A COMPARATIVE ESTIMATION OF MAIZE LEAF MOISTURE CONTENT ON SMALLHOLDER FARMING SYSTEMS USING UNMANNED AERIAL VEHICLE (UAV) BASED PROXIMAL REMOTE SENSING
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ABSTRACT

Understanding maize moisture conditions is necessary for crop monitoring and developing early warning systems to optimise agricultural production in smallholder farms. Therefore, this study evaluated the utility of UAV derived multispectral imagery and machine learning techniques in estimating maize leaf moisture indicators; equivalent water thickness (EWT), fuel moisture content (FMC) and specific leaf area (SLA). The results illustrated that both NIR and red-edge derived spectral variables were critical in characterising maize moisture indicators on smallholder farms. Furthermore, the best models for estimating EWT, FMC and SLA were derived from the random forest regression (RFR) algorithm with rRMSE of 3.13%, 1% and 3.48 %, respectively. The findings are critical towards developing a robust and spatially explicit monitoring framework of maize water status and serve as a proxy of crop health and overall productivity of smallholder maize farms.

Keywords: maize moisture stress, unmanned aerial vehicle, machine learning, precision agriculture.

INTRODUCTION

Crop moisture stress is one of the most drastic limiting factors of maize crop production (Avetisyan and Cvetanova, 2019). Maize (*Zea mays L.*) is an important grain crop that is mostly grown under rain-fed conditions and consumed by the majority of Southern Africa as a staple food (Ngoune Tandzi and Mutengwa, 2020). Considering that maize growth is sensitive to water stress (Daryanto *et al.*, 2016), it is imperative to develop optimal methods to quantify maize moisture stress, as it is a key pathway towards effectively monitoring drought impacts and deriving useful information that can be used to inform irrigation decisions.

A variety of physiological indicators have been developed to quantify crop moisture stress. These include equivalent water thickness (EWT), fuel moisture content (FMC) and specific leaf area (SLA) (Liu *et al.*, 2015; Zhang *et al.*, 2017; Zhou *et al.*, 2020). Although there have been various studies conducted in monitoring crop water status (Zhang *et al.*, 2019; Zhou *et al.*, 2020), there still is disagreement on the best-suited indicator for maize moisture content prediction at a leaf level in small fields.

In recent years, unmanned aerial vehicles (UAVs), commonly known as drones, have received widespread attention in precision agriculture (Maes *et al.*, 2018). Although UAV based proximal sensing has become a powerful tool for estimating physiochemical variations in vegetation, only a few studies have been conducted on identifying the best method as well as the best moisture indicators to evaluate maize crop moisture stress at a farm scale. Therefore, it is imperative that operational and robust regression algorithms are identified, tested and validated for their performance in predicting smallholder maize functional traits, such as moisture content. In this regard, this study sought to investigate the potential of UAV derived multispectral imagery and machine learning techniques in the remote estimation of smallholder maize moisture content. The objectives of this study were to: (1) evaluate the performance of five regression techniques in predicting maize moisture content, and (2) determine the most suitable indicator of smallholder maize moisture content. The anticipated results will help provide a technical approach for the quick and accurate monitoring of changes in either EWT, FMC or SLA, because of moisture variability, to inform irrigation decisions and planning of smallholder maize crops.

MATERIALS AND METHODS

Description of the study area

This study was conducted at Swayimane (29° 52' S, 30° 69' E), a communal area located within the uMshwathi Municipality, north-east of Pietermaritzburg, South Africa. Maize experimental plots were conducted in summer, which is the optimal maize growing season. The maize plot covered a spatial extent of 250 m^2 and was primarily rain-fed. The maize crop was sown in mid-November 2021. At the time the project commenced, the crop was 86 days' old, termed the reproductive phase of the growth cycle. Specifically, the maize seedlings were at an intermediate between the kernel blister stage (growth stage R2) and kernel milk stage (growth stage R3).

Field Sampling and water content measurements

Field data collection was conducted on the 11^{th} of February 2021 at Swayimane. The first fully developed leaf (first leaf below whorl) was collected from the top of the maize canopy at each sample point to measure leaf moisture content indicators. A LI-3000C Portable Area Meter combined with a LI-3050C Transparent Belt Conveyer Accessory with a one mm^2 resolution was used to measure the leaf area (A) of sampled maize leaves (Li-Cor, USA). The fresh weight (FW) of sampled maize leaves were obtained using a calibrated scale. Field measurements were conducted between 12:00 noon and 14:00 as this is the most optimal period of the day for crop photosynthetic activity (Sade *et al.*, 2015). The sampled maize leaves were then dried in an oven at 70° C until a constant dry weight (DW) was reached (approximately 48 hours). The A, FW and DW were then used as input variables to compute maize leaf moisture indicators using the following equations:

$EWT_{leaf} = (FW - DW) / A$ units: gm^{-2} (1)
$FMC_{leaf} = (FW - DW) / DW \times 100\ \%$ units: % (2)
$SLA_{leaf} = A / DW$ units: $g^{-1}\ m^2$ (3)

The computed data for each crop moisture indicator was integrated with the GPS location and converted into a point map that was overlaid with the UAV multispectral images of the study area.

The UAV platform, image acquisition and processing

The DJI Matrice 300 series (M300) and the MicaSense Altum imaging sensor were used to acquire images covering the maize field considered in this study. The Altum camera integrates a radiometrically calibrated thermal sensor with five spectral channels that measure reflectance in the visible to the non-visible light spectrum (i.e., blue, green, red, red-edge, NIR and thermal) at a ground sampling distance of 9.6 cm per pixel. The imagery derived from the imaging platform were orthomoisaced and pre-processed to enhance image features in Pix4D Fields photogrammetry software.

Model development and statistical analysis

The reflectance data obtained from the Altum multispectral and thermal bands were used to derive VIs. The sampled data were randomly split into training (70%) and validation data (30 %). The former was used in the model development and the latter in assessing the accuracy of predictive models. A comparative analysis was conducted between the support vector regression, random forest regression, decision trees regression, artificial neural network regression and the partial least squares regression algorithms in predicting leaf moisture content indicators (i.e. EWT, FMC and SLA). Lastly, the coefficient of determination (R2), the root mean square error (RMSE) was computed to evaluate performance of regression models in predicting leaf moisture content indicators.

RESULTS

Evaluation of maize moisture indicators and optimized regression models

Table 4 illustrates the model accuracies obtained in predicting leaf EWT, FMC and SLA based on the RFR, DTR, ANNR, PLSR and SVR regression techniques. The accuracies of the prediction models illustrated that the RFR was the most optimal technique for predicting crop moisture indicators. The results revealed that the optimal indicators of maize moisture content based on the RFR models were FMC_{leaf} and EWT_{leaf}, followed by SLA_{leaf}. Additionally, the UAV multispectral bands and derived VIs were successful in predicting all maize moisture content indicators.

Table 1. Prediction accuracies of EWT_{leaf}, FMC_{leaf} and SLA_{leaf} derived using optimal models based on the RFR, DTR, ANNR, PLSR and SVR regression models.

Model	EWT_{leaf} (g m^{-2})			FMC_{leaf} (%)			SLA_{leaf} (m^2 g^{-1})		
	R^2	RMSE	RRMSE	R^2	RMSE	RRMSE	R^2	RMSE	RRMSE
RFR	0,89	10,28	3,13	0,76	0,45	1,00	0,73	0,0004	3,48
DTR	0,73	25,16	7,67	0,65	1,08	1,35	0,7	0,0009	8,16
ANNR	0,84	14,29	4,35	0,34	1,54	1,92	0,68	0,0007	6,60
PLSR	0,74	17,1	5,15	0,45	0,48	0,60	0,6	0,0008	19,33
SVR	0,78	15,05	4,76	0,69	0,70	0,89	0,71	0,0005	18,82

DISCUSSION

Estimating maize moisture content indicators

Results in this study indicate that when estimating maize equivalent water thickness, an optimal estimation accuracy (rRMSE =3.13 % and R^2 =0.89) can be obtained based on spectral variables derived from the NIR section of the electromagnetic spectrum (NDVI, NIR, NDWI, and NDRE). This can be explained by the fact that leaves which are characterised by high moisture status reflect highly in the NIR region due to multiple scattering within the leaf cell, which is primarily controlled by leaf cuticles, mesophyll thickness and intercellular air spaces and is directly linked to leaf moisture content (Romero-Trigueros *et al.*, 2017; Sibanda *et al.*, 2021). Fuel moisture content (FMC) was optimally predicted to a model accuracy of rRMSE of 1 % and R^2 = 0.76. The results of this study show that FMC is particularly sensitive to the red-edge waveband and associated derivatives of these spectral channels. Such sensitivity of the red-edge band in predicting FMC can be explained by its positive association with crop biomass as well as chlorophyll content, which is also positively correlated with FMC (Sibanda *et al.*, 2021). This was the case in studies by Bar-Massada and Sviri (2020) and Cao and Wang

(2017) that confirmed a variation in the reflectance of green leaves under water stressed conditions in the red-edge band, making this wavelength a significant predictor of FMC. Furthermore, NDWI, which is primarily derived from the NIR band, has a significant influence in the prediction of FMC. This VI is particularly important in predicting moisture content as it is sensitive to the variations of leaf reflectance induced by water molecules and dry matter content, hence, strongly correlates to plant water stress (Zhang and Zhou, 2015). Furthermore, results illustrate that all maize leaf moisture content indicators were optimally predicted using UAV-derived data. Accordingly, FMC and EWT yielded the highest predictive power of moisture content, while SLA was effectively estimated. In comparison, the FMC and EWT are the most ideal crop water indicators for monitoring moisture stress using field spectroscopy techniques (Yi *et al.*, 2014; Liu *et al.*, 2015).

The performance of machine learning algorithms in predicting maize moisture content indicators

Results in this study show that the RFR approach is the most suitable explorative tool to predict all maize moisture content indicators. For instance, RFR optimally predicted FMC, EWT and SLA, producing the highest prediction accuracy (rRMSE = 1%, 3.13 % and 3.48 %). The RFR algorithm can effectively establish the relationship between leaf reflectance and maize moisture at a farm scale. The strength of RFR could be explained by the fact that the algorithm is not highly affected by noise in the data, hence there is a reduced risk of producing overfitting models (Abdel-Rahman *et al.*, 2013; Zhu *et al.*, 2017). In a similar study, Sibanda *et al.* (2021) confirmed the robustness of the RFR model in modeling moisture content elements, particularly FMC by achieving optimal R^2s as high as 1 and an RMSE of 16.4 %.

The SVR approach was also optimal in predicting maize leaf EWT, FMC and SLA. The strength of the SVR lies in its ability to circumvent outliers and exhibiting a high generalization capacity to handle unseen patterns (Liang *et al.*, 2018). The results in this study reveal that the SVR is similar to the RFR in predictive power. This could be explained by the fact that the SVR and RFR ensembles optimally operate with a relatively small number of training samples, which is often the case for data acquired at a field scale after avoiding spatial autocorrelation (Wang *et al.*, 2016; Zhu *et al.*, 2017) .Therefore, the results of this study demonstrate that the model properties of RFR and SVR are well suited for the estimation of smallholder maize moisture content.

CONCLUSION

The present study tested the utility of UAV-based multispectral data in a comparative approach of estimating moisture content using RFR, SVR, DTR, ANNR and PLSR machine learning techniques and EWT, FMC and SLA of maize crops in smallholder farms. This study demonstrates that UAV-derived multispectral data can predict maize moisture variations of smallholder farms with exceptional accuracy, hence can complement and inform farms drought-related water stress. However, there are research gaps that demand further inquiry, particularly on smallholder maize farms. Future studies should aim to evaluate the utility of UAV derived data and the optimal moisture indicators in characterising the variation of maize moisture content across different phenological stages. Additional studies are necessary to evaluate whether UAV sensors that measure spectral reflectance along the SWIR section of the electromagnetic spectrum improve the prediction of smallholder maize moisture content. Finally, this study was site and crop-specific, therefore, studies conducted across various climates, different smallholder crops and at a multi-temporal scale should be assessed to draw broad conclusions in characterising crop moisture stress.

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