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Digital soil mapping at local scale using a multi-depth Vis–NIR spectral library and terrain attributes

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ABSTRACT

Conventional soil mapping is costly and time consuming. Therefore, the development of quick, cheap, but accurate methods is required. Several studies highlight the importance of developing regional soil spectral libraries for digital soil mapping, but few studies report on the use of these libraries to aid digital mapping of soil types. This study aims to produce a digital soil map using as training set Visible and Near Infra-Red (Vis–NIR) spectra from local soil samples, a regional spectral library and terrain attributes. The soils were sampled in 162 locations on a 270-ha farm in the municipality of Piracicaba, São Paulo, Brazil. Spectra from topsoil and subsoil were measured in laboratory (400–2500 nm) and arranged as multi-depth spectra. Information was summarized by principal component analysis. Regression tree models were calibrated to predict principal components (PC) scores based on terrain attributes. After calibration, the models were applied to the entire study site, resulting in PC score maps. Fuzzy c-means and PC maps were used to define the soil mapping units (MU). Based on fuzzy centroids, representative samples (RS) were defined to the MU. Munsell soil color and soil order were predicted from soil spectra and used to characterize the MU. The regression tree model had a good fit for PC1, with an r^2 of 0.92, and a satisfactory r^2 for PC3, PC4, and PC5, respectively 0.58, 0.66 and 0.53. The fuzzy clustering defined seven MU. The R^2 for Munsell color predictions were 0.94 (hue), 0.96 (value) and 0.73 (chroma). Soil order had good agreement in validation, with kappa coefficient of 0.41. The methodology indicates the potential of Vis–NIR spectra to improve soil mapping campaigns and consequently provides a product similar to a conventional soil map.

1. Introduction

Choosing species and crop varieties adapted to the various kinds of soils delineated in maps could provide higher crop yields. However, soil maps with adequate scale for crop management are scarce (Mendonça-santos and Dos Santos, 2006). Ben-Dor et al. (2008) reported on high cost associated with soil surveying and mapping. One alternative to reduce costs could be the adoption of Digital Soil Mapping (DSM). A number of studies describe DSM techniques to create maps of soil attributes or even soil types (identified as taxonomic classes). In most cases, these maps are derived from a calibration set (punctual information related to chemical and physical properties or soil classification) and environmental covariates, such as terrain attributes and satellite images (Adhikari et al., 2014; Lagacherie et al., 2012; Vasques et al., 2015).

Visible and near-infrared (Vis–NIR) spectroscopy can be a useful indicator of soil variability (Demattê and Terra, 2014). The ability to obtain a large number of information at lower costs or short time allows increasing the number of observations and consequently improving digital soil mapping (Viscarra Rossel et al., 2009). Recently, the joint effort of researchers from several countries has resulted in the establishment of a global soil spectral library (Viscarra Rossel et al., 2016). These databases have a great potential to improve accuracy of digital soil maps, providing information about the most relevant soil attributes, enabling spatio-temporal monitoring of soils in many regions worldwide.

Given that soil spectra carry information about many soil attributes (Soriano-Disla et al., 2014), studies have suggested that the spectra could also be used to measure similarities between soil types and consequently provide soil classification (Vasques et al., 2014; Viscarra Rossel and Webster, 2011). Bellinaso et al. (2010) used a regional soil spectral library to describe and classify soil profiles according to the Brazilian Soil Classification System (SiBCS) (Embrapa, 2013). Ben-Dor et al. (2008) developed the 3S-HeD, a device able to improve reflectance data measurement on the field. The authors attached a field spectrometer to this device and performed a quantitative profile description based on

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Vis–NIR spectra. Vasques et al. (2015) elaborated a digital soil map of SiBCS suborder level based on satellite images, terrain attributes and interpolated average reflectance from soil Vis–NIR spectra.

While many studies apply Vis–NIR spectra to improve digital mapping of soil attributes, the synergy between proximal Vis–NIR sensing and soil types has been little explored. Clearly, there is a need for strategies using Vis–NIR spectra on DSM of soil types (identified as soil classes). The aim of our study was to test a digital mapping technique that uses as training set (i) soil spectra from local samples, (ii) a regional spectral library and (iii) terrain attributes. Spectra of local samples are used in many steps of the mapping process to (a) define the mapping units (MU), (b) select representative samples (RS) from each MU and (c) classify the soil types according to SiBCS order level (Embrapa, 2013).

2. Material and methods

2.1. Study site

The study site is a 270 ha farm located in the municipality of Piracicaba, São Paulo State, Brazil, between the coordinates 22°42′30″–22°43′27″S and 47°33′32″–47°34′45″W (Fig. 1). Lithology is diabases from the Serra Geral Formation, argillaceous siltstone and argillites from the Tatuí Formation and argillites from the Irati Formation (Vidal-Torrado et al., 1999). The climate is "Cwa" subtropical with dry winters and rainy summers (Koppen classification). Annual rainfall ranges from 1250 to 1500 mm. Relief consists of two interconnected hills with dominantly convex slopes ranging from 2% (on the hilltops) to 12% (on the foothills).

2.2. Data acquisition

A 30-meter resolution digital elevation model (DEM) of the study site was obtained from a topographical chart (1:10,000 scale) (Hutchinson, 1993). Later, the SAGA GIS (System for Automated Geoscientific Analyses) was used to derive the following terrain attributes: Altitude Above Channel Network (AACN), Aspect (ASP), Catchment Area (CA), Channel Network Base Level (CNBL), Curvature (CUR) (Zevenbergen and Thorne, 1987), Hillshade (HIL), Topographic factor (LSF), Slope (SLOP) (Horn, 1981), Stream Power (SP) (Moore et al., 1993), Terrain Roughness (TR), Topographic Wetness Index (TWI) (Moore et al., 1993), Vector Terrain Roughness (VTR) (Hoffman and Krotkov, 1990) and Wetness Index (WI) (Moore et al., 1993).

Soils were sampled with an auger along five toposequences, in a 30-meter interval, at two depths (0–20 cm and 80–100 cm). We collected 324 samples that were dried at 50 °C and sieved through a 2-mm mesh. Fractions smaller than 2 mm were used for laboratorial analyses. The color of dry soil was measured with a Minolta colorimeter (CR–300), adjusted to the Munsell color system (Campos et al., 2003). The soils were classified at the suborder level according to the Brazilian Soil Classification System (SiBCS) (Embrapa, 2013). The corresponding World Reference Base (IUSS Working Group WRB, 2014) and Soil Taxonomy (Soil Survey Staff, 2014) classes are shown in Table 1.

The soil samples spectra were measured in the laboratory using a FieldSpec Pro spectrometer (Analytical Spectral Devices, Boulder, CO) considering a spectral range between 400 and 2500 nm. The system geometry corresponded to the perpendicular position of the sensor in relation to the sample at a distance of 27 cm. The light source was positioned at 61 cm from the sample and at an angle of 20° with the zenith. The absolute reference standard used was a white spectralon plate.

2.3. Spatial modeling of soil multi-depth spectra

Spectra from the two sampled soil depths were joined in sequence to create a pseudo multi-depth soil spectrum (Vasques et al., 2014). The principal component analysis (PCA) was applied to summarize information in the spectra, resulting in 5 principal components (PC). The PCA was performed using the interactive NIPALS algorithm (Martens and Naes, 1989) implemented in Parles 3.01 (Viscarra Rossel, 2008).

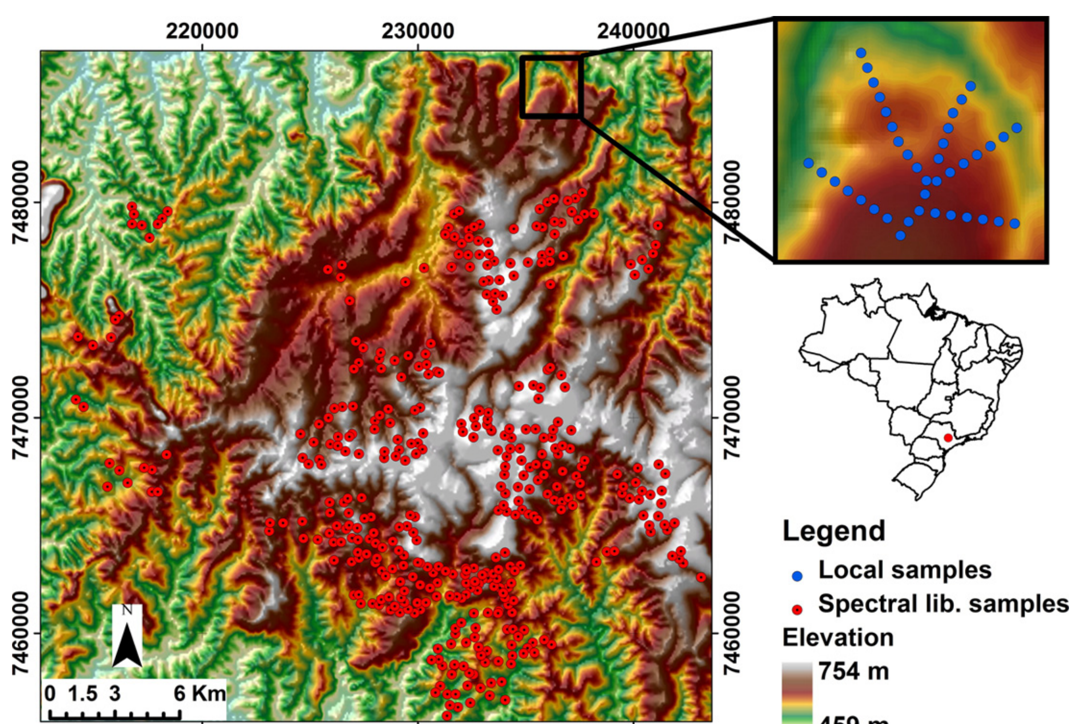

Fig. 1. Location of the study site, the samples collected in the site and samples from the regional spectral library.