#7639 CLOSING THE YIELD GAP IN AFRICA THROUGH SOIL ATTRIBUTE MANAGEMENT USING REMOTE SENSING AND PRECISION AGRICULTURE APPROACHES AT THE FIELD SCALE

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ABSTRACT

Intensive agriculture is a common practice to meet the high demand for food, leading to optimal use of fertilizers, water and agrochemicals. Therefore, it is necessary to identify and understand the spatio-temporal distribution of soil attributes in order to optimize the use of agricultural inputs (e.g. fertilizer, seed rate) at a specific site. For these purposes, the quantitative assessment and mapping of important soil attributes such as soil texture, soil organic carbon (SOC), soil nitrogen (N), and soil moisture content (CM) on the ground are essential. Since field measurements by conventional techniques of this soil attributes (i.e., N, , P, K, SOC) are difficult to perform and time-consuming, there is a need for an accurate and rapid approach for the measurement of soil attribute levels at the farm scale. Remote sensing sensors placed on an Unmanned Aerial Vehicle (UAV) is a rapid, cost-effective and a method that meet the requirement of spatial, spectral, and temporal resolution to quantify and monitor soil attributes (i.e., N, P, K, SOC) yield-related over agricultural land. In this study, soil attributes ground measurements and UAV imagery will be collected at agricultural fields from Morocco. The UAV spectral data will be collected using multispectral, hyperspectral, and thermal sensors and datasets generated by this project will support algorithm development. In terms of data statistical analysis, a number of typical machine and deep models will be explored to perform remote sensing image classification, including: Partial Least Squares, Random Forest, Support Vector Machine. The results of this study are expected to support the use of remote sensing derived soil attributes maps by farmers and managers to make precision farming decisions about how to properly manage nutrients and water in the soil for optimal yield.

Keywords: remote sensing, machine learning soil fertility, precision agriculture, yield gap, UAVs

INTRODUCTION

In Africa, which has the most population growth in the world, the agricultural system is characterized by the predominance of smallholder farmers. In most countries, smallholder agricultural systems are inefficient, and yields fall short of their potential; this phenomenon is known as yield gaps. Yield gap is defined as the difference between potential yield and actual yield (Lobell et al., 2009) and is an inevitable method to improve yields while decreasing the environmental impacts of agricultural systems. The variability of yields is strongly controlled by fertilizer use, irrigation management, and climate impact. Consequently, quantitative assessment and mapping of important soil attributes such as soil nitrogen (N), soil moisture content (MC), Phosphorus (P), Potassium (K), Soil organic Carbon (SOC), and soil texture (i.e., clay, sand, silt contents) on the ground are essential to tackle the yield gap closing.

The use of traditional soil laboratory analysis techniques is known to be costly and time consuming and requires efforts. To overcome these constraints, rapid, accurate and inexpensive methods of soil attributes measurement and monitoring are needed.

Laboratory Visible (VIS), infrared (IR), and Shortwave near infrared (SWIR) spectroscopy are alternative methods to laboratory analysis of soil chemical parameters, including SOC (Jiang and all, 2016), N, P, K, pH (Viscarra Rossel et al., 2006) and some physical parameters such as soil structure, density apparent and texture (Virgawati et al., 2018). Although laboratory spectroscopy has resulted in robust and accurate estimates of soil properties, this technique only provides an estimate at the location of the sampling point and geostatistical techniques should be used to derive continuous spatial information at large scale The use of hyperspectral remote sensing sensors on board drone-based platforms (also known as unmanned aerial vehicles, UAVs) has introduced new opportunities for providing spatially explicit spectral information detailed over multiple soil properties, including SOC content (Laamrani et al., 2019). This study is to develop and test methods to quantitatively generate accurate soil cover attributes needed for spatialized yield gap analysis, using laboratory spectroscopy and airborne hyperspectral data.

MATERIALS AND METHODS

Study Area

The study will take place in the region of Sidi Rahal in Morocco. The region is characterized by a semi-arid Mediterranean climate, with an average annual precipitation of around 250 mm and an evaporative demand of around 1600 mm per year according to the FAO method (Jarlan et al., 2015). The land is flat with an elevation of 550 m above sea level, and the soil is characterized by a fine texture with 47% clay, 33% silt and 18.5% sand. Agricultural fields, mainly irrigated and rainfed wheat crops, are dominant (Ezzahar et al., 2009).

Soil Sample Collection and Soil Attribute Measurements

For this study we have selected six soil attributes relevant for soil characterization: Total N, SOM, texture, P, and K. The total N will be measured using the kjeldahl method. SOM was determined using the Walkley-Black method (Walkley & Black, 1934) and used to determine SOC content using formulas in the literature. Soil texture (i.e., particle size distribution) will be obtained by the pipette method (ISO 11277:2009). Available P will be extracted with a combined solution of 0.1 M HCl and 0.03 M NH4F. Available K will be determined using Ammonium acetate NH_4OAc (1 M pH=7)

Spectral Measurements and Analysis

In this study we will collect spectral data from soil samples in the field and Laboratory using a FieldSpec 3 spectroradiometer sensor (Analytical Spectral Devices Inc.). FieldSpec 3 has three detectors and covers a wider spectral range (350–2500 nm) with a band resolution (width) of 3 nm wide in VNIR and 10 nm in SWIR.

Field reflectance measurements will be collected an airborne unmanned aerial vehicle (UAV) with sensors developed for deployment on UAV platforms. The images will be captured in sunny weather with clear skies over the soil samples and an average spectrum of each hyperspectral image will be calculated. The UAV-derived data will be collected on the same day as ground samples observations for optimal correspondence.

Statistical Analysis and Modeling

Identification of soil nutrients analysis data by several statistical parameters such as mean, maximum, minimum and median used to describe the central tendency and distribution of the values of soil parameters. The standard deviation, range and variance used to measure the dispersion between soil parameters. The skewness and kurtosis to measure the asymmetry of soil parameters. The use of a set of different models to quantify the relationtionship between soil attributes and the corresponding spectral reflectance measured. This ensemble will consist of different methods such as multivariate regression techniques, random forest regression (Breiman, 2001), support vector machine regression (Karatzoglou et al., 2004), and partial least squares (Mevik et al., 2015). The models will be evaluated by the following indices: coefficient of determination (R^2) and root mean square error (RMSE)

EXPECTED RESULTS

The results of this study are expected to demonstrate the ability of different precision agriculture and modeling approaches to analyses and predict soil attributes in Morocco using UAV spectral data. The study will also show the potential of remotely sensed data to build accurate maps of soil attributes, making it easier for farm managers to make decisions about how to properly manage nutrients and water in the soil and will ultimately lead to reducing the yield gap.

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