground corn biomass [Article]. Remote Sensing, 13(20), Article 4032. https://doi.org/10.3390/rs13204032

Kooistra, L., Leuven, R., Wehrens, R., Nienhuis, P., & Buydens, L. (2003). A comparison of methods to relate grass reflectance to soil metal contamination. International Journal of Remote Sensing, 24(24), 4995-5010.

Leroux, L., Castets, M., Baron, C., Escorihuela, M.-J., Bégué, A., & Seen, D. L. (2019). Maize yield estimation in West Africa from crop process-induced combinations of multi-domain remote sensing indices. European Journal of Agronomy, 108, 11-26.

Li, B., Xu, X., Zhang, L., Han, J., Bian, C., Li, G., Liu, J., & Jin, L. (2020). Above-ground biomass estimation and yield prediction in potato by using UAV-based RGB and hyperspectral imaging. ISPRS Journal of Photogrammetry and Remote Sensing, 162, 161-172.

Li, F., Hao, D., Zhu, Q., Yuan, K., Braghiere, R. K., He, L., Luo, X., Wei, S., Riley, W. J., & Zeng, Y. (2023). Vegetation clumping modulates global photosynthesis through adjusting canopy light environment. Global Change Biology, 29(3), 731-746.

Li, W., Niu, Z., Chen, H., Li, D., Wu, M., & Zhao, W. (2016). Remote estimation of canopy height and aboveground biomass of maize using high-resolution stereo images from a low-cost unmanned aerial vehicle system. Ecological Indicators, 67, 637-648.

Li, X., Geng, H., Zhang, L., Peng, S., Xin, Q., Huang, J., Li, X., Liu, S., & Wang, Y. (2022). Improving maize yield prediction at the county level from 2002 to 2015 in China using a novel deep learning approach. Computers and Electronics in Agriculture, 202, 107356.

Li, Z., Zhao, Y., Taylor, J., Gaulton, R., Jin, X., Song, X., Li, Z., Meng, Y., Chen, P., & Feng, H. (2022). Comparison and transferability of thermal, temporal and phenological-based in-season predictions of above-ground biomass in wheat crops from proximal crop reflectance data. Remote Sensing of Environment, 273, 112967.

Lischeid, G., Webber, H., Sommer, M., Nendel, C., & Ewert, F. (2022). Machine learning in crop yield modelling: A powerful tool, but no surrogate for science. Agricultural and Forest Meteorology, 312, 108698.

Liu, C., Liu, Y., Lu, Y., Liao, Y., Nie, J., Yuan, X., & Chen, F. (2019). Use of a leaf chlorophyll content index to improve the prediction of above-ground biomass and productivity. PeerJ, 6, e6240.

Liu, G., Yang, Y., Liu, W., Guo, X., Xie, R., Ming, B., Xue, J., Zhang, G., Li, R., & Wang, K. (2022). Optimized canopy structure improves maize grain yield and resource use efficiency. Food and Energy Security, 11(2), e375.

Liu, J., Fang, Y., Wang, G., Liu, B., & Wang, R. (2023). The aging of farmers and its challenges for labor-intensive agriculture in China: A perspective on farmland transfer plans for farmers' retirement. Journal of Rural Studies, 100, 103013.

Luo, S., Wang, C., Xi, X., Nie, S., Fan, X., Chen, H., Yang, X., Peng, D., Lin, Y., & Zhou, G. (2019). Combining hyperspectral imagery and LiDAR pseudo-waveform for predicting crop LAI, canopy height and above-ground biomass. Ecological Indicators, 102, 801-812.

Malthus, T. J., Andrieu, B., Danson, F. M., Jaggard, K. W., & Steven, M. D. (1993). Candidate high spectral resolution infrared indices for crop cover. Remote Sensing of Environment, 46(2), 204-212.

Mariye, M., Mariyo, M., Changming, Y., Teffera, Z. L., & Weldegebrial, B. (2022). Effects of land use and land cover change on soil erosion potential in Berhe district: A case study of Legedadi watershed, Ethiopia. International Journal of River Basin Management, 20(1), 79-91.

Meena, R. K., Reddy, K. S., Gautam, R., Maddela, S., Reddy, A. R., & Gudipalli, P. (2021). Improved photosynthetic characteristics correlated with enhanced biomass in a heterotic F 1 hybrid of maize (Zea mays L.). Photosynthesis Research, 147, 253-267.

Meiyan, S., Mengyuan, S., Qizhou, D., Xiaohong, Y., Baoguo, L., & Yuntao, M. (2022). Estimating the maize above-ground biomass by constructing the tridimensional concept model based on UAV-based digital and multi-spectral images. Field Crops Research, 282, 108491.

Mgbenka, R., Mbah, E., & Ezeano, C. (2016). A review of smallholder farming in Nigeria: Need for transformation. International Journal of Agricultural Extension and Rural Development Studies, 3(2), 43-54.

Miura, T., Yoshioka, H., Fujiwara, K., & Yamamoto, H. (2008). Inter-comparison of ASTER and MODIS surface reflectance and vegetation index products for synergistic applications to natural resource monitoring. Sensors, 8(4), 2480-2499.

Mu, C., Li, L., Zhang, F., Li, Y., Xiao, X., Zhao, Q., & Zhang, T. (2018). Impacts of permafrost on above-and belowground biomass on the northern Qinghai-Tibetan Plateau. Arctic, Antarctic, and Alpine Research, 50(1), e1447192.

Muruganantham, P., Wibowo, S., Grandhi, S., Samrat, N. H., & Islam, N. (2022). A Systematic Literature Review on Crop Yield Prediction with Deep Learning and Remote Sensing. Remote sensing, 14(9), 1990. https://www.mdpi.com/2072-4292/14/9/1990

Ndlovu, H. S., Odindi, J., Sibanda, M., Mutanga, O., Clulow, A., Chimonyo, V. G., & Mabhaudhi, T. (2021). A comparative estimation of maize leaf water content using machine learning techniques and unmanned aerial vehicle (UAV)-based proximal and remotely sensed data. Remote sensing, 13(20), 4091.

Ngoune Tandzi, L., & Mutengwa, C. S. (2019). Estimation of maize (Zea mays L.) yield per harvest area: Appropriate methods. Agronomy, 10(1), 29.

Niu, Y., Zhang, L., Zhang, H., Han, W., & Peng, X. (2019). Estimating above-ground biomass of maize using features derived from UAV-based RGB imagery [Article]. Remote Sensing, 11(11), Article 1261. https://doi.org/10.3390/rs11111261

Odebiri, O., Mutanga, O., Odindi, J., Naicker, R., Masemola, C., & Sibanda, M. (2021a). Deep learning approaches in remote sensing of soil organic carbon: A review of utility, challenges, and prospects. Environmental Monitoring and Assessment, 193, 1-18.

Odebiri, O., Mutanga, O., Odindi, J., Naicker, R., Masemola, C., & Sibanda, M. (2021b). Deep learning approaches in remote sensing of soil organic carbon: a review of utility, challenges, and prospects. Environmental Monitoring and Assessment, 193(12), 802. https://doi.org/10.1007/s10661-021-09561-6

Olson, D., & Anderson, J. (2021). Review on unmanned aerial vehicles, remote sensors, imagery processing, and their applications in agriculture. Agronomy Journal, 113(2), 971-992.

Onyango, C. M., Nyaga, J. M., Wetterlind, J., Söderström, M., & Piikki, K. (2021). Precision agriculture for resource use efficiency in smallholder farming systems in sub-saharan africa: A systematic review. Sustainability (Switzerland), 13(3), 1158.

Palacios-Rojas, N., McCulley, L., Kaeppler, M., Titcomb, T. J., Gunaratna, N. S., Lopez-Ridaura, S., & Tanumihardjo, S. A. (2020). Mining maize diversity and improving its nutritional aspects within agro-food systems. Comprehensive Reviews in Food Science and Food Safety, 19(4), 1809-1834.

Peter, B. G., Messina, J. P., Carroll, J. W., Zhi, J., Chimonyo, V., Lin, S., & Snapp, S. S. (2020). Multi-spatial resolution satellite and sUAS imagery for precision agriculture on smallholder farms in Malawi. Photogrammetric Engineering & Remote Sensing, 86(2), 107-119.

Polzin, M., & Hughes, J. (2023). Automation in steep terrain agriculture: an optimal controller to prevent tipping and slipping of tethered robots on slopes. Advanced Robotics, 37(15), 987-998.

Salem, H., Kabeel, A., El-Said, E. M., & Elzeki, O. M. (2022). Predictive modelling for solar power-driven hybrid desalination system using artificial neural network regression with Adam optimization. Desalination, 522, 115411.

Salinas-Melgoza, M. A., Skutsch, M., & Lovett, J. C. (2018). Predicting aboveground forest biomass with topographic variables in human-impacted tropical dry forest landscapes. Ecosphere, 9(1), e02063. https://doi.org/https://doi.org/10.1002/ecs2.2063

Saranya, T., Deisy, C., Sridevi, S., & Anbananthen, K. S. M. (2023). A comparative study of deep learning and Internet of Things for precision agriculture. Engineering Applications of Artificial Intelligence, 122, 106034.

Sharma, P., Leigh, L., Chang, J., Maimaitijiang, M., & Caffé, M. (2022). Above-ground biomass estimation in oats using UAV remote sensing and machine learning. Sensors, 22(2), 601.

Shi, H., & Xingguo, M. (2011). Interpreting spatial heterogeneity of crop yield with a process model and remote sensing. Ecological Modelling, 222(14), 2530-2541.

Sun, X., Yang, Z., Su, P., Wei, K., Wang, Z., Yang, C., Wang, C., Qin, M., Xiao, L., & Yang, W. (2023). Non-destructive monitoring of maize LAI by fusing UAV spectral and textural features. Frontiers in plant science, 14, 1158837.

Svedin, J. D., Kerry, R., Hansen, N. C., & Hopkins, B. G. (2021). Identifying within-field spatial and temporal crop water stress to conserve irrigation resources with variable-rate irrigation. Agronomy, 11(7), 1377.

Tang, Y., Zhou, R., He, P., Yu, M., Zheng, H., Yao, X., Cheng, T., Zhu, Y., Cao, W., & Tian, Y. (2023). Estimating wheat grain yield by assimilating phenology and LAI with the WheatGrow model based on theoretical uncertainty of remotely sensed observation. Agricultural and Forest Meteorology, 339, 109574.

Tollenaar, M., & Lee, E. (2002). Yield potential, yield stability and stress tolerance in maize. Field Crops Research, 75(2-3), 161-169.

Tripathi, A., Tiwari, R. K., & Tiwari, S. P. (2022). A deep learning multi-layer perceptron and remote sensing approach for soil health based crop yield estimation. INTERNATIONAL JOURNAL OF APPLIED EARTH OBSERVATION AND GEOINFORMATION, 113, 102959.

Tsai, C.-W., & Fang, Z.-Y. (2021). An effective hyperparameter optimization algorithm for DNN to predict passengers at a metro station. ACM Transactions on Internet Technology (TOIT), 21(2), 1-24.

Tucker, C. J., Elgin Jr, J., McMurtrey Iii, J., & Fan, C. (1979). Monitoring corn and soybean crop development with hand-held radiometer spectral data. Remote Sensing of Environment, 8(3), 237-248.

Vélez, S., Martínez-Peña, R., & Castrillo, D. (2023). Beyond Vegetation: A Review Unveiling Additional Insights into Agriculture and Forestry through the Application of Vegetation Indices. J, 6(3), 421-436.

Verschuur, J., Li, S., Wolski, P., & Otto, F. E. (2021). Climate change as a driver of food insecurity in the 2007 Lesotho-South Africa drought. Scientific reports, 11(1), 3852.

Vojnov, B., Jaćimović, G., Šeremešić, S., Pezo, L., Lončar, B., Krstić, Đ., Vujić, S., & Ćupina, B. (2022). The effects of winter cover crops on maize yield and crop performance in semiarid conditions—artificial neural network approach. Agronomy, 12(11), 2670.

Wang, F.-M., HUANG, J.-f., TANG, Y.-l., & WANG, X.-z. (2007). New vegetation index and its application in estimating leaf area index of rice. Rice Science, 14(3), 195-203.

Wang, X., Ren, H., & Wang, A. (2022). Smish: A novel activation function for deep learning methods. Electronics, 11(4), 540.

Wang, Y., Xiao, Z., & Cao, G. (2022). A convolutional neural network method based on Adam optimizer with power-exponential learning rate for bearing fault diagnosis. Journal of Vibroengineering, 24(4), 666-678.

Wu, C., Niu, Z., Tang, Q., & Huang, W. (2008). Estimating chlorophyll content from hyperspectral vegetation indices: Modeling and validation. Agricultural and Forest Meteorology, 148(8-9), 1230-1241.

Yang, B., Zhu, W., Rezaei, E. E., Li, J., Sun, Z., & Zhang, J. (2022). The optimal phenological phase of maize for yield prediction with high-frequency UAV remote sensing. Remote sensing, 14(7), 1559.

Yang, H., Ming, B., Nie, C., Xue, B., Xin, J., Lu, X., Xue, J., Hou, P., Xie, R., & Wang, K. (2022). Maize Canopy and Leaf Chlorophyll Content Assessment from Leaf Spectral Reflectance: Estimation and Uncertainty Analysis across Growth Stages and Vertical Distribution. Remote Sensing, 14(9), 2115.

Yue, J., Yang, H., Yang, G., Fu, Y., Wang, H., & Zhou, C. (2023). Estimating vertically growing crop above-ground biomass based on UAV remote sensing. Computers and Electronics in Agriculture, 205, 107627.

Zeng, Y., Hao, D., Huete, A., Dechant, B., Berry, J., Chen, J. M., Joiner, J., Frankenberg, C., Bond-Lamberty, B., & Ryu, Y. (2022). Optical vegetation indices for monitoring terrestrial ecosystems globally. Nature Reviews Earth & Environment, 3(7), 477-493.

Zeng, Z., Yao, Y., Liu, Z., & Sun, M. (2022). A deep-learning system bridging molecule structure and biomedical text with comprehension comparable to human professionals. Nature communications, 13(1), 862.

Zhai, W., Li, C., Cheng, Q., Mao, B., Li, Z., Li, Y., Ding, F., Qin, S., Fei, S., & Chen, Z. (2023). Enhancing Wheat Above-Ground Biomass Estimation Using UAV RGB Images and Machine Learning: Multi-Feature Combinations, Flight Height, and Algorithm Implications. Remote Sensing, 15(14), 3653.

Zhang, H., Zhao, S., Song, Y., Ge, S., Liu, D., Yang, X., & Wu, K. (2022). A deep learning and Grad-Cam-based approach for accurate identification of the fall armyworm (Spodoptera frugiperda) in maize fields. Computers and Electronics in Agriculture, 202, 107440.

Zhang, Y., Xia, C., Zhang, X., Cheng, X., Feng, G., Wang, Y., & Gao, Q. (2021). Estimating the maize biomass by crop height and narrowband vegetation indices derived from UAV-based hyperspectral images. Ecological Indicators, 129, 107985. https://doi.org/https://doi.org/10.1016/j.ecolind.2021.107985

ENHANCING THE ESTIMATION OF EQUIVALENT WATER THICKNESS IN NEGLECTED AND UNDERUTILIZED TARO CROPS USING UAV ACQUIRED MULTISPECTRAL THERMAL IMAGE DATA AND INDEX-BASED IMAGE SEGMENTATION

#11212

[1*]Helen S. Ndlovu, [1]John Odindi, [2]Mbulisi Sibanda, [1]Onisimo Mutanga
[1] Discipline of Geography and Environmental Science, School of Agricultural Earth and Environmental Sciences, University of KwaZulu-Natal, Scottsville, Pietermaritzburg 3209, South Africa; [2]Department of Geography, Environmental Studies & Tourism, Faculty of Arts, University of the Western Cape, Bellville, Cape Town 7535, South Africa.
*e-mail: 216016417@stu.ukzn.ac.za

ABSTRACT

Due to the impact of climate variability and change, smallholder farmers are increasingly faced with the challenge of sustaining crop production. Taro, recognized as a future smart neglected and underutilized crop due to its resilience to abiotic stresses, has emerged as valuable for diversifying crop farming systems and sustaining local livelihoods. Nonetheless, a significant research gap exists in spatially explicit information on the water status of taro, contributing to the paradox of its ability to adapt to diverse agro-ecological conditions. Precision agriculture, including the use of unmanned aerial vehicles (UAVs) equipped with high-resolution multispectral and thermal imagery, has proven effective in farm-scale monitoring and provides near-real-time information on crop water status. Hence, this study sought to evaluate the utility of multispectral and thermal infrared UAV imagery in understanding taro's water status. Leveraging deep learning techniques to evaluate the use of thermal remote sensing and three index-based segmentation techniques in predicting the canopy equivalent water thickness (EWT) of taro crops, this study sought to determine EWT as a proxy to its water status in smallholder farmlands. The study findings illustrate a significant difference in the prediction accuracies of taro EWT with and without the thermal band ($P < 0.05$). Additionally, results ($R^2 = 0.92$, RMSE = 8.04 g/m^2, and rRMSE = 15.31% including the thermal band and 0.91, 8.73 g/m^2, and 16.64% excluding the thermal band) reveal the value of the Excess Green minus Excess Red (ExGR) technique in accurately predicting EWT_{canopy}. Furthermore, the near-infrared, red edge, and thermal sections of the electromagnetic spectrum, together with their derived indices, were critical in estimating taro EWT. This study serves as a foundation for a robust, efficient, and spatially explicit monitoring framework of neglected and underutilized crops such as taro. Furthermore, this study offers valuable insights into neglected and underutilized crop water use within smallholder farming systems, critical for optimizing crop productivity and mitigating the effects of climatic variability and change.

INTRODUCTION

The world is challenged by the pressing need to sustain food supply and ensure food security due to climate change and the increasing global population (Din et al., 2022; Hillary Mugiyo et al., 2021). Recently, driven by water scarcity, there has been increasing interest in the potential use of neglected and underutilised crop species (NUS) in addressing food and nutrition challenges (Chivenge et al., 2015; Mabhaudhi et al., 2017; Hillary Mugiyo et al., 2021). NUS, characterised by historical domestication with limited scientific research and predominantly confined to smallholder farming systems, have emerged as key drought-tolerant crops for diversifying communal cropping systems (Chivenge et al., 2015; Mabhaudhi et al., 2017). Taro (*Colocasia esculenta (L)*) is one of the oldest and most widely cultivated NUS crops in the world's tropical and subtropical regions (Mabhaudhi et al., 2011; Mawoyo et al., 2017; Van Wyk, 2021). In South Africa, taro, locally known as *amadumbe*, is known to be heat tolerant and primarily cultivated for subsistence, especially within small and marginalised communities (Joshi et al., 2020; Mabhaudhi et al., 2014; Oyeyinka & Amonsou, 2020; Van Wyk, 2021). Taro is identified as a future smart food under the NUS category because of its edible tubers, which are rich in carbohydrates, protein, and vitamins (Kapoor et al., 2022; Li & Siddique, 2018). Despite taro and indeed other NUS's value, literature shows that they have largely been ignored.

Thermal infrared remote sensing has emerged as a valuable tool for crop water assessment and monitoring, offering a direct correlation with crop water biophysical and biochemical elements (Khanal et al., 2017; Messina & Modica, 2020). The recent advancements in image acquisition, like unmanned aerial vehicles (UAVs) mounted with light-weight multispectral sensors provide, spatially explicit near-real-time information on crop water status (Hussain et al., 2020). In addition to ultra-high spatial resolutions of UAV multispectral thermal imagery, image enhancement techniques and robust algorithms have been demonstrated to improve model accuracies. For instance, Index-Based Image Segmentation has been demonstrated to be effective in robustly segmenting plants in colour images, enabling the extraction of vegetation cover and removing soil background for enhanced crops spectral signatures (Hamuda et al., 2016). (Lu et al., 2022). The Excess Green (ExG) and Excess Red (ExR) indices were proposed by Woebbecke et al. (1995) and Meyer et al. (1999), respectively, to enhance plant segmentation accuracy by emphasizing plant greenness by accounting for the relative proportions of red and physiological green. Additionally, Meyer and Neto (2008) leveraged the strength of both ExG and ExR to develop the Excess Green minus Excess Red (ExGR) index to improve crop water assessment and monitoring using thermal remote sensing systems.

In this regard, leveraging the capabilities of deep learning, this study sought to assess the performance of thermal remote sensing and index-based segmentation techniques in improving canopy EWT estimation of smallholder taro crops using UAV multispectral thermal imagery. Specifically, the study sought to: (1) assess the potential of the UAV thermal band in estimating EWT of smallholder taro, (2) compare the performance of crop canopy images extracted using the ExG, ExR, and ExGR color indices in improving EWT estimations of taro crop, and (3) evaluate the potential of UAV multispectral thermal imagery in EWT estimations of taro crop in smallholder farming systems.

MATERIALS AND METHODS

Study area description and the experimental field

This research was conducted in the rural community of Swayimana, situated within the uMshwathi Municipality, northeast of Pietermaritzburg city, KwaZulu-Natal, South Africa (29°31′ 24'' S; 30°41′ 37'' E) (Figure 1).

The taro experimental plot was cultivated during the early rainy season, aligning with its optimal growing conditions. The selected plot covered 2864.56 m^2 and was rainfed. The taro crop was sown in mid-October 2022 and was approximately 171 days old at the time of the experiment. Specifically, the crop was intermediate between the late vegetative and early maturity growth stages. The selection of this growth stage is crucial for capturing the developmental dynamics of the crop during a period of heightened canopy growth, providing valuable insights for the research objectives.

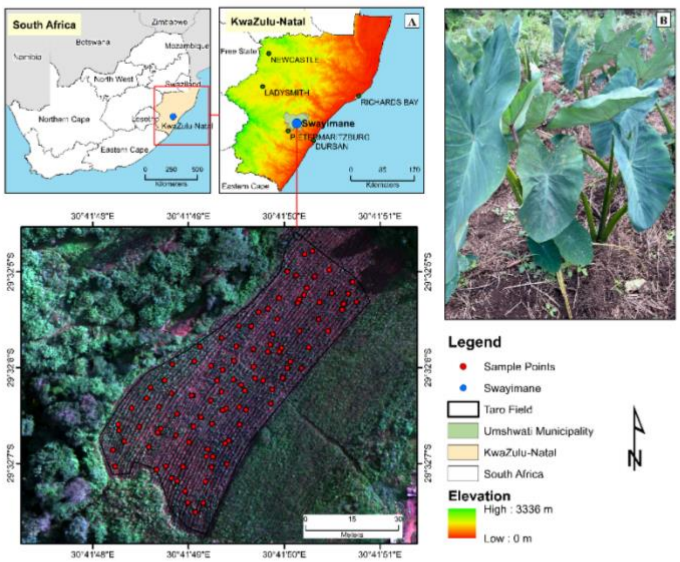


Figure 1. a) Location of experimental field in Swayimane and b) taro crops.

Field Sampling and in-situ measurements

A polygon delineating the taro field was created using Google Earth Pro and imported into ArcMap 10.6 to facilitate the generation of 100 stratified random sampling points. This approach was adopted to ensure variability and accurate representation of all taro crops within the field. These sampling points were subsequently uploaded into a Trimble handheld Global Positioning System (GPS) with a sub-centimetre accuracy, enabling precise location of each sampling point within the taro field. In-situ measurements were obtained at each sampling point to compute respective EWT values.

A portable LiCOR-2200C Plant Canopy Analyzer was used to obtain the leaf area index (LAI) of the crops. The LAI measurements were obtained using the 38° zenith angle with a 270° view cap and the ABBBB sequence, where A corresponds to a reference reading ‘above’ the canopy and B corresponds to a reading ‘below’ the canopy. Thereafter, the above ground biomass of each sampled crop was obtained, and the fresh weight (FW) obtained using a calibrated scale with a 0.5 g measurement error. The sampled biomass was then placed in a labelled brown paper bag and dried in an oven at 60 °C, until a constant dry weight (DW) was reached (approximately 72 hrs).

UAV platform and multispectral-thermal camera

The DJI Matrice 300 (M300) platform, mounted with a MicaSense Altum camera and Downwelling Light Sensor 2 (DLS 2) was used to collect multispectral-thermal imagery. A total of 1626 raw images of the experimental field were obtained and pre-processed in Pix4D photogrammetry software. Ground reference points surveyed prior to fieldwork were then used to improve the geometric accuracy of the acquired images in ArcGIS 10.6. Lastly, EWT_{canopy} in-situ measurements and the locational of each sampled taro point were overlaid with UAV multispectral-thermal image. The multispectral and thermal reflectance data of taro was extracted from the UAV imagery and used to derive vegetation indices (VIs) for the development of the EWT_{canopy} prediction model. These VIs were selected based on their optimal performance in literature and relationship with crop water status (Baluja et al., 2012; Ozelkan, 2020; Zhang & Zhou, 2019).

Index-based image segmentation of taro crops' spectral signatures

To delineate the crop canopy and eliminate soil background from the multispectral thermal image, an index-based segmentation technique was employed. Specifically, The Excess Green (ExG), Excess Red (ExR), and Excess Green minus Excess Red (ExGR) color indices were computed using the green, red, and blue bands of the UAV multispectral thermal imagery (Hamuda et al., 2016; Meyer et al., 1999; Meyer & Neto, 2008; Woebbecke et al., 1995). Finally, the threshold method was used to generate a binary image from the gray-level histograms obtained during the index-based segmentation process (Shu et al., 2021).

Model development and statistical analysis

In this study, we employed a deep machine learning approach to estimate EWT_{canopy} using UAV derived multispectral optical and thermal datasets. The study utilised a three-layer neural network model consisting of an input layer, a hidden layer, and an output layer. A rectified linear unit (ReLU) was applied to stimulate the EWT_{canopy} prediction model with the maximum epochs set to 200 interactions, indicating that the weights in the hidden layers were iteratively adjusted 200 times to reduce error and enhance EWT_{canopy} prediction accuracy. Thereafter, the SoftMax activation function was used to transform the raw outputs of the neural network into a vector of probabilities, and the Adaptive moment estimation (Adam) optimizer was used to optimise the results of the output model. Furthermore, the dropout regularization technique was applied to avoid overfitting and improve the generalization of the model (Deepan & Sudha, 2020). The hyperparameters of the DNN model were tuned to a learning rate of 0.001, batch size of 32 and an input and hidden layer dropout of 0.4 and 0.2, respectively.

RESULTS AND DISCUSSION

Performance of the thermal band in predicting EWT_{canopy} of taro crops

The performance of the thermal band in predicting EWT_{canopy} of taro crops revealed a consistent trend across the various index-based segmentation techniques. It was observed that the exclusion of the thermal band in EWT_{canopy} analysis resulted in lower estimation accuracies ($P < 0.05$), emphasising the importance of the thermal band in characterising taro crop water status. Surprisingly, our study found no significant difference in prediction accuracies when thermal data was considered in comparison to its exclusion in the ExGR-based model. These results underscore the effectiveness of the ExGR-based technique, particularly its robust performance irrespective of the inclusion and exclusion of the thermal channel.

Additionally, it was observed that the thermal band was among the topmost predictor variable across all EWT_{canopy} models. Literature confirms the invaluable role of thermal infrared remote sensing in assessing and monitoring crop water status, establishing a direct correlation with crop water biophysical and biochemical elements (Khanal et al. 2017, Messina and Modica 2020, Krishna et al. 2021). The use of thermal remote sensing is based on the premise that thermal characteristics of crop leaves are effected by leaf transpiration, which decreases in a state of water deficit, resultantly reducing leaf and canopy temperatures (Maes and Steppe 2012, Gerhards et al. 2019). The findings of this study align with a recent study by Guan and Grote (2023), which achieved an R^2 of 0.74 when incorporating the thermal channel, compared to an R^2 of 0.63 with the thermal band excluded, highlighting the integration of multispectral and thermal data and its combined value in understanding crop water status. The findings of this study are further corroborated by those of García-Tejero et al. (2018) who concluded that the thermal band is feasible for monitoring almond water stress for irrigation scheduling, and Cheng et al. (2023) who highlighted the applicability of thermal imaging in assessing the crop water conditions of summer maize crop.

Performance of index-based segmentation techniques for the estimation of taro EWT_{canopy}

This study shows that the inclusion of soil background reduces the accuracy of EWT_{canopy} predictions within taro crop (R^2 of 0.61, RMSE of 25.35 g/m^2, and rRMSE of 43.87%). It was noted that the prediction accuracy of taro EWT_{canopy} improved significantly after the removal of soil background through the ExGR-based image segmentation technique, yielding an optimal R^2 of 0.92, RMSE of 8.04 g/m^2 and rRMSE of 15.31. These results align with the broader consensus in the literature. Xu et al. (2021) and Li et al. (2022) for instance emphasized the challenge posed by soil background in influencing crop canopy spectra, particularly in UAV-derived imagery. Notably, while the ExG and ExR techniques demonstrated acceptable accuracy in quantifying taro EWT_{canopy} (R^2 of 0.90, and R^2 of 0.76, respectively), the ExGR method outperformed both these techniques. This notable enhancement can be attributed to the inherent capabilities of the ExGR technique in effectively mitigating soil background interference (Zhai et al. 2023). The comprehensive nature of the ExGR method combines the advantages of both the ExG and ExR by simultaneously leveraging ExG for extracting the crop canopy and ExR for eliminating background noise (Meyer et al. 2004, Hamuda et al. 2016, Riehle et al. 2020, Upendar et al. 2021).

Overall, the removal of soil background has proven imperative for enhancing the accuracy of taro EWT_{canopy} predictions. These findings are further supported by Shu et al. (2021) that reported a significant increase in prediction accuracy from R^2 of 0.45 and RMSE of 7.13 before to an R^2 of 0.74 and RMSE of 3.68 after performing soil background removal in estimating the SPAD chlorophyll content of a maize crop. These parallel findings underscore the significance of addressing soil background interference for accurate and reliable estimations in crop water-related assessments.

REFERENCES

Baluja, J., Diago, M. P., Balda, P., Zorer, R., Meggio, F., Morales, F., & Tardaguila, J. (2012). Assessment of vineyard water status variability by thermal and multispectral imagery using an unmanned aerial vehicle (UAV). Irrigation Science, 30, 511-522.

Chivenge, P., Mabhaudhi, T., Modi, A. T., & Mafongoya, P. (2015). The potential role of neglected and underutilised crop species as future crops under water scarce conditions in Sub-Saharan Africa. International journal of environmental research and public health, 12(6), 5685-5711. https://mdpi-res.com/d_attachment/ijerph/ijerph-12-05685/article_deploy/ijerph-12-05685.pdf?version=1432635125

Deepan, P., & Sudha, L. (2020). Object classification of remote sensing image using deep convolutional neural network. In The cognitive approach in cloud computing and internet of things technologies for surveillance tracking systems (pp. 107-120). Elsevier.

Din, M. S. U., Mubeen, M., Hussain, S., Ahmad, A., Hussain, N., Ali, M. A., Sabagh, A. E., Elsabagh, M., Shah, G. M., & Qaisrani, S. A. (2022). World nations priorities on climate change and food security. In Building Climate Resilience in Agriculture (pp. 365-384). Springer.

Hamuda, E., Glavin, M., & Jones, E. (2016). A survey of image processing techniques for plant extraction and segmentation in the field. Computers and Electronics in Agriculture, 125, 184-199.

Hilary van Wyk, R., & Oscar Amonsou, E. (2021). Physiochemical and functional properties of albumin and globulin from amadumbe (Colocasia esculenta) corms. Food Science and Technology.

Hlophe-Ginindza, S. N., & Mpandeli, N. (2020). The role of small-scale farmers in ensuring food security in Africa. Food Security in Africa, 1-12.

Hussain, S., Gao, K., Din, M., Gao, Y., Shi, Z., & Wang, S. (2020). Assessment of UAV-Onboard Multispectral Sensor for non-destructive site-specific rapeseed crop phenotype variable at different phenological stages and resolutions. Remote Sensing, 12(3), 397.

Joshi, B. K., Shrestha, R., Gauchan, D., & Shrestha, A. (2020). Neglected, underutilized, and future smart crop species in Nepal. Journal of Crop Improvement, 34(3), 291-313.

Kapari, M., Hlophe-Ginindza, S., Nhamo, L., & Mpandeli, S. (2023). Contribution of smallholder farmers to food security and opportunities for resilient farming systems. Frontiers in Sustainable Food Systems, 7, 1149854.

Kapoor, B., Singh, S., & Kumar, P. (2022). Taro (Colocasia esculenta): Zero wastage orphan food crop for food and nutritional security. South African Journal of Botany, 145, 157-169.

Khanal, S., Fulton, J., & Shearer, S. (2017). An overview of current and potential applications of thermal remote sensing in precision agriculture. Computers and Electronics in Agriculture, 139, 22-32.

Li, X., & Siddique, K. H. (2018). Future smart food. Rediscovering hidden treasures of neglected and underutilized species for Zero Hunger in Asia, Bangkok.

Lu, Y., Young, S., Wang, H., & Wijewardane, N. (2022). Robust plant segmentation of color images based on image contrast optimization. Computers and Electronics in Agriculture, 193, 106711.

Mabhaudhi, T., Chimonyo, V. G., & Modi, A. T. (2017). Status of underutilised crops in South Africa: Opportunities for developing research capacity. Sustainability, 9(9), 1569.

Mabhaudhi, T., Modi, A., & Beletse, Y. (2011). Growth response of selected taro [Colocasia esculenta (L.) schott] landraces to water stress. II International Symposium on Underutilized Plant Species: Crops for the Future-Beyond Food Security 979,

Mabhaudhi, T., Modi, A. T., & Beletse, Y. G. (2014). Parameterisation and evaluation of the FAO-AquaCrop model for a South African taro (Colocasia esculenta L. Schott) landrace. Agricultural and Forest Meteorology, 192, 132-139.

Mawoyo, B., Adebola, P., Gerrano, A. S., & Amonsou, E. (2017). Effect of genotypes and growth locations on composition and functional properties of amadumbe flours. Journal of Food Science and Technology, 54(11), 3577-3586.

Messina, G., & Modica, G. (2020). Applications of UAV thermal imagery in precision agriculture: State of the art and future research outlook. Remote Sensing, 12(9), 1491.

Meyer, G. E., Hindman, T. W., & Laksmi, K. (1999). Machine vision detection parameters for plant species identification. Precision agriculture and biological quality,

Meyer, G. E., & Neto, J. C. (2008). Verification of color vegetation indices for automated crop imaging applications. Computers and Electronics in Agriculture, 63(2), 282-293.

Mugiyo, H., Chimonyo, V., Sibanda, M., Kunz, R., Masemola, C., Modi, A., & Mabhaudhi, T. (2021). Evaluation of land suitability methods with reference to neglected and underutilised crop species: A scoping review. Land, 10(2), 125.

Mugiyo, H., Chimonyo, V. G., Sibanda, M., Kunz, R., Nhamo, L., Masemola, C. R., Dalin, C., Modi, A. T., & Mabhaudhi, T. (2021). Multi-criteria suitability analysis for neglected and underutilised crop species in South Africa. PLoS One, 16(1), e0244734.

Oyeyinka, S. A., & Amonsou, E. O. (2020). Composition, pasting and thermal properties of flour and starch derived from amadumbe with different corm sizes. Journal of Food Science and Technology, 57(10), 3688-3695.

Ozelkan, E. (2020). Water body detection analysis using NDWI indices derived from landsat-8 OLI. Polish Journal of Environmental Studies, 29(2), 1759-1769.

Shu, M., Zuo, J., Shen, M., Yin, P., Wang, M., Yang, X., Tang, J., Li, B., & Ma, Y. (2021). Improving the estimation accuracy of SPAD values for maize leaves by removing UAV hyperspectral image backgrounds. International Journal of Remote Sensing, 42(15), 5862-5881.

Van Wyk, H. R. A., O E. (2021). Physiochemical and functional properties of albumin and globulin from amadumbe (Colocasia esculenta) corms. Food Science and Technology.

Woebbecke, D. M., Meyer, G. E., Von Bargen, K., & Mortensen, D. A. (1995). Color indices for weed identification under various soil, residue, and lighting conditions. Transactions of the ASAE, 38(1), 259-269.

Zhang, F., & Zhou, G. (2019). Estimation of vegetation water content using hyperspectral vegetation indices: A comparison of crop water indicators in response to water stress treatments for summer maize. BMC ecology, 19(1), 1-12.

Zulu, N. N. (2022). Water Scarcity and Household Food Security: A Case of Ulundi Local Municipality in KwaZulu-Natal, South Africa. In Handbook of Research on Resource Management and the Struggle for Water Sustainability in Africa (pp. 127-148). IGI Global.

SUSTAINABILITY OF MAIZE PRODUCTION WITH FARMERS' PRACTICES AND REDESIGNED CROP MANAGEMENT PRACTICES IN CRV AND JIMMA OF ETHIOPIA

#11310

[1*]Workneh Bekere Kenea, [1]Amsalu Nebiyu, [2]Tesfaye Balemi
[1]Department of Horticulture and Plant Sciences, Jimma University, P.O. Box 307, Jimma, Ethiopia; [2]Crop Production Specialist, Food and Agriculture Organization, Semera Field Office, Semera, Ethiopia
[*]e-mail: tolawaq@gmail.com, +251-921235304

ABSTRACT

In this study, sustainability of maize production with farmer's practice (FP), redesigned plant density plus current fertilizer use (RDCF), current plant density plus redesigned fertilizer use (CDRF), and redesigned plant density plus redesigned fertilizer use (RDRF) were assessed at household level based on social, agronomic, economic and environmental principles. Farmers' preference, farm household (maize) grain self-sufficiency, gross margin, and nitrogen use efficiency were used as indicators for for the respective principles. The result revealed that the preference of RDRF was 95% and 100% in CRV and Jimma respectively whereas the preference of FP was 45% and 20% in the respective regions. With all production technologies, farmers in both regions could achieve their family grain self-sufficiency but surplus production varied with the technologies used for the production. In CRV, RDRF, RDCF, and CDRF were economically viable to fertilizer use. However, in Jimma, less than 50% of farm households profited from RDRF and CDRF production technologies. In CRV, maize production using all crop management practices was associated with soil mining whereas in Jimma, the use of RDRF technology resulted in 18% environmental sustainability. Based on (average) scores of the indicators, maize production with RDRF showed higher social and economic sustainability in CRV and Jimma whereas maize production with FP was the least sustainable maize system in both regions. We conclude that further redesigning maize management technologies that meet environmental goal is of paramount important for the current and future generations in CRV and Jimma, Ethiopia.

Keywords: Farm household, family grain self-sufficiency, weighted scores, N use efficiency

INTRODUCTION

The concept of sustainability was first used in Sweden in forest management sector (Wiersum, 1995) with the focus on sustainable timber production from sustainable tree production (Prins et al., 2023). Since then, it has been applied in many disciplines across the globe. Sustainability in agriculture refers to the ability of a farm or agricultural system to produce food, fiber, or other products indefinitely without damaging or depleting the resources pool on which it depends. In other words, it is fulfilling the need of the present generation without compromising the ability of future generations to do the same (Rasmussen et al., 2017;Erbaugh et al., 2019). Several studies have assessed sustainability of farming systems based on sustainability dimensions (Ezell et al., 2021). This enables the selection of systems (practices) that fulfill social (Mandipaza, 2022), agronomic, economic and environmental principles. This means that the technologies should be socially acceptable, increase production, economically viable and environmentally safe (Pretty, 2008). Principles are universal ambitious commitments that are explained in terms of indicators. As principles are not directly measurable parameters, indicators are often used. Whereas indicator has been defined by different scholars, the definitions have similar meaning. Indicators are variables that supply information about another variable that are difficult to measure (Büchi et al., 2019;Heink and Kowarik, 2010). Alternatively, indicators are defined as variables for which a quantitative value is determined and compared to a reference value (Girardin et al., 1999). Indicators are very helpful in decision making for policy makers and managers.

Despite the inconsistency of the frameworks and tools, sustainability of farming system has been well studied (Paas et al., 2021) in developed countries. However, such studies are rare in Ethiopian agriculture, especially in staple food crops such as maize. Most studies are focusing on options of yield increase (Srivastava et al., 2019) and other studies unraveled factors associated with yield increase (Abate et al., 2015). This study is therefore conducted to (1) to assess the social, agronomic, economic and environmental performance of technologies used for maize production, (2) to assess the grain self-sufficiency at household level and estimate the land area that is required for farm household grain self-sufficiency in CRV and Jimma, Ethiopia.

MATERIALS AND METHODS

Definitions of maize production technologies

1. Farmer practices (FP): It is the actual plant density and actual fertilizer amount used by farmers.
2. Current density and redesigned fertilizer (CDRF): It is the average plant density used by farmers whereas fertilizer use is re-designed based on 50% potential yield of the crop.
3. Redesigned density and current fertilizer (RDCF): In this production practice, plant density is redesigned (53,333 plant ha^{-1} in CRV and 62,000 plant ha^{-1} in Jimma) but the fertilizer use is the average rate used by farmers in the respective region.
4. Redesigned density and redesigned fertilizer (RDRF): This refers to a production practices in which both plant density and fertilizer uses are redesigned.

Household grain self-sufficiency

Total maize production (t) at household level was obtained from the product of maize cultivation area (ha) and maize yield (t/ha). Maize cultivation areas of the participated farms households were measured using a handheld geographic positioning system essential (area measure) for the participating farm households in 2017. The per capita maize requirement of the farm households was based on an adult male equivalent (AME) of the 2017 family composition. Accordingly, a female was equivalent to 0.82 AME whereas children (0–18 years old) were equivalent to 0.75 AME (FAO, 2001). The per capita maize requirement is 260 kg^{-1} $adult^{-1}$ $year^{-1}$ based on calorie content of the crop.

Technology preference

Participating farmers were invited to evaluate the performance of maize crop grown with each technology at crop maturity, moving from field to field. Simple questionnaires were prepared to assess their preference of the tested technologies (Fertilizer use and plant density). A common starting question was “Is this fertilizer use and plant density important to improve your livelihood by improving maize productivity?”. The farmers answered as no, partly or yes. To evaluate this response quantitatively and express in percentage (Equ. 1), the no, partly and yes options were assigned with 0, 0.5 and 1 numerical values (Sannou et al., 2023) respectively.

$$\underline{\bar{x}(\%)} = \left(\frac{\sum_{1}^{i} w_i \times x_i}{\sum_{i}^{n} X} \times 100\right) \quad \text{equ 1}$$

Gross margin at farm level

To assess economic sustainability of maize production, input cost (fertilizer and seed cost) and maize price during the growing period were documented separately. The amount of fertilizer (kg farm^{-1}) used at farm level was multiplied with fertilizer cost (ETB kg^{-1}) during the study period. Following similar procedure, the amount of maize seed (kg household^{-1}) used for planting for was multiplied with the seed cost (ETB kg^{-1}). Similarly, the amount of maize yield (kg household^{-1}) was multiplied with market price of the maize grain (ETB kg^{-1}). The value cost ratio was estimated from the ratio of monetary value of maize from each technology to the cost of the technology (fertilizer cost plus seed cost) for maize production by that technology.

Nitrogen use efficiency

The impact of each technology on the environment was assessed using nitrogen (N) use efficiency of the maize production system as an indicator. Nitrogen use efficiency in the system is given by the ratio of N output from the system to N input into the system (Marinus et al., 2023). The assessment of N use efficiency was based on the EUNEP (2015) framework. Based on the framework, the minimum and maximum N use efficiencies are 50% and 90% respectively and the maximum N surplus per season is 80 kg ha^{-1}. An N use efficiency below 50% or N surplus greater than 80 kgha^{-1} indicates high risk of N loss to the environment whereas an N use efficiency greater than 90% is associated with high risk of soil mining. According to this framework, the desired N output is 80 kg ha^{-1} N and this value was adjusted to 50% of the maize yield potential in this study (Marinus et al., 2023). For the FP yields, N output was estimated following (Njoroge et al., 2019) and the N removed in this case is 1.54% of the maize grain yield. The N input was the amount of N applied by the farmer for the FP and the N applied for the treatments for the on-farm experiments.

RESULTS AND DISCUSSION

Technology preference

The preference of FP, RDCF, CDRF and RDRF technologies by smallholder farmers in CRV and Jimma was presented by Table 1. Almost all farms in both regions fully preferred RDRF technology in both regions (Table 1). However, FP was the lowest preferred technology in CRV (45%) and Jimma (20%). The preference of CDRF and RDCF was modest.

Family grain self-sufficiency

All farm households can attain their grain self-sufficiency and even produce surplus maize grain under all production technologies in CRV and Jimma. Whereas the average maize production of the farm household in CRV was 7594.5 kg per season, the production ranged from 420 kg under FP to 22200 kg per household under redesigned planting density and redesigned fertilizer use (RDRF). However, the grain requirement of the household in this region was found to be 1024 kg/household/year to 5120 kg/house/year based on the family size. On average, a farm household in CRV requires 2444 kg of maize grain per year to be grain self-sufficient. The grain requirement of farm households in Jimma ranged from 1024 kg to 2304 kg year^{-1} during 2017 and 2018. However, the maize grain produced during 2017 and 2018 in Jimma ranged from 1313 kg year^{-1} to 30369 kg year^{-1}.

Table 1. Preference of maize agronomic practices by smallholder farmers in CRV and Jimma of Ethiopian.

Agronomic practices	Regions	
	CRV	Jimma
FP	45%	20%
RDCF	70%	65%
CDRF	65%	50%
RDRF	95%	100%

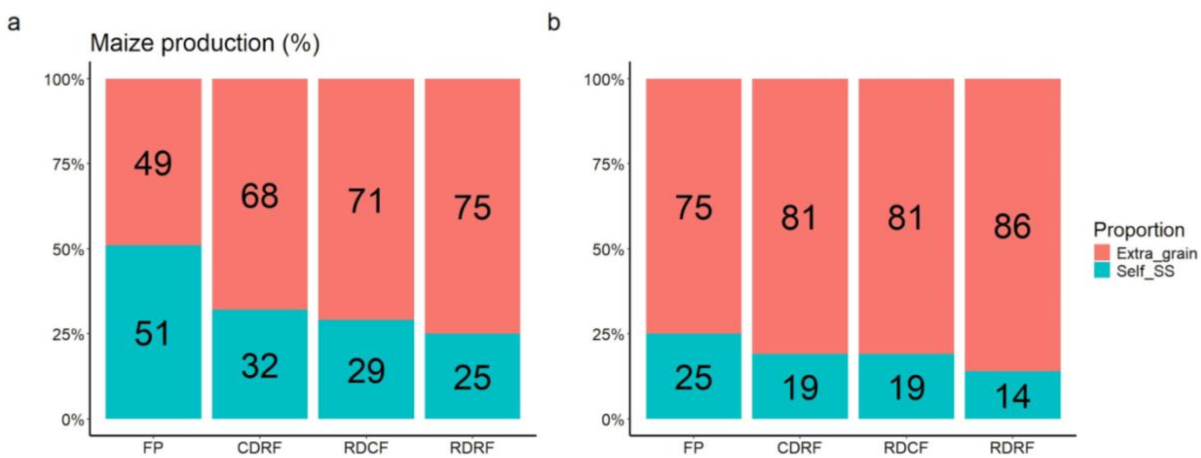


Figure 1. Proportion of maize grain for family self-sufficiency (blue bar) and extra production (red bar) under various crop management technologies in CRV (a) and Jimma (b). FP, CDRF, RDCF and RDRF represent farmer's practices, current density plus redesigned fertilizer, redesigned density plus current fertilizer and redesigned density plus redesigned fertilizer.

Marginal return

In Jimma, CDRF was economically viable for 54% farm households. In CRV, 91% of the farm households were profited from CDRF production technology. In this region, using RDRF has the same profitability (91%) with RDCF crop management technology. With the use of FP, however, only 18% of the farm households were profited. Based on average value cost ratio, RDCF, CDRF and RDRF were economically viable in CRV. In Jimma however, CDRF was not profitable whereas RDCF and RDRF of maize management practices were profitable at farm household level. In both regions, FP crop management was not economically viable at household level during.

Nitrogen use efficiency

Fig. 2 showed the N use efficiency in maze production with various maize crop management practices in CRV and Jimma. The N output outweigh the N input in various crop management technologies in both regions implying that all FP, CDRF, and RDCF technologies were associated with soil mining that put sustainability of maize production at risk. In CRV, none of the N use efficiency was in between a desirable range whereas in Jimma only 18% of the N use efficiency was in a desirable range. Below 21 kg ha^{-1} N input in CRV and below 80 kg ha^{-1} N input in Jimma, N use efficiency was associated with soil mining, putting the sustainability of maize production on the knife edge. In addition, maize production system in CRV did not result in risk of environmental pollution with surplus N whereas in Jimma, environmental risk from surplus N in maize production could be as high as 20%.

Table 2. Value cost ratio and percentage of profited households from maize agronomic practices in CRV and Jimma in 2017 and 2018.

Region	parameters	Production technologies			
		FP	CDRF	RDCF	RDRF
CRV	Average	-1.9	3.8	5.0	4.3
	Profitable households (%)	18	73	64	91
Jimma	Average	-0.62	0.56	1.82	1.34
	Profitable households (%)	23	23	54	54

FP, CDRF, RDCF and RDRF represent farmers practices, current density plus redesigned fertilizer, redesigned density plus current fertilizer and redesigned density plus redesigned fertilizer.

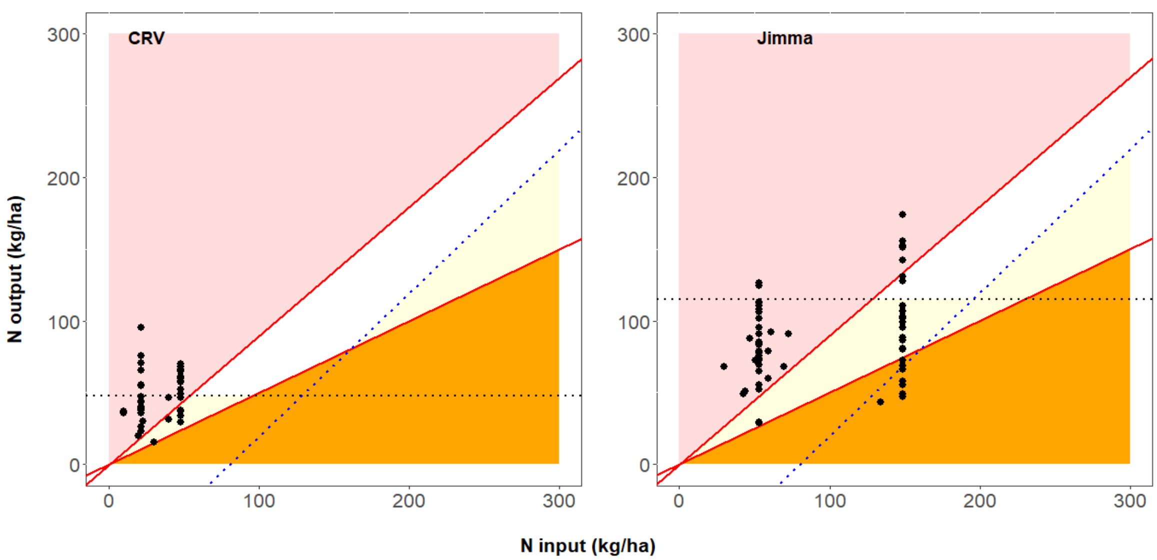


Figure 2. Actual and desired N use efficiencies in maize production in CRV and Jimma, in Ethiopia. The upper and the lower diagonal lines with a y-intercept of zero (red solid line) indicate an N use efficiency of 90% and 50% respectively. An N use efficiency above 90% shows a risk of soil N mining (pink color), while an N use efficiency below 50% indicates a risk of N losses to the environment (orange color). The space between these 50% and 90% N use efficiencies is further narrowed down (light yellow color); by a dotted diagonal line (blue) indicating a maximum N surplus of 80 kg N ha^{-1}, which, if exceeded, indicates a risk of N losses to the environment and a horizontal dotted line (black) indicating a targeted N output, which is equivalent to 50% of the water-limited yield potential per season (48 kg N ha^{-1} for CRV and 115 kg N ha^{-1} for Jimma) below this line indicate low productivity (light yellow). The remaining white area indicates the desired range of N use efficiencies.

The performances of maize production technologies in CRV and Jimma with all indicators were presented with Fig 3. Indicators with high scores were more sustainable except yield gap and land area required for grain self-sufficiency. The high score (percentage) of the yield gap and land area required for grain self-sufficiency was associated with low sustainability of the production system. In this line, the score of existing yield gap and land area for FP was higher in CRV and Jimma showing the low sustainability of the production system in this region.

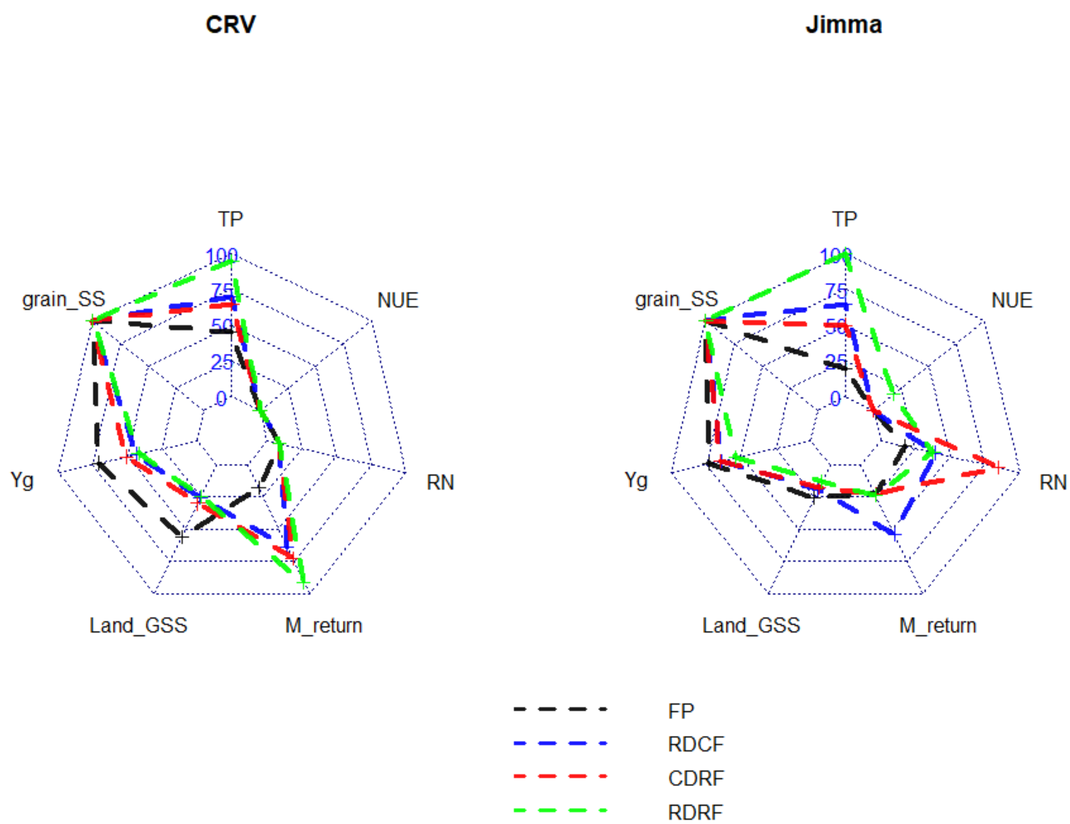


Figure 3. Performance of maize production technologies with average scores per indicator for farms in CRV and Jimma, Ethiopia. TP, Land_GSS, Yg, NUE stands for technology preference, land required for grain self-sufficiency, yield gap and nitrogen use efficiency whereas M_return, grain_SS and RN refer to marginal return grain self-sufficiency and return to N. All indicators except yield gap were assessed at farm household level. Yield gap was assessed at field level. FP, RDCF, CDRF and RDRF refer to farmer's practice, redesigned density with current fertilizer, current density with redesigned fertilizer and redesigned density with redesigned fertilizer.

REFERENCES

Abate, T., Shiferaw, B., Menkir, A., Wegary, D., Kebede, Y., Tesfaye, K., Kassie, M., Bogale, G., Tadesse, B. & Keno, T. 2015. Factors that transformed maize productivity in Ethiopia. Food Security, 7, 965-981.

Büchi, L., Georges, F., Walder, F., Banerjee, S., Keller, T., Six, J., Van Der Heijden, M. & Charles, R. 2019. Potential of indicators to unveil the hidden side of cropping system classification:

Differences and similarities in cropping practices between conventional, no-till and organic systems. European Journal of Agronomy, 109, 125920.
Erbaugh, J., Bierbaum, R., Castilleja, G., Da Fonseca, G. A. & Hansen, S. C. B. 2019. Toward sustainable agriculture in the tropics. World Development, 121, 158-162.
EUNEP, 2015. Nitrogen Use Efficiency (Schut et al.) - an indicator for the utilization of nitrogen in agriculture and food systems. Wageningen University, Alterra, Wageningen, the Netherlands.
Ezell, B., Lynch, C. J. & Hester, P. T. 2021. Methods for weighting decisions to assist modelers and decision analysts: A review of ratio assignment and approximate techniques. Applied Sciences, 11, 10397.
FAO/WHO/UNU (2001). Human energy requirements. Report of a joint FAO/WHO/UNU expert consultation, Rome
Girardin, P., Bockstaller, C. & Werf, H. V. D. 1999. Indicators: tools to evaluate the environmental impacts of farming systems. Journal of sustainable agriculture, 13, 5-21.
Heink, U. & Kowarik, I. 2010. What are indicators? On the definition of indicators in ecology and environmental planning. Ecological indicators, 10, 584-593.
Mandipaza, B. F. 2022. Socio-cultural dimensions of farming, small farm households and conservation agriculture in Nyanga District, Zimbabwe. University of Pretoria.
Marinus, W., Van De Ven, G. W. J., Descheemaeker, K., Vanlauwe, B. & Giller, K. E. 2023. Farmer responses to an input subsidy and co-learning program: intensification, extensification, specialization, and diversification? Agronomy for Sustainable Development, 43, 40.
Njoroge, S., Schut, A. G. T., Giller, K. E. & Zingore, S. 2019. Learning from the soil's memory: Tailoring of fertilizer application based on past manure applications increases fertilizer use efficiency and crop productivity on Kenyan smallholder farms. European Journal of Agronomy, 105, 52-61.
Paas, W., San Martín, C., Soriano, B., Van Ittersum, M. K., Meuwissen, M. P. & Reidsma, P. 2021. Assessing future sustainability and resilience of farming systems with a participatory method: A case study on extensive sheep farming in Huesca, Spain. Ecological Indicators, 132, 108236.
Pretty, J. 2008. Agricultural sustainability: concepts, principles and evidence. Philosophical Transactions of the Royal Society B: Biological Sciences, 363, 447-465.
Prins, K., Köhl, M. & Linser, S. 2023. Is the concept of sustainable forest management still fit for purpose? Forest Policy and Economics, 157, 103072.
Rasmussen, L. V., Bierbaum, R., Oldekop, J. A. & Agrawal, A. 2017. Bridging the practitioner-researcher divide: Indicators to track environmental, economic, and sociocultural sustainability of agricultural commodity production. Global Environmental Change, 42, 33-46.
Sannou, R. O., Kirschke, S. & Ghünther, E. 2023. Integrating the social perspective into the sustainability assessment of agri-food systems: A review of indicators. Sustainable Production and Consumption.
Srivastava, A. K., Mboh, C. M., Faye, B., Gaiser, T., Kuhn, A., Ermias, E. & Ewert, F. 2019. Options for sustainable intensification of maize production in Ethiopia. Sustainability, 11, 1707.
Wiersum, K. F. 1995. 200 years of sustainability in forestry: Lessons from history. Environmental Management, 19, 321-329.

OPTIMIZING MAIZE PRODUCTION THROUGH MINIMUM TILLAGE IN CONSERVATION AGRICULTURE (CA) SYSTEMS: EVIDENCE FROM MALAWI'S LOWLANDS

#11670

[1]Donald Nyamayevuab, [2]Isaiah Nyagumbob, [1]Liang Wei-lia, [1]Li Rui-qia
[1]College of Agronomy, Hebei Agriculture University, 289 Lingyusi Street, Baoding, Hebei, China; [2]International Maize and Wheat Improvement Center (CIMMYT), Box MP163, Mt Pleasant, 12.5 Km Peg, Mazowe Road, Harare, Zimbabwe
e-mail: i.nyagumbo@cgiar.org

ABSTRACT

Sustainable intensification in agricultural systems has been implemented and promoted across Sub-Saharan Africa (SSA) as a strategy for addressing low crop productivity often resulting in widespread food and nutritional insecurity. This study sought to assess the productivity potential of conservation agriculture (CA) cropping systems and associated crop establishment techniques. An on-station study was conducted at Chitala research station in Malawi. Maize grain productivity varied with crop establishment technique and cropping systems. Planting basins showed better performance during seasons with low to moderate wetness, and intervening less rainy months as observed in 2014/15 and 2015/16 cropping seasons. Conversely, direct seeding techniques with less soil surface disruption (dibble stick and Jab planter) performed better during seasons of high and persistent rainfall (2016/17 and 2017/18), with totals exceeding 800 mm. Rotation systems, particularly maize groundnut, outperformed other systems in maize grain yield, while intercropping systems incurred higher grain yield penalties among the tested systems. These results confirm previous findings on CA, indicating that rotating maize with legumes boosts maize grain yield, while maize-legume intercropping may reduce it.

INTRODUCTION

In SSA rainfall anomalies often lead to water stress, low crop yields accompanied by large yield gaps (Ligowe et al., 2017; Nyagumbo et al., 2020). This has resulted in widespread poverty, food insecurity and malnutrition (Makate et al., 2018). In effort to reduce the negative impacts of these challenges, conservation agriculture (CA) has gained significant attention across smallholder farmers, it has been promoted as a potential sustainable agricultural intensification technology in response to food insecurity and the adverse effects of climate (Omulo et al., 2024). Its principles hinge on reducing soil disturbance, crop diversification, and permanent soil cover (Mupangwa et al., 2021).

Minimum tillage as part of CA has been implemented across the region using varied crop establishment technologies such as manually prepared planting basins, jab planter and dibble sticks (Ngoma et al., 2015; Kidane et al., 2019). CA planting basins have been found useful in coping with rainfall variability and moisture deficits (Ngwira et al., 2013) as they improve conservation of soil moisture in the root zone thereby mitigating in-season dry spells (Ngwira et al., 2014). Alternative manual CA techniques, direct seeding using dibble stick or jab planter has also proved to be more profitable, less risky and also deliver labor reductions ranging between 45 to 55%

relative to the traditional farmer practice (Mupangwa et al., 2019). Crop diversification through legume inclusion into cereal based cropping systems has also been promoted as a solution to counter yield losses, enhance stability, and ensure nutritional security in a sustainable manner (Madembo et al., 2020).

The objective of this study was to evaluate the performance of maize cultivated as sole crop or integrated with grain legumes either as intercropping or rotation and to determine the maize grain yield performance of minimum tillage crop establishment techniques.

MATERIALS AND METHODS

The study was conducted, at Chitala research station in Malawi. The trial was laid out in a Randomized Complete Block Design with three replications of the 12 cropping systems. Cropping systems tested included conventional practice, CA sole maize, CA maize-legume intercrops and CA maize- legume rotations. Crop establishment techniques involved (1) the conventional semi-permanent hand hoed ridge and furrow system, (2) jab planter, (3) tapered wooden dibble sticks and (4) hand hoe prepared CA planting basins.

Using R (version 4.3.1), linear mixed models were fitted to test for significant differences in maize grain yield across treatments, seasons, cropping systems and to quantify the sources of residual variance in the data.

RESULTS AND DISCUSSION

Response of maize grain yield and total biomass to crop establishment techniques in different seasons

Crop establishment techniques significantly influenced maize grain and biomass yields across different seasons (Figure 1). During the 2014/15 and 2015/16 seasons, characterized by medium and low rainfall, planting basins and ridge-furrow systems yielded higher (4073 and 3907 kg ha^{-1} maize grain, respectively) compared to jab planter and dibble stick systems (3476 and 3213 kg ha^{-1}). Conversely, in the wetter 2016/17 and 2017/18 seasons, basin and ridge-furrow yields decreased (2807 and 2836 kg ha-1), while dibble stick and jab planter yields improved (3915 and 3256 kg ha-1). Biomass production showed a similar trend across these seasons. The CA basin system performance could potentially be attributed to its higher water harvesting capacity that promotes deeper water infiltration, better soil profile recharge and enhanced water retention capacity compared to dibble stick and jab planter (Nyagumbo et al., 2016). These results support the notion that CA basin systems can be an alternative and most preferred to drought prone regions of SSA (Mupangwa et al., 2017). These findings also agree well with regional findings in on-farm studies from southern Africa that put forward that CA basins can have negative impact on yields whenever incessant rainfall events leading to water logging, occurred (Mupangwa et al., 2012; Nyagumbo et al., 2020).

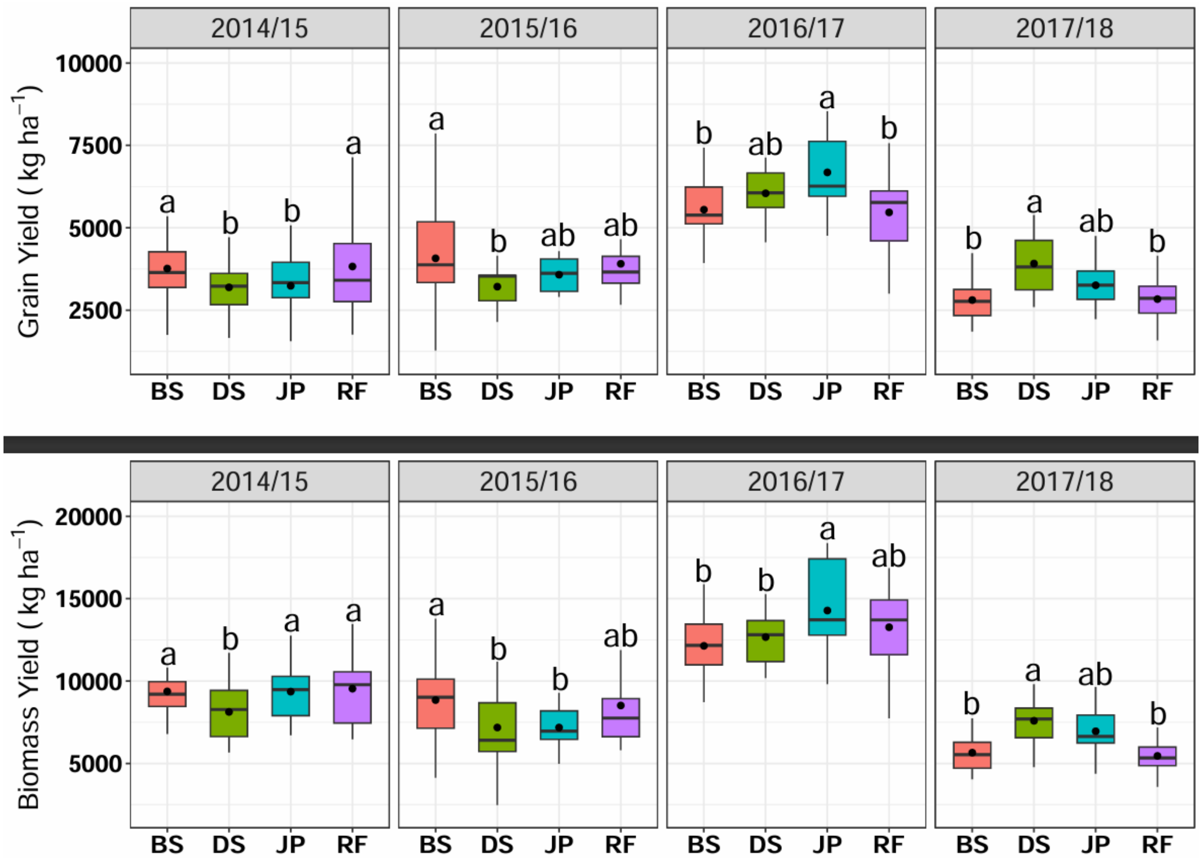


Figure 11. Interaction effects of season and crop establishment techniques on maize grain yield and total biomass during experimentation in Malawi Chitala (2014-2017). Circles inside boxes represent means, horizontal bar in the middle of each box represents the median, while lower and upper box plot boundaries represent the 25th and 75th percentiles respectively. Lower and upper whiskers represent the minimum and maximum values respectively. For each rainfall regime different letters above boxes indicate significant differences at 5% significance level between respective crop establishment techniques. Crop establishment techniques: BS = basin system, DS= dibble stick, JP= jab planter and RF= Ridge-furrow.

Maize grain yield under different cropping systems

Significant differences in maize grain yields were observed among cropping systems over four seasons (Figure 2, A-D). Maize-legume rotations consistently yielded the highest, while maize-legume intercropping systems had the lowest yields. Maize-groundnut rotation outperformed maize-cowpea intercropping by 1173, 878, 2700, and 987 kg ha^{-1} across the seasons. Within intercropping systems, maize-pigeon pea consistently yielded 9%, 4%, 45%, and 7% more than maize-cowpea. Similarly, maize-cowpea rotation surpassed maize-cowpea intercropping, with yield increases ranging from 725 to 2700 kg ha-1 across seasons. Maize grain yield advantage of the rotation system can be attributed to the high legume densities in rotation systems (i.e. the legume phase of the rotation) which may result in biological nitrogen fixation (BNF) that can supplement the applied mineral nitrogen thereby leading to high yield performance of rotation systems (Mutsamba et al., 2020; Mupangwa et al., 2021). Also, high plant density in intercropping systems combining maize and the associated legumes is usually 1.5–2 times the density of plants in sole crops, thus, resulting in inter and intraspecific competition for essential growth resources such as nutrients, water and light between maize and the companion legume and this can lead to suppression of component crop yields compared to rotations and sole systems (Madembo et al., 2020; Njira et al., 2021). In intercropping systems, maize-pigeon pea significantly outperformed maize-cowpea. Pigeon pea develops much slower initially, and its greatest demand for water and nutrients occurs after maize has been harvested and as such, there will be little competition with the primary maize crop (Kimaro et al., 2009; Madembo et al., 2020).

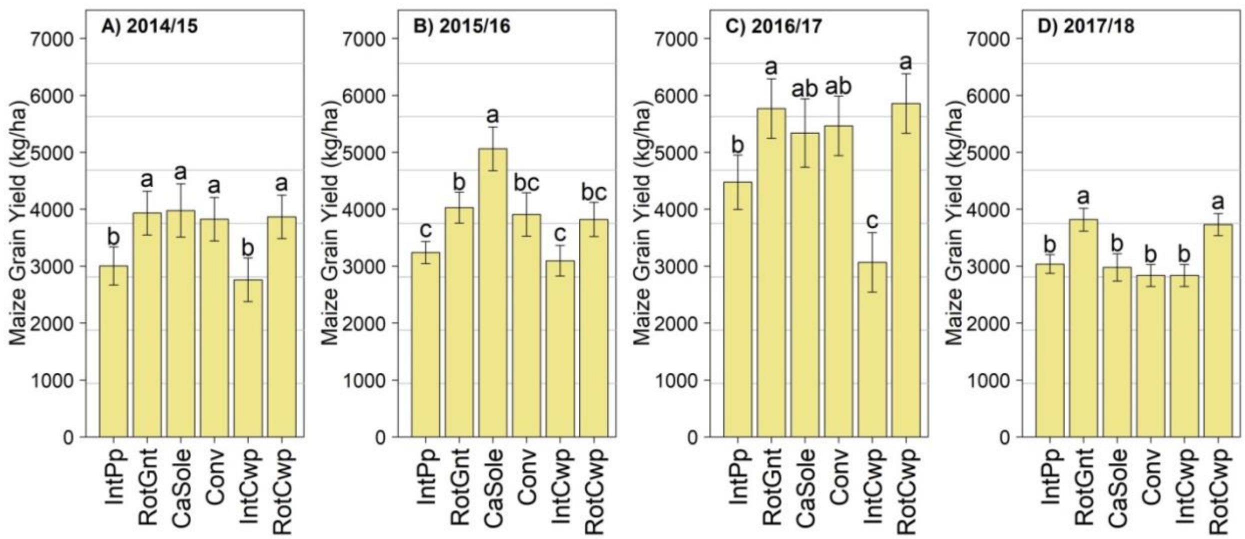


Figure 12. Mean maize grain yield of the tested cropping systems over four consecutive growing seasons (2014-15 to 2017-18) in Chitala, Malawi. For each season, different letters above bars indicate significant differences between respective cropping systems at $P < 0.05$. Cropping systems RotCwp = Maize-cowpea rotation, IntCwp = Maize-cowpea intercrop, RotGnt = Maize-groundnut rotation, IntPp = Maize-pigeon pea intercrop, MzSole = Maize sole and Conv = Conventional.

REFERENCE

Cooper, P. J.M., J. Dimes, K. P.C. Rao, B. Shapiro, B. Shiferaw, and S. Twomlow. 2008. "Coping Better with Current Climatic Variability in the Rain-Fed Farming Systems of Sub-Saharan Africa: An Essential First Step in Adapting to Future Climate Change?" Agriculture, Ecosystems and Environment 126(1–2): 24–35. doi:10.1016/j.agee.2008.01.007.

Kidane, Simon M., Dayton M. Lambert, Neal S. Eash, Roland K. Roberts, and Christian Thierfelder. 2019. "Conservation Agriculture and Maize Production Risk: The Case of Mozambique Smallholders." Agronomy Journal 111(6): 2636–46. doi:10.2134/agronj2018.05.0331.

Kimaro, A. A., V. R. Timmer, S. A. O. Chamshama, Y. N. Ngaga, and D. A. Kimaro. 2009. "Competition between Maize and Pigeonpea in Semi-Arid Tanzania: Effect on Yields and Nutrition of Crops." Agriculture, ecosystems & environment 134(1–2): 115–25.

Ligowe, Cleoups Nalivata, Njoloma Joyce, Makumba Wilkson, and Thierfelder Christian. 2017. "Medium-Term Effects of Conservation Agriculture on Soil Quality." African Journal of Agricultural Research 12(29): 2412–20. doi:10.5897/ajar2016.11092.

Madembo, Connie, Blessing Mhlanga, and Christian Thierfelder. 2020. "Productivity or Stability ? Exploring Maize-Legume Intercropping Strategies for Smallholder Conservation Agriculture Farmers in Zimbabwe." 185(April). doi:10.1016/j.agsy.2020.102921.

Makate, Clifton, Marshall Makate, and Nelson Mango. 2018. "Farm Household Typology and Adoption of Climate-Smart Agriculture Practices in Smallholder Farming Systems of Southern Africa." African Journal of Science, Technology, Innovation and Development 10(4): 421–39. doi:10.1080/20421338.2018.1471027.

Mugiyo, Hillary, Tedious Mhizha, and Tafadzwanashe Mabhaudhi. 2018. "Effect of Rainfall Variability on the Maize Varieties Grown in a Changing Climate: A Case of Smallholder Farming in Hwedza, Zimbabwe." (September). doi:10.20944/PREPRINTS201809.0152.V1.

Mupangwa, W., M. Mutenje, C. Thierfelder, M. Mwila, H. Malumo, A. Mujeyi, and P. Setimela. 2019. "Productivity and Profitability of Manual and Mechanized Conservation Agriculture (CA) Systems in Eastern Zambia." Renewable Agriculture and Food Systems 34(5): 380–94. doi:10.1017/S1742170517000606.

Mupangwa, W., I. Nyagumbo, F. Liben, L. Chipindu, P. Craufurd, and S. Mkuhlani. 2021. "Maize Yields from Rotation and Intercropping Systems with Different Legumes under Conservation Agriculture in Contrasting Agro-Ecologies." Agriculture, Ecosystems and Environment 306. doi:10.1016/j.agee.2020.107170.

Mupangwa, W., C. Thierfelder, and A. Ngwira. 2017. "Fertilization Strategies in Conservation Agriculture Systems with Maize-Legume Cover Crop Rotations in Southern Africa." Experimental Agriculture 53(2): 288–307. doi:10.1017/S0014479716000387.

Mupangwa, W., S. Twomlow, and S. Walker. 2012. "Reduced Tillage, Mulching and Rotational Effects on Maize (Zea Mays L.), Cowpea (Vigna Unguiculata (Walp) L.) and Sorghum (Sorghum Bicolor L. (Moench)) Yields under Semi-Arid Conditions." Field Crops Research 132: 139–48. doi:10.1016/j.fcr.2012.02.020.

Mutsamba, EF, I Nyagumbo, and W Mupangwa. 2020. "Forage and Maize Yields in Mixed Crop-Livestock Farming Systems: Enhancing Forage and Maize Yields in Mixed Crop-Livestock Systems under Conservation Agriculture in Sub-Humid Zimbabwe." NJAS-Wageningen Journal of Life Sciences 92: 100317.

Ngoma, Hambulo, Nicole M. Mason, and Nicholas J. Sitko. 2015. "Does Minimum Tillage with Planting Basins or Ripping Raise Maize Yields? Meso-Panel Data Evidence from Zambia." Agriculture, Ecosystems and Environment 212: 21–29. doi:10.1016/j.agee.2015.06.021.

Ngwira, Amos, Fred H. Johnsen, Jens B. Aune, Mulugetta Mekuria, and Christian Thierfelder. 2014. "Adoption and Extent of Conservation Agriculture Practices among Smallholder Farmers in Malawi." Journal of Soil and Water Conservation 69(2): 107–19. doi:10.2489/jswc.69.2.107.

Njira, Keston O.W., Ernest Semu, Jerome P. Mrema, and Patson C. Nalivata. 2021. "Productivity of Pigeon Pea, Cowpea and Maize under Sole Cropping, Legume–Legume and Legume–Cereal Intercrops on Alfisols in Central Malawi." Agroforestry Systems 95(2): 279–91. doi:10.1007/s10457-020-00589-0.

Nyagumbo, I, S Mkuhlani, D Kamalongo, D Dias, and M Mekuria. 2016. "Maize Yield Effects of Conservation Agriculture Based Maize–Legume Cropping Systems in Contrasting Agro-Ecologies of Malawi and Mozambique." Nutrient Cycling in Agro-ecosystems 105: 275–90.

Nyagumbo, Isaiah, Walter Mupangwa, Lovemore Chipindu, Leonard Rusinamhodzi, and Peter Craufurd. 2020. "A Regional Synthesis of Seven-Year Maize Yield Responses to Conservation Agriculture Technologies in Eastern and Southern Africa." Agriculture, Ecosystems and Environment 295(March): 106898. doi:10.1016/j.agee.2020.106898.

Omulo, Godfrey, Thomas Daum, Karlheinz Köller, and Regina Birner. 2024. “Unpacking the Behavioral Intentions of ‘Emergent Farmers’ towards Mechanized Conservation Agriculture in Zambia.” Land Use Policy 136: 106979.

Steward, Peter R, Andrew J Dougill, Christian Thierfelder, Cameron M Pittelkow, Lindsay C Stringer, Maxwell Kudzala, and Gorm E Shackelford. 2018. “Agriculture , Ecosystems and Environment The Adaptive Capacity of Maize-Based Conservation Agriculture Systems to Climate Stress in Tropical and Subtropical Environments : A Meta-Regression of Yields.” Agriculture, Ecosystems and Environment 251(September 2017): 194–202. doi:10.1016/j.agee.2017.09.019.

TerAvest, Dan, Lynne Carpenter-Boggs, Christian Thierfelder, and John P. Reganold. 2015. “Crop Production and Soil Water Management in Conservation Agriculture, No-till, and Conventional Tillage Systems in Malawi.” Agriculture, Ecosystems and Environment 212: 285–96. doi:10.1016/j.agee.2015.07.011.

Thierfelder, Christian, Rumbidzai Matemba-mutasa, W Trent Bunderson, Munyaradzi Mutenje, Isaiah Nyagumbo, and Walter Mupangwa. 2016. “Agriculture , Ecosystems and Environment Evaluating Manual Conservation Agriculture Systems in Southern Africa.” 222: 112–24.

USE OF DIGITAL EXTENSION TOOLS FOR AGRICULTURAL INFORMATION MANAGEMENT AMONG CASSAVA VALUE CHAIN ACTORS IN IBADAN METROPOLIS, OYO STATE, NIGERIA

#11756

[1]Olushola Fadairo, [2]Adenike Durojaiye, [3]Racheal Adegbayi
[1]Directorate of Entrepreneurship, Innovation and Sustainability Emmanuel Alayande University of Education, Oyo, Nigeria; [2]Department of Agricultural Science Education, Emmanuel Alayande University of Education, Oyo, Nigeria; [3]Department of Agricultural Extension Forestry Research Institute, Nigeria
e-mail: fadairoos@eauedoyo.edu.ng; dairom2@gmail.com

ABSTRACT

Poor coverage of farmers by extension services and other limitations necessitates the need to adapt the agricultural process to new opportunities, one of which is digital extension. This is moreso important for cassava value chain actors given the recognition of the crop for food security in Nigeria and its widespread promotion by several local and regional development interventions. Therefore, the use of digital extension tools for agricultural information management among cassava value chain actors in the Ibadan metropolis was investigated. Multi-stage sampling procedure was used to select 195 cassava value chain actors comprising extension workers, farmers, processors, and marketers. Data were collected using a structured questionnaire on their enterprise characteristics, awareness, access, and use of digital extension tools for agricultural information management. Data were analysed using frequency distribution, percentages, mean, and ANOVA at $\alpha_{0.05.}$ Respondents were mostly male (51.6%) and had 7.3±5.2 years of experience in the cassava value chain. Awareness and access levels to digital communication tools were high among the cassava value chain actors while the extent of use of the tools was still low. Agricultural extension workers were the highest user ($\bar{x}$=26.4) while the processors were least users ($\bar{x}$=15.0) of the digital extension tools. Awareness and use of digital tools for extension information management is still below average among the cassava value chain actors. More emphasis is required to be put on innovative digital information management systems in the traditional extension approach to promote its wider use.

Keywords: Digital extension, Information management, Cassava value chain, Innovative agriculture.

INTRODUCTION

Cassava is a major staple food and is widely grown across Nigeria owing to its wide adaptability, economic importance and acceptance. Oyo State in the South-west Nigeria is a major producer of cassava. In Nigeria, Cassava is increasingly becoming a raw material for food, feed and industrial applications. Nigeria is the largest producer of cassava, and 12th largest for maize in the world, amounting to annual production of about 60 million MT. Nevertheless, the nation is still known for producing below its capacity with a national average of 9 t/ha (FAOSTAT, 2018). Worse still, use of available improved technologies and innovations to address low cassava productivity in most cases, have been limited by ineffective information transfer among the actors in the value chain (Atser et al, 2024).

In Nigeria, agricultural extension services play critical roles in disseminating information on improved farm technologies to farmers. Unfortunately, the performance of these service providers has been largely disappointing in the recent past due to numerous intractable challenges which bothers on their effectiveness, efficiency and reach (Atser et al, 2024). These challenges include the significant financing shortfall for agricultural extension services, the low farmer-extension workers ratio, the aging of the extension agents and the dearth of new employees. Davis et al (2019) put the total workforce of public extension agents at roughly 7,000 and the ratio of extension agents to farmers at between 1:5,000 and 1:10,000. Additionally, 60% of extension agents were documented to be above the age of 40. Against this background, some authors have argued in support of digitalization of extension services as a powerful tool to reach most smallholder farmers (Adesope, 2021). This study was thus conducted to assess the existing digital extension landscape and use among the cassava value chain actors in Ibadan Metropolis, Oyo State, Nigeria, and the extension workers providing services to them.

METHODOLOGY

The study was carried out in Ibadan metropolis which is the capital of Oyo State, located in the southwestern Nigeria. The city has 11 Local Government Areas (LGAs) and covering an area of 129.65km2 has the largest human population in the state and is also renowned for largest land size in Nigeria. A multi-stage sampling procedure was used to select cassava farmers (44), processors (12), marketers (28) [who were registered with their commodity association] and agricultural extension workers (11) from three LGAs (Akinyele, Ido and Lagelu) in the study area. Data were collected using a structured questionnaire on respondents' enterprise characteristics, awareness, access, and use of digital extension tools for agricultural information management. Awareness was measures as yes and no; access was measured as always, sometimes and never; use was measured as frequently, occasionally, just a trial and never. Scores were allotted to the options following the Likert-type scale procedure. Data were analysed using descriptive statistics and ANOVA at $\alpha_{0.05}$.

RESULTS AND DISCUSSION

Table 1 shows that 51.6% of the respondents were male indicating almost a parity level of male and female involvement in the cassava value chain sub-sector in the study area. The respondents were mostly educated at Diploma/Certificate level (57.9%), aged 39.4±8.1 years, had 7.3±5.2 years of experience in the cassava value chain sub-sector and have attended 2.1±2.0 number of trainings on digital agricultural extension. The respondent's fair level of literacy, youthfulness and experience in the value chain presents an obvious advantage for improving the cassava production sub-sector in Nigeria if well harnessed.

Table 1. Respondents' personal characteristics.

Variables	F	%
Sex		
Male	49	51.6
Female	46	48.4
Education		
No education	1	1.1
Diploma/certificate	55	57.9
Bachelor and above	39	41.1
Years of experience	Mean/SD = 7.3±5.2	
Numbers of trainings attended	Mean/SD = 2.1±2.0	
Age in years	Mean/SD = 39.4±8.1	

Table 2 shows that virtual classroom (70.5%) and animated video clips (70.5%) enjoyed the most popularity of all the digital tools among the value chain actors. This was followed by mobile applications (66.3%) and skits (65.3%). Respondents (99.9%) were mostly unaware of mobile phones. Video conferencing and IITA news App as forms of digital extension tools. In similar vein, skits and virtual classroom ($\bar{x}$=1.12) were mostly accessible to the respondents among the digital extension tools while Mobile phone, video conferencing were least accessible ($\bar{x}$=1.1). This trend was also observed for use of the digital extension tools as virtual classroom and animated video clips ($\bar{x}$=2.69) were the mostly used of the tools in cassava value chain information exchange among the respondents. Largely, the distribution suggests a plausible interrelationships among the value chain actors' awareness, access and use of the tools. Literature posits that awareness, and access determines use of technology (Cui et al 2022).

Table 2. Awareness, access and use of digital extension tools among cassava value chain actors.

Digital tools	Awareness (%)	Access index	Use index
Mobile application e.g. e-diary, herbicide calculator	66.3	1.09	2.41
Interactive Voice Response (IVR)	63.2	1.06	2.44
Virtual Classroom e.g. Google meet	70.5	1.12	2.69
Web-based extension platform e.g. Farm Crowdy and Agro Data	57.9	0.90	2.13
Geographical Information System (GIS)	61.1	0.83	1.87
Animated video clips	70.5	1.09	2.69
Satellite system	55.8	0.70	1.66
Drones	55.8	0.63	1.48
Internet of things/Remote sensing	54.7	0.82	1.88
Skit	65.3	1.12	2.08
Mobile phone	1.1	0.10	2.41
Video conferencing	1.1	0.10	2.44
IITA news App	1.1	0.10	2.15

Table 3 shows that while awareness and access levels to digital communication tools were high among 57.9% and 53.7% of the cassava value chain actors, respectively, the extent of use of the tools for innovation dissemination and exchange was still low among most of the actors (51.6%). The low usage despite a high awareness and access are traceable to the problem of underinvestment and poor reach of the potential users by the e-digital extension service providers (Baconguis, 2022). This is addition to the challenge of poor internet connectivity.

Table 3. Categorization of cassava value chain actors based on their levels of awareness, access and use of digital tools.

	Awareness level		Access level		Use extent	
	F	**%**	**F**	**%**	**F**	**%**
Low	40	42.1	44	46.3	49	51.6
High	55	57.9	51	53.7	46	48.4
	Min=0; Max =12; 6.2±4.1		Min=0; Max=22; 9.4±6.8		Min=10; Max=40; 20.8±8.7	

Table 4 shows a significant difference in the use of digital extension tools among the cassava value chain actors (F=3.598; $p < 0.05$) with agricultural extension workers having the highest level of usage ($\bar{x}$=26.36) while the processors had the least usage level ($\bar{x}$=20.29).

Table 4. Difference in the use of agricultural digital extension tools among the cassava value chain actors.

	Sum of square	**df**	**Mean square**	**F**	**Sig**
Between groups	766.614	3	255.538	3.598	0.017
Within groups	6462.692	91	71.019		
Total	7229.305	94			
Mean Separation of value chain actors					
Processors $\bar{x}$=15.00	Marketers $\bar{x}$=20.29	Farmers $\bar{x}$=21.39	Agricultural extension workers $\bar{x}$=26.36		

REFERENCES

Adesope O.M. (2021). Agricultural Extension in Contemporary Nigeria. Optimizing Our Development Potentials. University of Port Harcourt Inaugural Lecture Series No170. Thursday June 17, 2021. 102p

Atser, G. L., Oluoch, M., Gambo, A., Diso, H. Z., Fadairo, O. S., & Jibrin, A. A. (2024). The commodity association traders/trainers extension approach: smallholder productivity, input and market linkages in Nigeria. African Journal of Food, Agriculture, Nutrition & Development, 24(3) (Kenya).

Baconguis, R. T. (2022). Agricultural technology: Why does the level of agricultural production remain low despite increased investments in research and extension? (No. 2022-06). PIDS Discussion Paper Series.

Cui, S., Li, Y., Jiao, X., & Zhang, D. (2022). Hierarchical linkage between the basic characteristics of smallholders and technology awareness determines Small-Holders' willingness to adopt green production technology. Agriculture, 12(8), 1275.

Davis K., Lion K., and Arokoyo T. (2019). Organizational Capacities and Management of Agricultural Extension Services in Nigeria: Current Status. South African Journal of Agricultural Extension Volume 47, No 2, 2019:118-127. Http://dx.doi.org/10.17159/2413-3221/2019/v47n2a508.

FAO Statistics (2013, June). Food and Agricultural Organisation, Data base results. Retrieved from June, 2015, FAO.

EMPOWERING SMALLHOLDER FARMERS: PRECISION AGRICULTURE MODELS IN AFRICA (A CASE STUDY OF NIGERIA)

Stephen Oluwaseun Popoola
Agro Optimizer Limited, Iseyin, Oyo State, Nigeria
e-mail: Popoolastepheno@gmail.com; +2349064685088

ABSTRACT

This paper investigates the transformative potential of precision agriculture (PA) in enhancing the productivity and sustainability of smallholder farmers across Nigeria. As the backbone of Africa's agricultural sector, smallholder farmers face persistent challenges, including resource scarcity, climate variability, and limited access to modern agricultural practices. By leveraging technologies such as GPS, remote sensing, and data analytics, PA offers innovative strategies to optimize resource use, improve crop yields, and support data-driven decision-making.

Utilizing a mixed-methods approach that includes field surveys, in-depth farmer interviews, and empirical yield analysis across three regions—Southwest, Northern, and Middle Belt—this study reveals significant regional disparities in PA adoption. The Southwest shows higher awareness and adoption rates, while the North faces greater challenges due to inadequate infrastructure and limited access to extension services. Key barriers identified include high implementation costs, insufficient training, and infrastructural gaps.

Despite these obstacles, the study finds that PA technologies substantially improve productivity, resource efficiency, and resilience in smallholder farming systems. The findings underscore the need for robust policy frameworks, targeted training programs, and scalable technology solutions to foster wider PA adoption. Ultimately, this research highlights actionable recommendations for stakeholders, including policymakers, agricultural extension services, and technology providers, to enhance food security and promote sustainable agricultural development in Nigeria and beyond.

INTRODUCTION

Agriculture remains the backbone of Africa's economy, supporting the livelihoods of millions, with smallholder farmers making up nearly 80% of the continent's agricultural workforce (AGRA, 2022). These smallholders are crucial to achieving food security and driving rural development, yet they face persistent challenges that hinder their productivity. Limited access to modern farming inputs, poor infrastructure, and increasing climate variability have led to stagnating agricultural outputs, exacerbating food insecurity and slowing economic growth (FAO, 2023; Jayne et al., 2019). As the world strives to meet the Sustainable Development Goals (SDGs), particularly Goal 2 (Zero Hunger) and Goal 13 (Climate Action), enhancing agricultural efficiency and resilience is more urgent than ever.

In recent years, precision agriculture (PA) has emerged as a transformative approach to modern farming. By leveraging technologies such as GPS navigation, remote sensing, drones, and data analytics, PA offers innovative solutions to optimize farming practices, enabling efficient resource use, better crop yields, and reduced environmental impact (Zhang et al., 2023; Gebbers & Adamchuk, 2021). The adoption of PA technologies can particularly benefit Africa's smallholder farmers, who operate under resource constraints but have significant potential to boost productivity through data-driven decision-making.

The critical question now is: why is it crucial to focus on precision agriculture for smallholder farmers in Africa today? As the continent grapples with rapid population growth, projected to reach 2.5 billion by 2050 (UN, 2023), there is an urgent need to increase agricultural productivity to meet rising food demands sustainably. Precision agriculture provides a pathway to enhance the efficiency of smallholder farms, reduce wastage of inputs like water and fertilizers, and build resilience against climate shocks (Mupangwa et al., 2024). However, despite its potential, the adoption of PA in Africa remains low due to high costs, limited infrastructure, and a lack of technical expertise among farmers (Makombe & Gachuiri, 2023).

This study delves into the application of precision agriculture models tailored for smallholder farmers in Africa. By examining the tangible impacts of PA on productivity, resource management, and sustainability, it seeks to identify both the opportunities and challenges associated with scaling these technologies in rural contexts. The research emphasizes the socio-economic significance of smallholder farmers, their operational constraints, and the barriers they face in adopting modern agricultural practices.

Ultimately, this study aims to uncover practical strategies to enhance the adoption of PA in Africa, contributing to broader global objectives, such as boosting food security, promoting sustainable agricultural practices, and advancing rural economic development. By bridging the gap between technology and smallholder needs, this paper underscores the transformative potential of precision agriculture in empowering African farmers, thereby supporting the continent's progress toward the SDGs.

METHODOLOGY AND RESULTS

Research Design

A descriptive research design was employed to assess awareness, challenges, and benefits of PA. Data was collected using structured questionnaires and in-depth interviews to understand socio-economic, infrastructural, and technological influences on PA adoption.

Sample Selection

The study focused on three regions in Nigeria—Southwest, Northern, and Middle Belt—chosen for their distinct agro-ecological characteristics:

Southwest: Better infrastructure and higher tech adoption.
Northern: Harsh climate, emphasizing the need for resource-efficient PA.
Middle Belt: A mix of rain-fed and irrigated farming practices.

A stratified random sampling method was used to select 300 smallholder farmers (100 per region) and conduct 30 interviews with agricultural stakeholders.

Data Collection
Data sources included:

Primary data: Structured questionnaires and semi-structured interviews with farmers to gather quantitative and qualitative insights on PA awareness and barriers.
Secondary data: Literature reviews, government reports, and agricultural databases to provide context.

Data collection took three months, with enumerators using local languages to ensure accuracy.

Data Analysis
Quantitative data was analyzed using SPSS for descriptive statistics and correlations. Qualitative data was transcribed and analyzed with NVivo for thematic insights.

Study Limitations
Geographical scope: Limited to three regions, potentially not reflecting national diversity.
Access to participants: Challenges in reaching remote areas may have affected data depth.
Technological literacy: Varying familiarity with technology among farmers might have impacted their responses.

RESULTS

The results of this study present a comprehensive analysis of the adoption of precision agriculture (PA) among smallholder farmers across the Southwest, Northern, and Middle Belt regions of Nigeria. The findings highlight regional disparities in awareness, adoption rates, and the effectiveness of extension services, which provide critical support for implementing PA technologies.

Regional Analysis of PA Awareness and Adoption
Southwest Nigeria demonstrated the highest levels of awareness and adoption of PA technologies, with 65% of surveyed farmers indicating familiarity with basic precision tools like GPS-enabled devices and soil sensors. This region benefits from better access to agricultural extension services, infrastructure, and proximity to urban centers, which facilitates exposure to modern farming techniques.

In contrast, Northern Nigeria, particularly in the semi-arid zones, showed lower awareness (38%) and adoption rates (20%). The harsh climatic conditions, coupled with limited infrastructure, impede farmers' access to PA resources. Additionally, literacy rates in this region are lower, which affects farmers' ability to adopt technologically advanced practices. However, those who did implement PA technologies, such as drip irrigation and soil moisture sensors, reported a noticeable increase in water-use efficiency, suggesting that targeted interventions could yield significant benefits.

The Middle Belt region exhibited moderate awareness (55%) and adoption levels (45%). This area benefits from a blend of rain-fed and irrigated farming, making it more adaptable to PA techniques like remote sensing for weather predictions and variable rate application of inputs. However, challenges such as inconsistent access to market information and limited financial resources continue to hinder widespread adoption.

Key Findings and Trends

The study found that:

Access to Extension Services: Farmers in the Southwest region had better access to agricultural extension officers (70%) compared to their counterparts in the Northern (30%) and Middle Belt regions (50%). The presence of well-funded agricultural programs and proximity to research institutes in the Southwest played a crucial role in this disparity.

Resource Availability: The Middle Belt region displayed a higher adoption of PA technologies compared to the North due to relatively better access to inputs like fertilizers, seeds, and mobile-based advisory platforms. This suggests that targeted resource allocation could significantly improve PA adoption in resource-constrained areas.

Perceived Benefits of PA: Across all regions, farmers who adopted PA reported improved crop yields (average increase of 25-30%) and resource efficiency, particularly in irrigation and fertilizer usage. However, the initial cost and technical expertise required for PA adoption were cited as major barriers.

Table 1. Awareness and Use of Precision Agriculture by Region.

Region	**Number of Respondents**	**Aware of Precision Agriculture (%)**	**Understand Precision Agriculture (%)**	**Use Precision Agriculture (%)**
Southwest (Iseyin and Oyo)	20	45%	35%	20%
Northern (Kano and Kaduna)	20	20%	15%	5%
Middle Belt (Benue State)	10	10%	5%	0%
Total	**50**	**28%**	**18%**	**12%**

This table provides a breakdown of the respondents by region and shows their level of awareness, understanding, and usage of precision agriculture technologies.

Table 2. Barriers to Precision Agriculture Adoption by Region.

Barrier	**Southwest (%)**	**Northern (%)**	**Middle Belt (%)**	**Total (%)**
High Cost of Technology	65%	75%	70%	70%
Lack of Infrastructure	55%	70%	75%	65%
Limited Knowledge and Training	45%	55%	80%	58%
Lack of Government Support	50%	50%	50%	50%

This table breaks down the specific barriers faced by farmers in each region, highlighting the differences in challenges faced by Southwest, Northern, and Middle Belt farmers.

Table 3. Perceived Benefits of Precision Agriculture.

Benefit	**Southwest (%)**	**Northern (%)**	**Middle Belt (%)**	**Total (%)**
Improved Yield	60%	55%	40%	52%
Reduced Input Costs	45%	40%	35%	40%
Better Water Management	50%	65%	30%	48%
Increased Market Competitiveness	35%	20%	15%	24%

This table summarizes the perceived benefits of precision agriculture as reported by the farmers, showing the variation across different regions.

Table 4. Regional Distribution of Respondents.

Region	**Number of Respondents**	**Percentage (%)**
Southwest	20	40%
Northern	20	40%
Middle Belt	10	20%
Total	**50**	**100%**

This table shows the total number of respondents surveyed across the three regions, along with the percentage distribution.

Table 5. Access to Extension Services.

Region	**Respondents with Access to Extension Services**	**Percentage (%)**
Southwest	8	40%
Northern	12	60%
Middle Belt	5	50%
Total	**25**	**50%**

This table shows the number of respondents in each region who have access to agricultural extension services and the percentage of those respondents relative to the total number in each region.

DISCUSSION AND RECOMMENDATIONS

Comparative Analysis with Other African Countries

The barriers to adopting PA observed in Nigeria mirror challenges faced in other parts of Africa, particularly in countries like Kenya, Tanzania, and Ghana. Similar issues—such as limited access to capital, inadequate infrastructure, and low levels of technological literacy—are common across the continent. In Kenya, for instance, while PA holds promise for smallholders, the cost of technology remains prohibitive for many, just as it does in Northern Nigeria. Meanwhile, Tanzania has made strides in mobile-based agricultural advisory services, which could serve as a model for improving PA adoption in Nigeria's Middle Belt region.

Implications for Policy and Practice

The disparities identified in this study highlight the need for region-specific interventions to promote PA adoption:

Strengthening extension services: Policymakers should prioritize training extension officers in the Northern region to enhance farmers' access to PA knowledge.

Subsidizing technology costs: Financial incentives, such as subsidies or low-interest loans, could make PA tools more accessible, particularly in resource-poor areas.

Leveraging mobile platforms: Expanding mobile-based advisory services, especially in the Middle Belt and Northern regions, could bridge the information gap and increase farmers' engagement with precision agriculture.

Recommendations for Stakeholders

1. **Farmers**:
   - Smallholder farmers should seek support from local cooperatives and agricultural organizations to gain access to precision farming technologies and training. Pooling resources can make technology more affordable.
   - Farmers should adopt lower-cost, locally adapted precision farming tools where available to help them transition into modern agricultural practices gradually.
2. **Policymakers**:
   - Policymakers should focus on **expanding agricultural extension services**, especially in underserved regions like the Southwest. Improved access will help bridge the gap in technical knowledge, which is crucial for adopting precision agriculture.
   - Governments need to **provide financial incentives** such as subsidies or grants to help farmers afford precision agriculture tools. Investments in **rural infrastructure**—such as reliable electricity and internet—are essential for enabling these technologies.
3. **Researchers**:
   - Future research should explore the adoption of precision agriculture in a wider range of regions, both in Nigeria and other African countries, to provide a more comprehensive understanding of the barriers and drivers in different contexts.
   - Researchers should also investigate the **long-term economic impacts** of precision agriculture on smallholder farmers, particularly focusing on yield improvements and sustainability, to inform more effective policy decisions

CONCLUSION

By addressing these barriers, Nigeria can better align with broader Sustainable Development Goals (SDGs), particularly SDG 2 (Zero Hunger) and SDG 12 (Responsible Consumption and Production), while fostering a more resilient agricultural sector capable of withstanding climate variability and resource limitations.

REFERENCES

Akanbi, W. B., & Olayanju, T. M. (2021). Precision agriculture: A pathway for smallholder farmers in Africa to enhance productivity and sustainability. African Journal of Agricultural Research, 16(12), 140-154. https://doi.org/10.5897/AJAR2021.15699

Alabi, J., & Eze, P. (2023). The impact of precision agriculture on smallholder farmers' productivity in Sub-Saharan Africa. African Journal of Agricultural Research, 18(5), 320-334. doi:10.5897/AJAR2023.12345

Bakhsh, A., & Khan, M. A. (2022). Assessing the socio-economic impacts of precision agriculture on smallholder farmers in the Punjab region of Pakistan. Journal of Precision Agriculture, 23(3), 439-455. https://doi.org/10.1007/s11119-021-09712-9

BusinessDay. (2023). High costs limit adoption of precision agriculture in Nigeria. Retrieved from https://businessday.ng

Choudhury, A., & Raghavendra, H. (2022). The role of technology in precision agriculture for smallholder farmers: A systematic review. Agricultural Technology, 12(4), 290-305. https://doi.org/10.1016/j.agt.2022.03.004

Davis, A. G., & McKenzie, H. (2021). The adoption of precision agriculture technologies by smallholder farmers: A global perspective. Journal of Agricultural & Food Information, 22(3), 202-218. https://doi.org/10.1080/10496505.2021.1943765

Elham, A., & Ebrahimi, A. (2021). Precision agriculture and its implications for smallholder farmers: Evidence from Iran. International Journal of Agricultural Sustainability, 19(1), 12-26. https://doi.org/10.1080/14735903.2021.1888342

Kumar, A., & Gupta, A. (2022). Precision agriculture technologies: Enhancing productivity and sustainability for smallholder farmers in India. Journal of Agricultural Science, 14(2), 112-125. https://doi.org/10.5539/jas.v14n2p112

Moges, A., & Sweeney, J. (2021). Enhancing the resilience of smallholder farmers through precision agriculture: Insights from Ethiopia. Agricultural Systems, 186, 102973. https://doi.org/10.1016/j.agsy.2021.102973

Nwosu, C., & Adewale, T. (2024). Addressing barriers to technology adoption: A case study of precision agriculture in West Africa. Journal of Sustainable Agricultural Technologies, 11(2), 85-97. doi:10.1016/j.jsat.2024.05.003

Nyangweso, P., & Obonyo, E. (2021). The impact of precision agriculture on smallholder farmers' livelihoods in Kenya. International Journal of Agricultural Economics and Rural Development, 14(1), 45-59. https://doi.org/10.1007/s40100-021-00401-6

Smith, R., & Owusu, D. (2023). Overcoming infrastructural challenges in the adoption of precision agriculture among smallholder farmers. International Journal of Agricultural Innovation, 7(3), 154-169. doi:10.1016/j.ijai.2023.03.007

United Nations Development Programme (UNDP). (2024). Enhancing food security through digital agriculture in Africa. Retrieved from https://www.undp.org

World Bank. (2023). Leveraging digital agriculture for sustainable development in Africa. Retrieved from https://www.worldbank.org

Yadav, A., & Singh, S. (2022). Leveraging precision agriculture for sustainable development among smallholder farmers in northern India. Sustainable Agriculture Research, 11(3), 89-99. https://doi.org/10.5539/sar.v11n3p89

SOCIAL SCIENCE APPLICATIONS IN PRECISION AGRICULTURE

ASSESSMENT OF ACCESS TO AND UTILISATION OF TREADLE AND HIP PUMP TECHNOLOGY BY FARMERS IN MACHAKOS COUNTY, KENYA

#11285

T. Gitau, G.B. Mose, and C. Masiga
Kenyatta University, Nairobi, Kenya
e-mail: terriewag88@gmail.com +254 728 805 205

ABSTRACT

The aim of this study was to assess the access to and utilization of the treadle and hip pump technology by farmers in Machakos County, Kenya so that gender responsive strategies can be suggested to improve the uptake of the technology among the farmers. This was due to low adoption of the two pumps in Machakos county after previous KickStart International and Washington State university (KSI/WSU) study that marketed and distributed the technology among farmers in the county. The specific objective in this paper was to examine the challenges facing farmers when accessing to and utilizing the pumps in the county that seemed to be in dire need of the pumps due to the arid and semi-arid climate, yet the adoption was too low. The study was guided by the social relations framework of analysis by Naila Kabeer which was complemented by the diffusion of innovations theory. The study used experimental and descriptive research designs for both qualitative and quantitative data. The study had 70 respondents comprising 42 farmers who were pump buyers purposively selected for the study and 28 pump non-buyers identified via snowball sampling method. Data were collected using interview schedules, key informant interview guides and focus group discussion guides. Findings reported major challenges to access to and utilization of the pump technology were at family level and market level. The study concluded that the use the treadle and hip pump technology was still appropriate in compared to the tools they were previously used to. However, the challenges faced by the farmers were both internal and external, i.e., from buyers and marketers to the environment in which the operated. The pump technology design hampered use by women since it required a lot of energy to use. The study recommended putting gender responsiveness in design of pumps, consistent intergenerational marketing and distribution of the pump technology with follow up by the innovation marketer for adoption among women, men and youth.

INTRODUCTION

Globally, farming is perceived as a lucrative venture in regions with sustained fertility and water resources. For arid and semi-arid region, farming has been a difficult and expensive venture as irrigation projects are required to enable food security for both domestic and commercial use. For this reason, the need to develop more approaches that will improve farming in arid and semi-arid areas became a necessity for non-governmental organizations (NGOs) and government stakeholders (Ivers & Cullen, 2011). Regardless of this provision, the need to develop small-scale farmers required cheap farming technology that they could use in smallholder farms. This led to embracing of technology in the agriculture sector. One of the technologies is the treadle pump, which was developed in 1979 by a team working with the Rangpur Dinajpur Rural Service (RDRS). The treadle pump extracted larger volumes of water more than the existing hand-operated pumps. The design of the pumps targeted the poor and those in remote areas with limited access to diesel and technical support (Purcell, 1997).

Asia was the birthplace of the treadle pump (Orr et al. 1991), for this reason, the demand for the technology in rural Bangladesh was significant. Its popularity then increased its supply across neighboring nations including India and Pakistan. In these regions, the number of rural farmers was massive as they solely depended on agriculture for their livelihood. Both men and women in the regions were provided with treadle water pumps. NGOs' involved in the programme wanted to increase the buying power of the consumer thus launching a purchasing plan that would fit the financial comfort of the farmers. The NGOs' provided pumps for irrigation projects on credit to farmers prior to agreeing to a payment plan (Prabhu, 1999). Since the creation of the treadle pump in Bangladesh, 1.4 million pumps had been sold to the local farmers by 1991 (Alistair et al. 1991). This depicted the importance of the affordable irrigation option.

The hip pump is a KSI innovation of the small-scale irrigation pump in terms of the body parts used to operate it, lighter weight and lower cost than the treadle pump. From these efforts, the treadle and hip pump technology is being used mainly in Kenya, Tanzania, Malawi, Zambia, Mali, Burundi, Sudan, Burkina Faso, Uganda and Rwanda (Sijali & Mwago, 2009). The popularity of the technology in these countries was mainly influenced by Kick Start International (KSI). The organization was born in Kenya, which increased the use of pumps in the country as well in East Africa.

Machakos County is one of the 47 counties in Kenya and formerly part of the Eastern province where the pump technology has been adopted, thus of interest to this study. An introduction of small-scale irrigation technology by KSI in conjunction with Washington State University (WSU) targeting women began in 2014 and ended in 2016 in the county. The goal of KSI/WSU was to offer the technology and purchasing plan fit to the financial comfort of women farmers and through comprehensive marketing of the pumps to assure as many sales as possible. The farmers were to purchase the pumps either in cash, on credit or savings options. The treadle pump cost KES 14,950 while the hip pump cost KES 9,500 which farmers were expected to pay back within six months. Pumps were provided to individuals but based on a group loan and repayment. Once pumps were distributed to the group members, the farmers were further taught how to use and maintain the technology KSI (2015).

This study sought to assess how the women farmers were accessing the KSI/WSU technology as well as utilizing the treadle and hip pump technology in their farms in Machakos County since the former study was not scaled up as envisioned. The researcher engaged with women farmers who took up the KSI/WSU pump technology and those who did not take up the technology, yet they had water available to irrigate their crops, i.e., the non-buyers in the study.

MATERIALS AND METHODS

The study used experimental and descriptive research designs for both qualitative and quantitative data. The study had 70 respondents comprising 42 farmers who were pump buyers purposively selected for the study and 28 pump non-buyers identified via snowball sampling method. Convenience sampling was used to sample the key informants i.e. chiefs, extension officers from various wards and KSI/WSU representative in the county. Data were collected using interview schedules, key informant interview guides and focus group discussion guides. The study's quantitative data was analyzed using SPSS version 23 to give descriptive statistics. Data were presented as percentages, frequencies, averages tabulations, histograms, and pie charts. Qualitative data were analyzed using content analysis, organized into themes and patterns formed, and presented in a narrative form and verbatim quotations.

RESULTS AND DISCUSSION

Challenges faced by farmers when accessing and utilizing the treadle and hip pump

This section covers the results and discussion that sought to find out the challenges that women farmers faced while accessing and utilizing the treadle and hip pump irrigation technologies. In the study 62(**88.6%**) stated that they had challenges while 8(**11.4%**) did not face challenges in the process of acquiring their pump. The researcher categorized the list of challenges given from individual responses and FGD discussions into themes under institutions in Naila Kabeer's social relations framework on how access to and utilization of the treadle and hip pump challenges were reworked in the four institutions categories of the family, community, market and state.

Table 1. Challenges as perceived by study respondents.

Levels of challenges	Buyers				Non buyers				KSI representative		Chiefs		Extension officers	
	Female		Male		Female		Male							
	No	%	No	%	No	%	No	%	No	%	No	%	No	%
Family	20	67	5	42	11	58	5	56	1	100	4	50	2	50
Community	21	70	3	25	6	32	7	78	1	100	6	75	1	25
Market	16	53	10	83	4	21	5	56	1	100	2	25	3	75
State	25	83	7	58	8	42	7	78	1	100	4	50	2	50
Average Family Community State Market	23(**54.5%**) 14(**47.5%**) 15(**50%**) 20(**68%**)				14(**50%**) 15(**55%**) 14(**50%**) 11(**38.5%**)				1(**100%**) 1(**100%**) 1(**100%**) 1(**100%**)		4(**50%**) 6(**75%**) 2(**25%**) 4(**50%**)		2(**50%**) 1(**25%**) 3(**75%**) 2(**50%**)	

Major challenges to access to and utilization of the pump technology among pump buyers were at family level and market level. At family level, the women willingness to acquire the pumps was met by the inability to do so due to lack of finances while at market level, the pump design itself required some gender responsive considerations as some women said it was tiresome for them to use.

> "The pump is tiresome and requires two people when using especially the pedalling part requires a lot of energy which we women lack. Personally, I am involved in directing the hose to the crops or tank while my husband or son pedals the pump" (Interview with a woman pump buyer at Kithimani 15/4/2017)

Community level and state challenges were reported too, however, solution to their contribution to the challenges would act as accessories to strengthen solutions at family and market level. Asked about the disparities in representation, a female extension officer from Machakos town Sub County had this to say,

> "We have previously experienced situations where male officers were chased from homes by some male homeowners especially when they appeared alone. Although this was partly solved by meeting the farmers in groups, some women in groups may not express themselves well in these groups which are also male dominated," said Mueni. (Key informant interview with Machakos sub county extension officer 15/2/2017)

Lack of water, finances, labor, time of pump repayment, priorities in a family, source of information about the pumps and distance to point of purchase of the pump were also critical. The following responses from the farmers informed part of the challenges.

> "The time limit for repayment was too short" (Interviews with a savings buyer from Machakos on 13/2/2017)

Group members from Kyangala also thought the distance to where they get the pumps was too far.

> "The distance to the market especially to vendors is far and I am unable to replace my rubber caps". (FGD with a group from Kyangala on 14/2/2017)

The challenges faced by the farmers were both internal and external, i.e., from buyers and marketers to the environment in which they operated.

The research recommended family level challenges to be addressed through education on importance of support of farm chores by everyone in the family regardless of their gender. Market level challenges to also be addressed by the marketer through design of pumps that are gender responsive to allow participation in utilization by all members of the family. Another gender aspect the marketer could utilize in marketing and distribution is through working with female opinion leaders, establish demonstration farms with female headed households as well as appointing enterprising lead farmers such as the group secretary and pump dealers to build supply networks and create linkages with farmers. This secretary could earn steady income from a profit-sharing model from sales. The marketer could also consider advertising and marketing that does not conform to gender stereotypes during promotional campaigns through promoting multiple range of products for women and men. The type of media chosen and content of message about the pump to reach women should consider their low mobility outside their home. Community level challenges could be adjusted through tapping on solutions at family level while state level challenges to be addressed in a bottom-up manner by marketers together with other key players in agriculture such as community-based organizations (CBO's), NGOs, self-help groups and faith-based organizations through lobbying for support at county and national level.

REFERENCES

Alistair, O., Islam, A. & Gunnar, B. (1991). The Treadle Pump: Manual Irrigation for Small Farmers in Bangladesh. R.D.R.D. Pdf.

Ivers, L. and Cullen, K. (2011). "Food insecurity: special considerations for women. The American Journal of Clinical Nutrition, 94, (6): 1740–1744.

KickStart International. Empowering women with technology. February 2015. http://www.kickstart.org/about-us/Women's%20Empowerment%20Report%20-%20KickStart%20International%20-%20February%202015.pdf

Orr, A., Islam, A. N., & Barnes, G. (1991). The treadle pump: manual irrigation for small farmers in Bangladesh. Dhaka: Rangpur Dinajpur Rural Service.

Prabhu, M. (1999). Marketing treadle pumps to women farmers in India. Gender & Development, 7(2), 25-33.

Purcell, R. (1997). Potential for small-scale irrigation in sub-Saharan Africa: the Kenyan example.

Sijali, V. & Mwago.M. (2009). Money Maker Pumps: Creating Wealth in Sub-Saharan Africa. http://siteresources.worldbank.org/AFRICAEXT/Resources/258643-1271798012256/YAC_chpt_18.pdf New York:United Nations

WATER MANAGEMENT FOR PRECISION AGRICULTURE

REAL-TIME MOISTURE CONTROL IN IRRIGATION SYSTEMS FOR WATER USE EFFICIENCY AND CLIMATE CHANGE RESILIENCE. A REVIEW

#11679

D. Kindikiza
West African Centre for Water, Irrigation and Sustainable Agriculture - University for Development Studies (WACWISA-UDS), Tamale, Ghana
e-mail: didierki2036@uds.edu.gh

ABSTRACT

Due to the increasing water scarcity and uncertainties of climate change, improving crop water use efficiency and productivity, at the same time minimizing detrimental effects on the environment to meet the world's rising food demand. Thus, is necessary to adopt innovative irrigation strategies, such as drip irrigation. Smart irrigation has a potential of improving water use efficiency in precision agriculture. Conventionally, irrigation systems rely on heuristic methods in order to schedule irrigation which either leads to over-irrigation or under-irrigation which affects water use efficiency. In this paper, we are describing and comparing different methods of irrigation water control strategies for irrigation decisions with their impact on climate change resistance. Those are open loop strategies that include manual, time and volume-based control against closed loop types which are composed of optimal, artificial intelligence and linear controls. Furthermore, the paper is reflecting on automation in different irrigation systems.

This review paper has important implications for farmers and agricultural stakeholders, to adapt technologies, as it offers practical solutions to address the ongoing challenges emanated from water scarcity and climate change.

Keywords: Soil moisture control, Irrigation systems, Water use efficiency, Climate change.

INTRODUCTION

Climate change and increasing population do impose additional pressure to Global water resources use and scarcity, that are vital for agricultural production (Ungureanu *et al.*, 2020). According to the United Nations Department of Economic and Social Affairs (2019), the world population will hit 9.7 billion by 2050 translating into increased demand for nutritious food and water resources. The Food and Agricultural Organization (FAO) forecasts a more than 50 % increase in irrigated food production by 2050, which will require a 10 % increase in water abstracted for agriculture, provided water productivity improves (Food and Agriculture Organization, 2017). The land on which food is cultivated does not expand, which means agricultural cropping systems need to utilize the available water and land resources efficiently to feed the future population. Understanding the mechanisms that can improve water use efficiency and result in significant water savings and higher yield is therefore paramount (Saleem et al., 2013).

Smart irrigation control in precision agriculture is becoming popular due to water saving ability buy providing water to the desirable location (root zone) and maximizing yield. Sensor-based decision support and automation can reduce significantly manual intervention while operation irrigation systems (Klein et al., 2018). Moreover, irrigation soil moisture control strategies, take into consideration plants response to water stress, changing weather variables through Internet of Things (IoT) monitoring (Abioye et al., 2020).

This paper implication provides valuable insights into the potential benefits of smart irrigation control systems for water use efficiency and contribute to the development of more sustainable solution for climate change resilience through agricultural irrigation for food security.

MATERIALS AND METHODS

This review applied methods of selecting the works of literature that are published on precision irrigation and all its existing control strategies includes an extensive search through a different multidisciplinary online database, such as Elsevier, Springer, Taylor & Francis, Google Scholar, and other high ranked Scopus indexed journals. The emphases were placed on numerous research articles and books related to irrigation water control and monitoring strategies were considered too. The keyworks; soil moisture control strategies, irrigation systems, water use efficiency and climate change were followed to relate the articles. Therefore, the papers were selected, read and summarised to ensure the systematic flow of the ideas.

DISCUSSION

Irrigation Water Control Techniques in Precision Agriculture

Irrigation control strategies are divided into open-loop systems and closed-loop systems. While open-loop systems apply a preset action like in simple irrigation timers, closed-loop systems receive feedback from sensors, make decisions and apply the resulting decisions to the irrigation system. Figure 1 presents a detailed classification of irrigation control strategies derived from literature studies.

Climate Resilience Action

The data-driven models developed by the authors were able to estimate reference temperatures, enabled automated calculation of the crop-water-stress index for effective assessment of crop water stress (Vallejo-Gómez et al., 2023). There is a need to evaluate stochastic and Hybrid MPC strategies for efficient irrigation scheduling in open-field agriculture. There are many uncertainties and unpredictable disturbances from the environment unlike in a greenhouse where environmental conditions are controlled.

Application of Real - time Moisture Control Strategies in Agriculture

Owing to the similarity of agricultural processes to industrial processes, Model Predictive Control has been applied in product processing, agricultural production, greenhouses and irrigation systems (Bwambale et al., 2023) . Model predictive control has been applied in canal flow control and regulation, agricultural machinery, production, and processing and irrigation scheduling.

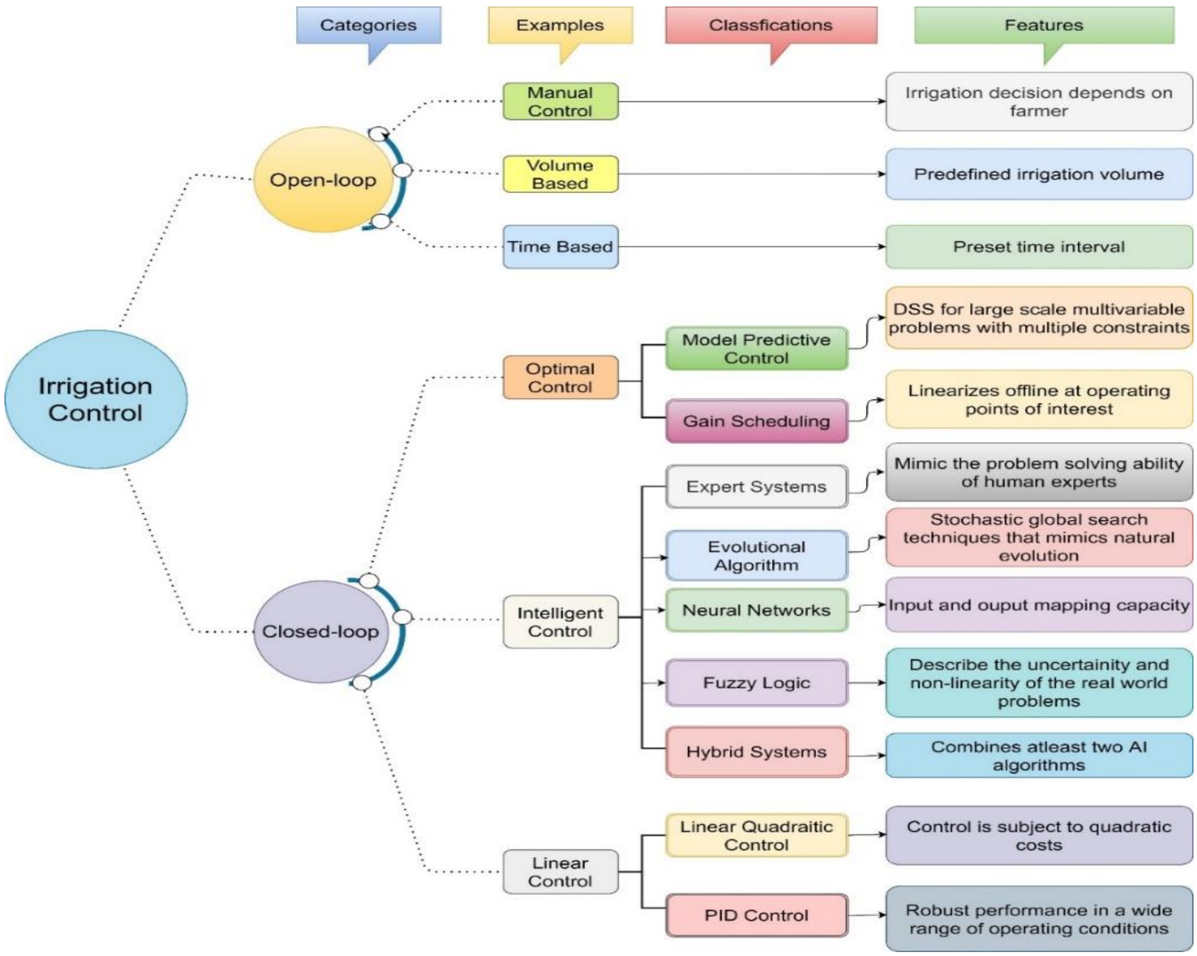


Figure 1. Classification of Irrigation Control Strategies. Adapted from (Abioye *et al*., 2020b; Erion *et al*., 2023).

CONCLUSION

In this review, the systematic review conducted here shows that the literature on smart irrigation control strategies shows a significant importance in agricultural water use efficiency as well as climate change resilience. Therefore, this is considered a rising research niche to which we can continue to contribute from many points of view, as mentioned throughout the text. Regarding the technological aspects of the analysed works, it became evident that embedded systems are preferred in the implementation of smart irrigation system prototypes, which use technologies considered to be of interest for this work, like Model Predictive Control. However, smart irrigation systems usually involve a significant cost, affordability must not be forgotten, and that implies the involvement of different stakeholders is a must as the availability and accessibility is not an issue.

REFERENCES

Abioye, E. A., Abidin, M. S. Z., Mahmud, M. S. A., Buyamin, S., Ishak, M. H. I., Rahman, M. K. I. A., Otuoze, A. O., Onotu, P., & Ramli, M. S. A. (2020). A review on monitoring and advanced control strategies for precision irrigation. Computers and Electronics in

Agriculture, 173(August 2019). https://doi.org/10.1016/j.compag.2020.105441

Bwambale, E., Abagale, F. K., & Anornu, G. K. (2023). Model-based smart irrigation control strategy and its effect on water use efficiency in tomato production. Cogent Engineering, 10(2). https://doi.org/10.1080/23311916.2023.2259217

Food and Agriculture Organization, F. (2017). The future of food and agriculture Trends and challenges.

Klein, L. J., Hamann, H. F., Hinds, N., Guha, S., Sanchez, L., Sams, B., & Dokoozlian, N. (2018). Closed Loop Controlled Precision Irrigation Sensor Network. IEEE Internet of Things Journal, 5(6), 4580–4588. https://doi.org/10.1109/JIOT.2018.2865527

Saleem, S. K., Delgoda, D. K., Ooi, S. K., Dassanayake, K. B., Liu, L., Halgamuge, M. N., & Malano, H. (2013). Model Predictive Control for Real-Time Irrigation Scheduling. IFAC Proceedings Volumes, 46(18), 299–304. https://doi.org/10.3182/20130828-2-SF-3019.00062

Vallejo-Gómez, D., Osorio, M., & Hincapié, C. A. (2023). Smart Irrigation Systems in Agriculture: A Systematic Review. Agronomy, 13(2), 1–25. https://doi.org/10.3390/agronomy13020342

UPLAND RICE YIELD RESPONSE TO SOIL MOISTURE VARIABILITY WITH DEPTH ACROSS FERRALSOLS AND GLEYSOLS IN WESTERN UGANDA

#11659

[1*]Matila Tom Micah; [1]B. Kiconco; [1]L. Abasize; [1]P. Tamale; [1]E. Opolot; [1]P. Ebanyat; [2]T. Oberthur, [1]P. Musinguzi

[1]School of Agricultural Sciences, Makerere University, Kampala, Uganda; [2]African Plant Nutrition Institute, Benguérir, Morrocco

[*]e-mail: tommicahmatila@gmail.com

ABSTRACT

Soil moisture is a vital factor in boosting rice productivity by influencing the growth of healthy plants. In mid-western districts like Kikuube where rainfall is unpredictable, maintaining optimal soil moisture differs between a bountiful harvest and crop failure. Effective soil moisture management leads to improved water use efficiency, allowing crops to withstand periods of drought. This study assessed upland yield response to soil moisture variations with soil depth in Ferralsols and Gleysols for two seasons: (August to December 2023 and March to June 2024). Twenty-four (24) access tubes were installed in six fields, each field having four (4); three (3) fields of Ferralsols and three (3) for Gleysols, from which soil moisture content was measured using the Diviner 2000 at 10 cm intervals to a 1m depth. Calibrated rain gauges were also installed in each field to measure the daily rainfall received. Soil physical properties such as texture, bulk density, infiltration rates, soil water holding capacity, field capacity, and permanent wilting point (PWP) were determined. In Ferralsols, the soil moisture decreased with an increase in depth whereas in Gleysols, the soil moisture increased with an increase in depth. The increase in soil moisture with an increase in depth is attributed to the contribution of capillary rise for Gleysols. Gleysols registered higher yields of 5,840kg ha^{-1} compared to 3,527kg ha^{-1} in the Ferralsols–during the March-June 2024 season which had a high rainfall variability. However, high yields (6,375 kg ha^{-1}) in Ferralsols were registered in the August-December 2023 growing season characterized by less rainfall variability. Both Ferralsols and Gleysols are suitable for upland rice production. Nevertheless, in high variability of rainfall, the continuous supply of water by capillarity in Gleysols meets the crop water requirements unlike in Ferralsols.

INTRODUCTION

Upland rice cultivation is a prevalent agricultural practice in many regions of the world (Gadal et al., 2019), including western Uganda, where it plays a crucial role in food security and income generation for smallholder farmers (Agric, 2023). This crop exhibits a complex yield response to soil moisture variability, particularly when grown in Ferralsols and Gleysols (Niang, 2019). These soil types are characterized by their unique properties and moisture dynamics and play a crucial role in the growth and productivity of upland rice. Ferralsols, typically found in tropical regions with high rainfall, are deeply weathered, leached soils with a high content of iron and aluminum oxides, which can significantly influence the water-holding capacity and, consequently, the moisture availability of rice plants (S. Michael, 2023). On the other hand, Gleysols are often located in low-lying areas and are prone to waterlogging due to poor drainage, affecting root development and nutrient uptake in rice crops (Bado et al., 2018). In western Uganda, the bimodal rainfall pattern contributes to the variability of soil moisture with depth, impacting the yield of upland rice across these soil types. During the rainy seasons, Ferralsols provide adequate moisture for rice growth, but the challenge arises in managing excess water in Gleysols to prevent detrimental effects on the crop (Ojara et al., 2024). Conversely, in the dry seasons, the retention of soil moisture becomes critical, especially in Ferralsols, to sustain the rice during periods of water scarcity. A Study (Singh et al., 2017) has shown that upland rice varieties exhibit different physiological responses to soil moisture stress, with some genotypes demonstrating tolerance by maintaining growth and yield under varying moisture regimes. The ability of rice plants to adapt to moisture stress is linked to traits such as root depth and density, which determine the extent of water uptake from different soil layers (Sandhu et al., 2016). In Ferralsols, deeper root systems can access moisture from lower soil horizons, while in Gleysols, rice varieties with a higher tolerance to waterlogged conditions may fare better.

MATERIALS AND METHODS

Two seasons were considered in this study (August to December 2023 and February to June 2024). Six experimental plots on both Ferralsols (3) and Gleysols (3) were set up in Kikuube District. For each plot, four fertilizer treatments were applied. These included full package fertilizer recommendation (20kg N/ha + 30kg K/ha of DAP at planting, 20kg N/ha (Urea) + 40kg K/ha (MoP) at tillering and 20 kg N/ha (Urea) + 40kg K/ha (MoP) at panicle formation), half package (10kg N/ha + 15kg K/ha of DAP at planting, 10kg N/ha (Urea) + 20kg K/ha (MoP) at tillering and 10 kg N/ha (Urea) + 20kg K/ha (MOP) at panicle formation), quarter package (5kg N/ha + 7.5kg K/ha of DAP at planting, 5kg N/ha (Urea) + 10kg K/ha (MoP) at tillering and 5 kg N/ha (Urea) + 10kg K/ha (MoP) at panicle formation), and the Farmer management practices (Control). In each plot, four access tubes and one fabricated rain gauge were installed for reading soil moisture data by the Diviner 2000 at an interval of 10 cm to 100cm depth and recording on-site daily rainfall respectively. The Diviner 2000 was first calibrated to local soil conditions, likewise, fabricated rain gauges were also calibrated using the standard rain gauge at Makerere University Weather Station (the ratio of the value of the standard rain gauge to the value of the fabricated rain gauge) forming the calibration factor. Soil moisture data was read at least four times a week at an interval of one day. Weed management was done effectively from the time of planting by application of Butanil-S as a pre-emergence herbicide at the time of sowing and Butanil N70 + Butanil 2-4D as post-emergence herbicides. Pest management was also done using Roket type of pesticide only where there were cases of pests. The general rice yield was considered for this study as presented in the results below.

RESULTS AND DISCUSSION

Yield

There is a variation of upland rice production in the two soil types in Kikuube district. In both seasons 2023B, Ferralsols exhibited a higher yield (6,375kg/ha) than Gleysols (5,714kg/ha) whereas, in season 2024A, Gleysols had a higher yield (5,840kg/ha) than Ferralsols (3,527kg/ha). However, the variation in yields in both soil types and seasons is insignificant at $p<0.05$ (Figure 1).

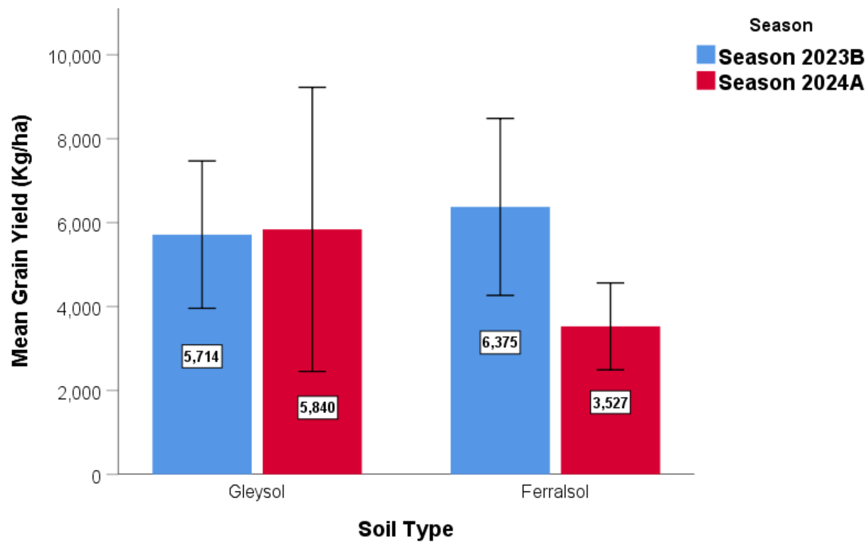


Figure 1. Rice yield for two seasons.

Soil moisture variation

Generally, soil moisture decreased with an increase in depth in Ferralsols whereas in Gleysols, the soil moisture content increased with an increase in soil depth (Figures 2 and 3 respectively).

DISCUSSION

Ferralsols and Gleysols are two distinct soil types that exhibit unique moisture variation profiles due to their inherent properties. The presence of micro-aggregates in Ferralsols enhances moisture storage at field capacity, which is crucial for crops like upland rice that rely on consistent moisture availability for optimal growth. The variation in soil moisture with depth (Increase with depth) Figure 2(A) in Gleysols significantly impacts the root development of upland rice, as the roots are not able to penetrate deeply enough to access the moisture in lower layers during drier periods. The effect of soil moisture on upland rice yield is profound since it is typically grown in rain-fed conditions, highly sensitive to soil moisture variability. Studies have shown that soil moisture stress during critical growth stages, such as panicle development, severely impacts the growth and yield of upland rice. For instance, improved upland rice varieties like NAMCHE 5 have demonstrated excellent performance under limited soil moisture conditions through early heading and maturity, contributing to higher grain yield. This is mainly due to their ability to produce heavier straw yield, an abundant number of productive tillers, higher filled spikelets, and heavier weight of seeds, which collectively enhance the harvest index and adjust to the soil moisture conditions. Furthermore, climate variability has been found to influence soil moisture levels and, consequently, rice production. Rain-fed upland rice systems are more vulnerable to these variations than irrigated paddy rice, with about 10% of the variance in rice production anomalies on a national level co-varying with soil moisture changes.

(A) (B)

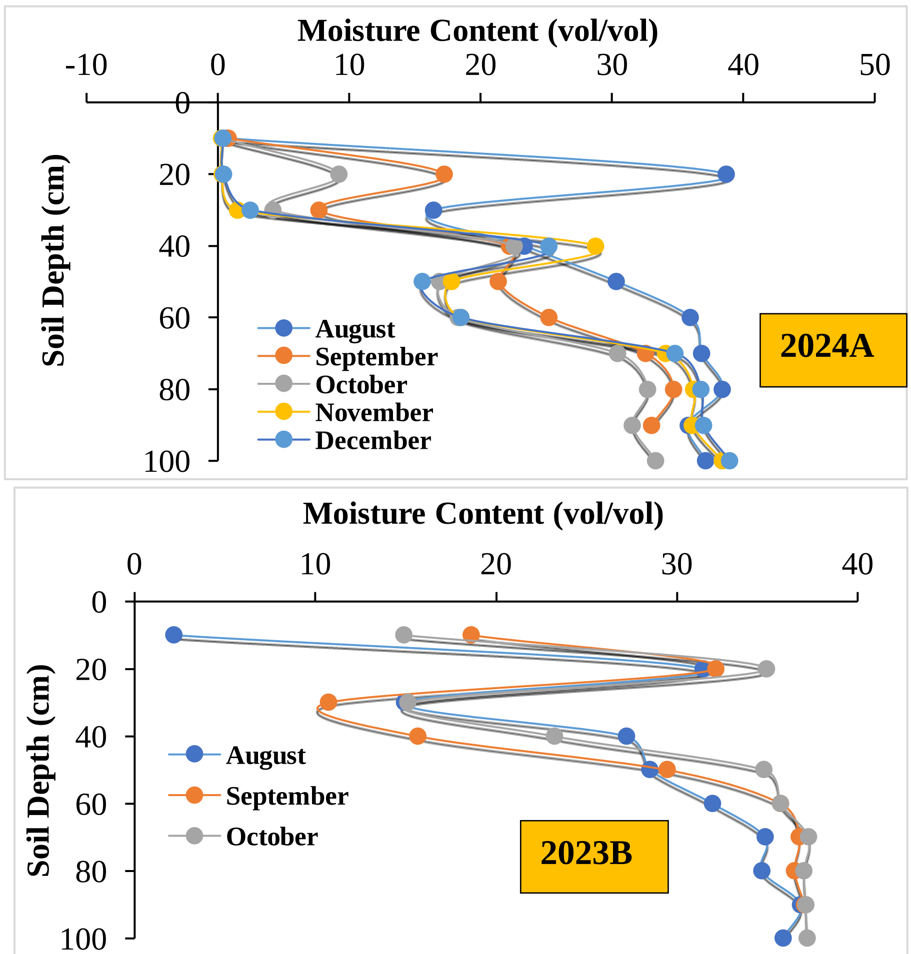


Figure 2. Variation of soil moisture with depth; (A) Gleysols (B) Ferralsols.

CONCLUSION

Understanding the dynamics of soil moisture in Ferralsols and Gleysols is essential for predicting and managing the yield of upland rice, which is a staple food for millions of people worldwide. Effective water management strategies, including the selection of rice varieties with drought tolerance and the timing of planting to coincide with optimal soil moisture conditions, are critical for sustaining rice production in the face of changing climate patterns and soil moisture regimes.

REFERENCES

Agric, F. (2023). https://doi.org/10.18697/ajfand.124.23140. 23(9), 24507–24522.

Bado, V. B., Djaman, K., & Mel, V. C. (2018). Developing fertilizer recommendations for rice in Sub-Saharan Africa, achievements and opportunities. Paddy and Water Environment, 16(3), 571–586. https://doi.org/10.1007/s10333-018-0649-8

Gadal, N., Shrestha, J., & Pokharel, B. B. (2019). A review on production status and growing environments of rice in Nepal and in the world A review on production status and growing environments of rice in Nepal and in the world. March. https://doi.org/10.26832/24566632.2019.0401013

Niang, A. (2019). Rice yield gaps in West Africa Abibou Niang.

Ojara, M. A., Namumbya, S., Ogwang, B. A., & Limbu, P. T. S. (2024). Regional and farm level droughts characteristics for southwestern Uganda during 1981–2017. Soil Security, 15(June), 100148. https://doi.org/10.1016/j.soisec.2024.100148

S. Michael, P. (2023). the Importance of Sustainable Management of Acid Soils in the Humid Tropics Under Climate Change and the Future Research Directions. In Ecofeminism and Climate Change (Vol. 4, Issue 1). https://doi.org/10.26480/efcc.01.2023.29.40

Sandhu, N., Anitha Raman, K., Torres, R. O., Audebert, A., Dardou, A., Kumar, A., & Henry, A. (2016). Rice root architectural plasticity traits and genetic regions for adaptability to variable cultivation and stress conditions. Plant Physiology, 171(4), 2562–2576. https://doi.org/10.1104/pp.16.00705

Singh, B., Reddy, K. R., Redoña, E. D., & Walker, T. (2017). Screening of Rice Cultivars for Morpho-Physiological Responses to Early-Season Soil Moisture Stress. Rice Science, 24(6), 322–335. https://doi.org/10.1016/j.rsci.2017.10.001

RAINWATER HARVESTING AND NUTRIENT INTENSIFICATION IN MAIZE-LEGUME FARMING SYSTEMS IN SEMI-ARID ZIMBABWE

#11639

*E. Mutsamba-Magwaza, D. Nyamayevu, I. Nyagumbo, R. Mandumbu, G. Nyamadzawo
International Maize and Wheat Improvement Centre (CIMMYT)-Zimbabwe, 12.5 km Peg Mazowe Road, Harare, Zimbabwe
*e-mail: efmagwaza@gmail.com; +263773047109

ABSTRACT

Agricultural productivity in Zimbabwe is declining mainly due to climate change, high cost of fertilizers and inherently poor soil fertility. In response to these challenges, most smallholder farmers are implementing either rainwater harvesting (RWH) or integrated soil fertility management (ISFM). This study sought to investigate the role of integrating the tied-contour RWH (TC-RWH) technique and ISFM on soil moisture, soil fertility, crop growth, and subsequent crop yields in semi-arid areas of Zimbabwe. A split-split-split plot design was established where water harvesting technologies namely tied contour (TC) and standard contour (SC) were considered as the main plots, cropping system (sole maize, sole cowpea and maize-cowpea intercrop) as sub-plots, different N-levels as sub-sub plots and manure as sub-sub-sub plots. Manure application demonstrated a higher grain yield advantage by 297 kg ha^{-1} over treatments without manure. Similarly, top dressing yielded more grain yield by 1146 kg ha^{-1} than untopdressed plots. Intercropping had a total systems' biomass yield 4397 kg ha^{-1} while cowpea sole and maize sole yielded 3863 and 3247 kg ha^{-1} respectively. Standard contours without manure had the least total biomass output. With respect to soil moisture, sole cowpea under SC retained more moisture than intercropped plots and sole maize during first season. The Land Equivalent Ratio of 1.3 kg ha^{-1} obtained signifies a greater land productivity and efficiency realized through intercropping compared to sole cropping systems. The study shows that when rainfall is abundant, as in the first season, sole cowpea conserves more moisture under standard contours than intercrops and sole maize. However, when conditions are dry, as in the case of the second season, sole and intercrops performed similarly. On the other hand, under excessively dry environments, sole maize systems with lower plant populations conserve moisture than sole cowpeas and maize-cowpea intercrop while in wet conditions, intercrops conserve more moisture than sole crops. Overall, in the sandy soils, failure to apply top dressing and manure resulted in serious yield penalties.

INTRODUCTION

The majority of smallholder farmers in Zimbabwe are located in semi-arid areas where rainfall is low (Mupangwa, Makanza, et al. 2021), and soils are inherently poor. Of the little rain that is received in the semi-arid regions, most is lost as runoff, and very little water is harvested for plant growth or future use (Nyamadzawo et al. 2012). Expansion of cultivatable areas and the practice of crop rotations have been ways of increasing crop productivity (Mupangwa et al., 2021; Nyagumbo et al., 2016) in Sub-Saharan Africa (SSA), but is no longer sustainable with SSA's population expected to increase by 2050 (Trisos et al., 2022). Additionally, exorbitant prices of inorganic fertilizers resulted in many farmers applying no to low rates of inorganic fertilizers, thus leading to poor yields.

Some smallholder farmers are already practicing water harvesting (Madamombe et al. 2024), and maize legume intercropping/rotations (Thierfelder et al. 2024), whilst adding organic and or inorganic fertilizers (Mutsamba, Nyagumbo, and Mupangwa 2019). To increase agricultural productivity in these areas, there may be a need to combine various techniques such as in-field water harvesting techniques, nutrient intensification and integrated nutrient management in semi-arid conditions. Specifically, this study investigated the role of integrating tied-contour rainwater harvesting (TC-RWH) technique and ISFM on soil moisture, soil fertility, crop growth and subsequent crop yields in semi-arid areas of Zimbabwe.

MATERIALS AND METHODS

The study was carried out in Mutoko District located in the semi-arid region of Zimbabwe. Mutoko receives annual rainfall of 450-600 mm and mean temperatures of about 35°C. The soils (Table 1) are mainly predominated by low fertile inherent granitic sandy soil (Lixisols: (FAO 2014). The suitable farming systems in these regions are semi-intensive farming systems with a mixture of crops and livestock.

Table 8. Soil characteristics of the experimental site before trial establishment.

% Carbon	Colour	Texture	pH ($CaCl_2$)	N (ppm)	P (ppm)	K (meq/100g)	Ca (meq/100g)	Mg (meq/100g)
1.19	PB	Mgs	5.05	29.5	37.5	0.15	1.35	0.49

Where PB =Pale brown colour and Mgs = Medium grained sand

The experiment was laid out in a split-split-split plot design, replicated three times on one on-farm field from 2020/21 to 2021/22 agricultural seasons. Water harvesting structures (tied and standard contours) were the main plots, cropping systems (maize-cowpea intercrops and the respective sole crops) were the sub-plots, N-fertiliser rates (top dressed and untopdressed) were the sub-sub plots, and the manure application (with or without) were the sub-sub-sub plots (Fig 1b).

Tied contours (Fig 1a) measuring 0.3 m deep and 1 m wide were prepared at a slope of 1:250. The cross ties were placed after every 5 m with a breadth of 0.5 m and a small opening was made at the upper side of the tie to allow water to flow from one compartment to another when it was full. SCs were made at a gradient of 1:250 with the same measurements as of tied contours. SCs are existing water channels designed at 1:250 gradient to dispose of field water. Both TCs and SCs were spaced at 8 m. Top dressing of ammonium nitrate (34.5% N) was applied to maize only at the different specified rates 3-4 weeks after planting.

Crop height, chlorophyll, NDVI and soil moisture were measured using a meter rule, chlorophyll meter (Apogee Instruments, MC 10), handheld green seeker (SPL technologies and a Field Scout$_{TM}$ TDR 300 soil Moisture Meter (Spectrum Technologies, Inc.) respectively. Daily rainfall was recorded using a rain gauge mounted at the experimental site. Analysis of variance (ANOVA) across treatments was conducted using R-software to determine the effects of tied contours, fertiliser and manure use on chlorophyll, NDVI, plant height and grain yield. For significant treatment*season interactions, each season was the analysed separately.

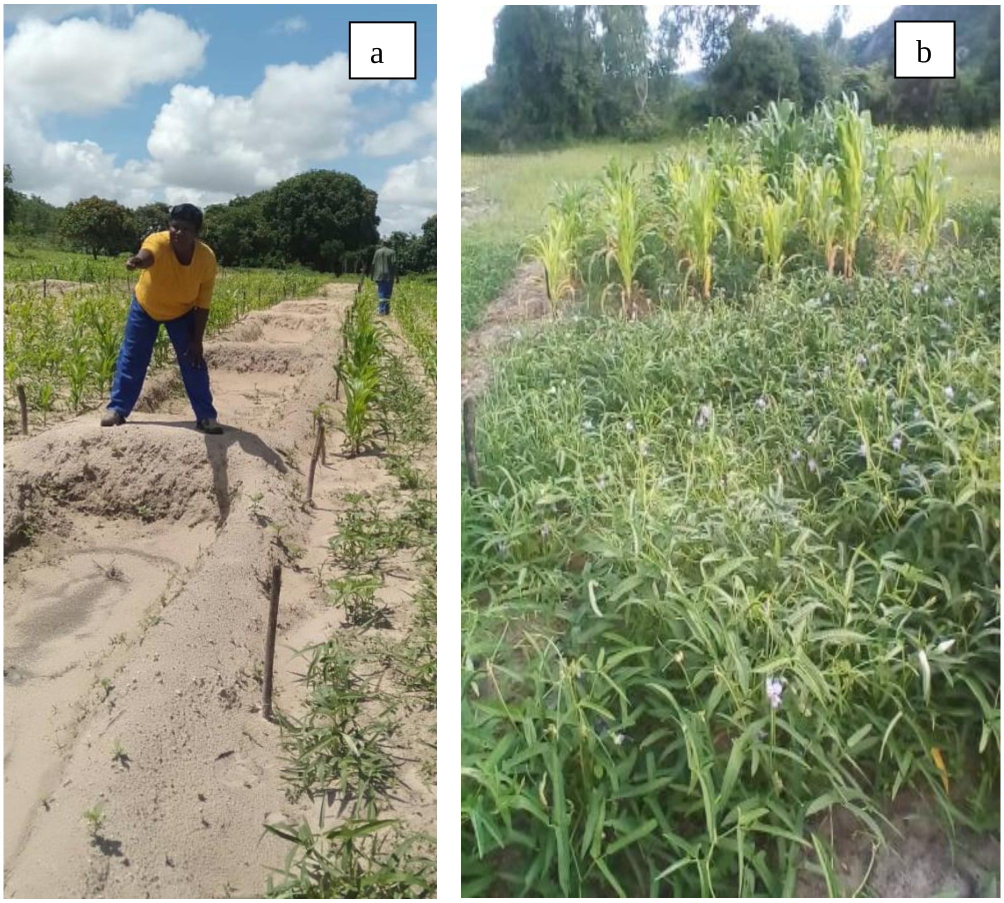


Figure 1. Picture of a) tied ridges b) cropping systems (maize-cowpea intercrop and sole cowpeas) and maize with and without top dressing.

RESULTS AND DISCUSION

The 2020-21 and 2021-22 seasons received a total annual rainfall of 684 mm and 461 mm respectively. There 4-way interaction between the cropping systems, water harvesting techniques, manure application and top-dressing application was insignificant. Across the two cropping seasons, it was observed that manure application demonstrated a higher grain yield advantage by 297 kg ha^{-1} over treatments without manure. Similarly, top dressing yielded more grain yield by 1146 kg ha^{-1} than untopdressed plots. In addition, the application of top dressing significantly increased total biomass yield compared to untopdressed plots. However, there was no significant difference in total above-ground biomass in plots applied manure and those without manure. The results clearly indicate that despite the importance of inorganic fertilisers, it is crucial to acquire nutrients from diverse sources, including organic materials like livestock manure and nitrogen-fixing legumes (Sanginga and Woomer 2009). The use of both organic and inorganic inputs is important because both resources fulfil different functions towards plant growth and neither of them is available or affordable in sufficient quantities (Vanlauwe et al. 2015).

Total biomass yield was significantly affected by cropping system, where maize-cowpea intercrop had significantly higher output than sole maize, concurring with (Mutsamba, Nyagumbo, and

Mupangwa 2019). Intercropping yielded 4397 kg ha^{-1} while cowpea sole and maize sole yielded 3863 and 3247 kg ha^{-1} respectively. Standard contours without manure had the least total biomass output. In other studies, tied ridging and rip & potholing yielded 25% more grain yield than conventional mouldboard ploughing (Nyagumbo and Bationo, 2011). The Land Equivalent Ratio (LER) of 1.3 kg ha^{-1} obtained signifies a greater land productivity and efficiency realized through intercropping compared to sole cropping systems, concurring with (Bitew and Abera 2019; Mutsamba, Nyagumbo, and Mupangwa 2019).

On soil moisture, sole cowpea under SC retained more moisture than intercropped plots and sole maize during first season. This can be attributed to the ability of cowpea reducing evaporation from the soil surface. As sole cowpeas' plant populations doubled that of sole crops, it translated to higher ground coverage and there was no competition for moisture due to adequate rains received. However, during the second season under SC, all cropping systems performed similarly due to very low rainfall amounts received. Conversely, under TC, intercrop systems had higher soil moisture content compared to the sole cowpea and maize during first season, while sole maize had higher soil moisture compared to intercrops during the second season. Given the dry conditions experienced during the second season, sole maize retained more moisture compared to sole cowpea and intercrop systems. This may be due to high plant densities in intercrops and sole cowpea competing for soil moisture in the root zone. This can be attributed to high plant densities in intercrops and sole cowpea competing for soil moisture in the root zone, as studies have reported that intercrops often have lower soil moisture than sole crops due to greater root moisture extraction (Eskandari and Kazemi 2011). This contradicts with (Ghanbari et al. 2010) who showed that maize monocrop tend to have a lower soil moisture content compared to sole cowpea due to high soil water losses through evapotranspiration..

Top dressed plants under TC displayed greater heights compared to plants under SC. This is attributed to the water harvesting under TCs compared to SCs which disposed water due to gradient. Manure application led to taller plants during second seasons. Intercropped plots had higher NDVI than sole maize indicating the benefits of biological nitrogen fixation (Franke et al. 2018). NDVI was measured during the second season only when the green seeker was made available. In conclusion, the benefits of water harvesting are determined by rainfall received.

REFERENCES

Bitew, Yayeh, and Merkuz Abera. 2019. "Conservation Agriculture Based Annual Intercropping System for Sustainable Crop Production: A Review." Indian Journal of Ecology 46(2): 235–49.

Eskandari, Hamdollah, and Kamyar Kazemi. 2011. "Weed Control in Maize-Cowpea Intercropping System Related to Environmental Resources Consumption." Notulae Scientia Biologicae 3(1): 57–60.

FAO. 2014. World Reference Base for Soil Resources' International Soil Classification System.

Franke, A. C., G. J. van den Brand, B. Vanlauwe, and K. E. Giller. 2018. "Sustainable Intensification through Rotations with Grain Legumes in Sub-Saharan Africa: A Review." Agriculture, Ecosystems and Environment 261(September 2017): 172–85. doi:10.1016/j.agee.2017.09.029.

Fredriksen, Birger, and Ruth Kagia. 2013. "Attaining the 2050 Vision for Africa: Breaking the Human Capital Barrier." Global Journal of Emerging Market Economies 5(3): 269–328.

Ghanbari, Ahmad, Mehdi Dahmardeh, Barat Ali Siahsar, and Mahmoud Ramroudi. 2010. "Effect of Maize (Zea Mays L.)-Cowpea (Vigna Unguiculata L.) Intercropping on Light Distribution, Soil Temperature and Soil Moisture in Arid Environment." Journal of Food, Agriculture & Environment 8(1): 102–8.

Madamombe, Sandra Makaita, Stanley Karanja Ng'ang'a, Ingrid Öborn, George Nyamadzawo, Ngonidzashe Chirinda, Job Kihara, and Libère Nkurunziza. 2024. "Climate Change Awareness and Adaptation Strategies by Smallholder Farmers in Semi-Arid Areas of Zimbabwe." International Journal of Agricultural Sustainability 22(1): 2293588.

Mupangwa, W., R. Makanza, L. Chipindu, M. Moeletsi, S. Mkuhlani, F. Liben, I. Nyagumbo, and M. Mutenje. 2021. "Temporal Rainfall Trend Analysis in Different Agro-Ecological Regions of Southern Africa." Water SA 47(4): 466–79. doi:10.17159/WSA/2021.V47.I4.3844.

Mupangwa, W., I. Nyagumbo, F. Liben, L. Chipindu, P. Craufurd, and S. Mkuhlani. 2021. "Maize Yields from Rotation and Intercropping Systems with Different Legumes under Conservation Agriculture in Contrasting Agro-Ecologies." Agriculture, Ecosystems and Environment 306. doi:10.1016/j.agee.2020.107170.

Mutsamba, E. F., I. Nyagumbo, and W. Mupangwa. 2019. "Forage and Maize Yields in Mixed Crop-Livestock Farming Systems: Enhancing Forage and Maize Yields in Mixed Crop-Livestock Systems under Conservation Agriculture in Sub-Humid Zimbabwe." NJAS - Wageningen Journal of Life Sciences (November). doi:10.1016/j.njas.2019.100317.

Nyagumbo, Isaiah, and André Bationo. "Exploring Crop Yield Benefits of Integrated Water and Nutrient Management Technologies in the Desert Margins of Africa : Experiences from Semi-Arid Zimbabwe." : 1–23.

Nyagumbo, Isaiah, Siyabusa Mkuhlani, Charity Pisa, Donwell Kamalongo, Domingos Dias, and Mulugetta Mekuria. 2016. "Maize Yield Effects of Conservation Agriculture Based Maize???Legume Cropping Systems in Contrasting Agro-Ecologies of Malawi and Mozambique." Nutrient Cycling in Agroecosystems 105: 275–90. doi:10.1007/s10705-015-9733-2.

Nyamadzawo, G., P. Nyamugafata, M. Wuta, J. Nyamangara, and R. Chikowo. 2012. "Infiltration and Runoff Losses under Fallowing and Conservation Agriculture Practices on Contrasting Soils, Zimbabwe." Water SA 38(2): 233–40. doi:10.4314/wsa.v38i2.8.

Ofori, Samuel Appiah, Samuel Jerry Cobbina, and Samuel Obiri. 2021. "Climate Change, Land, Water, and Food Security: Perspectives From Sub-Saharan Africa." Frontiers in Sustainable Food Systems 5: 680924. doi:10.3389/fsufs.2021.680924.

Sanginga, N., and P.L. (eds.). Woomer. 2009. Integrated Soil Fertility Management in Africa: Principles, Practices and Developmental Process. Nairobi: Tropical Soil Biology and Fertility Institute of the International Centre for Tropical Agriculture.

Thierfelder, Christian, Blessing Mhlanga, Isaiah Nyagumbo, Kelvin Kalala, Esau Simutowe, Mazvita Chiduwa, Chloe MacLaren, João Vasco Silva, and Hambulo Ngoma. 2024. "Two Crops Are Better than One for Nutritional and Economic Outcomes of Zambian Smallholder Farms, but Require More Labour." Agriculture, Ecosystems & Environment 361: 108819.

Trisos, Christopher, Ibedun Adelekan, Edmund Totin, A Ayanlade, J Efitre, A Gemeda, K Kalaba, et al. 2022. "Africa. In: Climate Change 2022: Impacts, Adaptation and Vulnerability. Contribution of Working Group II to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change."

Vanlauwe, B., K. Descheemaeker, K. E. Giller, J. Huising, R. Merckx, G. Nziguheba, J. Wendt, and S. Zingore. 2015. "Integrated Soil Fertility Management in Sub-Saharan Africa: Unravelling Local Adaptation." Soil 1(1): 491–508. doi:10.5194/soil-1-491-2015.

FACTORS INFLUENCING FARMERS' DECISIONS ON TIMING AND APPLICATION RATES OF IRRIGATION WATER IN MWALA, MACHAKOS COUNTY

#11284

D.M. Onyancha, C.K.K. Gachene, and G. Kironchi
University of Nairobi, Nairobi, Kenya
e-mail: deborahmongína@gmail.com; +254 713 377 983

ABSTRACT

This study examines the factors influencing farmers' water application decisions in arid and semi-arid regions, where water scarcity is a significant challenge due to unreliable rainfall. The research involved interviews with 41 farmers from the Equity Group Foundation extension scheme, focusing on their irrigation practices, including scheduling, timing, application rates, and considerations of plant and soil conditions. Additionally, soil samples from farms using furrow, drip, sprinkler, and hosepipe irrigation systems were analyzed, with field measurements taken to estimate water application rates. The findings reveal that farmers prioritize plant conditions (97% degree of importance) when deciding when to irrigate, followed by soil conditions and days since the last irrigation (both 95%), with recent rainfall also playing a key role (87%). For determining the amount of water to apply, soil conditions were deemed most important (80% importance), followed by plant conditions (75%) and recent temperature (70%). The study also found that water application amounts often exceeded the crops' requirements across all irrigation methods, with furrow irrigation having the highest flow rate (0.479 litres per second). The soils were found to have high coarse-textured contents, resulting in low moisture retention capacities and high hydraulic conductivity. The study concludes that proper irrigation scheduling is essential for effective water use and recommends enhancing extension services to provide farmers with training on soil water holding capacity, crop water needs, and plant characteristics to guide irrigation decisions.

Key words: Irrigation scheduling, Plant conditions, Soil conditions, Irrigation requirement

INTRODUCTION

Water scarcity and the growing competition for resources, especially in arid and semi-arid regions, have made efficient water use in agriculture increasingly critical (Priyan, 2021). To address this challenge, proper irrigation scheduling has become essential for minimizing water wastage. For farmers to make informed decisions on how often and how much water to apply, they must have accurate information about crop water use and soil moisture content (Ara et al., 2021; Lakhiar et al., 2024). Several key factors influence irrigation decisions, including the properties of the soil, characteristics of the crops, availability of water, and climatic conditions such as rainfall and temperature (Gu et al., 2020; Zinkernagel et al., 2020). Understanding soil type and its water-holding capacity is vital for determining the frequency of irrigation, as different crops require varying amounts of water throughout their growth cycles, depending on environmental conditions (Pereira et al, 2021, Plett et al., 2020).

Effective irrigation scheduling not only optimizes the use of water but also ensures the efficient use of energy and other agricultural inputs, leading to improved crop yields, enhanced crop quality, and lower production costs (Ray and Majumder, 2024, Lakhiar et al., 2024). Despite these benefits, research has shown that many farmers fail to practice proper irrigation scheduling, often due to a lack of understanding of crop water needs or because water is perceived as being inexpensive (Sun et al., 2022; Fernández García et al., 2020). This study explores the factors that influence farmers' decisions regarding the timing and application rates of irrigation water in Mwala, Machakos County, Kenya.

MATERIALS AND METHODS

Study design and data collection

The study was realized from survey statistics and field measurements done at the study area, Mwala, Machakos County. The specific irrigation scheduling technique adopted by farmers in irrigating crop(s), the factors influencing their timing and application rates, and any additional information including the plant and soil conditions, planting dates and the farmers' source of technical advice was obtained in form of an interview questionnaire. This was administered to the forty-one purposefully selected farmers who are registered by the Equity Group Foundation extension scheme.

Laboratory soil analyses and field assessments of irrigation timing and application rates

Baseline soil characterization was done through laboratory analyses of disturbed and undisturbed samples collected from farms using furrow, drip, sprinkler, and hosepipe irrigation systems, focusing on soil texture, organic carbon, hydraulic conductivity, moisture retention, and bulk density. The data collected to estimate the irrigation timing and application rates for the various irrigation methods in the field measurements included: flow rate, the volumes of water applied and dimensions of the irrigation units. The flow rate (Q) was assessed by measuring the time (T) required to fill containers of a known volume (V) for drip, sprinkler and hosepipe irrigation systems using Equation 1 as described by Trimmer (1994):

$$Q = \frac{\Delta V}{\Delta t} \qquad \text{Equation 1}$$

where: Q= flow rate in liter per second (l/s), V= volume in liters (l), t= time in seconds (s)

Furrow irrigation timing and application rates were estimated by measuring furrow lengths, recording water flow times at various stations, and periodically measuring inflow and outflow rates. The final inflow-outflow measurements and the maximum depth of flow were then recorded according to the methods as outlined by Vázquez et al. (2005) (Equation 2)

$$Q \times t = d \times A \qquad \text{Equation 2}$$

where: Q= flow rate, in liters per second (l/s); t= set time or total time of irrigation (s); d= depth of water applied (mm) and A= area irrigated (m^2).

Soil samples were collected at different depths along furrows to estimate the wetting front by measuring moisture content differences, with this process replicated three times on three farmers' fields. Measurement of the amount of irrigation water applied (d) in mm is deduced by (Equation 3):

$$d(mm) = \frac{Q(l/s)}{A(m^2)} \qquad \text{Equation 3}$$

where: Q= flow rate, in liters per second (l/s); d= depth of water applied (mm) and A= area irrigated (m^2).

The collected data was analyzed using ANOVA in Genstat 15th version, with significance determined at $P \leq 0.05$, and further analysis was conducted using SPSS (Ver 21)

RESULTS AND DISCUSSION

Timing of irrigation application rates

The results of the analysis of farmers' responses showed that majority ranked plant conditions (97%), soil conditions (95%), days since last irrigation (95%), and recent rainfall (88%) as the most critical factors in determining when to irrigate using a Likert scale. Key soil conditions included moisture, soil type, and topography, while plant factors included crop type, drought sensitivity, development stage, and fruiting. Farmers varied their irrigation schedules based on weather conditions and relied on personal experience, extension personnel, and consultants for guidance. These findings are consistent with recent studies by Dong (2022) and Owino and Söffker (2022) which highlighted the importance of soil and plant conditions, weather, and evapotranspiration in efficient irrigation scheduling.

Factors Influencing Irrigation Application Amounts

Regarding the amount of water applied, farmers identified soil moisture, water-holding capacity, soil texture, topography, and plant conditions (such as stress, growth stage, rooting depth, and crop yield) as the most important factors. However, while all farmers timed their irrigation, 60% did not monitor the exact amount of water applied, often relying on rough estimates. Only 40% carefully checked water application by visually assessing soil wetness or timing the emptying of tanks. This lack of precise monitoring is concerning in water-scarce regions like Mwala, Machakos County, as it could lead to either under- or over-irrigation, thereby failing to meet crop needs or wasting water. These findings align with studies by Singh et al. (2024) and Nesamvuni et al. (2022), which reported that farmers often apply excess water due to perceived yield benefits or the inconvenience of irrigation scheduling. However, careful water management is crucial for maximizing irrigation efficiency, conserving water, and reducing energy use (Ray and Majumder, 2024, and Kilemo, 2022).

Measurement of Irrigation Water

The results as illustrated in Figure 1 show that furrow irrigation exhibited the highest quantities of irrigation water application per irrigation event as compared to the other systems. Drip had the least but required more applications especially for mangoes and oranges. This data collection on irrigation monitoring was done in the mid growth stage of the crops during the dry season. The application amounts were then compared to the CROPWAT computed data on irrigation water requirements to assess whether the farmers were practicing efficient irrigation application. The lowest average differences between applied water and the irrigation requirements were observed in vegetables, which was 8 mm and bananas 3 mm, and the largest in mangoes, 75 mm and oranges, 64 mm; followed by French beans, 36 mm, maize, 25 mm, and tomatoes, 18 mm. From these comparisons, it is revealed that farmers were irrigating more than was required on the crops especially on oranges and mangoes.

Field measurements revealed significant differences in flow rates among irrigation systems, with furrow irrigation exhibiting the highest flow rate (0.479 l/s), use of hosepipe, 0.232 l/s, sprinkler, 0.074 l/s and drip irrigation the lowest (0.003 l/s). The lower flow rates in drip and sprinkler systems are attributed to their more controlled water application methods, making them more efficient compared to furrow and hosepipe systems. These findings are supported by studies such as Asif et al. (2024) and Olamide et al. (2022), which demonstrated that drip irrigation systems use less water and are more efficient than furrow systems.

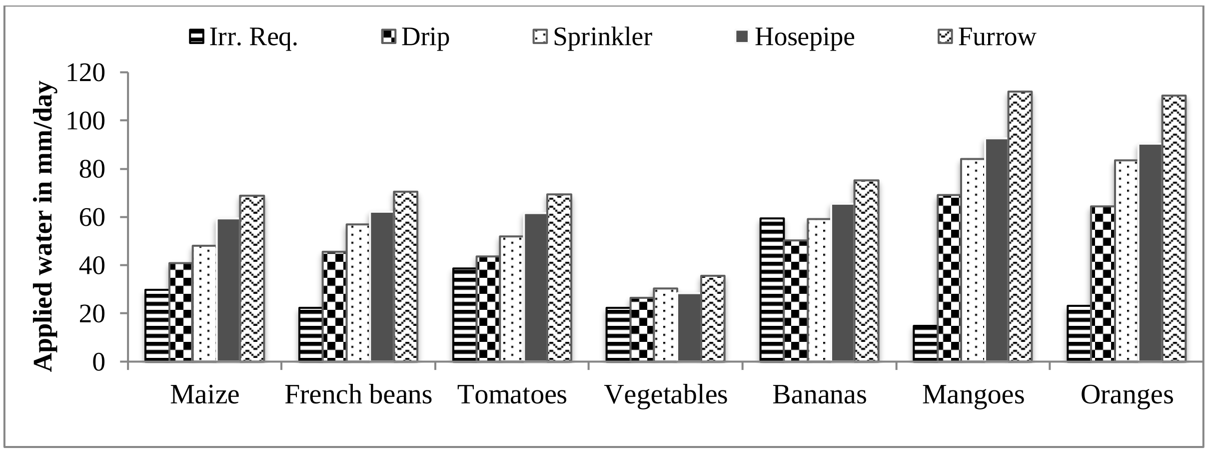


Figure 13. Comparison of applied water and irrigation requirements of various crops.

Soil-Water Relationships

Soil properties under different irrigation systems were also examined, revealing significant differences in sand content, bulk density, hydraulic conductivity, and soil moisture retention (Table 1). Soils under hosepipe irrigation exhibited the highest sand content and hydraulic conductivity, leading to faster water infiltration and lower water retention capacity. This contrasts with drip irrigation, which showed lower sand content and higher water retention. These findings align with studies by Rivier et al. (2022) and Wang et al. (2021), which highlighted the impact of soil texture on hydraulic properties and irrigation efficiency. Additionally, the low organic carbon content in soils (ranging from 0.68% to 0.91%) was attributed to the arid and semi-arid conditions of the study area, as noted by Lei et al. (2022) and Hag Husein et al. (2021). The lack of organic matter application by farmers further exacerbated this issue, emphasizing the need for improved soil management practices to enhance irrigation efficiency.

Table 1. Soil properties under different irrigation methods.

Soil properties	Irrigation methods				L.S. D	p Value
	Drip	Furrow	Hosepipe	Sprinkler		
Hydraulic conductivity (cm/hr)	0.48a	0.69b	3.09d	2.36c	**0.09**	<.001
Soil moisture retention (vol%)	95.80c	92.67c	81.00a	87.89b	**3.54**	<.001
Bulk density (g/cm^3)	1.31a	1.47b	1.65c	1.54b	**0.08**	<.001
Organic carbon (%)	0.76ab	0.91b	0.68a	0.84b	**0.15**	0.037
Sand (%)	64a	72bc	77c	71b	**6.10**	0.01
Clay (%)	29b	22ab	20a	23a	**4.77**	0.011
Silt (%)	7a	6a	3a	6a	**3.65**	0.105

CONCLUSIONS AND RECOMMENDATIONS

The study assessed factors influencing farmers' decisions on irrigation timing and water application, revealing that plant and soil conditions, recent rainfall, and days since last irrigation were key determinants. Results showed significant differences in water application rates and net irrigation requirements across irrigation methods, with furrow and hosepipe methods applying the most water due to higher flow rates. Farmers' limited knowledge on proper irrigation scheduling often led to excessive water use, which could be mitigated by improving extension services, training on soil and crop characteristics, and encouraging better water management practices, such as reducing irrigation time and applying manure to enhance soil water retention.

REFERENCES

Ara, I., Turner, L., Harrison, M. T., Monjardino, M., DeVoil, P., & Rodriguez, D. 2021. Application, adoption and opportunities for improving decision support systems in irrigated agriculture: A review. Agric. Water Manag. 257. 107161.

Dong, Y. 2022. Irrigation Scheduling Methods: Overview and Recent Advances. In Irrig. Drain. —Recent Advances. IntechOpen. https://doi.org/10.5772/intechopen.107386

Fernández García, I., Lecina, S., Ruiz-Sánchez, M. C., Vera, J., Conejero, W., Conesa, M. R., ... & Montesinos, P. 2020. Trends and challenges in irrigation scheduling in the semi-arid area of Spain. Water. 12(3), 785.

Gu, Z., Qi, Z., Burghate, R., Yuan, S., Jiao, X., & Xu, J. 2020. Irrigation scheduling approaches and applications: A review. J. Irrig. Drain. Eng. 146(6), 04020007.

Hag Husein, H., Lucke, B., Bäumler, R., & Sahwan, W. 2021. A contribution to soil fertility assessment for arid and semi-arid lands. Soil Syst. 5(3), 42.

Lakhiar, I. A., Yan, H., Zhang, C., Wang, G., He, B., Hao, B., ... & Rakibuzzaman, M. 2024. A Review of Precision Irrigation Water-Saving Technology under Changing Climate for Enhancing Water Use Efficiency, Crop Yield, and Environmental Footprints. Agriculture. 14(7), 1141.

Lei, Z. H. O. U., Xu, S. T., Monreal, C. M., Mclaughlin, N. B., Zhao, B. P., Liu, J. H., & Hao, G. C. 2022. Bentonite-humic acid improves soil organic carbon, microbial biomass, enzyme activities and grain quality in a sandy soil cropped to maize (Zea mays L.) in a semi-arid region. J. Integr. Agric. 21(1), 208-221.

Nesamvuni, A. E., Tshikolomo, K. A., Mpandeli, N. S., de Bruyn, M., Hlophe-Ginindza, S., & van Niekerk, J. 2022. Perceptions on irrigation water supply and utilisation by smallholder agricultural enterprises in Vhembe district of Limpopo Province, South Africa. Technium Soc. Sci. J., 27, 968.

Olamide, F. O., Olalekan, B. A., Tobi, S. U., Adeyemi, M. A., Julius, J. O., Oluwaseyi, F. K., Olamide, F. O., Olalekan, B. A., Tobi, S. U., Adeyemi, M. A., Julius, J. O., & Oluwaseyi, F. K. 2022. Fundamentals of Irrigation Methods and Their Impact on Crop Production. In Irrig. Drain. —Recent Advances. IntechOpen. https://doi.org/10.5772/intechopen.105501

Owino, L., & Söffker, D. 2022. How much is enough in watering plants? State-of-the-art in irrigation control: Advances, challenges, and opportunities with respect to precision irrigation. Front. Control Eng. 3. https://doi.org/10.3389/fcteg.2022.982463

Pereira, L. S., Paredes, P., Hunsaker, D. J., López-Urrea, R., & Shad, Z. M. 2021. Standard single and basal crop coefficients for field crops. Updates and advances to the FAO56 crop water requirements method. Agric. Water Manag. 243, 106466.

Plett, D. C., Ranathunge, K., Melino, V. J., Kuya, N., Uga, Y., & Kronzucker, H. J. 2020. The intersection of nitrogen nutrition and water use in plants: new paths toward improved crop productivity. J. Exp. Bot. 71(15), 4452-4468.

Priyan, K. 2021. Issues and challenges of groundwater and surface water management in semi-arid regions. Groundwater Resour. Dev. Plan. 1-17.

Ray, S., & Majumder, S. 2024. Water management in agriculture: Innovations for efficient irrigation. Modern Agronomy; Sil, P., Chhetri, P., Majumder, S., Santosh, DT, Eds, 169-185.

Rivier, P. A., Jamniczky, D., Nemes, A., Makó, A., Barna, G., Uzinger, N., ... & Farkas, C. 2022. Short-term effects of compost amendments to soil on soil structure, hydraulic properties, and water regime. J. Hydrol. Hydromech. 70(1), 74-88.

Singh, K., Jhorar, R. K., Sidhpuria, M. S., Kumar, M., & Mehla, M. K. 2024. Impacts of improved irrigation application efficiency and groundwater levels on energy use for crop production in a semi-arid region of India. Environ. Dev. Sustain. 26(4), 10145–10162. https://doi.org/10.1007/s10668-023-03139-7

Sun, X., Ritzema, H., Huang, X., Bai, X., & Hellegers, P. 2022. Assessment of farmers' water and fertilizer practices and perceptions in the North China Plain. Irrig. Drain. 71(4), 980-996.

Wang, D., Wang, Z., Zhang, J., Zhou, B., Lv, T., & Li, W. 2021. Effects of soil texture on soil leaching and cotton (Gossypium hirsutum l.) growth under combined irrigation and drainage. Water, 13(24), 3614.

Zinkernagel, J., Maestre-Valero, J. F., Seresti, S. Y., & Intrigliolo, D. S. 2020. New technologies and practical approaches to improve irrigation management of open field vegetable crops. Agric. Water Manag. 242. 106404.

COMPARATIVE ASSESSMENT OF LANDUSE LANDCOVER CHANGES ON WATER QUALITY OF RIVER KADUNA FROM 2012-2020 AT WUYA, NIGER STATE, NIGERIA

#11238

[1]S.U. Ibrahim, [2]M.O. Dania, [3]F.O Yusufu, [4]R.J Kolo, [5]S.O.E. Sadiku
Department of Water Resources, Aquaculture and Fisheries Technology, School of Agriculture and Agricultural Technology, Federal University of Technology, Minna, Niger State Nigeria.
e-mail: suibrahim@futminna.edu.ng; +234(0)7039025846, +234(0)9066425223

ABSTRACT

The study investigates the effects of land use land cover changes on water quality of River Kaduna from 2012-2020 at Wuya, Niger state, Nigeria using Landsat 7 imagery. Five classes of LULC types where selected and used as basis for classification. Also, five (5) sampling stations selected on the water body for water quality analysis which were collected once monthly for a period of six months from February 2020 to July 2020. The results of LULC classification depicts an increase in water body from 2.241km^2 in 2012 to 3.029km^2 in 2020 while Agricultural areas increased drastically from 4.718km^2 in 2012 to 22.862km^2 in 2020. Physical and Chemical parameters showed range values of Total dissolved solids varying from (15.54±18.00 - 61.00±21.38) in 2012 while (3.67±1.05 - 5.67±2.57) in 2020, Alkalinity was between (31.33±8.08 - 62.33±17.79) in 2012 whereas (21.33±11.55 - 29.33±6.11) in 2020, Hardness ranged from (38.67±4.16 - 51.33±10.26) in 2012 whereas (15.00±1.73 - 22.33±7.77) in 2020. The result showed no significant difference ($p > 0.05$) except Total dissolved solids, Alkalinity and Hardness which recorded higher values on both seasons across stations and months. In general, the study revealed increase in agricultural area drastically, so there is a need to constantly monitor and update the check list of land use land cover, Physical and Chemical parameters changes in and around the River to control anthropogenic pollution from residence, on the water and from nearby farmlands.

Keywords: Land Use Land Cover, Water Quality, River, Wuya, Physical and Chemical

INTRODUTION

Land use is simply human activities that explores the usage of land, and Land cover on the other hand can be seen as the amount of vegetation on land surfaces. Water quality could be referred to as a measure of water use for different purposes (drinking, industrial, agricultural, recreational and habitat) using various parameters such as physical, chemical and biological parameters which varies according to location, time, weather and sources of pollution (Giri and Qiu, 2016).

The impact of Land use is high on water quality of rivers and inland water bodies found in Nigeria due to the high rate of human interaction, this also result to change in land cover patterns within the watershed of rivers. As human activities increase in an area, there is change in Land use Land cover (LULC) hence affects the management of that area, the water quality of rivers and runoffs.
Remote sensing techniques have been recognized as a powerful means to obtain information on Earth's surface (Schneider, *et, al.* 2010). Through supervised classification, the relationship

between land use/land cover was analyzed using QGIS tool for change detections and how it relates to water quality around River Kaduna downstream at Wuya for the years 2012 and 2020.

MATERIALS AND METHODS

The Study Area

Wuya located in Niger State. It is just some few kilometres from Bida, at a latitude of 09°08'. 622" N and longitude of 05°50'. 258" E with an elevation of 75.1M. The prominent feature which can serve as a landmark in identifying the river is an MTN network mask mounted few meters to the river and an overhead bridge that connect both ends of the River together to allow for easy passage of travellers, cars, goods and services to and from across both ends of the river. The River is a major source of water for domestic activities for the community.

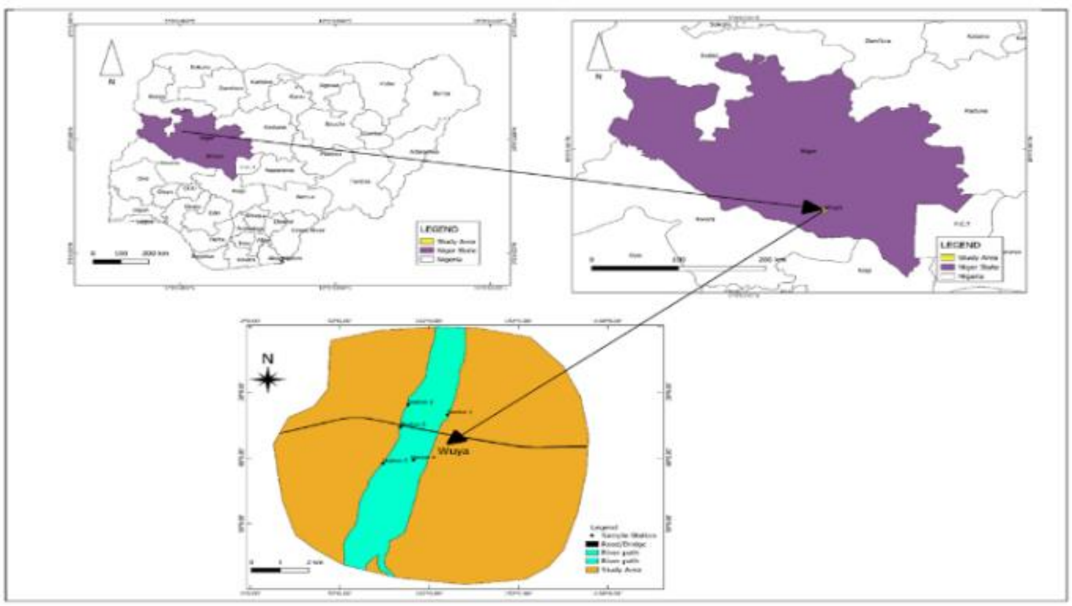


Figure 1. Nigeria indicating Niger state and the study area.

The study was carried out in six month (6) from February and July 2020.Water samples were collected once monthly for the period from 5 sampling stations. Five classes of LULC types where selected (Water bodies, Agricultural areas, bare surfaces, Natural vegetation, Settlements) and used as basis for classification of the LULC around the River using QGIS tool.

Site Selection

Station 1 had its land use classification as natural vegetation. This area consists of naturally growing plants with little interference with human activities, (where pipes for irrigation purpose were mounted). On coordinates point of 09°08'.061" N, 05°49'.858" E, and elevation as 71.1m.

Station 2 had its land use classification as agricultural area. This consists of where farming activities and irrigation take place on coordinates 09°08'.141"N, 05°50'094"E and elevation as 70.6m.

Station 3 had its land use classification as settlements on coordinates as 09^{o}08’.686” N, 05^{o}50’.070” E and elevation as 69.0m.

Station 4 had its land use classification as water body. This area consists of a large volume of water towards the middle of the river. The area recorded coordinates as 09o08’.853”N, 05o50’109” E and elevation as 67.0m.

Station 5 had its land use classification as bare surface. This area is a plain ground with sharp sand around and no grasses growing. The area recorded coordinates as 09^{o}08’.784” N, 05^{o}50’.302” E and elevation as 65.9m.

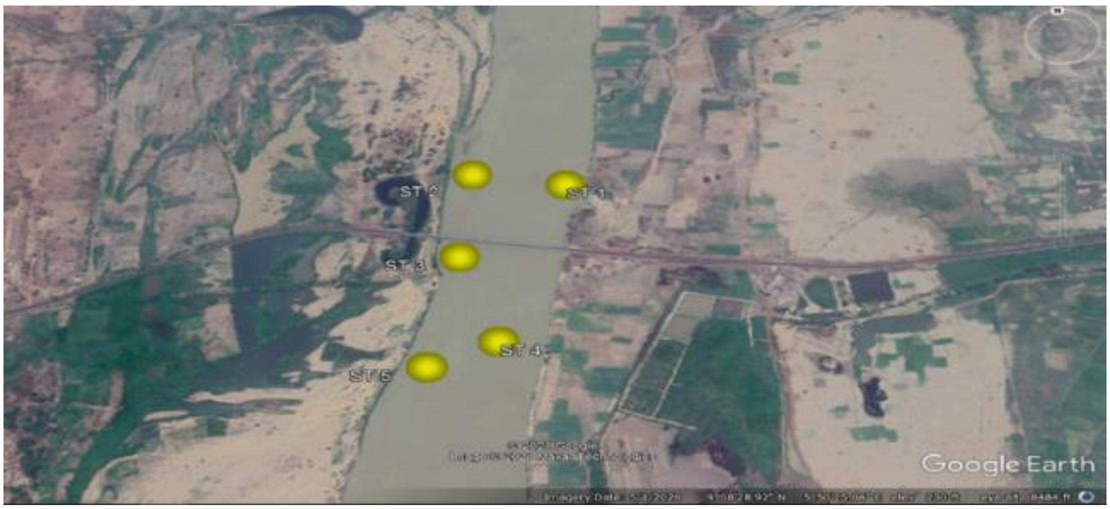


Figure 2. Google Earth Image of River Wuya showing selected sites.

Landsat 7 data was gotten for the study area of 2012 and 2020 from earth explorer which collected a panchromatic (black and white) imagery and multispectral imagery which was then imported into remote sensing image processing software (QGIS tool) for analysis.

RESULTS AND DISCUSSION

The result in Figure 3 depicts changes in classified land use land cover imagery of 2012 and 2020 with a rise in agricultural areas, lesser bare surfaces and natural vegetation in 2020 while Figure 4 compares the percentage changes in land use land cover around the study area.

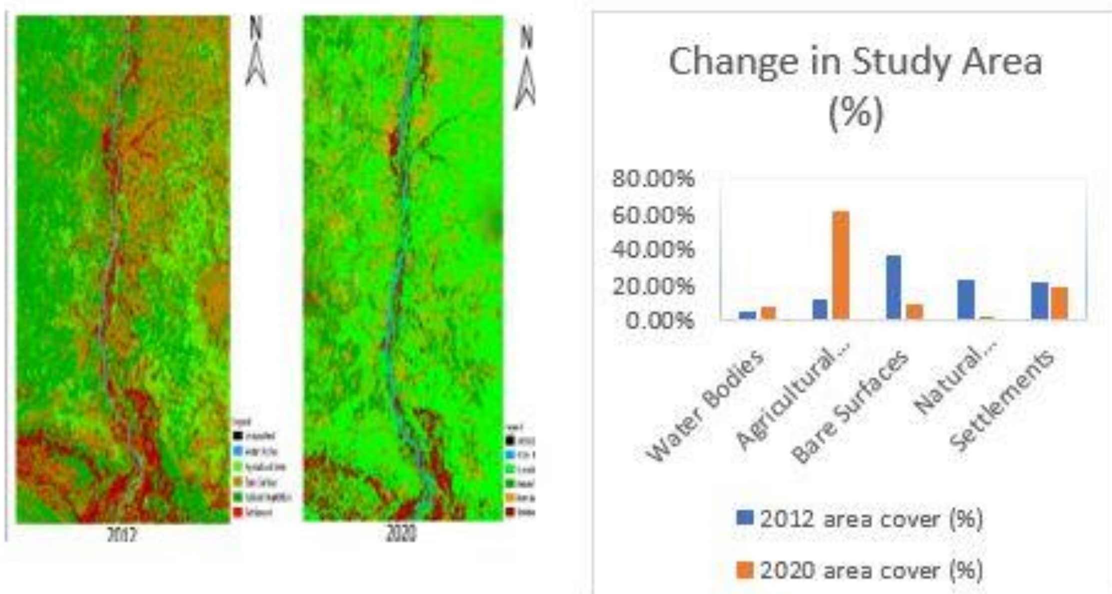


Figure 3. Classified Land sat image of the Land Use Land Cover around the study area in (2012 and 2020) with Comparison of their Percentage changes.

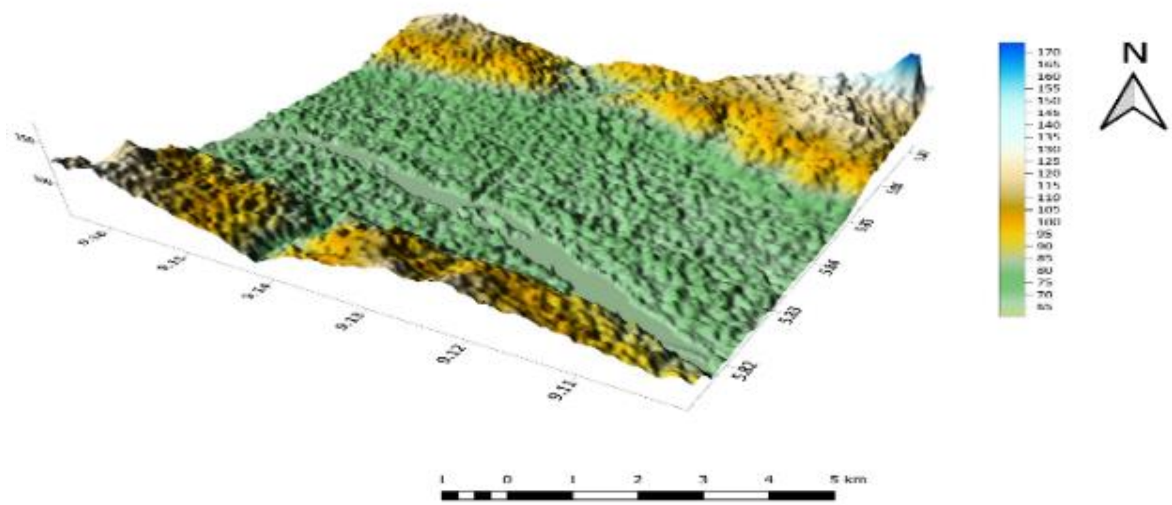


Figure 4. Digital Elevation Model of the Study Area.

Table 2. Magnitudes, percentage and average rates of change in Land Use Land Cover around study area (2012 and 2020).

LULC Types	2012 Area (Km^2)	2020 Area (Km^2)	Magnitude of Change (km^2)	% Change	Average Rate of Change (Km^2)	Remark
Water Bodies	2.241	3.0285	0.7875	2.24	0.3514	Increase
Agricultural Area	4.7178	22.8618	18.144	48.42	3.8458	Increase
Bare Surfaces	13.6728	3.5532	-10.1196	27.07	-0.7401	Decrease
Natural Vegetation	8.7471	1.0098	-7.1937	19.27	-0.8845	Decrease
Settlements	8.2035	7.1289	-1.0746	3.0	-0.1309	Decrease
Total	**37.5822**	**37.5822**	**0.5436**	**100**	**2.4417**	Increase

Table 2 above depicts that there was a decrease in the area covered by bare surfaces from 13.673km^2 in 2012 to 3.553km^2 in 2020 which relates directly with natural vegetation which also decreased in area covered from 8.747km^2 in 2012 to 1.010km^2 in 2020 due to anthropogenic activities. An increase in water body of the area was recorded from 2.241km^2 in 2012 to 3.029km^2 in 2020 this could be attributed to the change in vegetation type as part of land preparation, increase in runoff, uncontrolled human activities, demand for firewood and so on. There was a decrease in Settlements of the area from 8.204km^2 in 2012 to 7.129km^2 in 2020 which could be related to the increase in water body of the area that may have caused flooding in settlements along the water shed and made settlers relocate. A drastic increase in agricultural areas was recorded from 4.718km^2 in 2012 to 22.862km^2 in 2020. The highest increase maybe because of conversion bare surfaces into farmlands as agriculture is one of the main sources of income for the riparian communities and it is practiced all year round such irrigation. With these changes in land use land cover effects, water quality is highly affected and needs to be controlled. Relationships between land use land cover and surface water quality are relevant topics for discussion as human activities increase in a watershed (Ding, *et al.* 2015).

The physico-chemical parameters results vary across the sampling stations in both seasons (Table 3 and 4 below).

Hydrogen ion Concentration: pH recorded its highest value across stations for 2012 in the dry season ($7.22{\pm}0.18^a$) at station 1 with its lowest value in the wet season ($6.86{\pm}0.77^a$) at station 2.While 2020 had its highest recorded value across stations in the wet season ($6.83{\pm}0.02^a$) at station 4 with its lowest value in the dry season ($6.20{\pm}0.43^a$) at station 5.There was no significant difference ($p>0.05$) for pH across means. Ideal range for pH 6.5 – 7.5 (Ding *et al.*, 2015). pH recorded negative correlation with Phosphate and positive correlation with total suspended solids, alkalinity, hardness and nitrate.

Temperature: Biological and chemical changes of water are greatly influenced by temperature, with the ideal range being 26^{o}C – 32^{o}C (Ding *et al.*, 2015). Highest value across stations was recorded for 2012 in the dry season (34.77±4.13^{o}C) at station 2 with its lowest value in the wet season (27.67±1.15^{o}C) at station 4. highest recorded value across stations in the dry season (31.66±0.75^{o}C) at station 3 with its lowest value in the wet season (27.63±1.66^{o}C) at station 4. There was no significant difference ($p>0.05$) across means. A slightly negative correlation was recorded against dissolve oxygen.

Table 3. Dry Season Stations Variation (February - April 2012 and 2020).

Parameters	Years	SAMPLE STATIONS 1	2	3	4	5
pH	2012	7.03±0.70[a]	6.86±0.77[a]	6.90±0.56[a]	7.00±0.64[a]	7.00±0.45[a]
	2020	6.82±0.04[a]	6.82±0.04[a]	6.81±0.02[a]	6.83±0.02[a]	6.83±0.05[a]
T(^{0}C)	2012	29.33±0.57[a]	29.00±1.00[a]	28.00±0.00[a]	27.67±1.15[a]	28.00±1.73[a]
	2020	27.67±1.50[a]	27.80±1.65[a]	27.77±1.55[a]	27.63±1.66[a]	27.77±1.66[a]
EC	2012	92.33±30.62[a]	83.00±64.86[a]	67.33±33.32[a]	69.67±42.19[a]	67.00±44.44[a]
	2020	76.67±18.90[a]	65.67±5.86[a]	64.33±5.51[a]	67.33±5.51[a]	58.00±16.82[a]
DO (Mg/l)	2012	12.67±3.06[a]	12.00±2.00[a]	10.67±4.16[a]	11.33±5.03[a]	14.00±5.29[a]
	2020	10.67±3.06[a]	9.33±1.16[a]	10.67±2.31[a]	13.33±3.05[a]	10.00±3.46[a]
TDS (Mg/l)	2012	61.00±21.38[a]	55.00±44.23[a]	44.33±22.81[a]	45.67±28.68[a]	44.33±29.87[a]
	2020	4.91±1.21[a]	4.20±0.37[a]	4.12±0.35[a]	4.30±0.34[a]	3.67±1.05[a]
Alkalinity (Mg/l)	2012	62.33±17.79[a]	56.66±5.77[a]	57.00±18.36[a]	51.66±7.64[a]	53.00± 28.05[a]
	2020	28.00±4.00[a]	28.00±10.58[a]	29.33±6.11[a]	29.33±2.31[a]	30.67±6.11[a]
Hardness (Mg/l)	2012	38.67±4.16[a]	42.00±15.87[a]	37.33±8.08[a]	51.33±10.26[a]	39.33±18.58[a]
	2020	15.00±1.73[a]	18.00±5.29[a]	20.67±3.06[a]	21.00±2.00[a]	17.33±5.03[a]
PO_4 (Mg/l)	2012	0.70±0.47[a]	0.62±0.48[a]	0.66±0.50[a]	0.66±0.47[a]	0.80±0.63[a]
	2020	2.94±0.51[a]	2.40±0.37[a]	2.96±0.49[a]	2.49±0.21[a]	2.81±0.18[a]
NO_3 (Mg/l)	2012	2.88±0.93[a]	2.90±0.76[a]	2.84±.89[a]	3.04±0.72[a]	2.95±0.86[a]
	2020	0.22±0.02[a]	0.33±0.19[a]	0.24±0.04[a]	0.24±0.04[a]	0.24±0.03[a]

Means in the same row having the same superscript are not significantly different from other means (p>0.05)

Table 4. Wet Season Stations Variation (May - July 2012 and 2020).

Parameters	Years	SAMPLE STATIONS 1	2	3	4	5
pH	2012	7.22±0.18[a]	7.11±0.07[a]	7.04±0.19[a]	7.11±0.19[a]	7.07±0.15[a]
	2020	6.51±0.76[a]	6.41±0.41[a]	6.27±0.54[a]	6.21±0.53[a]	6.20±0.43[a]
T(^{0}C)	2012	32.17±4.65[a]	34.77±4.13[a]	32.87±5.22[a]	29.33±1.15[a]	30.17±0.28[a]
	2020	31.46±0.71[a]	31.50±0.75[a]	31.66±0.75[a]	31.43±0.80[a]	31.43±0.77[a]
EC	2012	76.00±27.84[a]	72.67±25.42[a]	78.00±27.06[a]	83.00±36.01[a]	79.67±32.87[a]
	2020	87.00±37.32[a]	77.00±24.27[a]	78.33±27.47[a]	85.00±39.00[a]	93.67±28.75[a]
DO (Mg/l)	2012	8.00±3.46[a]	7.83±0.29[a]	6.33±0.58[a]	8.00±2.00[a]	8.47±1.50[a]
	2020	11.33±2.31[a]	11.33±4.16[a]	12.67±1.16[a]	11.33±3.05[a]	10.00±0.00[a]
TDS (Mg/l)	2012	48.88±16.92[a]	46.60±15.54[a]	15.54±18.00[a]	52.70±23.40[a]	50.53±21.17[a]
	2020	5.67±2.57[a]	5.24±2.08[a]	5.19±2.06[a]	4.79±1.37[a]	5.45±1.23[a]
Alkalinity (Mg/l)	2012	33.33±11.55[a]	39.33±13.61[a]	41.33±18.90[a]	31.33±8.08[a]	34.67±12.86[a]
	2020	21.33±11.55[a]	24.00±12.00[a]	26.67±2.31[a]	26.67±6.11[a]	32.67±6.43[a]
Hardness (Mg/l)	2012	38.00±7.21[a]	45.33±9.87[a]	46.67±10.07[a]	41.33±6.11[a]	43.33±3.06[a]
	2020	23.67±14.15[a]	19.33±8.08[a]	22.33±7.77[a]	31.00±12.29[a]	28.67±4.16[a]
PO_4 (Mg/l)	2012	0.80±0.14[a]	0.88±0.23[a]	0.94±0.16[a]	0.77±0.06[a]	0.88±0.10[a]
	2020	3.15±0.29[a]	2.68±0.14[a]	3.16±1.28[a]	2.70±0.32[a]	2.54±0.24[a]
NO_3 (Mg/l)	2012	2.59±0.94[a]	2.64±1.25[a]	3.27±1.75[a]	2.57±1.48[a]	2.65±1.57[a]
	2020	0.21±0.05[a]	0.22±0.04[a]	0.21±0.04[a]	0.24±0.07[a]	0.23±0.09[a]

Means in the same row having the same superscript are not significantly different from other means (p>0.05).

CONCLUSION

The study on the comparative analysis of land use and land cover changes on water quality of River Wuya using QGIS, exposed causes of the land use and variation in physicochemical parameters. The use of QGIS allowed a more graphical representation on the study area to see trends and how land use land cover changed over time. The variations of land use land cover changes & physico-chemical parameters may be due to climate change, land use types, human activities, change in vegetation types, erosion due to the cut down of trees and more land rendered plain and open.

REFERENCES

Ding J, Jiang Y, Fu L, Liu Q, Peng Q, Kang M. 2015. Impacts of land use on surface water quality in a subtropical river basin: a case study of the Dongjiang River Basin, Southeastern China. Water, 7(8), 4427-4445.

Giri C, Zhu Z, Reed B (2005) A comparative analysis of the global land cover2000 and MODIS land cover data sets. Remote Sens Environ 94:123–132

Schneider, A.; Friedl, M.A.; Potere, D. Mapping global urban areas using MODIS 500-m data: New methods and datasets based on ‘urban ecoregions’. Remote Sens. Environ. **2010**, 114, 1733–1746.

DESIGN AND DEVELOPMENT OF A LORA COMMUNICATION SYSTEM FOR SCALABLE SMART IRRIGATION SYSTEMS

#11694

[1*]J. Ikabat, [2]P. Hess, [3]J. Wanyama, [4]E. Bwambale, [5]P. Nakawuka, [6]I. Kabenge, [7]S. Felicioni, [8]A. Bühlmann, [9]T. Anken, [10]J.H. Muyonga

[1,3,4,5,6,10]Makerere University, Kampala, Uganda; [2,7,8,9]Agroscope, Wädenswil and Tänikon, Switzerland

[*]e-mail: joelikabat30@gmail.com, +256750377244

ABSTRACT

The adoption of smart irrigation in Sub-Saharan countries such as Uganda is still hindered by several challenges, primarily related to the high initial costs, infrastructure dependence, and limited hardware availability. This study aimed to address these challenges by developing and testing an affordable smart irrigation system based on LoRa radio technology. The system design incorporates readily available hardware components and Chirpstack open-source software, which serves as both the LoRaWAN Network and Application server for scalable and license-free radio operation. A real-world scenario functionality test was conducted at the Makerere University Agricultural Research Institute Kabanyolo (MUARIK) in which a smart valve was connected to the LoRa gateway at two different locations. Two connection parameters, the Signal to Noise Ratio (SNR) and Received Signal Strength Indicator (RSSI), were compared to analyze the range and reliability of the system. Results demonstrated robust communication, particularly in areas with fewer obstructions, highlighting the importance of optimal antenna placement to ensure efficient communication to automate irrigation systems as well as agricultural systems. The LoRa radio enhances smart irrigation by offering low power consumption, long-range capabilities, and collaborative farmer access, which helps reduce initial costs. This system improves water efficiency and crop yields, aiding smallholder farmers in adapting to climate variability and promoting sustainable agriculture in Uganda.

INTRODUCTION

Agriculture remains a fundamental pillar of the economy in many Sub-Saharan African countries, including Uganda, where most farmers are smallholders residing in rural areas. These farmers frequently encounter significant challenges, such as food insecurity exacerbated by a rapidly growing population [1], [2]. Traditionally, Uganda's agriculture has relied heavily on natural climatic patterns, particularly the two annual wet seasons [3]. Furthermore, anthropogenic climate change has increasingly disrupted these patterns, leading to more frequent and severe dry spells, floods, and rising temperatures, all of which threaten food security [4], [5].

In light of these challenges, policymakers have emphasized the critical role of irrigation in enhancing food security amidst climate variability [6]. Initiatives such as the Micro-scale Irrigation Program supported by the World Bank and administered by Uganda's Ministry of Agriculture, Animal Industry, and Fisheries (MAAIF), are advancing sustainable agricultural practices by providing subsidized irrigation equipment and training to smallholder farmers. The adoption of technology-enabled smart irrigation has emerged as a vital strategy for adapting to climate change due to the potential benefits of these technologies which include increased agricultural productivity and more efficient use of resources, thereby contributing to the sustainability and resilience of food production systems. This is achieved through the deployment of extensive sensor networks that monitor crop water needs, coupled with automated actuators like pumps and valves.

Despite these advantages, the adoption of smart irrigation technologies in Uganda faces significant obstacles such as financial constraints that are a major barrier, as the average annual income of farming households in Uganda is only USD 222 [7]. Additionally, infrastructure challenges such as frequent power outages and limited internet availability hinder the effective operation of IoT-powered smart irrigation systems. Wanyama et al. [8] also identified the lack of material and service supply as a burden to irrigation adoption in many regions of Uganda. LoRa radio technology is particularly well-suited for connecting smart components due to its low power consumption and long-range coverage, making it ideal for IoT and smart farming applications [9], [10]. This article aims to propose a smart irrigation system designed to overcome these challenges, focusing on affordability, resilience to infrastructure limitations, and the use of readily available materials to ensure successful broad adoption in Uganda.

MATERIALS AND METHODS

Study Site

The study was carried out at the Makerere University Agricultural Research Institute Kabanyolo (MUARIK), located 21km north of Kampala city center, Uganda. The institute is located at coordinates 00°27'06.000" N, 32°03'60.240" E, with an altitude varying between 1250 and 1320 meters above sea level in the Wakiso district.

System Design and Assembly

In alignment with the principles of affordability and accessibility, the components for the system were selected based on their low cost and availability, either through international delivery or local sourcing in Uganda. To ensure independence from internet infrastructure, a local processing approach was adopted. The system includes battery backups to mitigate the effects of power outages. An overview of the proposed smart irrigation system is illustrated in Figure 1(a).

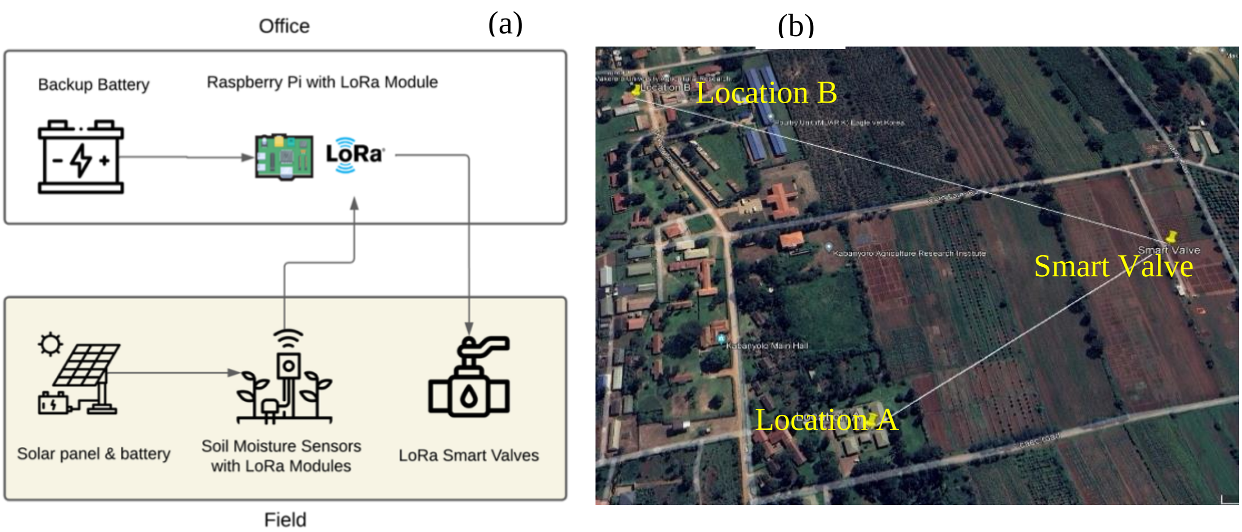


Figure 14. (a) Design overview of proposed LoRa Smart irrigation system, (b) Map of the locations and distances of the functionality test.

The system features a proposed sensor node positioned at the field level, which connects common soil moisture sensors, such as the commercial Watermark sensor [WATERMARK 200SS, Irrometer Company, Riverside, USA] or the more cost-effective Chameleon sensors [Chameleon Sensor Array, VIA Ltd, Melbourne, Australia], to an enclosed LoRa module consisting of an interface module [SMX, EME Systems, Berkeley, USA], a microcontroller [HUZZAH32, Adafruit Industries, New York, USA] and a LoRa transmitter [E220-900T22D LoRa Wireless UART Module, Ebyte, China]. These components are powered by a waterproof battery and solar panel [EESBAO-35W, Shenzen Tengyunfei Technology Co., Shenzen City, China]. The collected data is transmitted to a LoRa gateway unit, which is typically located in an office, farmer's house, or community center.

At the core of the gateway unit is a microcontroller [Raspberry Pi 4B, Raspberry Pi Ltd, Cambridge, United Kingdom], which is connected to a LoRa concentrator board [GPMLx9332-PX V3, Greenpalm, Hangzhou, China] and a 0.5-dB antenna. The gateway operates on open-source software [Chirpstack V4, Orne Brocaar, Amsterdam, The Netherlands], which includes network and application server functionality. To safeguard against power interruptions, a small uninterruptible power supply [UPS Module 3s, Waveshare, Shenzen, China] is integrated into the system. When irrigation is required, a command is sent to activate a wireless motorized shut-off smart valve [STREGA, Ohain, Belgium] that is programmed to open for a specific period depending on the soil’s antecedent soil moisture and its field capacity. The valve is set to operate as a Class A LoRa device.

Functionality Test

The system was tested for its functionality by studying the signal strength and connectivity using the Received Signal Strength Indicator (RSSI) and Signal to Noise Ratio (SNR) of the periodic upload messages sent by the smart valve to the gateway communicating its status information (e.g. temperature and battery level) to the gateway. The valve was installed at an existing drip irrigation system at the Department Demonstration plot located at the study site and gateway set to operate in the 868 Mhz frequency. Two different locations were chosen: Location A had a much more unobstructed line of sight to the valve at a distance and elevation difference of 402 m and 7.6 m, and location B was obstructed by several buildings and vegetation. It also had a greater distance and elevation difference to the valve of 660 m and 8.5 m (Figure 1(b)). For each site, 10 of these messages were analyzed for their RSSI and SNR values to assess the quality of the connection.

RESULTS AND DISCUSSION

The test of the system's functionality confirmed full operation between the gateway unit and the smart valve. The signal strength data showed that connectivity was stronger in areas with a clearer line of sight (Location A) than with more obstacles (Location B).

When analyzing the data packets sent to the gateway (Figure 2), Location B exhibited generally worse connectivity as compared to Location A with the SNR values here ranging between -12.5 to -18.8 dB and averaging -15.7 dB. RSSI values ranged from -93 to -98 dBm, with an average of -96.3 dBm as the valve communicated at a Spreading Factor of 12. On the other hand, the SNR values at Location A ranged from -2 to 6 dB, with an average of 2 dB. RSSI values ranged from -96 to -102 dBm, averaging -98.7 dBm as the valve communicated at a Spreading Factor of 7 after applying Adaptive Data Rate (ADR) protocol at both locations. This explains the lower RSSI values for Location B as the valve used more battery power to ensure the same communication. Additionally, the presence of blockages from buildings and vegetation, along with the effects of ambient factors like temperature and relative humidity, significantly impact signal strength, as corroborated by studies from Antoine-Santoni [11] and Iova [12]. The function test results highlight the critical role of antenna positioning on signal strength. For optimal performance, the LoRa antenna should be installed above all obstructions to ensure a clear line of sight to the smart valve.

This study introduces a cost-effective smart irrigation system for small-scale Ugandan farmers, using affordable, locally sourced components and open-source ChirpStack software to reduce expenses and reliance on commercial services. The system is adaptable to different Raspberry Pi models and supports advanced irrigation algorithms [8] to improve water efficiency and crop yields. It's designed to withstand Uganda's infrastructure challenges with a UPS and local computing, ensuring operation during power outages and without depending on unreliable rural internet. While the chosen motorized valve is costly, it is crucial to highlight the need for a more affordable low-pressure option such as latched solenoid valves as suggested by Maksudjon [13]. The system's use of LoRaWAN technology allows a single gateway to support an entire community, reducing individual costs and promoting community collaboration as demonstrated in the work of Dongore [14].

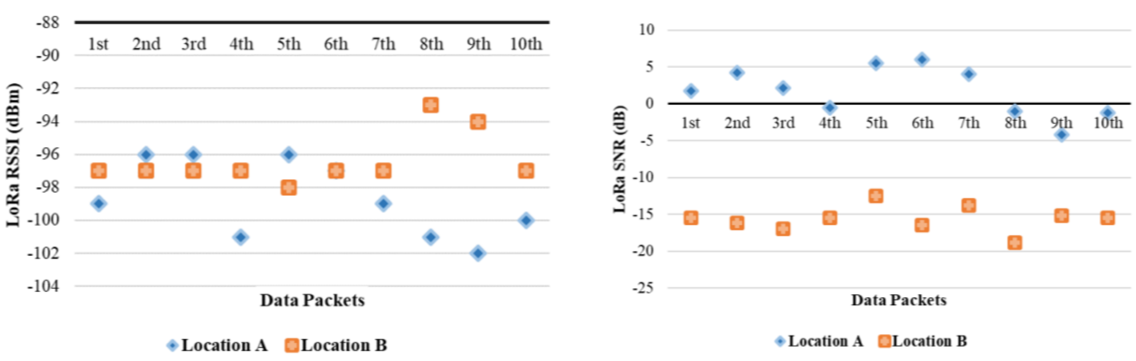


Figure 15. Visualization of the signal strength parameters RSSI (a) and SNR (b) received during the system functionality test.

CONCLUSION AND RECOMMENDATION

The study reviews challenges in smart irrigation in Uganda and proposes a LoRa-based system to address them. While the system shows promise, it requires field testing with sensor nodes to evaluate its scalability and effectiveness on smallholder farms. Successful implementation could lead to nationwide adoption, helping farmers increase profitability, sustainability, and resilience to climate change.

ACKNOWLEDGEMENT

Authors are grateful to the European Union's Horizon 2020 research and innovation programme which funded this work through FoodLAND project under grant agreement No 862802**.**

REFERENCES

[1] B. Barasa, "Local and regional variations in conditions for agriculture and food security in Uganda," AgriFoSe2030, 2018. Accessed: Aug. 19, 2024. [Online]. Available: https://nru.uncst.go.ug/handle/123456789/5781

[2] D. N. Mubiru et al., "Climate trends, risks and coping strategies in smallholder farming systems in Uganda," Clim. Risk Manag., vol. 22, pp. 4–21, Jan. 2018, doi: 10.1016/j.crm.2018.08.004.

[3] M. R. Jury, "Uganda rainfall variability and prediction," Theor. Appl. Climatol., vol. 132, no. 3, pp. 905–919, May 2018, doi: 10.1007/s00704-017-2135-4.

[4] M. A. Islam, "Agricultural Adaptation to Climate Change: Issues for Developing Countries," Glob. Discl. Econ. Bus., vol. 2, no. 2, Art. no. 2, Dec. 2013, doi: 10.18034/gdeb.v2i2.178.

[5] U. Nuwagira and I. Yasin, "Review of the Past, Current, and the Future Trend of the Climate Change and its Impact in Uganda," East Afr. J. Environ. Nat. Resour., vol. 5, no. 1, Art. no. 1, Apr. 2022, doi: 10.37284/eajenr.5.1.605.

[6] J. Wanyama et al., "Irrigation Development in Uganda: Constraints, Lessons Learned, and Future Perspectives," J. Irrig. Drain. Eng., vol. 143, no. 5, p. 04017003, May 2017, doi: 10.1061/(ASCE)IR.1943-4774.0001159.

[7] F. Atube, G. M. Malinga, M. Nyeko, D. M. Okello, S. P. Alarakol, and I. Okello-Uma, "Determinants of smallholder farmers' adaptation strategies to the effects of climate change: Evidence from northern Uganda," Agric. Food Secur., vol. 10, no. 1, p. 6, Feb. 2021, doi: 10.1186/s40066-020-00279-1.

[8] J. Wanyama et al., "A systematic review of fourth industrial revolution technologies in smart irrigation: Constraints, opportunities, and future prospects for sub-Saharan Africa," Smart Agric. Technol., vol. 7, p. 100412, Mar. 2024, doi: 10.1016/j.atech.2024.100412.

[9] "LoRa PHY | Semtech." Accessed: Aug. 19, 2024. [Online]. Available: https://www.semtech.com/lora/what-is-lora

[10] A. Pagano, D. Croce, I. Tinnirello, and G. Vitale, "A Survey on LoRa for Smart Agriculture: Current Trends and Future Perspectives," IEEE Internet Things J., vol. 10, no. 4, pp. 3664–3679, Feb. 2023, doi: 10.1109/JIOT.2022.3230505.

[11] T. Antoine-Santoni, B. Poggi, D. Araujo, and C. Babatounde, "Factors Influencing LoRa Communication in IoT Deployment: Overview and Experience Analysis," Apr. 2022. doi: 10.5220/0011102600003194.

[12] O. Iova et al., "LoRa from the city to the mountains: Exploration of hardware and environmental factors," in International Conference on Embedded Wireless Systems and Networks (EWSN) 2017, Uppsala, sweden, 20-22 February 2017, Uppsala University, 2017, pp. 317–322. Accessed: Apr. 30, 2024. [Online]. Available: https://openpub.fmach.it/handle/10449/42132

[13] M. Usmonov and F. Gregoretti, Design and implementation of a LoRa based wireless control for drip irrigation systems. 2017, p. 253. doi: 10.1109/ICRAE.2017.8291389.

[14] A. Dongare et al., "OpenChirp: A Low-Power Wide-Area Networking architecture," in 2017 IEEE International Conference on Pervasive Computing and Communications Workshops (PerCom Workshops), Mar. 2017, pp. 569–574. doi: 10.1109/PERCOMW.2017.7917625.

EVALUATING THE IMPACT OF SEASONAL WEATHER VARIABILITY ON SOIL MOISTURE CONSERVATION UNDER MULCHING SYSTEMS FOR DATE PALM PRODUCTION IN OASES

#11301

[1,3]U. Safi, [2]E.J. Mustapha, [1]O. Abdallah, [3]S. Ahmed
[1]Mohammed VI Polytechnic University, Benguérir, Morocco; [2]Agronomic and Veterinary Institute Hassan II, Rabat, Morocco; [3]National Institute for Agricultural Research, Rabat, Morocco
e-mail: safi.uwase@um6p.ma +212708362464

ABSTRACT

Efficient soil moisture conservation is crucial for sustaining date palm production in arid Moroccan oases, where water scarcity is a significant challenge. This study evaluates how different mulching materials affect soil moisture retention in these regions. The research focuses on three mulching materials: polyethylene plastic (PP), polypropylene woven ground cover (PWGC), and date palm residues (DPR), examining their effectiveness under varying seasonal climates. Results demonstrate that the PP+DPR combination was the most effective in conserving soil moisture at shallower depths during high temperatures, while DPR and PWGC+DPR provided consistent moisture retention at greater depths. The findings highlight the importance of mulching systems in mitigating weather variability impacts, enhancing soil moisture conservation that can sustain the date palm production in arid regions.

INTRODUCTION

The date palm (Phoenix dactylifera) holds considerable importance in Moroccan oases. It primarily contributes to creating a favorable agricultural microclimate for other crops, which helps safeguard the land against desertification (Abdelaaziz et al., 2024). Furthermore, scientific research has demonstrated that date fruits to be highly nutritious and possess medicinal properties (Ouamnina et al., 2024). Consequently, date palm production is economically valuable in this region.

However, due to the climatic conditions in arid regions where precipitation is inadequate to offset evapotranspiration, irrigation becomes necessary to meet the water needs for date production (Yan et al., 2022). Though, with climate change, water resources in arid regions are becoming increasingly scarce over time. Thus, implementing solutions for reducing water usage and conservation are crucial in these areas (Morante-Carballo et al., 2022).

Mulching, a well-known water conservation practice, has demonstrated potential in enhancing soil moisture retention, reducing evaporation, and stabilizing soil temperature (Ramakrishna et al., 2006). Considering the interaction between the land and atmosphere, as weather transitions from winter to summer, fluctuations in atmospheric temperature and precipitation impact soil moisture content (Cho et al., 2016). Hence, mulching serves as a buffer by mitigating the adverse effects of these interactions.

This study aims to evaluate the effectiveness of three mulching materials—polyethylene plastic (PP), polypropylene woven ground cover (PWGC), and date palm residues (DPR)—in conserving soil moisture in date palm production under varying seasonal climate conditions. The implementation of mulching systems may mitigate the effects of weather variability on soil moisture and enhance date palm production by stabilizing soil temperature, reducing evaporation, improving moisture retention and promoting the transpiration of the plants, particularly during periods of extreme seasonal changes.

MATERIALS AND METHODS

Experimental Site

The experiment began in early April 2024 and ended August 2024 at the experimental farm of the National Institute of Agricultural Research (INRA), located in Errachidia Province in the South-East of Morocco. The experiment occupies an area of a half hectare.

Experimental Design

This experiment was conducted on a date palm (Phoenix dactylifera) on the variety called *Nadja*, that is known for its resistance to the famous date palm disease *Bayoud* and other important agronomic traits. Drip irrigation was employed throughout the experiment, with the same amount of water applied across all treatments. However, the irrigation schedule differed, where from April to the end of May irrigation was done three times a week, and from June till August, irrigation was done four times a week.

Three mulching materials were tested: polyethylene plastic (PP), polypropylene woven ground cover (PWGC), and date palm residues (DPR). The synthetic mulches (PP and PWGC) were combined with the organic mulch (DPR). The experiment was set up using a randomized complete design, comprising 72 palm trees divided into 36 experimental units, each containing 2 trees, with 9 replications. Each experimental unit represented a different mulching treatment. The mulching treatments were distributed as follows:

- T0: Control (non-mulch) treatment (NM)
- T1: Organic mulch made from ground dry date palm leaves (DPR)
- T2: Polyethylene plastic (PP) combined with date palm residues (DPR)
- T3: Polypropylene woven ground cover (PWGC) combined with DPR

Data Collection

To measure soil moisture content as a representation of the entire field, 24 date palm trees with different mulching systems were selected. For each tree, a profile probe tube was installed at 30 cm from the irrigation dripper. Soil moisture data were collected consecutively on irrigation days, one hour before, using the Profile Probe (PR2) sensor that uses the gravimetric method. This sensor measured and recorded soil moisture data at depths of 0-100 mm, 100-200 mm, 200-300 mm, 300-400 mm, 400-600 mm, and 600-1000 mm.

Data analysis

The experimental data collected were analyzed with d software tools, specifically Python's Matplotlib and R's ggplot2. These tools facilitated the precise visualization and comparison of soil moisture content across various experimental conditions, enhancing the clarity and interpretability of the data. Microsoft excel was used to analyze the weather data (temperature and precipitation)

RESULTS AND DISCUSSION

1. Weather variability (average temperature and precipitation)

Figure 1 illustrated the variations in average temperature and precipitation from April 1st to August 21st at the experimental farm in the Errachidia region. The graph indicated that average temperatures gradually increase from April, reaching a peak during the mid-summer months (June to August) and remaining consistently high. Although there were minor fluctuations, the mean temperatures generally fell between 20°C and 35°C. In contrast, the precipitation pattern remains relatively low throughout this period, with occasional spikes representing rainfall events, but most days experience little to no precipitation.

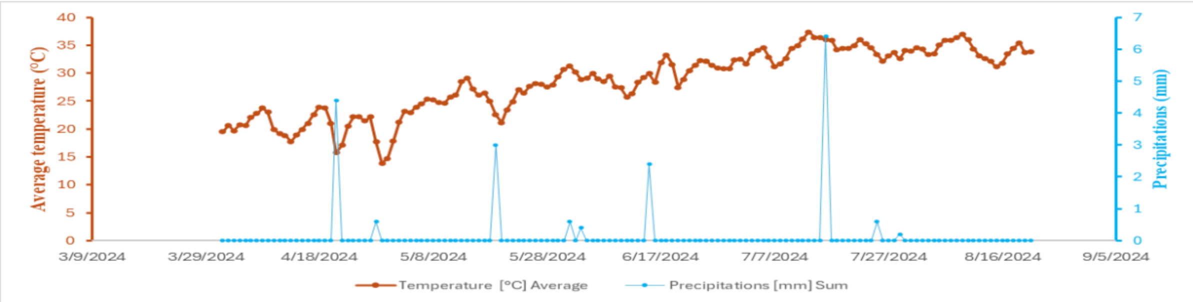


Figure 1. Temporal Trends in Average Temperature and Precipitation from March to August.

2. Mulching materials on soil moisture retention at different depths under seasonal temperature fluctuations.

Figures 2 and 3 demonstrated that different mulching systems (DPR, PP+DPR, and PWGC+DPR) had a significant impact on soil moisture retention across various soil depths and seasonal temperature fluctuations, compared to no mulch (NM). At depths of 100mm, 200mm, and 300mm, Figure 2 showed that the PP+DPR mulching system was the most effective in conserving soil moisture, particularly as temperatures increase, outperforming other mulching type, though there was an increase in irrigation schedule. Conversely, the NM system consistently proved to be the least effective, especially under conditions of high temperature variability. Additionally, at a depth of 400mm, the PP+DPR system markedly increased soil moisture levels with rising temperatures, while both DPR and PWGC+DPR systems also exhibited strong moisture retention capabilities, demonstrating their ability to maintain consistent soil moisture in deeper soil profiles under varying temperature conditions.

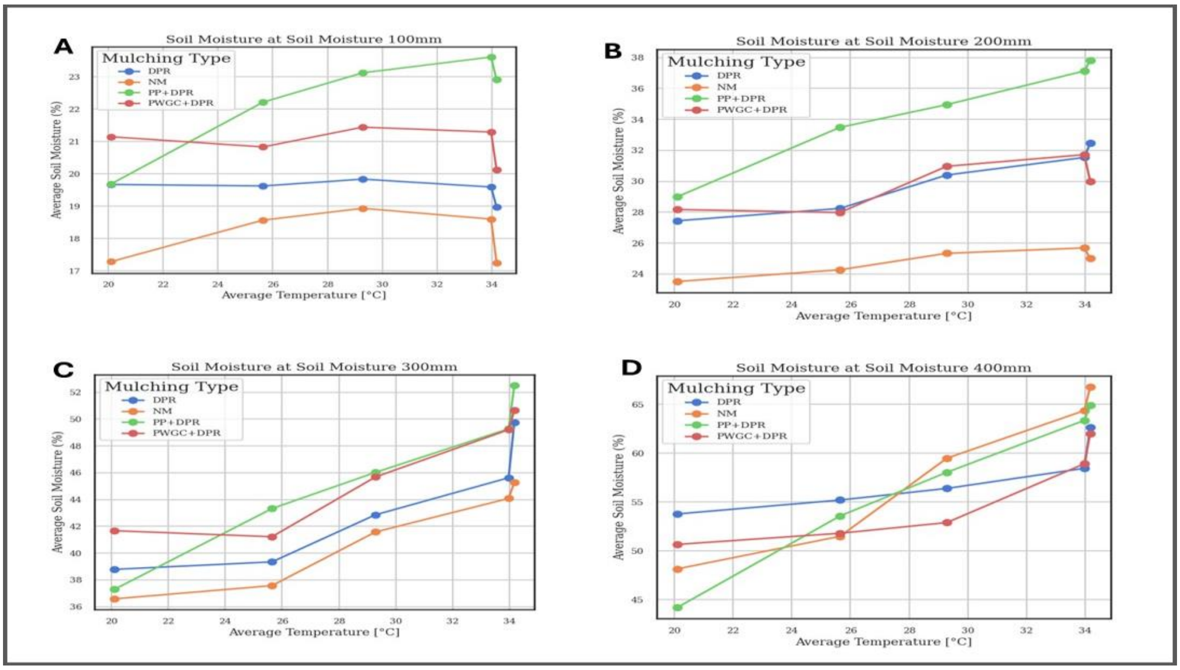


Figure 2. Soil moisture variability at 100mm (A), 200mm (B), 300mm(C) to 40mm (D)soil depth at date palm experiment with seasonal temperature variation from April (Spring) to August (summer) under different mulching systems (DPR (Dry palm residue), PP (Polyethylene plastic) + DPR, PWGC ((Polypropylene woven ground cover) +DPR, NM (Non-mulch)).

A study conducted by Ma et al. (2009) on corn plastic mulching in the East area of Jilin Province clearly reported that the corn soil moisture increased under plastic mulching particularly in the dry and rainless days, which quite like our study especially for the topsoil profile.

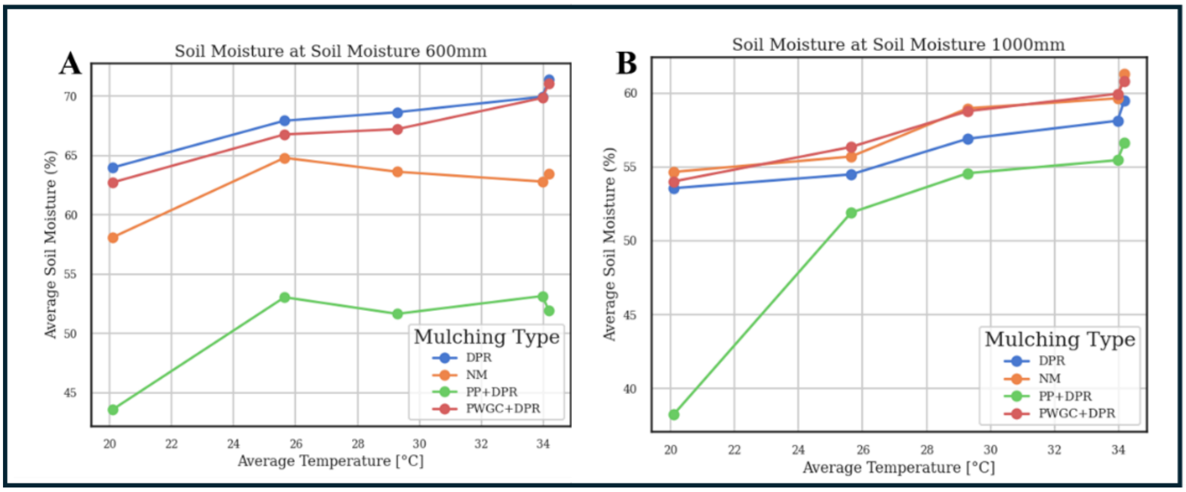


Figure 3. Soil moisture variability at 600mm (A) and 1000mm (B) soil depth at date palm experiment with seasonal temperature variation from April (Spring) to August (summer) under different mulching systems (DPR (Dry palm residue), PP (Polyethylene plastic) + DPR, PWGC ((Polypropylene woven ground cover) +DPR, NM (Non-mulch)).

At a depth of 600mm (Figure 3(A)), the DPR system was the most effective in conserving soil moisture as temperatures increase. The PWGC+DPR system also performed well, closely matching the effectiveness of the DPR system, and both outperform the NM system. At a depth of 1000mm (Figure 3(B)), soil moisture retention varied among the different mulching systems, with the DPR and PWGC+DPR systems providing the most consistent moisture retention as temperatures rise. The NM system exhibited minimal variation, suggesting that deeper soils retain moisture more naturally. Meanwhile, the PP+DPR system, effective at shallower depths, showed reduced effectiveness at both 600mm and1000mm soil depths. These results matches with the findings in the study that Yin et al. (2022) conducted on the effect of plastic film mulching system on deep soil moisture where they found that plastic mulching reduced soil water storage (SWS) in the 0–100 cm- 200cm and 300 cm soil profile. This shows that less water is accumulated in the deeper soil profile compared to other mulching systems.

INFLUENCE OF MULCHED-DRIP IRRIGATION SYSTEM ON YIELD AND PHYSIOLOGICAL ATTRIBUTES OF PEPPER VARIETIES IN SOUTHWEST, NIGERIA

[1]I.A. Kehinde, [1*]O.O. Fawibe, [1]A.S. Oyelakin
[1]Department of Pure and Applied Botany, Federal University of Agriculture Abeokuta, PMB 2240, Alabata, Abeokuta, Nigeria
*e-mail: fawibeoo@funaab.edu.ng

ABSTRACT

The unpredictable rainfall pattern due to climate change pose a major challenge to pepper production and its yield outcome in Southwest, Nigeria; therefore, prompting the need for supplementary irrigation practice. The field study assessed the influence of mulched-drip irrigation on yield and agronomic characteristics of three varieties of pepper. The experiment was arranged in a split-plot design with three replicates. The irrigation type; rainfed (RF), drip irrigation with plastic -film (DIP), and drip irrigation with biodegradable film (DIB) served as the main plot while the subplots included three *Capsicum frutescens* varieties: var. baccatum (var. A) var. abbreviatum (var. B), and var. acuminatum (var. C Although the total water supplied to the DIP and DIB increased by 51.7% and 60.3%, respectively compared with RF, the yield of Capsicum also significantly increased by 53.6% and 55.7% under DIP and DIB, respectively. The increased yield outcomes under mulched-drip irrigation were ascribed to the significant increase in chlorophyll content, leaf area and total biomass of Capsicum. Notably, DIP and DIB similarly influenced yield and agronomic attributes of Capsicum; however, DIP saved 13.3% of irrigated water more than DIB. The yield of the *Capsicum frutescens* varieties were comparable. In conclusion, mulched-drip irrigation irrespective of mulch type significantly increased the yield of pepper in Southwest, Nigeria and could serve as supplementary irrigation technique for the promotion of pepper.

Keywords: water-saving irrigation, climate-smart, pepper, intermittent drought

INTRODUCTION

Pepper (*Capscicum frutescens*) is a popular vegetable in West Africa, with economic, food and medicinal importance (Dagnoko *et al.*, 2013). However, its production is heavily dependent on the availability of water, especially during the flowering and fruiting stages (Mackic *et al.*, 2023). Nigeria produces about 50% of the pepper consumed in Africa (Idowu-Agida *et al.*, 2010). Although pepper is widely cultivated throughout Nigeria, yields obtained by farmers are often very low (Idowu-Agida *et al.*, 2010), as a result of the rainfed agricultural practice with unpredictable precipitation patterns. Due to high sensitivity of pepper to shortfall in water supply, plant growth and biomass production are restricted causing severe yield losses (Shama *et al.*, 2019).

Mulched-drip irrigation has become increasingly acceptable and practiced as a water-saving technique that involves the use of drip pipes for water application under a protective film cover (Fawibe *et al.*, 2020; Wang *et al.*, 2023). The technique has been reported as a climate-smart agricultural practice in different regions of the world- China (Wang *et al.*, 2024); Italy (Sifola *et al.*, 2024); India (Job *et al.*, 2018); and Japan (Fawibe *et al.*, 2019). Mulch directly prevents the exchange of water vapour between the soil surface and atmosphere thereby suppress weed growth, reduce soil water evaporation, optimize soil temperature and promote plant growth and yield of high-quality crops (Lamont, 2017; Zhang *et al.*, 2019). In recent years, varying mulch types have been developed with variation in colour and composition (Nithisha et al., 2022). Despite the diverse benefits of plastic films; its removal from the soil after harvest remains difficult and laborious due to the adhesion of the soil particles to the film; hence, resulting in fragmentation of the plastics (Qi *et al.*, 2022). To ensure food security in a sustainable environment, biodegradable mulch (BDM) has been developed. Biodegradable film has shown to disintegrate into CO_2 and H_2O through the process of oxidation and microbial degradation (Amanna *et al.*, 2021). However, it remains unknown if it could produce comparable results with the plastic film mulch. Hence, this study aimed to determine the yield and agronomic characteristics of pepper varieties under mulched drip irrigation techniques compared with conventional cropping practices.

MATERIALS AND METHODS

A field experiment was conducted at the experimental farm of the Department of Pure and Applied Botany, Federal University of Agriculture, Abeokuta (7.0728ºN, 3,3367ºE) from April to September 2023.

Experimental Design and field management

The experimental plots were arranged in a split-plot design (main plot: irrigation and mulching system; subplot: Capsicum varieties) with three replicates. The main plot consisted of three irrigation and mulching systems: rain-fed (RF), drip irrigation with plastic-film mulching (DIP) and drip irrigation with biodegradable film mulch (DIB). The subplots included three *Capsicum frutescens* varieties: var. baccatum (var A) var. abbreviatum (var. B), and var. acuminatum (var C). The RF plots depended on rainfall and the total amount of rainfall during the experimental period was recorded.

In both DIB and DIP plots, drip tubes, each of 6 m long were laid beneath a black polyethylene plastic film and a biodegradable film, respectively. The drip pipes were connected to a source of water (reservoir) and irrigation water supplied to DIP and DIB was measured with an installed flow meter at 75% field capacity (Fawibe et al., 2020). Basal application of 100 kg/ha of NPK (15:15:15) was carried out, while weeding was done at intervals in all experimental plots when necessary.

Plant Sampling and Analyses

Chlorophyll content and leaf area were measured at vegetative and flowering stages using SPAD-502 (Konica Minolta Co., Ltd.) and leaf area meter (Portable Leaf Area Meter, Hangzhou Mindfull Technology Co. Ltd, China), respectively. Pepper plants covering an area of 1m^2 were harvested at the maturity stage and oven-dried at 80°C for 72 hours to determine the total biomass. At the fruiting stage, fruit of each variety covering an area of 2 m^2 were harvested weekly for 4 weeks to determine the average yield per hectare. The harvest index and water use efficiency were also calculated.

Statistical analysis

Data were analyzed using Analysis of variance (ANOVA) and means were separated by Duncan's multiple range test when the effects are significant at $p<0.05$.

RESULTS AND DISCUSSION

The total water supplied to the Capsicum species through DIB and DIP systems were 60.2% and 51.7% higher than that of the RF (Table 1); however, commensurate quantities of yields were produced with an increased rate of 55.7% and 53.6%, respectively (Table 2). The increased yield outcomes could be attributed to the significant increase in photosynthetic-associated parameters such as chlorophyll content and leaf area under both DIB and DIP. The significant increase in chlorophyll concentration and leaf area of Capsicum varieties under DIB and DIP compared to CF enabled both photosystem II and photosystem I to harvest light over a larger surface area thereby producing more assimilates for increased growth and development (Feng *et al*., 2015). The non-significant variation in the growth and yield parameters of the Capsicum varieties under varying treatments could be attributed to the similarity in their ability to adapt to mild water stress caused by intermittent rainfall during the period of plant growth.

Our study shows that the use of either plastic-film or biodegradable film mulch similarly influenced the growth and yield of capsicum varieties; however, DIP saved 19% of irrigated water more than DIB. This is attributable to the texture, thickness, and composition of the materials used. The biodegradable film used in this study was composed of starch-based materials, cellulose acetate, and cellulose nitrate that gradually disintegrated into CO_2 and H_2O through the process of oxidation and microbial degradation (Amanna *et al.*, 2021).

CONCLUSION

The use of drip irrigation with mulching practices (DIB and DIP) significantly increased the yield and agronomic attributes of capsicum varieties compared with the conventional rainfed method by alleviating mild drought stress because of dwindling rainfall pattern especially during the flowering and fruit formation stages.

Table 1. Irrigation precipitation and total water input under rainfed and drip irrigation with different mulch types.

	Irrigation (mm)	Precipitation (mm)	Total water supplied (mm)
RF	35	720	755
DIB	490	720	1210
DIP	425	720	1145

Total water supplied = Irrigation water + precipitation; RF, DIB, and DIP indicate rainfed, drip irrigation with biodegradable mulch, and drip irrigation with plastic film mulch, respectively.

Table 2. Yield, harvest index, and water-use efficiency of Capsicum varieties under varying irrigation and mulching practices.

Irrigation	Varieties	Yield (t/ha)	Fruit length (cm)	Fruit width (cm)	Fruit length-width ratio	Total dry weight (t/ha)	HI	WUE (kg/m^3)
RF	A	2.25^a	2.70^a	1.60^a	1.66^a	3.98^b	0.56^a	0.31^a
	B	2.32^a	2.76^a	1.70^a	1.57^a	4.06^b	0.50^b	0.32^a
	C	2.49^a	2.83^a	1.73^a	1.63^a	4.59^a	0.61^a	0.34^a
DIB	A	3.54^a	3.56^a	2.30^a	1.55^a	6.11^a	0.57^a	0.29^a
	B	3.75^a	3.60^a	2.26^a	1.58^a	6.88^a	0.54^a	0.31^a
	C	3.69^a	3.60^a	2.43^a	1.48^a	6.48^a	0.57^a	0.30^a
DIP	A	3.57^a	3.46^a	2.36^a	1.46^a	6.12^b	0.58^a	0.31^a
	B	3.61^a	3.46^a	2.43^a	1.42^a	6.73^a	0.53^{ab}	0.31^a
	C	3.66^a	3.56^a	2.53^a	1.40^a	6.99^a	0.52^b	0.31^a
Irrigation (I)		***	***	***	***	***	ns	ns
Varieties (V)		ns	ns	ns	ns	*	*	ns
I X V		ns	ns	ns	ns	ns	ns	ns

Values within a column for each irrigation type followed by different superscripts letters are significantly different at $p<0.05$ by Duncan's multiple range test. * and *** are significant differences at $p < 0.05$ and $p < 0.001$ respectively; ns means non-significant by ANOVA. var. baccatum (var. A) var. abbreviatum (var. B), and var. acuminatum (var. C).

Table 3. Chlorophyll content and leaf area of Capsicum varieties under varying irrigation and mulching practices

Irrigation	Varieties	Chlorophyll content		Leaf Area (cm^2)	
		Vegetative stage	Flowering stage	Vegetative stage	Flowering stage
RF	A	26.83^a	25.96^a	10.26^a	27.26^b
	B	27.80^a	26.93^a	11.43^a	30.03^a
	C	27.63^a	27.73^a	12.03^a	30.53^a
DIB	A	38.23^a	38.23^a	19.03^b	60.36^b
	B	39.50^a	38.33^a	19.26^b	69.63^a
	C	37.66^a	38.73^a	21.63^a	74.23^a
DIP	A	38.56^a	39.40^a	13.70^b	53.53^b
	B	39.30^a	38.00^a	15.63^b	58.73^b
	C	38.86^a	40.80^a	18.46^a	68.96^a
Irrigation (I)		***	***	***	***
Varieties (V)		ns	ns	***	***
I X V		ns	ns	ns	ns

Values within a column for each irrigation type followed by different superscripts letters are significantly different at $p<0.05$ by Duncan's multiple range test. *** indicates significant differences at $p < 0.001$ while ns means non-significant by ANOVA. var. baccatum (var. A) var. abbreviatum (var. B), and var. acuminatum (var. C).

REFERENCES

Amanna, R., Mahal, Z. Vieira, E.C.S., Samavi, M., Rakshit, S.K. (2021). Plastics: Toward a Circular Bioeconomy. In: Circular Bioeconomy-Current Status and Future Outlook. Biomass, Biofuels, Biochemicals, pg 781-811

Dagnoko, S., Yaro-Diarisso, N., Sanogo, P.N., Adetula, O., Dolo-Nantoume, A.,Gamby-Toure, K., Traore, A., Katile, S. and Diallo-Ba, D. (2013). Overview of pepper (Capsicum spp) in West Africa. African Journal of Agricultural Research, 8(13): 1108-1114

Fawibe, O.O., Honda, K., Taguchi, Y., Park, S. and Isoda, A. (2019). Greenhouse gas emissions from rice field cultivation with drip irrigation and plastic film mulch. Nutrient Cycling in Agroecosystems, 113, 51-62.

Fawibe, O.O., Hiramatsu, M., Taguchi, Y., Junfa, W. and Isoda, A. (2020). Grain yield, water-use efficiency and physiological characteristics of rice cultivars under drip irrigation with plastic-film-mulch. Journal of crop improvement, 34 (3): 414-436.

Feng, Y., Chen, R., Hu, J., Zhao, F., Wang, J., Chu, H. and Lin, X. (2015). Bacillus asahii comes to the fore in organic manure-fertilized alkaline soils. Soil Biology and Biochemistry, 81:186-194.

Idowu-Agida, O.O., Ogunniyan, D.J. and Ajayi, E.O. (2010). Flowering and fruiting behavior of long cayenne pepper (Capsicum frutescens L.) collected from the south eastern Nigeria. Proceedings of the 27th HORTISON, conference, Kano, 11-16th October, 2009, 127-132

Job, M., Rusia, D.K., Dinmani, and Singh, V.K. (2018). Effect of drip irrigation and plastic mulch on yield, water use efficiency of Cauliflower. Journal of Pharmacognosy and Phytochemistry, 2018: 2556-2560

Lamont, W.J. (2017). Plastic mulches for the production of vegetable crops. In: A guide to the manufacture, performance, and potential of plastics in Agriculture. Plastic Design Library pg 45-60

Mackic, K., Bajic, I., Pejic, B., Vlajic, S., Adamovic, B., Popov, O. and Simic, D. (2023). Yield and Water Use Efficiency of Drip irrigation of pepper. Water, 15(16) 2891

Nithisha, A., Bokado, K., Charitha, K.S. (2022). Mulches: Their impact on the crop production. The Pharma Innovation Journal, 11(7): 3597-3603

Qi, Y., Ossowicki, A., Yergeau, E., Vigani, G., Geissen, V. (2022). Plastic mulch film residues in agriculture: impact on soil suppressiveness, plant growth and microbial communities. FEMS Microbiology Ecology, 98 (2)

Shama, S., Leskovar, D., Crosby K. (2019). Genotypic differences in leaf, gas exchange and growth responses to deficit irrigation in reticular and indonus melons (Curcumis melo L). Photosynthetica, 57: 237-247.

Sifola, M.I., Cozzolino, E., Ciancolini, A., Falce, M., Raimo, F., Enotrio, T., Sicignamo, M., Baiano, S. and Paino, L. (2024). Crop management system consisting of biodegradable mulching film + drip irrigation increases yield and quality of flue-cured Tobacco. Sustainability, 16(16): 7089

Wang, J., Fawibe, O.O., Fawibe, K.O. and Isoda, A. (2023). Water productivity, sink production, and varietal differences in panicle structure of rice (Oryza sativa L.) under drip irrigation with plastic-film mulch. Field Crops Research, 291: 1-11.

Wang, C., Li, S., Huang, S. and Feng, X. (2024). A review of the application and impact of drip irrigation under plastic mulch in agricultural ecosystems. Agronomy, 2024 14(8): 1752

Zhang, G., Wu, H., Jiang, K., & Li, Z. (2019). Microplastics in soils: A review of possible sources, analytical methods and ecological impacts. *Journal of Hazardous Materials*, 400, 123328.

SMARTSPROUT: LEVERAGING IOT FOR SUSTAINABLE AND EFFICIENT SMART IRRIGATION SYSTEMS IN AFRICA

Oyedepo John Adebayo and Oluyege, Damilola Emmanuel
Institute of Food Security, Environmental Resources and Agricultural Research, Federal University of Agriculture, P.M.B. 2240, Abeokuta. Nigeria
e-mail: oyedepoja@funaab.edu.ng; +2348032485583

ABSTRACT

Water scarcity and inefficient irrigation practices are critical challenges in agriculture, these has been exacerbated by climate change and a growing global population. This paper introduces **SmartSprout**, an IoT-based smart irrigation system designed to optimize water usage and improve crop yields sustainably. The system integrates soil moisture sensors, RTC modules, solenoid valves, and wireless connectivity to automate and optimize irrigation based on real-time data. This study details the hardware and software design, prototype testing, market potential, and socio-environmental impacts of SmartSprout. The results demonstrate its potential to revolutionize irrigation practices for smallholder and commercial farmers globally.

INTRODUCTION

Efficient water management is a cornerstone of sustainable agriculture, especially in the context of escalating water scarcity and climate change. Traditional irrigation practices often result in resource inefficiency and suboptimal crop health, a challenge that has catalyzed the integration of smart technologies into agriculture [1]. IoT-based smart irrigation systems have demonstrated the potential to address these issues by offering precise, automated water management tailored to crop needs. Recent advancements in sensor technologies, such as soil moisture and weather monitoring, have enhanced their applicability and reduced costs, making them more accessible to farmers in resource-constrained settings.

Studies highlight that IoT-enabled systems can reduce water usage by 20-40% while improving yields, contributing to global food security. This paper introduces SmartSprout, as an affordable and scalable smart irrigation solution designed to empower both smallholder and commercial farmers intensify off season farming. The prototype aims to revolutionize water management in agriculture thus enhancing sustainable year-round crop production across Africa [2]

MATERIALS AND METHODS

System Overview

Drip irrigation remains for example is one of the most innovative means of supplementary water supply to crops today. A typical drip irrigation system consists of drip tapes or tubes, sub-main pipes, connectors, filters and the fertigator connected to a source of water. With the introduction of internet of things, it has been possible to automate operations thus making the process fully computerized. In this paper, the performance of drip irrigation is presented as improved in reducing labour requirements, efficient water use, remote management of farms, real-time monitoring of soil, moisture and increased productivity. The schema in figure 1 is the general architecture of the SmartSprout system.

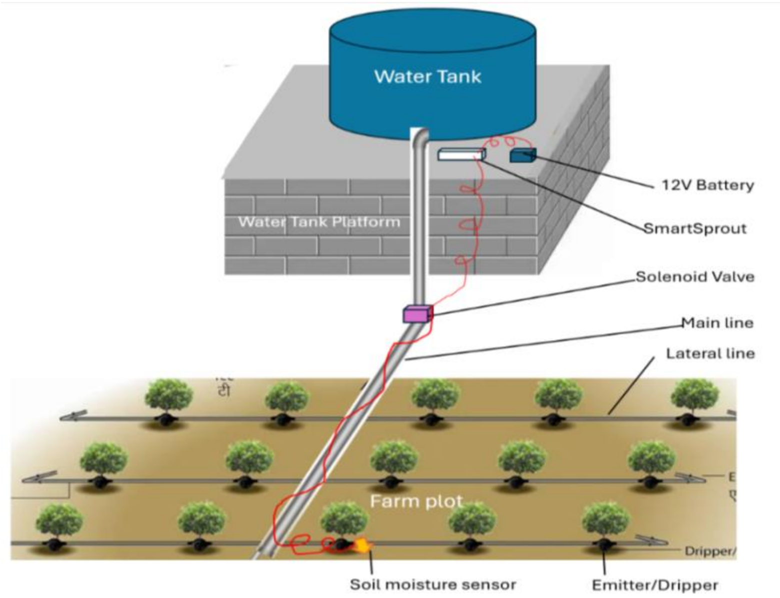


Figure 1. The layout of the SmartSprout connected with Drip Irrigation System.

Water from the tank is released to the field through the pilot-operated solenoid valves. The opening or closing of the orifice in the solenoid valve body is determined by the instructions of the actuator which are derived from the module of the Real Time Clock (RTC) and the soil moisture sensor. In this case, water is allowed through the solenoid valve when the soil moisture is low, and the time is in the morning or evening. Water is prevented to flow through the valve where the two conditions are not met. At field capacity the solenoid valve locks water from reaching the main irrigation line [3].

Hardware Components and Specifications

Soil Moisture Sensor

Model: Capacitive Soil Moisture Sensor v1.2

Specifications:

- Operating Voltage: 3.3V–5V.
- Analog Output Range: 0–3.3V, mapping precise soil moisture levels.
- **Enhanced Feature:** Corrosion-resistant coating ensures longevity, even in high-salinity soils, while delivering accurate data critical for precise irrigation scheduling.

RTC Module

Model: DS3231 Real-Time Clock Module

Specifications:

- Accuracy: ±2 ppm from 0°C to +40°C, maintaining high precision across varied environmental conditions.
- Features: Built-in temperature-compensated crystal oscillator ensures consistent timing, critical for automated irrigation cycles.
- **Application:** Allows synchronization with seasonal and diurnal crop water requirements.

Solenoid Valve

Model: 12V DC Solenoid Valve

Specifications:

- Voltage: 12V DC
- Flow Control: Adjustable for both partial and full irrigation requirements.

- Durability: Engineered with anti-corrosive materials, ideal for long-term deployment in diverse soil and water conditions.
- **Improved Design:** Enables precision in water delivery, reducing wastage and optimizing soil saturation.

Microcontroller

Model: ESP32

Specifications:

- Dual-core processor: Xtensa 32-bit LX6, providing robust computational capacity.
- Connectivity: Integrated Wi-Fi and Bluetooth allow seamless remote operation and real-time updates.
- GPIO Pins: Supports multiple peripheral integrations, enabling scalability for additional sensors or modules.
- **Advancement:** The combination of high-speed processing and low power consumption makes the ESP32 ideal for sustainable, solar-powered systems.

Power Supply

- **Solar Panel and Battery**: 12V, 10W solar panel with a 12V, 7Ah rechargeable battery.

Enclosure

- **Material**: Polycarbonate casing with IP65 rating for water and dust resistance.

The SmartSprout solution is a very portable but intricate tool. Figure 2 shows the system in a polycarbonate enclosure and the battery.

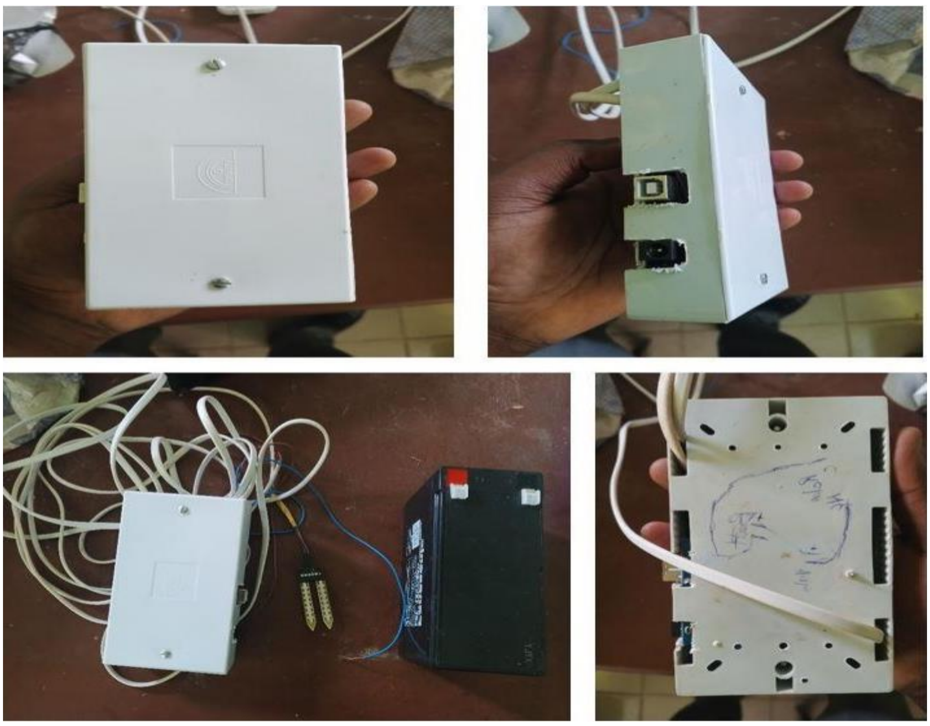


Figure 2. Polycarbonate casing (from all sides) enclosing all components with the exception of the solar panel battery.

Software Architecture

Programming Environment: Arduino IDE for microcontroller programming.

Libraries Used:

- WiFi.h and HTTPClient.h for wireless communication.
- DS3231.h for RTC integration.
- AnalogRead.h for soil moisture sensor calibration.

Data Processing:

- Logic for threshold-based irrigation control implemented in C++.
- MQTT protocol for real-time data transmission to the cloud.

Visuals and Flow Diagrams

System Architecture Diagram

A flow diagram depicting the SmartSprout system:

- **Input Sensors**: Soil moisture sensor and RTC module.
- **Processing Unit**: ESP32 microcontroller.
- **Actuation**: Solenoid valve controlling water flow.
- **Power Source**: Solar panel and battery system.
- **Output**: Mobile app displaying real-time data and enabling remote control.

The **System Architecture Flow Diagram** for the SmartSprout system as requested. It visually represents the connections between the key components:

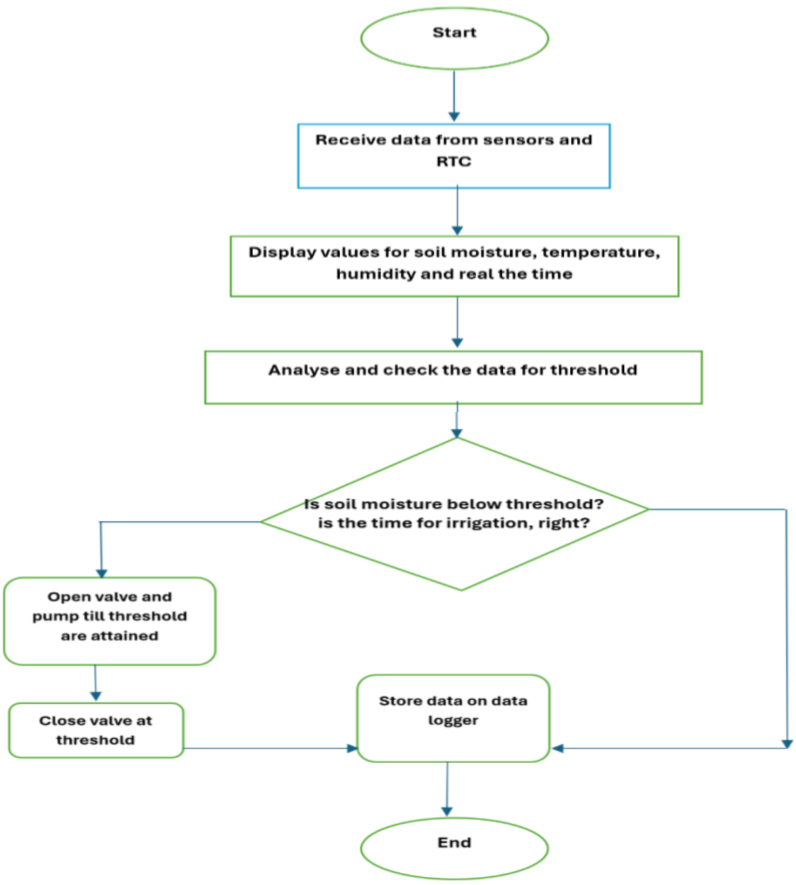


Figure 3. A flow diagram depicting the SmartSprout system [4].

The flow clearly shows how data and power flow through the system for optimal operation. You can download and integrate the diagram into your work [].

Field Setup Illustration
A labelled image of the prototype deployed in a test farm, showing the placement of components:

- Sensor embedded in soil.
- Protective enclosure housing the microcontroller and other electronics.
- Water delivery via pipes controlled by the solenoid valve.

Prototype Testing and Results
The SmartSprout prototype was field-tested in various agricultural settings. Key performance metrics included:

- **Irrigation Efficiency**: Reduced water usage by 30% compared to traditional methods.
- **Soil Moisture Maintenance**: Maintained optimal soil moisture levels (20–40%) for maize and tomato crops.
- **Power Efficiency**: Solar-powered system provided uninterrupted operation for 72 hours during cloudy conditions.

Case Study 1 from Prototype Testing: Small mother trials plot at the Institute of Food Security, Environmental Resources and Agricultural Research Federal University of agriculture Abeokuta in Southwest

Crops: Pepper and tomatoes.
Setup: 0.1-hectare plot with one soil moisture sensor.
Results:

1. **Water Savings**: 25% reduction in water usage compared to manual methods.
2. **Yield Improvement**: 15% increase in crop yield due to consistent moisture levels.
3. **User Feedback**: Farmers reported improved ease of irrigation management.

Case Study 2: Demonstration at the maiden edition of the TETFUND National Research Fair/Exhibition at the Eagle Square Abuja Nigeria.
Setup: Micro demonstration-plot with a network of sensors.
Results:

1. **Energy Efficiency**: Solar power sustained operations during peak sunny periods. Real-Time Clock (RTC) works effectively to control when to irrigate and when not. Regardless of aridity signals from the Soil moisture Sensor, the RTC ensured that the solenoid valve does not open until the cool of the day. This proofs efficiency in preventing irrigating at hot periods and scorching plant roots.
2. **Scalability**: Modular design allowed for easy expansion across additional plots.
3. **Impact**: Significant labor cost reductions and better crop uniformity.

Market Potential
Target Audience
SmartSprout is designed for:

- Smallholder farmers in water-scarce regions.
- Commercial farmers focusing on large-scale efficiency.
- NGOs promoting sustainable agricultural practices.

Market Growth

The global smart irrigation market, estimated at $1.5 billion in 2022, is expected to grow to $3.2 billion by 2030, with a CAGR of 10%.

Impact Assessment

Social Impact

SmartSprout empowers smallholder farmers by providing them access to advanced technology, improving crop yields, and enhancing food security in resource-constrained regions.

Economic Impact

Efficient water management reduces operational costs, increases profitability, and fosters sustainable economic growth in rural communities.

Environmental Impact

By optimizing water usage, SmartSprout significantly reduces water waste and contributes to biodiversity conservation.

Scaling and Future Work

Scaling Strategies

- **Production**: Establishing partnerships with manufacturers to streamline component procurement.
- **Market Outreach**: Tailored marketing campaigns targeting water-scarce regions.
- **User Support**: Comprehensive training programs for farmers.

Future Enhancements

- **Machine Learning Integration**: Predictive algorithms for irrigation scheduling based on weather forecasts.
- **Advanced Sensors**: Integration of nitrate and pH sensors for nutrient monitoring.
- **Mobile Application**: Real-time monitoring and control via an intuitive user interface.

CONCLUSION

SmartSprout offers a transformative solution for addressing water scarcity and improving irrigation practices. By combining IoT technology with sustainable design principles, it empowers farmers, enhances productivity, and reduces environmental impact.

REFERENCES

1. Bahn, R. A., Yehya, A. A. K., & Zurayk, R. (2021). Digitalization for sustainable agri-food systems: potential, status, and risks for the MENA region. *Sustainability*, *13*(6), 3223.
2. García L, Parra L, Jimenez JM, Lloret J, Lorenz P. IoT-Based Smart Irrigation Systems: An Overview on the Recent Trends on Sensors and IoT Systems for Irrigation in Precision Agriculture. *Sensors*. 2020; 20(4):1042. https://doi.org/10.3390/s20041042
3. Obaideen, K., Yousef, B. A., AlMallahi, M. N., Tan, Y. C., Mahmoud, M., Jaber, H., & Ramadan, M. (2022). An overview of smart irrigation systems using IoT. *Energy Nexus*, *7*, 100124.
4. Shamsudeen, S. (2021). Automated Soil Moisture Sensor Irrigation System using Microcontroller. An unpublished undergraduate research report at the department of computer Science, Federal University, Dutsima. Pg 78

apni
www.apni.net

UM6P
University
Mohammed VI
Polytechnic
um6p.ma

ISPA
International Society of Precision Agriculture
www.ispag.org

AAPA
AFRICAN ASSOCIATION *for*
PRECISION AGRICULTURE
www.paafrica.org/AAPA

PRECISION AGRICULTURE *in* ACTION *for* AFRICA