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Sample planning for quantifying and mapping magnetic susceptibility, clay content, and base saturation using auxiliary information

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ABSTRACT

There is a great global demand for detailed soil property description; therefore, an ideal site-specific sampling has become indispensable to meet this demand. This study aimed to assess the implications of incorporating geological, geomorphological, and pedological information in reducing the required sampling density for magnetic susceptibility (MS), clay content (CC), and base saturation (BS) characterizations. The study area is located in Guatapará-SP (Brazil) and has 870 ha. A total of 371 samples were collected at a depth of 0–0.25 m for assessing magnetic susceptibility (MS), clay content, and base saturation (BS). A density of one sample was considered every 2.6, 3, 4, 5, 6, 7, 8, 9, 11, and 14 ha. The incorporation of secondary information in a geostatistical framework was performed by means of simple kriging with varying local means. Accuracy assessment of the spatial estimates at each sampling density, with and without incorporating secondary information, was performed by using external validation. For MS, geology and geomorphology information were responsible for about 45% and 44% spatial continuity, respectively. As for CC, these results were higher, being of 54% (geology) and 53% (geomorphology). Conversely, no spatial variability was detected for these properties by using pedological information. For BS, there was no relationship between secondary information and its spatial continuity. Incorporating geological and geomorphological information to MS data enabled a reduction in the number of samples required of 37% and 44%, respectively, in order to represent its spatial pattern. Likewise, this information provides a 35% reduction in the required sampling density for CC. However, secondary information was no helpful in decreasing sampling density for BS. In brief, incorporating pre-existing information can ensure a high quality of estimates and decrease the number of samples required for a detailed description for both MS and CC. Estimates of spatial patterns with geological and geomorphological information for modeling of soil properties might have a greater potential of use for environmental model composition.

1. Introduction

Recent changes in land use and intensification of formation and degradation processes have compromised soil and environment quality. In this context, there is a great demand for detailed information about soil in order to perform a sustainable management (Grunwald et al., 2011; Brevik et al., 2016; Hengl et al., 2017). Soil mapping is one of the key tools to meet this demand and as a strategic planning of agricultural, urban, and management activities of soil variability (Li and Heap, 2008). Once at the level of detail required (Delden et al., 2011), soil maps can be used for delineating areas with deficiency or toxicity of a particular chemical element (Chen et al., 2016). Besides, these maps highlight the relationship between soil properties and agricultural productivity, animal production, and human health (White and Zasoski, 1999; Siqueira et al., 2016), besides playing a key role in optimization of sampling plans (Vašát et al., 2010; Montanari et al., 2012) and agricultural inputs (White and Zasoski, 1999).

Several protocols for soil modeling and mapping have been developed to assist the understanding of its variability (Minasny and McBratney, 2016). According to Castrignanò et al. (2009), the main

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methodologies used can be divided into two groups: (i) protocols that consider the soil as a discontinuous unit, in which is possible its division into a discrete number of classes; and (ii) protocols that consider the soil as a continuous body, which quantitatively describe the variation of variables in space. The first is represented mainly by mapping methodologies by the similarity between pedons (Soil Survey Staff, 1975), in addition to free and categorical mappings, in which concepts of soil-landscape relationship are used (Hudson, 1992). The second is represented mainly by mappings using geostatistical analysis (Oliver and Webster, 2014).

However, when considering the soil as a continuous body, several researchers have observed that the variability of its properties matches the geological variation (Liu et al., 2013; Siqueira et al., 2014), relief form (Siqueira et al., 2010; Quijano et al., 2011; Camargo et al., 2016), and agricultural management practices (Liu et al., 2013). Thus, hybrid mapping protocols, in which both concepts are brought together, have stood out for the last decade, especially for studies on local and regional scales (McBratney et al., 2000). In addition, hybrid mapping techniques are commonly used in other areas such as geological mapping, in which information from soil maps on detailed scales can be used to construct more accurate geological maps than the traditional method (Brevik and Miller, 2015).

In these protocols, previously acquired information such as geological, geomorphological, or pedological maps, or even property maps, on less detailed scales, can be used along with quantitative analyses (e.g. geostatistical analysis) to refine the mapping units and increase the understanding and reliability of the spatial patterns (Castrignanò et al., 2009; Cambule et al., 2013; Hengl et al., 2014, 2017; Vasques et al., 2016).

For constructing and delineating these soil maps, sample planning by means of identifying the appropriate sampling density presents an important stage to be assessed (McBratney et al., 2002; Vašát et al., 2010; Siqueira et al., 2014). Sampling density directly influences the level of detail to be obtained (scale or resolution) (Delden et al., 2011) and mapping costs (Demattê et al., 2007). Measures such as the Shannon diversity index (Minasny et al., 2010) can be used as the first indication of soil pedodiversity intensity (variability) at large scales. For more detailed scales (regional or local), the study of incorporation of secondary information into geostatistical models (Castrignanò et al., 2009; Cambule et al., 2013; Vasques et al., 2016) and use of properties with potential for identifying the variation of soil formation processes (magnetic susceptibility–MS, electrical conductivity, and diffuse reflectance spectroscopy) (Bilgili et al., 2011; Siqueira et al., 2014; Mirzaeitalarposhti et al., 2017) represent an increasing research activity. However, the secondary information often used have quantitative (satellite information, electrical conductivity, and MS) (Benedetto et al., 2012) and non-qualitative or categorical nature (Castrignanò et al., 2009).

Qualitative information, which is often available at no charge, has a great potential to integrate sample planning of soil properties (Cambule et al., 2013). However, one of the main difficulties is the definition of what information should be used for the sample planning and mapping of soil properties (Miller et al., 2015). Hengl et al. (2014) state that information on climate, lithology, biomass indexes and taxonomic units are the main covariates for modeling soil properties on a global scale. For regional and local scales, information on geomorphology, lithology, and pedology present a great potential (Anderson et al., 2003; Vasques et al., 2016). The hypothesis of this research is that the knowledge on soil formation factors (geology and landscape shape), often previously mapped and available at no charge, should be considered at the time of mathematical modeling. Its incorporation may assist in delineating spatial patterns of soil properties, as well as reducing the required sampling density for representing the phenomenon under study. In this sense, this study aimed to assess the incorporation of geological, geomorphological, and pedological information in reducing the required sampling density for characterizing magnetic susceptibility, clay content, and base saturation.

2. Materials and methods

2.1. Description of the area and sampling

The study area was located in Guatapará, São Paulo State, Brazil (Fig. 1a). Its central coordinates are 21°28′40″S and 48°01′38″W, with an altitude ranging from 649 to 519 m. According to Thornthwaite (1948), the local climate can be defined as B1rB′4a′, which means a humid mesothermal climate with small water deficit and summer evapotranspiration lower than 48% of the annual evapotranspiration. The local natural vegetation consisted of a tropical semideciduous forest. Currently, the area is cultivated with sugarcane under mechanized harvesting system for over 10 years.

The area has three parent materials related to the transition between the Basalt of the São Bento Group, Serra Geral Formation (SG), Eluvial-Colluvial Deposit (ECD), and Alluvial Deposit (AD) (IPT – Instituto de Pesquisas Tecnológicas do Estado de São Paulo, 1981; GEOBANK, 2014) (Fig. 1b). Technical visits were carried out in the area in order to verify the geological information. Geomorphometric compartments were identified according to the methodology proposed by

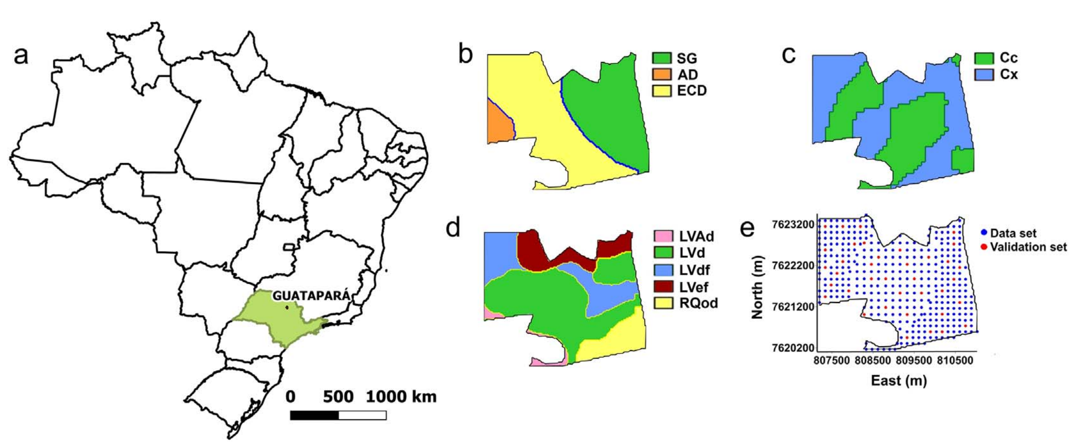

Fig. 1. Characterization of the study area. Location of the sampling area (a); geological map at scale 1:500,000 (SG–Serra Geral; AD–Alluvial Deposit; ECD–Eluvial-Colluvial Deposit) (b); geomorphometric map at scale 1:100,000 (Cc–concave; Cx–convex) (c); pedological map at scale 1:12,000 (LVAd (SiBCS: *Latossolo Vermelho-Amarelo distrófico com textura média*; Soil Taxonomy: Typic Hapludox); LVd (SiBCS: *Latossolo Vermelho distrófico com textura média*; Soil Taxonomy: Typic Hapludox); LVdf (SiBCS: *Latossolo Vermelho distroférrico com textura argilosa*; Soil Taxonomy: Typic Hapludox); LVef (SiBCS: *Latossolo Vermelho eutroférrico com textura argilosa*; Soil Taxonomy: Typic Eutrudox); RQod (SiBCS: *Neossolo Quartzarênico órtico distrófico com textura arenosa*; Soil Taxonomy: Typic Quartzipsamment)) (d); spatial distribution of samples (e).

Vasconcelos et al. (2012) (Fig. 1c), in which areas that present concave (Cc) and convex (Cx) horizontal curvatures were identified. For identifying these curvatures, SRTM information with a horizontal resolution of 90 m and vertical precision of the order of 15 m were used. Initially, a pre-treatment (median filter) of this information was conducted in order to remove values with variation higher than 10 m. Subsequently, a data interpolation was carried out by using the Topogrid method (Hutchinson, 1989). A geomorphometric signature was generated from the interpolated data (for details, see Vasconcelos et al., 2012). Point values of this signature were normalized by dividing them by the maximum point value found producing values ranging from − 1 to 1. After standardization, negative values were considered as belonging to the convergent curvature (concave) and those positive as belonging to the divergent curvature (convex).

The pedological map (at scale 1:12,000), generated by the Centro de Tecnologia Canavieira (CTC) (Sugarcane Technology Center) (Fig. 1d), registers the occurrence of the following mapping units 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, a regular sampling grid containing 371 points separated by minimum distances ranging from 145 m to 174 m was installed covering a total area of about 870 ha (Fig. 1e). Previously the beginning of modeling, 10% of points (N = 37) were randomly selected for constructing a data set to be used in the validation process. Point distribution and the representative area of each compartment delimited in Fig. 1b–d are shown in Table 1.

From the original sampling density (one point every 2.6 ha), different sampling densities were considered using 334, 290, 218, 174, 145, 124, 109, 97, 79, and 62 points that are equivalent to a density of one point every 2.6, 3, 4, 5, 6, 7, 8, 9, 11, and 14 ha, respectively. Points that integrated the densities were randomly selected using the methodology developed in other studies (Teixeira et al., 2013; Siqueira et al., 2014). The lowest sampling density (one point every 14 ha) used was determined by following the principles of geostatistical analysis regarding the need for at least 50 pairs of points for each experimental semivariance calculation (Goovaerts, 1997). At each point of the sampling grid, samples were collected at a depth of 0–0.25 m for determining the magnetic susceptibility (MS), clay content, and base saturation (BS). This depth was chosen for being used by the São Paulo State sugarcane sector in determining soil management (Siqueira et al., 2014).

2.2. Laboratory analyses

Magnetic susceptibility (MS) in a low frequency (0.47 kHz) was determined at 10 g of air-dried soil using a Bartington MS2 equipment coupled to a Bartington MS2B sensor (Dearing, 1994). Clay content was determined by the pipette method by using a NaOH 0.1 mol L^{-1} solution as a chemical dispersant and mechanical agitation at a low speed for 16 h (EMBRAPA, 1997). Base saturation (BS) was calculated from the values of Ca, Mg, K (extracted by means of the ion exchange resin method) (Raij, 2001), and H + Al, being the exchangeable acidity (Al^{3+}) determined according to Raij and Zullo (1977).

2.3. Data analysis

2.3.1. Descriptive statistics

Soil property variability was previously described by means of calculating the mean, 95% confidence interval, and coefficient of variation for each studied compartment.

2.3.2. Geostatistical analysis

Spatial variability of assessed properties was determined by calculating and modeling the experimental variogram based on the theory of regionalized variables and intrinsic hypothesis principles (Oliver and Webster, 2014). The stationarity required to the use of geostatistics was assessed through trend analyses using linear and quadratic regressions for the Latitude and Longitude axes and their interactions (Davis, 1986).

In this study, spherical, exponential, and Gaussian models were tested. The choice of the best-adjusted model to the variograms was based on cross-validation, linear and angular regression coefficient between observed and estimated values, and residual sum of squares (RSS) obtained for model adjustment (data not shown) (Oliver and Webster, 2014).

After modeling the variogram, interpolation was performed by means of ordinary kriging (OK) and simple kriging with a varying local mean (SK_{VLM}). OK technique was used to interpolate soil properties without secondary information. On the other hand, SK_{VLM} technique was used aiming at incorporating categorical secondary information related to geology (Fig. 1b), geomorphology (Fig. 1c), and pedology (Fig. 1d) in the variability models of the studied soil properties (for more details, see Isaaks and Srivastava, 1989).

Table 1
Distribution of sampling points and area of each geological, geomorphological, and pedological compartment.

	Geology			Geomorphology		Pedology				
	SG[a]	AD[b]	ECD[c]	Cc[d]	Cx[e]	LVAd[f]	LVd[g]	LVdf[h]	LVef[i]	RQod[j]
N	144	23	204	142	229	13	161	87	57	53
Area (ha)	353.8	46.3	469.8	361.8	508.2	23.4	423.7	184.1	134.0	104.9
Area (%)	40.7	5.3	54.0	41.6	58.4	2.7	48.7	21.2	15.4	12.0

(N = 371).
[a] Serra Geral.
[b] Alluvial Deposit.
[c] Eluvial-Colluvial Deposit.
[d] Concave.
[e] Convex.
[f] *Latossolo Vermelho-Amarelo distrófico com textura média* (Typic Hapludox).
[g] *Latossolo Vermelho distrófico com textura média* (Typic Hapludox).
[h] *Latossolo Vermelho distroférrico com textura argilosa* (Typic Hapludox).
[i] *Latossolo Vermelho eutroférrico com textura argilosa* (Typic Eutrudox).
[j] *Neossolo Quartzarênico órtico distrófico com textura arenosa* (Typic Quartzipsamment).

Table 2
Mean, 95% confidence interval, and coefficient of variation (%) for magnetic susceptibility (MS), clay content, and base saturation (BS) according to stratifying compartments.

	MS ($\times 10^{-8}$ m^3 kg^{-1})			Clay content (g kg^{-1})			BS (%)		
	Mean	CI (95%)	CV	Mean	CI (95%)	CV	Mean	CI (95%)	CV
Geology									
SG[a]	2899	2489–3309	81	349	314–384	56	58	56–61	24
AD[b]	1503	1106–1900	58	325	296–354	20	54	49–59	20
ECD[c]	1966	1701–2231	92	321	298–345	50	54	52–56	25
Geomorphology									
Cc[d]	1796	1480–2113	100	305	280–330	47	55	52–57	25
Cx[e]	2611	2317–2906	82	349	323–374	53	56	54–58	24
Pedology									
LVAd[f]	355	162–548	81	273	239–306	18	56	45–66	29
LVd[g]	1502	1242–1761	104	286	263–308	46	55	53–57	21
LVdf[h]	3665	3390–3940	33	438	412–464	26	57	53–61	29
LVef[i]	4783	4363–5204	31	524	492–555	21	53	49–57	26
RQod[j]	206	143–268	102	113	102–125	35	59	55–64	24
Total area	2299		89	332		51	56		25

[a] Serra Geral.
[b] Alluvial Deposit.
[c] Eluvial-Colluvial Deposit.
[d] Concave.
[e] Convex.
[f] *Latossolo Vermelho-Amarelo distrófico com textura média* (Typic Hapludox).
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[h] *Latossolo Vermelho distroférrico com textura argilosa* (Typic Hapludox).
[i] *Latossolo Vermelho eutroférrico com textura argilosa* (Typic Eutrudox).
[j] *Neossolo Quartzarênico órtico distrófico com textura arenosa* (Typic Quartzipsamment).

2.3.3. *Comparison of maps*

The accuracy of estimates with and without incorporation of secondary information in the assessed sampling density was verified by estimating the relative root mean square error (RRMSE) (Eq. (5)) (Li and Heap, 2008) applied to the validation data set (Fig. 1e).

$$RRMSE = \left\{ \frac{1}{n} \sum_{i=1}^{n} [(p_i - o_i)/o_i]^2 \right\}^{0,5} \tag{5}$$

Where n is the number of estimated values ($N = 37$), p_i is the value estimated at the point i, and o_i is the property value observed at the point i. Lower RRMSE values are related to a higher accuracy of estimates. This methodology is similar to that used by Teixeira et al. (2013) for assessing the estimated spatial patterns using the secondary information to the models.

3. Results and discussion

The average values of MS in the total area (2299×10^{-8} m^3 kg^{-1}) was not covered by the confidence intervals estimated at 95% probability (95% CI) after the stratification by geology, geomorphology, and pedology (Table 2). This is the first indication that these compartments have an influence on MS values and their limits should be considered during the analysis of spatial continuity.

The 95% confidence intervals for MS after the stratification by geology indicate that SG formation (2899×10^{-8} m^3 kg^{-1}) significantly differs from the others (ECD = 1966×10^{-8} m^3 kg^{-1} and AD = 1503×10^{-8} m^3 kg^{-1}). Values found for SG formation are similar to those found for African soils that have basic and ultrabasic rocks as parent materials (Preetz et al., 2008). These high values are related to the parent material (SG) that was formed from a magma with high Fe concentrations under high temperature, which favors magnetite formation (Preetz et al., 2009).

The parent materials ECD and AD presented MS values higher than those reported by other authors for sedimentary rocks (Preetz et al., 2008; Camargo et al., 2014), which is due to the diversity of rock formation originated from the sedimentary material. Thus, if the weathered rock has ferric minerals, the formed sedimentary rock may present higher MS values even after sedimentation process. Moreover, these high values could be attributed to the manual harvest management after sugarcane burning in the previous crop cycles. According to Schwertmann (1985), the presence of fire can promote the transformation of pedogenetic iron oxides and subsequent neoformation of maghemite, which has a high magnetic potential. It is estimated that during the process of sugarcane burning, soil temperature in the surface layer varies from 160 to 200 °C (Ripoli and Ripoli, 2004) as maghemite formation can occur at temperatures below 250 °C (Liu et al., 2010).

Considering the landscape shape as stratifier and 95% confidence intervals, higher MS values were observed on Cx surface (2611×10^{-8} m^3 kg^{-1})when compared to Cc surface (1796×10^{-8} m^3 kg^{-1}). Siqueira et al. (2010) assessed MS determination in sandstones of the Adamantina formation with a low total iron content in the soil (Fe_2O_3 < 40 g kg^{-1}) and also observed the influence of these shapes in MS differentiation, with values of 130×10^{-8} m^3 kg^{-1} for Cc and 330×10^{-8} m^3 kg^{-1} for Cx. Quijano et al. (2011) studied the relationship between MS and relief characteristics in an area without geological variation and observed higher MS values in convex areas because of the oxidative character of the environment, which would provide the neoformation of minerals with a more magnetic expression. Oxidizing environments can promote a total or partial magnetite oxidation and maghemite neoformation (Dearing, 1994; Ker, 1998). In this study, the highest MS values found for Cx surface can also be explained by the location of a large part of this surface (27%) be on the SG geology, which has the highest MS values.

Using the pedological mapping units found in the area as stratifiers, higher MS values are observed in the sequence LVef > LVdf > LVd > LVAd = RQod (95% confidence interval). MS values are higher for soils with a high iron content (ferric soils), presenting values of 4783×10^{-8} m^3 kg^{-1} (LVef) and 3665×10^{-8} m^3 kg^{-1} (LVdf).

For clay content, the overall average (332 g kg^{-1}) was contemplated by the confidence intervals of compartments stratified by geology and geomorphology. Thus, in this study, only pedological mapping units present influence on clay content. Although the parent material (Siqueira et al., 2014) and landscape shape (Sanchez et al.,

2013) present influences on soil texture, better results are expected in the stratification by using pedological mapping units due to clay content be considered as a diagnostic property in their identification (EMBRAPA, 2006). The average clay contents stratified by soil type presented the following sequence: LVef > LVdf > LVd = LVAd > RQod (95% confidence interval).

For BS values, the average in total area (56%) was covered at all 95% confidence intervals after stratification, indicating no influence of geology, geomorphology, and pedology on this property. Intensive soil management during crop cycles can lead to a relative homogenization of the area, reducing the influence of factors and processes that are intrinsic to soil. Cardoso et al. (2014) found a high anthropogenic influence on the variability of soil chemical properties in a sugarcane area, mainly affecting the nutrients with less mobility in soil.

The variation inferred that by the coefficient of variation (CV) indicates a greater MS heterogeneity (89%) in relation to clay content (51%) and BS (25%) (Table 2). The low variation of BS is attributed to a similar management over crop cycles (Panosso et al., 2012). The highest CV values for MS are related to a higher sensitivity of this property to changes in processes and formation factors of soil (geology and landscape shape), as can be verified by comparing the confidence intervals. Several authors (Matias et al., 2014; Siqueira et al., 2014), when studying soils with a variation of total iron (Fe_2O_3) from 40 to 180 g kg^{-1}, also observed a greater MS sensitivity to changes in geology and landscape shape in relation to physical and chemical soil properties.

In general, property stratification as a function of pedology and geology promoted reductions in CV values when compared to those found for the total area (without stratification). The stratification based on landscape shape promoted the decrease in CV values only for BS. This decreased CV indicates that the known compartments are promoting the identification of areas more homogeneous with each other, which is another indication that this information should be incorporated into future spatial analysis and decision-making processes such as the identification of areas of specific management.

For MS and clay content, the highest average reductions in CV were promoted by the stratification based on pedological compartments (18.8% and 21.8%, respectively), followed by the stratification by geology (12% and 9%, respectively) and geomorphology (2% and 1%, respectively). When soil compartments are considered, the greatest CV reduction may be related to a higher degree of compartmentalization and detailing (5 classes) of the area in relation to geology (3 classes) and geomorphology (2 classes). However, smaller areas (increased number of polygons in an area) does not guarantee the variability control within each delineated polygon and hence a CV reduction.

Although CV value is an indicative of property variation, it does not include the existing spatial relationships between the analyzed samples. Geostatistical analyses, which are based on constructing and modeling the experimental variogram (Oliver and Webster, 2014), allow the spatial verification of interrelations between soil properties (Yang et al., 2016), as well as the spatial influence determination of stratifiers on estimates of unsampled locations (Goovaerts, 1997; Vasques et al., 2016).

The influence of incorporation of stratifying compartments on geostatistical models was assessed as a function of sampling density of one point every 2.6, 3, 4, 5, 6, 7, 8, 9, 11, and 14 ha (Fig. 2). In order to verify the variability captured or promoted by different stratifiers (geology, geomorphology, and pedology), variogram parameters adjusted to the data without considering the secondary information (conventional) were compared to variograms considering such information (Goovaerts, 1997).

All theoretical models adjusted to the experimental variograms were spherical, which is the most used in soil science (Cambardella et al., 1994) and describes properties with abrupt changes along the surface under study (Oliver and Webster, 2014). This characteristic allows stating that it would be possible to use vector categorical maps (geological, geomorphological, and pedological) to assist in the delimitation of spatial patterns of soil properties since these maps present the same characteristics of abrupt changes in space. For MS and clay content, the spatial dependence could not be detected in the density of one point every 14 ha when pedological information was incorporated. For BS, no spatial dependence was observed in the lowest assessed density. Siqueira et al. (2014), when assessing the effect of sampling density in capturing the spatial dependence of MS, clay content, and BS, found that BS is more sensitive to the decreased sampling density when compared to the other properties. Nanni et al. (2011), also assessing the sampling density in a geological transition region, found that variogram ranges for BS presented 21% variation in relation to sampling density, being the most sensitive property to this variation.

The average values of range found for MS (1326 m) and clay content (1274 m), not considering the secondary information, are relatively close to the ranges found by Campos et al. (2007) in a sandstone-basalt litosequence (range of clay content = 1211 m) and Matias et al. (2014) in a sandstone-basaltic transition with mudstone influence (range of MS = 1881 m and range of clay content = 930 m). Thus, the protocols and results developed in this study have the potential for use in regions with geological transitions. In contrast, the lowest average value of range for BS (776 m) indicates its lower spatial continuity. Similar results were found by other authors (Marques et al., 2014; Yang et al., 2016), who observed a lower spatial continuity of chemical properties when compared to physical and mineralogical properties. The similarity between the range values of MS and clay content may be an indicative of a high spatial association between these properties (Peluco et al., 2013). This association allows the use of MS as a covariate in estimating clay content in the soil (Hanesch and Scholger, 2005; Siqueira et al., 2010, 2014).

The average degree of spatial dependence (DSD) of the variograms of MS (0.15) and clay content (0.24) can be classified as strong, characterized by the $C_0/(C_0 + C_1) \leq 0.25$ ratio; for BS, DSD value (0.60) can be classified as moderate ($0.25 < C_0/(C_0 + C_1) \leq 0.75$). According to Cambardella et al. (1994), the strong spatial dependence of soil properties is related to its interaction with intrinsic factors (parent material, climate, and relief) whereas the moderate spatial dependence is attributed to extrinsic factors such as the management of agricultural practices. These results confirm those observed in Table 2, in which the influence of geology, geomorphology, and pedology is found for MS and clay content whereas the BS variability can be attributed mainly to agricultural management (anthropic factor).

Variographic models that use information about geology and geomorphology presented the highest average values of range for MS (1924 and 1914 m, respectively) and clay content (1968 and 1946 m, respectively). The highest spatial continuity observed (higher range value of the variogram) is due to the increased capturing of spatial variation by means of these stratifiers and relative data homogenization due to a higher spatial continuity of these compartments. The difference between the average range values with and without secondary information indicates the capturing of variation or the variation fraction due to stratifier factors. Thus, geological information is responsible for about 45% and 54% of the spatial variation of MS and clay content, respectively. Geomorphology, in its turn, accounts for about 44% and 53% of the spatial variability of MS and clay content, respectively.

The information of pedological mapping units promoted a decrease in the average values of range for MS and clay content (841 and 857 m, respectively). Thus, these mapping units promote rather than reduce an increased spatial variation of models by 37% and 33% for MS and clay content, respectively. This result contrasts with that observed in Table 2, in which pedological mapping units contribute to the reduction of CV values. This result indicates that although the pedological map (at scale 1:12,000) identify regions with similar properties, its delineation is not appropriate to compose spatial models.

Maps of pedological mapping units or taxa are delimited by means of the tacit knowledge of pedologists (Hudson, 1992) and aim to

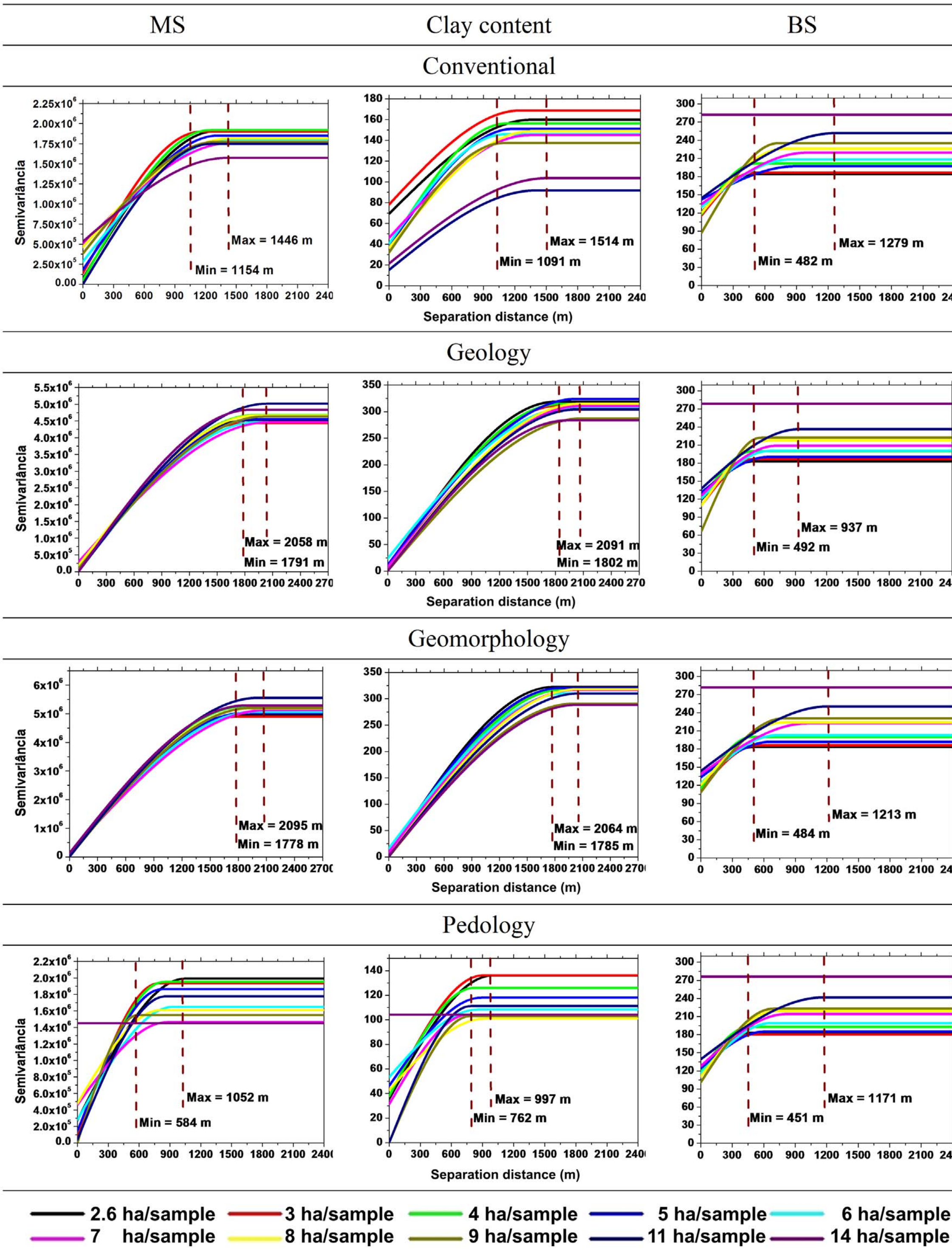

Fig. 2. Variogram models adjusted to the magnetic susceptibility (MS), clay content, and base saturation (BS) data at sampling densities as a function of the used stratifiers. Dashed lines indicate the highest (Max) and lowest (Min) range found among the assessed sampling densities.

minimize the variance within classes and maximize the variance between mapped classes (Castrignanò et al., 2009). This knowledge is based primarily on soil-landscape paradigm and local geological information (Hudson, 1992). Although this information includes the main factors responsible for soil property variability, direct information on their spatial continuity is often ignored at delineation time. Several authors (Burrough, 1991; McBratney et al., 2000, 2003; Legros, 2006) have proposed the inclusion of knowledge on spatial variability of soil properties for composing maps of mapping units. On the other hand, geological and geomorphological limits are easily identified in the field and even somewhat detailed maps (geological map with a scale of 1:500,000 and geomorphological map with a scale of 1:100,000) express variability classes of properties in the field (Vidal-Torrado et al., 2005).

For BS, all the assessed stratifier agents promoted a spatial variation, resulting in an increase of about 19% (geology), 4% (geomorphology), and 14% (pedology). This fact confirms again that the anthropic management is the main active factor in the spatial variation of this property.

The influence of different sampling densities can be observed by the difference between models and parameters of variograms of each property (Teixeira et al., 2013). Models with no secondary information presented higher variation in their parameters (C_0, $C_0 + C_1$, and range) as a function of the studied sampling densities. This result indicates that the use of secondary information may soften the effects of reduced sampling density. The ideal sampling density for soil properties is the focus of several studies due to its key role for planning and, especially, enabling the local variability characterization of soil properties for different purposes (Kerry et al., 2010; Bilgili et al., 2011; Nanni et al., 2011; Montanari et al., 2012; Cherubin et al., 2014; Siqueira et al., 2014).

In general, the lowest values of range and C_0 were found for the highest sampling densities (one point every 2.6 and 3 ha) and the highest values were found for the lowest sampling densities (one point every 7 and 11 ha). Other researchers (Bilgili et al., 2011; Nanni et al., 2011; Teixeira et al., 2013) found this same trend. The value of C_0 indicates the non-captured variation by spatial dependency structure, being the result of the sum of variations due to measurement errors and from variations existent at a smaller scale than the assessed (Oliver and Webster, 2014). The low increase in range values as sampling density decreases is due to the higher initial spacing between samples. In addition, the increase in the number of points and reduction in the spacing between samples promote a greater capture of structural variability, resulting in lower C_0 values.

Spatial patterns of MS, clay content and BS estimated for the density of one point every 2.6 ha without considering the information of stratifiers are shown in Fig. 3. Spatial patterns of MS and clay content were similar ($r = 0.913$, $p < 0.001$), with higher values at the top right of the map, which is the region that represents the geology SG, convex geomorphology, and the soil classes LVef and LVdf. The lowest values can be observed at the bottom of the map, which represents the region located mainly on the geology ECD and soil mapping unit RQod. These results confirm those reported in Table 2. The high association between MS and clay content, also reported in other studies (Hanesch and Scholger, 2005), is due to the fact that the studied soils are highly weathered and originated from parent materials with the presence of Fe while facilitating the formation of clay and iron oxides with magnetic expression potential.

At the center of the maps of MS and clay content, located on the geological transition AD/ECD, a marked influence of geomorphology is observed. This transition may be considered relatively softer than the transition SG/ECD due to the greater similarity between parent materials. Fürst et al. (2010), assessing the spatial estimation of MS through covariates and multiple regression analysis, observed that geomorphological parameters presented a greater contribution to the models at larger scales whereas geological parameters presented a greater contribution at smaller scales.

At the top of the maps of MS and clay content, the spatial continuity is higher in the latitudinal direction (east–west). This direction coincides with the higher spatial continuity presented by mapping units in the pedological map (Fig. 1). Thus, in this region, the influence of mapping units can be observed in the values of MS and clay content, as observed in Table 2. However, the boundaries of mapping units and spatial patterns of MS and clay content do not coincide precisely in space, indicating the spatial loss of this relationship. This result was previously indicated by variographic analysis (Fig. 2), in which the stratification by means of soil mapping units promotes a decrease in spatial continuity of the analyzed properties.

The spatial patterns of BS presented linear correlation values of -0.20 ($P < 0.001$) and -0.23 ($P < 0.001$) with the spatial patterns of MS and clay content, respectively. Other authors (Siqueira et al., 2010; Matias et al., 2014) also observed this inverse relationship. These results are due to the inverse relationship between BS and CEC, the latter being directly dependent on quality and quantity of clay and soil organic matter in the soil.

The highest BS values are concentrated mainly on the right side of the map, which is a region characterized by geology SG and soils LVef, LVdf, and RQod. Although at all stages of this study the stratification of BS has promoted a low reduction in CV values (Table 2) when geological compartments were considered, its spatial pattern indicates that this stratifier may present itself as a contributing factor to BS values. Liu et al. (2013) studied the spatial variation of soil nutrients in agricultural areas and observed their spatial relationship with geology only on assessments at a large scale whereas at more detailed scales soil management was the main conditioning factor of variability. Spatial patterns of BS present more continuity in the latitudinal direction of the map, which is the direction of the sugarcane row and other agricultural practices. Panosso et al. (2012) also observed this lower variation in chemical properties in the direction of sugarcane row.

The quality of spatial estimates as a function of the different assessed densities and the use of secondary information is presented in Fig. 4. Analyzing the RRMSE indexes, greater variations of MS are observed, followed by clay content and BS depending on the reduction of sampling density and incorporation of secondary information, being these results similar to those found by Siqueira et al. (2014). When associated with auxiliary information, MS presented higher gains in representing the spatial continuity because this property is highly responsive to pedoenvironmental changes such as those related to geology (Fialová et al., 2006) and landscape shape (Jong et al., 2000).

For MS, the stratifiers (geology and geomorphology) positively contributed for capturing the spatial variation. These contributions are evidenced only at densities lower to one point every 5 ha. The lack of contribution to higher densities is because the intense sampling can reproduce the limits of isolines accurately, even those due to stratifier factors. Sanchez et al. (2013) studied the spatial variation of physical and chemical soil properties in coffee areas at a density of one point every 4 ha and found that an intense sampling led to isoline capture due to geomorphological limits. Some authors have proposed the use of

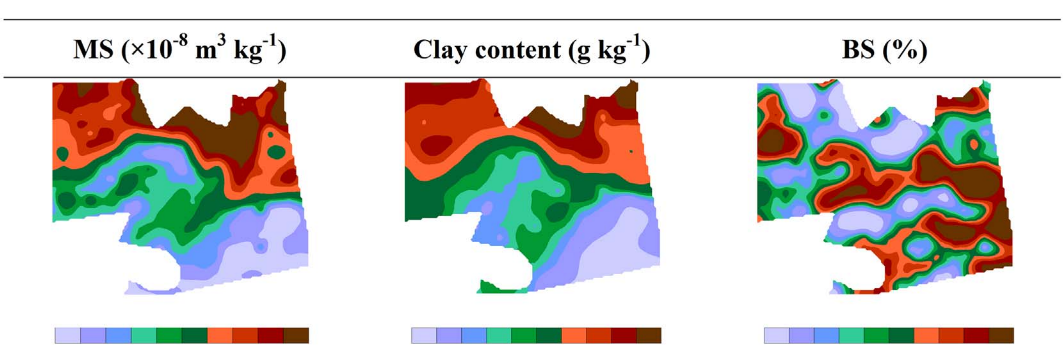

Fig. 3. Spatial pattern of magnetic susceptibility (MS), clay content, and base saturation (BS) at a density of one sample every 2.6 ha without considering secondary information. Class intervals were identified according to data percentile.

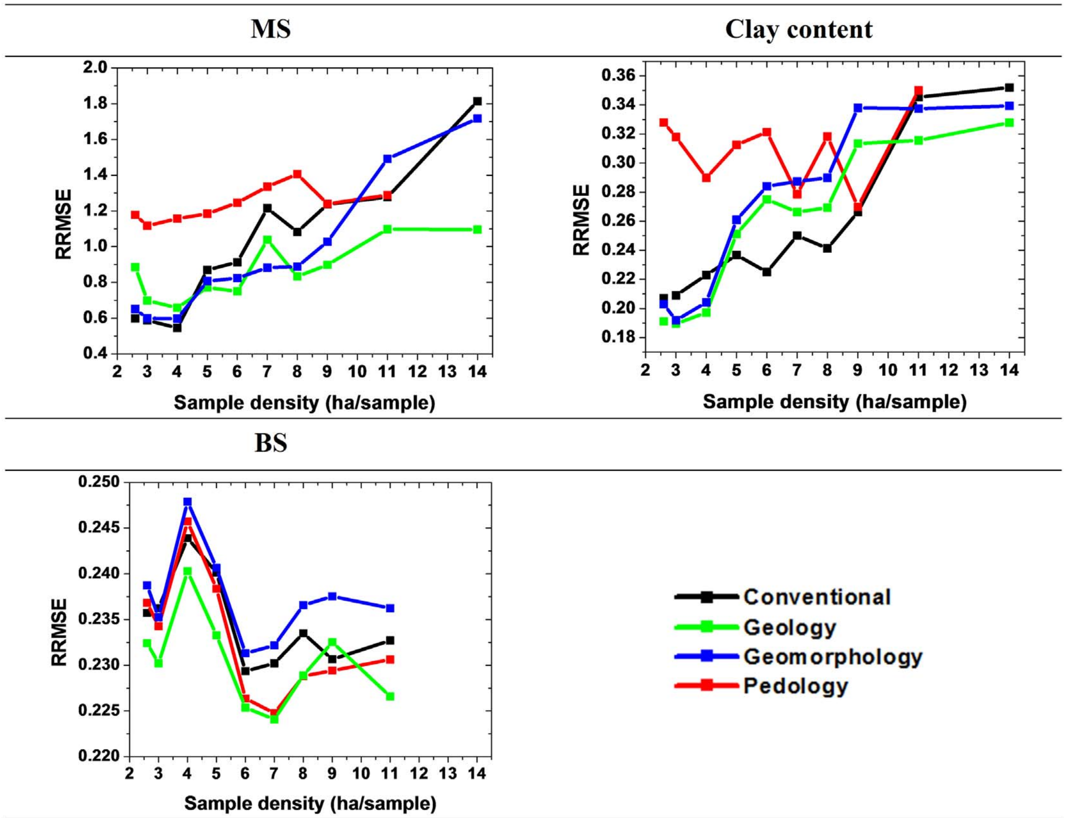

Fig. 4. Relative root mean square error (RRMSE) estimated from the external validation as a function of the assessed densities with and without (conventional) the use of secondary information (geology, geomorphology, and pedology).

intensive sampling for capturing and understanding the spatial variability of properties and mapping units (Minasny and McBratney, 2007; Silva et al., 2014). However, the costs of such studies hamper their use in large areas (Demattê et al., 2007).

The use of stratifiers in modeling MS promoted an increase in the accuracy of estimates, which ranged from 11.3% (one sample every 5 ha) to 39.6% (one sample every 14 ha) for geology and from 5.4% (one sample every 14 ha) to 27.3% (one sample every 7 ha) for geomorphology. The use pedological information, in its turn, promoted a decrease in the accuracy of estimates at all the assessed sampling densities, ranging from 0.2% (one sample every 9 ha) to 112.0% (one sample every 4 h). The greatest contribution of geology contrasts to its smaller scale (1:500,000) when compared to the other maps (geomorphology with a scale of 1:100,000 and pedology with a scale of 1:12,000). However, in regions with the presence of litosequence, geology represents the main effect on soil magnetic properties (Fialová et al., 2006; Yang et al., 2016). The composition of parent material (chemistry, mineralogy, texture, and permeability) and its structure (bedding, vertical and lateral variations of layers, and fractures) guide landscape evolution, being the relief characteristics a response to this factor (Huggett, 2007). Thus, part of the variability promoted by the transition between landscape shapes can also be expressed by geological transition (Sinowski and Auerswald, 1999; Brevik and Miller, 2015).

In addition, the spatial patterns of the sampling density of one sample every 5 ha, without considering auxiliary information, and a density of one sample every 8 ha, considering the geology in the modeling process, present similar results for MS. This indicates the possibility of reducing by 37% the number of samples without changing the accuracy of map obtained through the incorporation of secondary information of open access (GEOBANK, 2014, available on http://geobank.sa.cprm.gov.br). In its turn, the use of information on geomorphology at a density of one sample every 9 ha presents a similar accuracy to the density of one sample every 5 ha without secondary information, indicating the possibility of reducing by 44% the samples necessary for modeling. According to Demattê et al. (2007), the great number of samples needed to characterize agricultural areas at a detailed level can derail the application of techniques such as the precision agriculture. McBratney et al. (2002) state that data collection is the most difficult and costly stage in the process of soil modeling. Thus, techniques that allow the reduction of sampling density have an important research activity (Kerry et al., 2010; Bilgili et al., 2011; Teixeira et al., 2013; Siqueira et al., 2014; Brevik et al., 2016; Mirzaeitalarposhti et al., 2017). In addition, this type of information can mark out the collect planning of soil samples for locations without detailed knowledge of variability or locations that require a higher level of details.

For clay content, the incorporation of auxiliary information promoted smaller gains in accuracy when compared to those reported for MS (Fig. 4), ranging from 6.9% (one sample every 14 ha) to 11.6% (one sample every 4 ha) when geological information is considered and from 2.1% (one sample every 2.6 ha) to 8.4% (one sample every 4 ha) when considering the geomorphological information in the modeling process. A similar accuracy can also be observed between spatial patterns at the sampling density of one sample every 2.6 ha without considering auxiliary information and at a density of one sample every 4 ha using the geological and geomorphological information, indicating a reduction by 35% in the number of collected samples without changing the accuracy of the obtained map.

These results contradict the great similarity between the spatial patterns (Fig. 3) and between the variograms (Fig. 2) of these properties due to the incorporation of auxiliary information. Castrignanò et al. (2009) found no differences between the accuracy of clay maps when topographical and pedological information (soil mapping units) were considered. Benedetto et al. (2012) used auxiliary information from two geophysical sensors (ground-penetrating radar and electromagnetic induction) to predict soil clay content. However, these authors failed to capture a large portion of clay variability, demonstrating the great complexity of this property. Hengl et al. (2014), when mapping soil properties on a global scale by means of models with secondary information, found that the texture properties are more difficult to map than physical and chemical soil properties. However, models that consider auxiliary information and provide results similar or slightly lower than those presented by other models that not consider it may have a greater potential of use for the composition of environmental models (Odeh et al., 2007).

The difference between variable responses (MS and clay) due to the incorporation of auxiliary information is related to (i) lower variability of clay content in relation to MS (Table 1), resulting in a lower response to compartment changes; (ii) greater influence of surface entrainment of clay, promoting a relative homogenization of its contents in transition regions between compartments; and (iii) higher error involved in its determination in the laboratory. According to Cantarella et al. (2006), particle size analyses present errors ranging from 15 to 32% in Brazilian laboratories. In contrast, MS determination presents a more accuracy for being a simple, fast, and secure methodology (Dearing, 1994). Therefore, due to the high correlation between these variables and the high error in determining clay content, the use of MS in determining clay content can be an interesting alternative technique to decrease the overall error (Siqueira et al., 2010; Peluco et al., 2013).

Small differences were observed between spatial patterns of BS before and after considering the information from stratifiers. This small influence also indicates that the anthropogenic factor is the promoting and/or controlling agent of the variability of this property. Holmes et al. (2005) assessed the multi-scale variability of nutrients in tropical soils and found that the change in soil use is the main active factor in the variability at a large scale.

Due to the higher geology contributions found at all stages of this study, especially in relation to MS and clay content, this might be the main factor controlling the variability of the assessed properties. Although in this study this high association is used to provide information aiming at mapping soil properties, in some cases the reverse path can be followed. Brevik and Miller (2015) pointed out that information on soil spatial patterns can be used in geological mapping when at detailed scales, producing maps with a more accuracy and less use of resources and time than traditional methodologies.

The results found in this study present a potential to be extrapolated to about 44,000 ha of the São Paulo State, Brazil (Siqueira et al., 2014), which have the same geological transition discussed in this study, and also to other regions with similar geological transitions. In addition, for regions with large geological transitions, their spatial continuity and limits could present greater influence on the spatial variability understanding of soil properties than the limits of geomorphological and pedological compartments (Nanni et al., 2011; Liu et al., 2013; Matias et al., 2014; Yang et al., 2016). However, for regions with a soft geological transition or under the same geology, the limits of geomorphological compartments could describe more precisely the variability of soil properties (Siqueira et al., 2010; Sanchez et al., 2013).

Recently, Hengl et al. (2014) proposed a first approach to the global mapping of some properties and mapping units with a resolution of 1 km. However, despite the high-resolution map presented by the authors, the low validation values for some properties and the scarcity of soil information at detailed scales for regions in Asia, Africa, and Latin America indicate that the regional or local models still need to be developed (Grunwald, 2009). In this sense, the results presented in this study can assist in identifying the variables used as secondary information for mapping soil properties at regional and local scales, as well as provide information for sample planning of soil properties and further details of spatial estimates.

4. Conclusions

The use of auxiliary information reduces the effect of reducing the sampling density of soil properties. Incorporating geology and geomorphology information into MS and clay content estimates reduce the number of samples required for an accurate spatial representation and it should be considered at the time of sample planning. For BS, the incorporation of this information does not provide a reduction in sampling density. The greatest gains in MS spatial continuity in relation to clay content and BS, when auxiliary information is considered, are due to its high response to pedoenvironmental changes such as those caused by geological and geomorphological transitions.

The pedological information allows identifying regions with similar properties, but its delineation is not adequate to compose spatial models. This reinforces the need to include the information about the spatial variability of soil properties in the composition of maps of mapping units.

The results presented in this study may assist in determining sample planning for locations without prior knowledge of variability, as well as assist in detailing the variability of studies at small scales that require local or regional sample planning.

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