#7462 MAPPING SPATIAL VARIABILITY OF SOIL NUTRIENT DEFICIENCIES IN SMALLHOLDER VILLAGES – A PREREQUISITE FOR IMPROVED CROP PRODUCTION IN AFRICA

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ABSTRACT

Various approaches to derive decision support for site-specific soil fertility management were assessed in a smallholder farming system, a village in western Kenya. The results indicate that at least a small number of soil analyses from the village is important. A collaborative approach among farmers within an area or village can facilitate detailed and cost-effective soil properties mapping, where parts of samples are analyzed in the laboratory, and most samples are scanned by a combination of sensors. Maps from continental geodatabases were less useful.

INTRODUCTION

Precision agriculture in the context of smallholder farming, the dominating type of agricultural production in many parts of Africa, can be regarded as adapting the management to match the specific needs of individual plots. Management of soil fertility through balanced crop nutrition that takes account of site-specific deficiencies in macronutrients and micronutrients is needed to close the yield gap to remedy hidden hunger (Kihara et al., 2016, 2020). A fundamental prerequisite is the availability of basic information on soil properties at a detailed enough level. Such detailed soil information is often missing, but there are different ways in which it can be acquired. Traditional soil mapping by collecting and analyzing soil samples may be regarded as too expensive for small-scale farmers. However, recently, global or continental digital soil property maps of high spatial resolution have become available, including maps of predicted concentrations of many nutrients of interest (Hengl et al., 2017). Such data sources provide great opportunity to enable spatially extensive recommendations with improved and sustainable nutrient management advice (Rurinda et al., 2020). On another spatial scale, an alternative is to use proximal soil sensors that rapidly can measure many soil samples (Viscarra Rossel et al., 2011). So far, however, such sensors normally do not directly measure the soil property of interest, but require some mathematical/statistical models in order to determine that soil property. As with data from general geodatabases, the accuracy of generated results can be difficult or impossible to judge for the local farmer or advisor.

In this case study we have assessed various approaches to derive decision support for site-specific soil fertility management in a smallholder farming system. Our study area is a village in western Kenya. The aim was to compare and discuss different methods to generate practically useful soil information for farms in this village: *i*) a regional soil dataset covering the watershed within which the village is located, *ii*) a continental publicly available digital soil database produced by machine learning methods, *iii*) soil maps derived by interpolation of local soil sample data, iv) the continental map downscaled by local soil samples, and *v*) information derived by three proximal soil sensors (near- and mid-infrared spectroscopy and portable x-ray fluorescence) from local calibration models.

MATERIALS AND METHODS

One hundred sixty-six topsoil (0-20 cm) samples were collected in Mukuyu village (covering about 400 ha) in western Kenya following a random stratified sampling design, where each sample consisted of four subsamples from a 16 m^2 area. The most important crops in Mukuyu are maize (*Zea mays* L.) and beans (*Phaseolus vulgaris* L.), primarily produced for subsistence by smallholder farmers. The average farm size is 1.5 ha (Djurfeldt & Wambugu, 2011). From the surrounding watershed covering 11000 ha, a regional topsoil dataset of 200 samples was available. All soil samples were analyzed by the Crop Nutrition Laboratory Services. Among the analyzed properties, we have in this study used soil clay content, pH_{H2O}, cation exchange capacity (CEC), total carbon content, and the contents of plant-available fractions (Mehlich-3) of phosphorous (P), potassium (K), magnesium (Mg), calcium (Ca), sulfur (S) and zinc (Zn). Further details on sampling and laboratory analyses were reported in e.g. Piikki et al. (2016). The 166 soil samples of Mukuyu were divided into validation and calibration samples sets: 56 validation samples (selected by a stratified random strategy) and three sets of calibration samples (30, 70 and 110 samples, respectively) randomly selected from the remaining samples. The ICRAF Soil-Plant Spectral Diagnostics Laboratory (Nairobi, Kenya) analyzed all soil samples from Mukuyu by near infrared (NIR; Bruker FT-NIR MPA) and mid-infrared (MIR; Bruker FT-MIR Tensor27/HTs XT) spectroscopy, and portable X-ray fluorescence (PXRF; Bruker Tracer Vi). To remove noise and avoid overlapping spectral regions, the 1000-2500 nm range was used for the NIR analysis and the 2500-16300 nm range (4000-614 cm^{-1}) for the MIR analysis. The NIR and MIR spectral data, expressed as absorbance, were transformed and smoothed by first-order, 21- and 7-point Savitzky-Golay derivative, respectively (Savitzky & Golay, 1964). For PXRF data, we used 26 elements that had registered concentrations above the level of detection in all except three samples. Calibration models for each soil property were constructed for each calibration set with partial least squares regression (PLSR; for NIR and MIR data) and multivariate regression splines (for PXRF data). For each of the validation samples, data of all the above soil properties were extracted from the online continental soil database iSDAsoil with 30-m spatial resolution (https://www.isda-africa.com/isdasoil/; Hengl et al., 2020). Ordinary block kriging was used for interpolation of regional and local soil data, and values were extracted for the validation sample locations. The iSDA data were downscaled with regression kriging combined with the local calibration datasets (following the method described in Nijbroek et al., 2018). The Nash-Sutcliffe modelling efficiency (E) was used to compare observed soil analyses values and predicted values with the different methods (1 = perfect match; 0 and below not better than or worse than using the average).

RESULTS AND DISCUSSION

Soil analyses from the validation farms in Mukuyu indicate that soils in general have a low pH and are relatively low in organic matter (low TC) and have low CEC (Table 1). Among the nutrients presented in Table 1, especially plant-available contents of P, Ca, S and Zn are low in the area. The 10^{th} percentile (*p*10) values show that most nutrients are very low in some parts. Statistics for these farms derived from regional maps covering the entire Murugusi watershed show that the median value is captured relatively well, but that the range of data and the values in specific plots are difficult to assess. The iSDA database performs even worse in terms of capturing the spread of data, but the median is fairly accurate for some properties (clay content, pH, CEC and plant-available contents of P, K and Ca are within about 20% of the observed median).

The modelling efficiencies for the tested methods can be examined in Table 2. Using already available map products (regional map and continental database, respectively) was clearly not successful. To have at least 30 local soil analyses was a major improvement. Just by interpolating these soil data gave models that were better than using the village average. Downscaling of the continental database by the local soil samples did improve the performance of that dataset, but it was not better than just interpolating the soil data. Models based on the spectral methods were in most cases the best approach. Even a limited number of local soil analyses was sufficient to construct calibration models for NIR, MIR and PXRF sensors useful for rapid and functioning assessment of clay content, TC content, pH, CEC, Ca and Mg. If only 30 calibration samples were available, especially the MIR models performed well. However, for P and Zn, (and to some extent for K and S) none of the tested methods were useful, not even when as many as 110 local observations were used for model calibration. Note, however, that we did not assess the performance of sensors calibrated on the national level, but earlier studies have shown that such models can be improved by spiking with local data (e.g. Wetterlind & Stenberg, 2010; Nocita et al., 2015). Another option not tested is to combine different sensors in the modelling. In previous research in an area in central Kenya, it was possible to generate well performing local models for all of these soil nutrients except for P when multiple sensors were combined (Piikki et al., 2016).

Digital soil mapping, where digital soil properties maps are created by empirical modelling using spatial covariates, has become increasingly used at all spatial scales. This is of course particularly interesting in areas where soil sampling and chemical analysis are sparse, since it may provide easily accessible information at a seemingly high detail. As has been shown here and in earlier research care must be taken before such data is applied for decision support at the farm or field level (Nijbroek et al., 2019; Söderström et al., 2017). The best approach to use such products is to combine the data with some local data to both assess the performance, and if needed use the local data for downscaling. Systems for this purpose are now available, e.g. GSDM online (https://gsdm.online; Nzuki, 2019).

To conclude, in order to produce detailed information of soil conditions for smallholder farms for more accurate management decision, this study conducted in western Kenya suggests that at least a small number of soil analyses from the village is important. A collaborative approach among farmers within an area or village can facilitate detailed and cost-effective soil properties mapping, where parts of samples are analyzed in the laboratory, and most samples are scanned by a combination of sensors.

ACKNOWLEDGEMENTS

Funding; VGR/SLU (contract: RUN 2018-00141), Formas/SIDA (contract: 220-1975-2013), Formas (contract: 220-2014-00646), BMZ (contract: 81206681), and GIZ (contract: 81193729). Thanks to the farmers in Mukuyu and the surrounding watershed for good collaboration. The soil samples were collected by J. Mukulama, S. Munialo, J. Mutua, S. Nyawade, R. Rogito, and G. Kavochi.

Table 1. Summary statistics (10th, 50th and 90th percentiles) of soil analyses from samples collected at 56 smallholder farms in Mukuyu village in western Kenya. Similar statistics are shown for the regional soil maps of the Murugusi watershed, as well as for the iSDA continental soil database.

	Village samples (n=56)			Regional map			Continental database		
	p10	*Median*	*p90*	*p10*	*Median*	*p90*	*p10*	*Median*	*p90*
Clay (%)	22	36	42	30	32	33	38	40	42
TC (%)	0.93	1.31	1.82	1.18	1.42	1.78	2.01	2.22	2.45
pH	5.0	5.4	6.0	5.2	5.7	6.2	5.7	5.7	5.8
CEC ($cmol_c$ kg^{-1})	5.7	8.5	13.3	7.8	10.6	15.2	9.0	10.0	11.0
P (ppm)	5.5	13.9	26.3	11.6	15.4	18.2	10.0	11.0	12.2
K (ppm)	55	130	218	87	125	220	122	134	148
Ca (ppm)	342	787	1310	652	991	1800	812	945	1097
Mg (ppm)	73	117	267	108	163	239	134	164	181
S (ppm)	4.5	10.8	15.5	5.6	7.0	10.9	4.5	5.0	5.0
Zn (ppm)	1.0	2.0	4.6	0.9	1.7	2.8	3.3	3.7	3.7

Table 2. Modelling efficiency (E) for predictions of soil properties of 56 smallholder farms in Mukuyu village using various methods. Cells are coloured according to performance: darkest is the best (>0.70) – to uncoloured (<0.10) indicating a model similar to the village average or worse.

	Clay (%)	TC (%)	pH	CEC ($cmol_c$ kg^{-1})	P (ppm)	K (ppm)	Ca (ppm)	Mg (ppm)	S (ppm)	Zn (ppm)
Regional map	0.11	-0.31	-0.15	-0.08	-0.04	0.18	-0.64	0.05	-0.73	-0.23
Continental map	-0.85	-5.54	-0.16	0.01	-0.19	-0.03	-0.07	0.15	-2.45	-0.32
30 soil analyses										
Interpolation	0.29	0.36	0.09	0.26	-0.21	-0.03	0.33	0.46	0.35	-0.06
Downscaling	0.24	0.15	0.05	0.26	-0.25	-0.02	0.20	0.46	0.20	-0.11
NIR	0.42	0.08	0.31	0.41	-0.07	0.20	0.43	0.42	0.11	0.03
MIR	0.79	0.76	0.52	0.50	-0.21	0.11	0.46	0.67	0.00	0.03
PXRF	0.80	0.14	-0.52	0.58	-0.06	-0.94	0.37	0.62	-0.09	0.14
70 soil analyses										
Interpolation	0.12	0.30	0.05	0.22	-0.34	0.12	0.17	0.23	0.28	-0.58
Downscaling	0.09	0.14	0.00	0.15	-0.33	0.12	-0.26	0.24	0.21	-0.71
NIR	0.63	0.61	0.48	0.70	-0.07	0.30	0.71	0.66	0.18	-0.02
MIR	0.83	0.85	0.79	0.83	-0.23	0.12	0.94	0.83	0.08	-0.23
PXRF	0.77	0.48	0.40	0.78	-0.17	-0.25	0.74	0.71	-0.29	0.04
110 soil analyses										
Interpolation	0.29	0.28	0.03	0.27	-0.05	0.14	0.20	0.41	0.27	-0.44
Downscaling	0.21	0.21	0.04	0.26	-0.05	0.14	0.12	0.42	0.25	-0.49
NIR	0.62	0.41	0.71	0.78	-0.01	0.43	0.79	0.74	0.17	-0.48
MIR	0.84	0.86	0.67	0.81	-0.11	-2.95	0.80	0.88	0.35	-11.20
PXRF	0.84	0.56	0.44	0.62	-0.63	0.14	0.65	0.83	0.09	0.13

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