#7563 MAPPING AND ASSESSING FERTILITY OF AFRICAN SOILS USING HIGH-RESOLUTION REMOTE SENSING AND MACHINE LEARNING APPROACHES

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ABSTRACT

Africa is far from exploiting its true agricultural potential. United Nations Food and Agriculture Organization (FAO) indicates that the continent has 60% of non-cultivated lands worldwide. While it is well established that soil fertility is one of the major limiting factors, only limited information is available on soil nutrient contents and nutrient availability in the African soils. Soil fertility of agricultural fields is related to many physical and chemical properties, such as the clay, sand, and organic matter (OM) contents; cation exchange capacity (CEC); pH; and available nutrients such as Nitrogen (N), Phosphorus (P), and Potassium (K). In agriculture, characterising soil fertility is a key prerequisite to improve farms profitability through best qualitative and quantitative crops harvesting. In this context, several studies have evaluated the diagnosis of fertility attributes utilizing sampling grids with different spacings. Due to many challenges associated with the spatiotemporal characterization of soil attributes and the high cost of sampling grids methods, remote sensing technologies have been introduced as an efficient alternative tool for the monitoring of agricultural soils. This alternative technology can minimize the effort and time related to sample collection and the cost of laboratory analysis. In addition, these technologies are widely accepted as a cost-effective and non-destructive sensing tool for characterising soil attributes (i.e., N, P, K, OM). Another important feature of these remote sensing technologies is the possibility of registering spectral data on images using remote sensing platforms such as Unmanned Aerial Vehicle (UAV) equipped with multi-sensors (i.e., multispectral, hyperspectral, thermal). In this study, soil fertility ground measurements and UAV imagery will be collected over representative regions across Morocco where different varieties of crops are planted. The UAV spectral data collected using hyperspectral sensors, and soil fertility parameters derived from laboratory analysis will be used to calibrate machine learning models. We anticipate that we can achieve much more accurate relationships among observed reflectance and soil fertility parameters, thanks to the large range of reflectance of the hyperspectral images (Visible to Short Wave Infrared) and the capacity of machine learning techniques to model non-linear correlations. Soil fertility is a key piece of information in agricultural lands asset management. Adding to that the capacity of the mapping solution to be developed to map soil fertility properties from local to regional scales, a broad range of stakeholders, with varying and often unexpected levels of potential interest in the results of the current project. Thus, this is expected to create a novel agricultural service for the African farming community contributing to unlock the potential of African agricultural lands.

Keywords: African farming community, digital soil mapping, hyperspectral remote sensing, infrared, machine learning, precision agriculture, short-wave infrared, soil fertility, UAV, visible

INTRODUCTION

Information about soil nutrient contents is key for explaining measured crop responses to soil fertility management practices and for updating and upscaling of soil fertility management recommendations, especially in a continent like Africa, where according to Lebtahi (2017), 60% of the world's potential for land cultivation. Yet, most of this land is in poor condition and unable to satisfy the needs of agricultural production. As the population increases so too will the demand for soil nutrient rich land to meet the needs of food production. This growing need for land restoration is also paralleled by a need for agricultural and ecological data in Africa.

For the management of soil fertility of agricultural fields, physical and chemical properties, such as the clay, sand, and organic matter (OM) content; cation exchange capacity (CEC); pH; and available nutrients, should be known at proper spatial resolution. The spatiotemporal variability of these attributes is dynamic, occurring with different amplitudes of variation and spatial patterns. These variations occur according to the classical factors of soil formation (McBratney et al., 2003) and owing to minor alterations caused by a combination of local factors such as relief and management (Viscarra Rossel & Lobsey, 2016).

Digital Soil Mapping helps meet these needs with a gridded Soil Information System (SIS). Besides, by integrating remote sensing data, the SIS can be updated so frequently.

LITERATURE SURVEY

Several local studies have characterized the spatial dependence of physical and chemical attributes via geostatistical analysis (Nanni et al., 2011; Montanari et al., 2012). Results show that sample grids greater than 100 × 100 m (1 sample/ha) are not efficient for characterizing the variability of most soil fertility attributes (Wetterlind et al., 2010).

Generally, factors related to the soil class and its formation (e.g., texture) require a lower sampling density. However, for pH and available P, K, Ca, Mg, and other chemical attributes, a higher sample density is required to characterize the variability (Wetterlind et al., 2010). Schirrmann and Domsch (2011) did not achieve good spatial models for the available K. According to the authors, the microscale variation of available K, with a spatial dependence range less than 25 m, limited the characterization of this nutrient.

Owing to the challenges associated with the spatiotemporal characterization of soil attributes, sensing technologies have been introduced as an efficient tool for the monitoring of agricultural soils. This alternative would minimize the effort related to sample collection and cost of traditional laboratory analyses.

Soil sensors can be classified based on their design concept as follows: (i) optical/radiometric, (ii) electrical/electromagnetic, (iii) electrochemical, and (iv) mechanical (Adamchuk et al., 2004; Kuang et al., 2012). These allow the measurement of the soil capacity to (i) absorb, reflect, and/or emit electromagnetic energy; (ii) accumulate or conduct electrical charge; (iii) release ions; and (iv) resist mechanical distortions (Viscarra Rossel & Lobsey, 2016), respectively.

Diffuse Reflectance Spectroscopy (DRS) is widely accepted tool for characterising soil features because of low operating cost, non-destructive with little or no sample preparation (Stenberg et al., 2010). Another important feature of DRS is the possibility of registering spectral data on points or images using different platforms, e.g., using sensors directly on the field, using benchtop sensors in the laboratory with sampled material, or using Remote Sensing Platforms with multi or hyperspectral cameras. DRS involves remote, proximal (in-field), or laboratory measurements and is a promising technique for digital soil mapping (McBratney et al., 2003) and Precision Agriculture (Adamchuk et al., 2004).

DRS has been used in Soil Science since the beginning of 1950. However, only in the last three decades has it gained importance with the development of more practical applications (Viscarra Rossel et al., 2011).

Several scientific studies have successfully estimated soil physical and chemical properties using DRS in the spectral regions of the visible (vis; 400–700 nm) and Near-Shortwave Infrared (NSIR; 700–2500 nm) (Viscarra Rossel et al., 2006). Moreover, DRS has been successfully applied directly in the field using sensors embedded in mobile platforms (Mouazen et al., 2007; Christy, 2008).

Worldwide, many attempts have been made to predict the physical and chemical attributes of soil using vis-NSIR spectra. In general, calibrations of organic and total C, total N, and clay content are more likely to succeed because clay minerals and OM are the spectrally active soil constituents, with well-known spectral features in the vis-NSIR region (Ben-Dor, 2002).

Other soil attributes (e.g., CEC, pH, and V %) do not present absorption features in this spectral region and, hence, their correlations with vis-NSIR spectra are generally weak (Stenberg et al., 2010). However, there may be exceptions, as observed by Demattê et al. (2017) for available Mg and K in Brazilian tropical soils and by Mouazen and Kuang (2016) for available P in soils of temperate regions.

These occasionally successful calibrations can be attributed to the covariance of soil attributes with some spectrally active constituents (Kuang et al., 2012). This behavior has generally been observed at the local level. In agricultural soils, this explanation is reasonable because nutrients are depleted with plant production, which is related to productivity. Depending on the degree to which the productivity is regulated by the clay and soil OM, the available nutrients will be associated with these variables and, consequently, with the vis-NSIR spectrum (Stenberg et al., 2010; Iticha & Takele, 2019).

Regarding the African context, The Africa Soil Information Services project has developed a gridded Soil Information System of Africa at 250 m resolution (pixel = 6.25 ha) showing the spatial distribution of primary soil properties of relatively stable nature, such as depth to bedrock, soil particle size fractions (texture), pH, contents of coarse fragments, organic carbon and exchangeable cations such as Ca, Mg, Na, K and Al and the associated cation exchange capacity (Hengl et al., 2017).

These maps were derived from a compilation of soil profile data collected from current and previous soil surveys. As a spatial prediction framework, they used an ensemble of random forest and gradient boosting machine-learning techniques. Furthermore, as inputs to train the model, they used the most complete compilation of soil samples obtainable and a diversity of soil covariates (primarily based on remote sensing data) (Hengl et al., 2017).

DISCUSSION OF RESULTS FROM LITERATURE

From the previous literature survey, the following points are worth highlighting:

- According to this literature survey, the only study that was done in the African context (Hengl et al., 2017) was limited to some sub-Saharan African countries. Thus, it does not include countries like Morocco. Furthermore, the use of Remote Sensing data was limited to derive some covariates like Digital Elevation Model (DEM) and time-series vegetation indices. Thus, the use of high-resolution hyperspectral images is not yet explored.
- The soil fertility management requires high sampling density as reported by (Wetterlind et al., 2010). Thus, the use of geostatistical methods is not practical especially in African countries where farmers that choose to do chemical analysis of their farmland's soil generally limited the number of soil samples to 1 sample per farmland (independently of the farmland area and soil characteristics variability). This results in a broader grid density than what is recommended. Having said that, the development of remote sensing-based mapping techniques is of major importance to overcome the cost and the effort related to soil sampling.
- As stated by Stenberg et al., 2010; Kuang et al., 2012; Iticha & Takele, 2019, successful calibrations using vis-NSIR spectrum can be attributed to the covariance of soil attributes with some spectrally active constituents (eg. clay and soil OM), which depends on the degree to which the productivity is regulated by the clay and soil OM. This common observation between those studies stressed the local character of calibrating successful spectral-based models.

The use of high resolution hyperspectral (vis-NSIR) imaging in African countries, is expected is to help developing new mapping techniques for soil fertility parameters estimation and, thus, better agricultural soils management. High resolution (equivalent to a very high-density soil sampling grid) and high accuracy soil fertility prediction data-driven based-models is expected to be achieved. Hence, the interest in carrying out this study.

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