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Mapping units based on spatial uncertainty of magnetic susceptibility and clay content

Daniel D.B. Teixeira[a,*], José Marques Jr.[b], Diego S. Siqueira[b], Vinicius Vasconcelos[c], Osmar A. Carvalho Jr.[d], Éder S. Martins[e], Gener T. Pereira[f]

[a] Center of Agrarian Sciences, University of Marília (Unimar), Brazil
[b] Department of Soils and Fertilizers, State University of São Paulo (UNESP), Research Group CSME — Soil Characterization for Specific Management, Jaboticabal, São Paulo, Brazil
[c] Department of Ecology, University of Brasília (UNB), LSIE — Laboratory of Spatial Information Systems, Brasília, DF, Brazil
[d] Department of Geography, University of Brasília (UNB), LSIE — Laboratory of Spatial Information Systems, Brasília, DF, Brazil
[e] Embrapa Cerrados, Brasília, DF, Brazil
[f] Department of Exact Sciences, State University of São Paulo (UNESP), Research Group CSME — Soil Characterization for Specific Management, Jaboticabal, São Paulo, Brazil

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ABSTRACT

This study aimed to use spatial uncertainty of magnetic susceptibility (MS) and clay content to improve soil-mapping units. In an experimental area of 870 ha, a regular sampling grid containing 371 points was set, in which MS and clay content were assessed at a depth range of 0–0.25 m. Using a digital elevation model and field observations, a 4440-m transect was established on the study area from hilltop to the foothill, toward the gentlest slope. Standard deviation maps based on 200 realizations of the sequential gaussian simulation measured spatial estimate uncertainties. To limit transition zones along the transect, uncertainty isolines representative of the transition between soil-mapping units were selected. Both attributes presented peaks of uncertainties near the change of mapping units, previously known. Uncertainty zones, previously delineated, ranged from 45 to 210 m and from 60 to 170 m, for MS and clay content, respectively. However, after extrapolating the uncertainties to the side of the transect, amplitude changes of the uncertainty zones were observed, especially in the transition regions between landscape shape and geology. Delineation of mapping units, which incorporated the uncertainties of MS and clay content, was similar. However, due to lower cost and promptness, MS becomes the most feasible alternative. Knowing spatial uncertainties enables readjusting limits in maps of soil-mapping units and may support identification of most favorable regions for determining modal pedon representative of each unit.

1. Introduction

Pedological maps have great potential of contributing to increase agricultural production (Grunwald et al., 2011; Brevik et al., 2016), farming planning and modeling of environmental impacts (Rogowski and Wolf, 1994). However, potential limitations may hamper or even preclude the use, such as: (i) subjectivity, since the delimitations of limits of the mapped units depend on the experience and impressions of the mapper (Bazaglia Filho et al., 2013); (ii) lack of representation of the spatial and temporal variability patterns of soil attributes (Rogowski and Wolf, 1994); (iii) definition of arbitrary limits for distinguishing between different soil units (Phillips, 2013); and (iv) lack of detail due to scale of information (Sarmento et al., 2017).

Bazaglia Filho et al. (2013), comparing soil mapping units performed by different mappers, observed a great influence of performer on delimitation of soil management units, mainly in their limits. Studies conducted in the area of soil digital mapping (Nanni et al., 2014) also show difficulty in the accurate mapping of soil transitions. This inaccuracy in the limits of soil maps are the result of using the criteria established by the classification key, leading to the distinction between soils with similar behaviors and the combination of others with different behaviors (Phillips, 2013).

Some methods attempt to overcome these problems through the incorporation of the spatial variability of soil attributes (Siqueira et al., 2015) using hybrid mapping techniques (Legros, 2006; Vincent et al., 2018; Teixeira et al., 2017). Such methods are typically tested using

* Corresponding author.
E-mail address: danielteixeira@unimar.br (D.D.B. Teixeira).

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validations (Mirzaeitalarposhti et al., 2017; Hengl et al., 2017) and error analysis (Cambule et al., 2014), providing only an overview of the error associated with the mapping. In this sense, techniques that assess and incorporate the uncertainties associated with information from soil maps promote an advance in knowledge of mapping errors (Castrignanò et al., 2008; Brevik et al., 2016). The identification and determination of uncertainties can be performed directly on the mapping units using fuzzy logic (Zhu, 1997) and indicative simulation techniques (Silva et al., 2015), or on soil attributes, especially by means of geostatistical simulations (Grunwald et al., 2007; Castrignanò et al., 2008; Teixeira et al., 2012; Viscarra-Rossel et al., 2014) and error propagation techniques (Hengl et al., 2014).

The uncertainties determined in soil units are used to identify the probability of certain class be correctly defined (Phillips, 2013). Its use is difficult since it is necessary the knowledge of a great number of modal pedons for its determination (Silva et al., 2015). In its turn, the uncertainty in spatial assessment of soil attributes is used for identifying sites that require increased number of samples (Teixeira et al., 2012), constructing estimating scenarios (Grunwald et al., 2007), and providing an indirect measure of the estimate quality generated at each site (Viscarra-Rossel et al., 2014). Despite the requirement for a great number of samples, mainly to meet the principles of geostatistical analysis (Isaaks and Srivastava, 1989), the sampling of soil attributes is faster, simpler and cheaper than the pedon sampling. Therefore, for soils with little vertical variation of diagnostic attributes or covariative attributes to them, spatial uncertainty of attributes is proposed in determining the uncertainty of mapping units and thus incorporate simultaneously the information about the spatial variability of soil attributes into the generated map.

The definition of the attributes to be used in the identification of uncertainties is of great importance. Silva et al. (2015) proposes the uncertainty assessment for soil diagnostic attributes (color, texture gradient, base saturation, clay and sand content and soil organic carbon). For tropical soils, soil mineralogy and clay content have great relationship with the taxonomic classes of soil (Costa et al., 1999) and directly influence the definition of mapping units (Marques Jr. et al., 2014; Siqueira et al., 2015). The magnetic susceptibility (MS) is covariative of factors and processes of soil formation, in addition to be closely related to its mineralogy (Camargo et al., 2014; Sarmast et al., 2017). The increasing use of MS is due to the simplicity and low cost in its determination (Dearing, 1994) and high relation with soil physical, chemical and mineralogical attributes (Siqueira et al., 2010). Thus, the hypothesis of this research is that the incorporation of uncertainties of soil attributes covariative of factors and processes of soil formation (MS and clay content) can assist in delineating mapping units, as well as in the readaptation of the limits between soil units, simultaneously incorporating information on spatial variability of soil attributes. In this sense, the objective was to use the spatial uncertainty of MS and clay content for improving soil-mapping units.

2. Materials and methods

2.1. Description of the area and sampling

The study area has central coordinates of 21°28′40″S and 48°01′38″W and is located in Guatapará city, São Paulo State, Brazil (Fig. 1a). The local natural vegetation consisted of semideciduous tropical forest. Currently, the area is cultivated with sugarcane under mechanical harvesting system for over 10 years. According to Thornthwaite (1948), the region's climate can be defined as B1rB′4a′, i.e., a humid mesothermal climate with small water deficit and summer evapotranspiration lower than 48% of the annual evapotranspiration.

The area is located in a geological transition between the Basalt of the São Bento Group, Serra Geral Formation (SG), Eluvial-Colluvial Deposit (ECD) and Alluvial Deposit (AD) (IPT, 1981; Geobank, 2014) (Fig. 1b). The area presents concave (Cc) and convex (Cx) horizontal curvatures (Fig. 1c). These curvatures were identified by the SRTM information with horizontal resolution of 90 m and vertical precision of the order of 5 m. Initially, a median filtering was used to remove values with variation higher than 10 m and data interpolation using the TOPOGRID tool, available in ArcGIS software, which is a routine based on algorithm developed in Hutchinson (1989). From the interpolated data, the geomorphometric signature (image of the horizontal curvature) was generated. Subsequently, the signature values were normalized through the division by the maximum value found producing values ranging from − 1 to 1. The negative values were considered as belonging to the convergent curvature (concave) and the positive to the divergent curvature (convex). For more details, see Vasconcelos et al. (2012).

According to the soil map (scale of 1:12,000) generated by the Centro de Tecnologia Canavieira (Sugarcane Technology Center) (Fig. 1d), the area registers five soil mapping units. These units are classified according to the Sistema Brasileiro de Classificação de Solos (SiBCS) (Santos et al., 2013) and Soil Taxonomy: LVAd (SiBCS: *Latossolo Vermelho-Amarelo distrófico com textura media*; Soil Taxonomy: Typic Hapludox); LVd (SiBCS: *Latossolo Vermelho distrófico com textura media*; Soil Taxonomy: Typic Hapludox); LVdf (SiBCS: *Latossolo Vermelho distroférrico com textura argilosa*; Soil Taxonomy: Typic Hapludox); LVef (SiBSC: *Latossolo Vermelho eutroférrico com textura argilosa*; Soil Taxonomy: Typic Eutrudox); RQod (SiBCS: *Neossolo Quartzarênico órtico distrófico com textura arenosa*; Soil Taxonomy: Typic Quartzipsamment).

In the experimental area was installed a regular sampling grid containing 371 points separated at minimum distances ranging from 145 to 174 m, covering a total area of about 870 ha (Fig. 1e). The resulting sampling density (0.4 samples ha^{-1}) is in accordance with the indication of the *Procedimentos Normativos de Levantamentos Pedológicos* (Normative Procedures of Soil Surveys) (Embrapa, 1995). At each point of the sampling grid, samples were collected within a depth range of 0–0.25 m for determining MS and clay content. This depth is used by the São Paulo State sugarcane sector in determining soil management (Teixeira et al., 2017). Thus, the protocol developed in this study can be easily incorporated in this sector without require huge changes.

With the support of the digital elevation model and field observations, one transect of 4440 m was identified in the study area from the top of hillside to the foothill, toward its most gentle slope (Fig. 1e). This transect includes two geological classes, both curvatures and all pedological mapping units present in the area.

2.2. Laboratory analyses

The MS was determined in a low frequency (0.47 kHz) using 10 g of air-dried soil in a Bartington MS2 equipment coupled to a Bartington MS2B sensor (Dearing, 1994). The clay content was determined by the pipette method, using NaOH 0.1 mol L^{-1} as a chemical dispersant and mechanical agitation at low speed for 16 h (Embrapa, 1997).

2.3. Data analysis

2.3.1. Descriptive statistics

The variability of soil attributes was previously described by means of the construction of boxplot graphics as a function of the geological, geomorphological and pedological compartments. The boxplot graphics present the values of minimum, maximum, first quartile (Q1), second quartile (median), third quartile (Q3) and interquartile range (IR). Values higher than Q3 + 1.5 × (Q3 − Q1) or lower than Q1–1.5 × (Q3 − Q1) are considered outliers.

2.4. Geostatistical analysis

The spatial variability of the variables was determined using the experimental variogram modeling based on the theory of regionalized variables (Isaaks and Srivastava, 1989). In this study, spherical,