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Estimating soil total nitrogen in smallholder farm settings using remote sensing spectral indices and regression kriging

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ABSTRACT

Mapping soil nutrients can help smallholder farmers identify soil nutrient status and implement site-specific soil management schemes. In the past, Digital Soil Mapping has seldom been utilized to guide soil nutrient management in smallholder farm settings in South India. The objective of this research was to analyze the spatial resolution effects of different remote sensing images on soil total nitrogen (TN) prediction models in two smallholder villages, Kothapally and Masuti in South India. Regression kriging (RK) was used to characterize the spatial pattern of TN in the topsoil (0–15 cm) by incorporating spectral indices with different spatial resolutions. The results suggested that soil moisture, vegetation, and soil crusts can contribute to the conservation of soil TN in both study areas. Soil prediction models with different spatial resolutions showed a similar spatial pattern of soil TN. The results also demonstrated that the effect of very fine spatial remote sensing spectral data inputs does not always lead to an increase of soil prediction model performance. A RapidEye-based (5 m) soil TN prediction model had lower prediction accuracy than a Landsat 8-based (30 m) soil TN prediction model in Masuti. WorldView-2/GeoEye-1/Pleiades-1A-based (2 m) soil TN prediction models had the highest prediction accuracy in both study areas. The spectral indices based on new bands of WorldView-2 such as coastal, yellow, red edge, and new near infrared bands had relatively strong correlations with soil TN. The utilization of Very High Spatial resolution images such as WorldView-2 in Digital Soil Mapping could improve soil model performance and spatial characterization. Remote sensing-based soil prediction models have high potential to be widely applied in smallholder farm settings.

1. Introduction

Low and erratic precipitation, drought stress, high temperatures, low biomass, and low soil productivity have major impacts on crop yields in arid and semi-arid farmland in South India (Srinivasarao et al., 2013). Soil nutrient storage is essential and important in semi-arid tropical soils, especially those that are used to maintain food security and soil security in smallholder farm settings. Unlike research focusing on soil sampling and traditional soil laboratory analysis (Ouyang et al., 2013; Venkanna et al., 2014), Digital Soil Mapping (DSM) utilizes categorical and continuous environmental variables to predict soil properties on multiple scales (McBratney et al., 2003; Xu et al., 2017) and is more practical, economical, and suitable for sustainable soil management. However, the application of Digital Soil Mapping (DSM) in smallholder farm settings worldwide is only in its beginning stages due to lack of financial and technical support and historical datasets.

Remote sensing images can provide soil-landscape information such as soil moisture (Bertoldi et al., 2014), vegetation indices (Kross et al., 2015), and land surface temperature (Weng et al., 2014), and are widely utilized in DSM research (Gray et al., 2016; Nigel and Rughooputh, 2010). The past few decades have seen the emergence of various new remote sensing products, which can provide soil-landscape

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information at various scales. Remote sensing images such as Landsat 8 images (30 m) are easily obtained throughout the world. Commercial remote sensing satellites such as WorldView-2 (2 m) and SPOT 5 (10 m) also provide detailed landscape information at relatively fine spatial resolution. As a result, there is a trade-off between choosing fine spatial resolution and coarse spatial resolution remote sensing imagery in DSM.

Some research has indicated advantages to the use of fine spatial resolution images for soil prediction in terms of error assessment and accuracy (Sumfleth and Duttmann, 2008; Vaudour et al., 2013). Other research demonstrated that the highest spatial resolution environmental variables may not always produce the most accurate soil prediction. According to Schmid et al. (2008), ASTER images (30 m) have longer spectral domain and more bands than IKONOS images (4 m). They also have higher prediction capability than IKONOS images in predicting soil classes. Kim and Zheng (2011) demonstrated that fine scale topographic information is not always optimal for understanding soil spatial variability. However, there has been little research analyzing the effects of remote sensing spectral indices with fine to medium spatial resolution (2 m to 30 m) on soil prediction models in regions such as smallholder farm settings.

Unlike ordinary kriging, regression kriging includes deterministic and stochastic components (Hengl et al., 2007). The deterministic component is often a multi-linear regression model between the target soil property and auxiliary environmental variables such as vegetation indices and land use types (Samuel-Rosa et al., 2015). The stochastic component is a spatially correlated random field of residuals from the deterministic component. This spatially correlated random component is usually fitted by variogram and interpolated by ordinary regression (Mora-Vallejo et al., 2008). Regression kriging has been widely applied in the DSM domain (Kuriakose et al., 2009; Mishra et al., 2012; Sun et al., 2012), and has attained better prediction results compared with ordinary kriging (Hengl et al., 2007; Mirzaee et al., 2016). The objectives of this research were to: 1) characterize the spatial pattern of soil Total Nitrogen (TN) in two smallholder villages, Kothapally and Masuti, South India and 2) test and evaluate the spatial resolution effects of spectral indices from Landsat 8 (30 m), RapidEye (5 m), and WorldView-2/GeoEye-1/Pleiades-1A (2 m) on soil TN prediction models in both study areas.

2. Material and methods

2.1. Description of the study areas

Kothapally is a smallholder village located in Ranga Reddy District, Telangana State, India (Fig. 1). It experiences a hot and dry semi-arid climate with an annual rainfall of 802 mm (Sreedevi et al., 2004). Cotton (*Gossypium hirsutum*) and rice (*Oryza sativa*) are the major crops planted in the rainy season. Sorghum (*Sorghum bicolar*) is the predominant crop type in the dry season. The monsoon season is from June to September with the precipitation averaging 755 mm. Vertisols are the major soil type in Kothapally. A detailed description of Kothapally is given by Xu et al. (2017).

Masuti is another smallholder village located in Basavana Bagevadi Tehsil, Bijapur District, Karnataka State, located in South India (Fig. 1). It is 513 km from the state capital, Bangalore. It also experiences a semi-arid climate with temperature variations between 20 °C and 42 °C. The annual rainfall ranges from 569 to 595 mm. The soils in this area vary between dark greyish brown and dark brown to dark reddish brown. Soil texture varies from loam to clay according to investigation by the International Crops Research Institute for the Semi-Arid Tropics (ICRISAT). Sorghum (*Sorghum bicolar*), tomato (*Lycopersicon esculentum* var. *esculentum*), and onion (*Allium cepa*) are the three major crops in the dry season (Table 1). Cotton (*Gossypium hirsutum*), rice (*Oryza sativa*), and maize (*Zea mays*) are the three major crops in the rainy season (Table 1).

2.2. Soil sampling and laboratory analysis

Soil samples were divided into four classes (green, dark, light, and intermediate areas) based on unsupervised classification application in the ERDAS 2011 software (Earth Resource Data Analysis System Inc., Atlanta, GA). Based on the four classes of soil, a stratified random sampling method was performed in ArcMap 10 (Environmental Systems Resource Institute, ArcMap 10.0 ESRI, Redlands, California) using the "SamplingTool_10" (Buja and Menza, 2013) add-in. In total, 255 soil samples at 0–15 cm were collected in Kothapally in May 2012, and 259 soil samples at 0–15 cm were collected in Masuti from February to March 2013 by the ICRISAT and the University of Florida (Fig. 1). Geographic attributes of each soil sample point such as x and y coordinates, were obtained from a Differential Global Positioning System (DGPS) with sub-meter accuracy (Trimble Navigation Ltd., Sunnyvale, California, USA). GPS post-correction was performed by Aimil Ltd. (www.aimil.com) in Hyderabad, India. Site-specific descriptions, including soil types, crop types, soil color and tillage methods, were recorded at each sampling point. After air-drying for one week, all the soil samples in both study areas were sieved through a 2-mm sieve, then analyzed for soil TN based on a concentration basis (mg kg^{-1}) (Krom, 1980) in ICRISAT.

2.3. Remote sensing data collection and processing

Cloud-free satellite remote sensing imagery, including one WorldView-2 image (2 m), one GeoEye-1 image (2 m), two RapidEye images (5 m), and two Landsat 8 images (30 m) in Kothapally, and one WorldView-2 image, one Pleiades-1A image (2 m), two RapidEye images, and two Landsat 8 images in Masuti, were acquired to extract environmental variables in soil TN prediction models (Table 2). Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) Global Digital Elevation Model (DEM) data were obtained in order to extract topographic attributes in both study areas. Table 2 lists all the satellite remote sensing images in the two study areas.

The original pixel values of raw remote sensing images are Digital Numbers (DNs). Radiometric calibration was applied to transform the DNs to top-of-atmosphere spectral radiance using different algorithms depending on the remote sensing products. Atmospheric correction was utilized to convert all the spectral radiance images into surface reflectance images using the Fast Line-of-Site Atmospheric Analysis of Spectral Hypercubes (FLAASH) tool in the ENVI 5.0 software (Exelis Visual Information Solutions, Boulder, Colorado).

2.4. Spectral indices extraction

Multiple spectral indices were extracted from Landsat 8, RapidEye, WorldView-2, GeoEye-1 and Pleiades-1A in the two study areas. Topographic attributes such as elevation (m), slope (degree), aspect (degree), flow direction, and flow accumulation were extracted from the ASTER Global DEM. Table 3 lists all the environmental variables including spectral indices, topographic attributes and geographic attributes in this research. Selected environmental variables were incorporated into the soil TN prediction models.

2.5. Regression kriging

The ordinary kriging method predicts the soil property by calculating the weighted average of the observations (Webster and Oliver, 2001):

$$\hat{z}(s_0) = \sum_{i=1}^{n} \lambda_i * z(s_i) \tag{1}$$

where $\hat{z}(s_0)$ is the predicted value of the target soil properties at an unvisited location s_0, given its coordinates, the sample $z(s_0)$, $z(s_0)$, …, z