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Assessment of soil health indicators for sustainable production of maize in smallholder farming systems in the highlands of Cameroon

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ABSTRACT

Agricultural intensification has been recognized as one of the solutions to increase food production to feed the ever-increasing population in sub-Saharan Africa. This can partly be achieved if quantitative and up-to-date information on soil health indicators are not available. This study used the land health surveillance framework, which combines ground-sampling schemes based on sentinel site and infrared spectroscopy to select a minimum dataset of soil health indicators to identify key land constraints for maize production and target potential interventions. We found high variability in soil properties in the study area which was mainly due to inherent soil conditions and land management practices. The most variable soil properties ($CV > 0.38$) were nitrogen (N), electric conductivity (ECd), exchangeable bases (ExBas), boron (B), calcium (Ca), potassium (K), magnesium (Mg), manganese (Mn) and phosphorus (P). Moderate variability ($0.2 < CV < 0.38$) was observed for carbon (C), silt and sand, while properties with least variability ($CV < 0.2$) were pH and aluminium (Al). The effects of land-use and soil depth were significant ($p < 0.05$) for most of the soil properties. Principal component analysis (PCA) identified soil nutrient availability, metal concentration and texture as the three main factors that explain most of the variability observed. Significant interactions were observed between soil properties confirming the need for a minimum dataset of indicators. ExBas, B, pH, Mn, ECd, P and clay content formed the minimum dataset of soil health indicators for the study area. The results also showed that the soils of the study site are marginally suitable for the production of maize (*Zea mays* L.). Low limitations with respect to exchangeable bases (Ca, Mg, K and Na) and severe limitations with respect to B (<0.15 mg kg^{-1}), pH (<6.20), P (<6.5 mg kg^{-1} soil) and clay content ($>63\%$) were detected. However, potential for improvement exists through integrated soil management practices that include the use of organic and inorganic fertilizers, minimum soil tillage, and inclusion of legumes in crop rotations that could improve soil physical and chemical properties.

1. Introduction

Increasing agricultural production to feed the ever-increasing population is most challenging in Sub-Saharan Africa (SSA) because of soil degradation, most often linked to unsustainable agricultural practices (Verhulst et al., 2011; Turmel et al., 2015). The discrepancy between crop yield and population growth raises doubt about how millions of smallholder farmers will feed themselves, and how the current production system can generate enough to feed the non-agricultural population. This is particularly the case as the amount of additional arable land that can be brought into cultivation continues to decline (Ricker-Gilbert et al., 2014). Intensification to increase agricultural productivity is seen as one of the solutions and entails enhancing the capacity of soil to augment yields per hectare, increase cropping intensity per unit of land, and change land use from low value crops to those that receive higher market prices. This cannot be achieved if quantitative and up-to-date information are not available to assess changes in soil quality (Pattison et al., 2008), and the effects of these changes on soil capacity to support plant growth and provide ecosystem services (Firbank et al., 2013; Smith et al., 2013). In an agricultural context, high soil quality means a highly productive soil with low levels of degradation and high capacity to withstand extreme weather events and reduce nutrient loss (Karlen et al., 2013).

Changes in soil quality can be assessed by measuring appropriate indicators and comparing them with desired values (critical limits or threshold level), at different time intervals, for a specific use in a

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selected agro-ecosystem (Arshad and Martin, 2002). Soil health indicators refer to measurable soil attributes that influence the capacity of soil to deliver ecosystem services. Soil attributes that are most sensitive to management are most desirable as indicators (Arshad and Martin, 2002). They are responsive to agricultural management, reflect changes in soil functional properties (Allen et al., 2011), and are being increasingly used to assess the current condition or trend of soil health (Congreves et al., 2015).

Given the complex nature of soil systems, the multifunctional services that they are called upon to provide, and their spatial variability, measurement of soil health indicators across landscapes, soil types and agro-ecological zones presents major scientific and policy challenges. There is debate about appropriate methods for soil health assessment, as no single indicator will encompass all aspects of soil health, nor would it be feasible (or necessary) to measure all possible indicators.

Soil health indicators have to be sensitive to changes caused by land management practices, cover a wide range of environments and integrate physical, chemical and biological properties (Doran et al., 2002). Each selected indicator must also be easily and reproducibly measurable (Yemefack et al., 2006). While assessing soil health indicators, there is always a tendency to measure all properties, which is time consuming, laborious and expensive particularly in sub-Sahara Africa where resources are limited. Instead, there should be a minimum dataset (MDS) of soil health indicators that is responsible for at least 80% of the variation of site's soil properties, relate to soil functions and facilitate improvements in soil health management (Qi et al., 2009; Liu et al., 2014). Efforts are under-way worldwide to assess soil health and previous studies have proposed indicators that could be used to assess soil quality (Govaerts et al., 2006; Yao et al., 2013), but very limited chemical properties have been used due to high cost of soil sample analysis, as well as the absence of reliable and accurate methods of analysis. This deficiency is not only in sustainable land management, but also in many monitoring initiatives in agriculture, environment and livelihoods (Shepherd et al., 2015).

The land health surveillance concept is able to provide more recent and up-to-date information useful for the assessment of soil health indicators through a participatory framework that combines ground-sampling schemes based on sentinel sites, and infrared spectroscopy (Vågen et al., 2006). The scientific rigor of the concept gives it the potential to provide appropriate guidelines and directives for site-specific interventions, as well as consolidating scientific principles and approaches for informed policy and practices (Shepherd et al., 2015).

The objectives of this study were therefore to assess the current level of soil chemical properties, identify the most sensitive and reliable soil health indicators as well as key constraints of land to maize production, and recommend potential interventions for the highlands of Cameroon. Although a holistic dataset of soil health indicators should include physical, chemical and biological properties, this study focused on chemical properties because they are the most important factors that have been reported to affect crop growth and are easily affected by land management (Mairura et al., 2007).

2. Materials and method

2.1. Study site

The study was carried out in a “sentinel site” located in the Western Highlands of Cameroon (Fig. 1). The site is largely an agrarian on which featured the major characteristics of the highlands and is dominated by subsistence agricultural systems where smallholder farmers grow a range of crops. Rainfall varies from 1500 to 1800 mm per year, and exhibits a rainy season from March to October with peaks in August, and a dry season between November and February. The topography is undulating with altitude ranging between 1200 and 1800 masl, and the vegetation is predominantly savannah with patches of gallery and montane forests. The mean daily minimum and maximum temperatures are 18 and 28 °C, respectively. Most of the soils in the area are Ferralsols, and are known to be generally acidic. Due to anthropogenic activities, the resulting spatial patterns of the study site are landscape mosaic dominated by agricultural activities (88%), and the four predominant land-use systems are cropland, fallow, forest, grassland and grazing.

2.2. Soil sampling framework

The study used the land degradation surveillance framework (LDSF) to measure and monitor land health indicators following the procedure described by Vagen et al. (2012) and Shepherd et al. (2015). The LDSF is a spatially stratified, random sampling design framework built around a hierarchical field survey (Fig. 2) and sampling protocol using the concept of sentinel site. A sentinel site is a demarcated landscape (10 × 10 km) that is representative of a larger area, subdivided into 16 clusters (Fig. 3a) of 10 plots (1000 m^2) randomly allocated. Within each of these plots, four sub plots (100 m^2) were established, one at the centre of the plot and the three others surrounding the centre plot, disposed at 120° (Fig. 3b). Soil samples were collected for each of the subplots at two depths – topsoil (0–20 cm) and subsoil (20–50 cm) using an auger, and pooled together for each depth to obtain two composite samples for the plot. The total number of samples was 160 for the topsoil and 157 for the subsoil given a total of 317 samples (three subsoil samples were not obtained because the soil was too shallow).

2.3. Soil samples laboratory and spectral analysis

Soil samples ($n = 317$) were air-dried, crushed using a wooden rolling pin and passed through a 2-mm sieve. They were then finely ground to powder and loaded into micro-cups for Mid Infrared (MIR) analysis, and scanned using a Bruker Alpha Drift FT MIR Spectrometer. Reference samples ($n = 32$) collected from the first plots of each of the 16 clusters ($n = 16$ for topsoil and 16 for subsoil) were analyzed for fifteen chemical properties using the conventional wet chemistry methods. The properties include nitrogen (N), soil organic carbon (SOC), clay, silt, sand, electric conductivity (ECd), exchangeable bases (ExBas), aluminium (Al), boron (B), calcium (Ca), potassium (K), magnesium (Mg), manganese (Mn), phosphorus (P) and pH. The analyses were conducted at the Crop Nutrition (Cropnut) Laboratory in Nairobi.

A soil MIR spectral library consisting of 317 samples was used, which included 32 reference soil samples that had analytical data on soil properties obtained using the soil analytical methods described above. The MIR spectra were preprocessed using Savitzky-Golay first derivative with a smoothing interval of 21 points (Terhoeven-Urselmans et al., 2010). Using Radom Forest (RF) regression method, soil properties data from the conventional methods for the reference samples were used to train the preprocessed spectra. Then the fitted regression models were then used to predict soil values for the rest of the samples based including the calibration samples (Hengl et al., 2015). The predicted soil properties were then used for landscape-scale assessment of spatial variation.

2.4. Statistical analysis

Descriptive statistics (mean, and coefficient of variation) were used to describe the soil properties. Significant differences between land-use types were tested by analysis of variance (ANOVA), while Pearson correlation coefficients were used to assess the relationships among pairs of properties. Principal component analysis (PCA) was used to identify properties that explain most of the variability and to select the most appropriate indicators that influence soil quality. ANOVA was conducted using SAS (MIXED procedure, restricted maximum likelihood estimation method) with three sources of variation – land use, soil depth, and interaction between land use and depth (all fixed