GEOMORPHOMETRIC SEGMENTATION OF COMPLEX SLOPE ELEMENTS TO CONTRIBUTE TO DETAILED DIGITAL SOIL MAPPING IN SOUTHEAST BRAZIL

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ABSTRACT

Hillslope elements have considerable potential in predicting soil attributes and types in the landscape, making them likely to be a useful basis for detailed soil mapping. The goal of this research was to apply a previously developed digital hillslope position (DHP) model, calibrate it as needed to a Brazilian landscape, and test its utility as a basis for identification of detailed soil map units. The study area covers 2,500 ha and is located on the border between the municipalities of Piracicaba and Santa Bárbara d'Oeste, São Paulo state, Brazil. A digital elevation model (DEM), with spatial resolution of 5 meters, was used to obtain slope gradient, profile curvature and relative elevation with different analysis scales. Hierarchical rules for these digital terrain derivatives were used to segment the landscape into hillslope positions. The user-calibrated hillslope position model was verified against local experience by identifying the hillslope position in the field and comparing it with the model classification using the Kappa statistic and a confusion matrix. Soil samples were collected across multiple hillslopes with different lithologies. The samples were analyzed for chemical composition and particle size distribution. The measured soil properties were assessed for statistical significance by variance analysis among hillslope position, parent material, and the interaction between the two. Student’s t-tests were performed iteratively across each hillslope position within a given parent material to identify specifically which soil properties were significantly different among the hillslope position map units. Variance analysis of soil samples located within the respective parent material map units identified significant differences for all soil properties measured, but only for some soil properties when categorized by DHP. Focusing on the parent material with a sufficient quantity of samples, there was always at least one hillslope position that was significantly different from the others for each soil property.

Because each of these map units presented a significant difference in at least one soil property, they are useful for detailed soil mapping.

Keywords: digital terrain analysis; decision tree; hillslope elements; map units; soil property; Oxisols

1. Introduction

The goal of soil mapping is to communicate as much soil variation in the landscape as appropriate for the map scale. Because soil profile properties cannot be observed directly from above ground, soil maps have an assemblage of areas of the same nature, known as map units (Legros, 2006), that associate sets of soil profile properties with features that can be delineated from more readily observable information. Therefore, the challenge is to find the best basis for identifying the map units to differentiate the variation of soil properties in the landscape.

There are only exploratory or reconnaissance soil maps covering most of the Brazilian territory and soil types corresponding to the soil series concept are not yet established (Lepsch, 2013; Carvalho et al., 2015). Because of the available soil maps' coarse cartographic scale, they are not useful for farming and civil engineering management decisions at field or catchment scales (Sanchez et al., 2009). Only 0.25% of the Brazilian territory is covered by 1st or 2nd order soil maps (scale ≤1:35,000) (Carvalho et al., 2015; Mendonça-Santos and Santos, 2007). This coverage is much less than other countries of similar size, such as the USA, where the National Cooperative Soil Survey (NCSS) has mapped the soils of nearly every county at the 2nd order scale (1:15,840 - 1:24,000), identifying map units at the soil series level.

These soil maps were produced from a combination of soil-landscape relationships based on the tacit knowledge of field experienced pedologists, with field observations and point measured soil properties (Hudson, 1992). Because this knowledge is based on the mapper's experience, it is not explicit for other mappers and it is difficult to quantify and reproduce for detailed scale (Shi et al., 2009). Although the soil-landscape paradigm has been a useful qualitative predictor of similar soil forming environments (Hudson, 1992), the many quantitative relationships between soil profile attributes and environmental covariates have yet to be fully elucidated.

Slope gradient and profile curvature are known to affect the soil attributes' spatial distribution (MacMillan et al., 2000; Mohammadi et al., 2016; Park et al., 2001; Pennock, 2003). However, these digital terrain derivatives do not always appear to correlate with soil properties as expected. This potential mismatch is likely due to the wrong analysis scale being selected for analysis, among other things (Drăguţ et al., 2009; Miller, 2014). A way to improve this situation is to document and make explicit all aspects of defining landscape features mapped according to the tacit knowledge acquired over the years by soil survey experts (Bathgate and Duram, 2003). Thus, a quantitative approach to generate and store information of the landscape characteristics would be useful for soil mapping in an objective, consistent, updatable, and reproducible method.

Among the detailed landscape features, hillslope elements have considerable potential to predict the soil attributes and types because they identify functional zones in the context of water and sediment flow in a landscape (Gerrard, 1992; Ruhe, 1960; Ruhe and Walker, 1968; Wysocki et al., 2011). Hillslope position as defined by Ruhe (1960) and Wysocki et al. (2011) consists of five elements: summit, shoulder, backslope, footslope, and toeslope. Summits and shoulders are located in the highest part of a hill. Backslopes are zones of transport where materials are removed and transported through the most inclined part to the lower hillslope elements, which are the footslopes and toeslopes (Wysocki et al., 2011). In certain geomorphic conditions, some hillslope elements may be absent and/or occur in an alternating pattern, such as a footslopes below a shoulder, lacking a backslope in between. An example of this type of hillslope element pattern is observed when complex slopes are mapped with a high level of detail (Figure 1) (Wysocki et al., 2011).

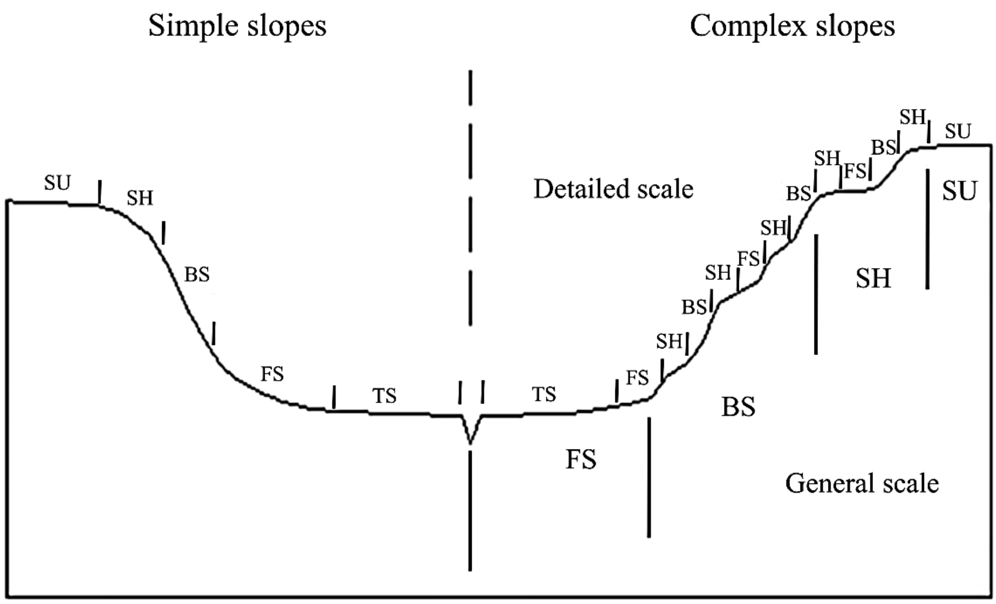

Figure 1. Diagram of simple slopes *versus* complex slopes based on the hillslope position model by Ruhe (1960) (after Wysocki et al., 2011). SU: Summit, SH: Shoulder, BS: Backslope, FS: Footslope, and TS: Toeslope.

Several studies have carried out a quantitative categorization of general landscape features (Burrough et al., 2000; Cunha et al., 2018; Drăguţ and Blaschke, 2006; Drăguţ and Dornik, 2016; Etzelmüller et al., 2007; Iwahashi and Pike, 2007; Jasiewicz and Stepinski, 2013; Jasiewicz et al., 2014Vannametee et al., 2014;), and some others at the sub-landform or hillslope scale (Gökgöz and Baker, 2015;

MacMillan et al., 2003; Qin et al., 2009; Zhu et al., 2018). In this regard, Miller and Schaetzl (2015a) captured the tacit knowledge of soil scientists to quantify the analysis scales and thresholds of the digital terrain derivatives equivalent to soil scientists' assessment of hillslope position in the field. This digital hillslope position (DHP) model used slope gradient, relative elevation, and profile curvature at different analysis scales to apply the hillslope position concept to a digital elevation model (DEM). The validation of this model showed 59% agreement between soil scientists' field assessments and the final DHP model's prediction, which was considered reasonable given the potential variability between different soil scientists.

The digital segmentation of hillslope elements is promising for soil mapping for several reasons, among them: (a) consistent selection of representative sites for morphological description and collection of soil samples (Drăguţ and Dornik, 2016; Park and Van De Giesen, 2004; Yang et al., 2012; Zhu et al., 2008; Zhu et al., 2010), (b) delineation of mapping units (Moravej et al., 2012), (c) disaggregation of complexes in the soil map units with more than one soil type, improving both the detail and the applicability (Miller and Schaetzl, 2015a; Odgers et al., 2014), and (d) support in the prediction of soil properties in areas that present similarity of soil formation factors, highlighting both parent material and relief (MacMillan et al., 2000; Pennock and Corre, 2001).

The goal of this research was to calibrate the DHP model developed by Miller and Schaetzl (2015a) as needed for a Brazilian landscape. After that, this model was tested to verify its effectiveness for identification of detailed soil map units.

2. Methods

2.1 Location and characterization of the study area

The study area covers 2,500 ha and is located on the border between the municipalities of Piracicaba and Santa Bárbara d'Oeste, São Paulo state, Brazil. The climate is classified as Cwa in the Köppen classification system, which is characterized by a humid subtropical mesothermic temperature regime with dry winters between June and August, and rainy summers between November and January (Alvares et al., 2013). The area is mostly cultivated with sugarcane, with some remnants of native vegetation and exotic species such as Pinus and Eucalyptus trees.

The area is geomorphologically located within the Paulista Peripheral Depression, which has an area approximately 100 km wide and 400 km long (Bigarella et al., 1965; Penteado, 1969). Parent materials are from members of the Irati, Tatuí, and Itararé formations (Figure 2) (Vidal-Torrado, 1994). During the Upper Neogene and Quaternary periods, unconsolidated clayey sediments recognized as from the Rio Claro Formation (Neo-Cenozoic coverage) were deposited in the study area from other parts. These sediments were reworked and subjected to pedogenesis cycles that occurred during the semiarid phases in Brazil, coinciding with the Late Pleistocene glacial periods of North America (Penteado, 1969). These clayey superficial deposits remain on summits, at altitudes around 600-630 meters (Penteado, 1976), and correspond to thick depositions (from five to ten meters), mainly with soils classified as Oxisols (polygenetic soil) (Vidal-Torrado et al., 1999). This area was selected for this study because of its diversity of parent material and geoforms. Another reason for selecting this area was the availability of a geologic map at the scale of 1:25,000 (Figure 2), which allowed us to compare the variation of soil attributes between hillslope positions within areas mapped as the same parent material.

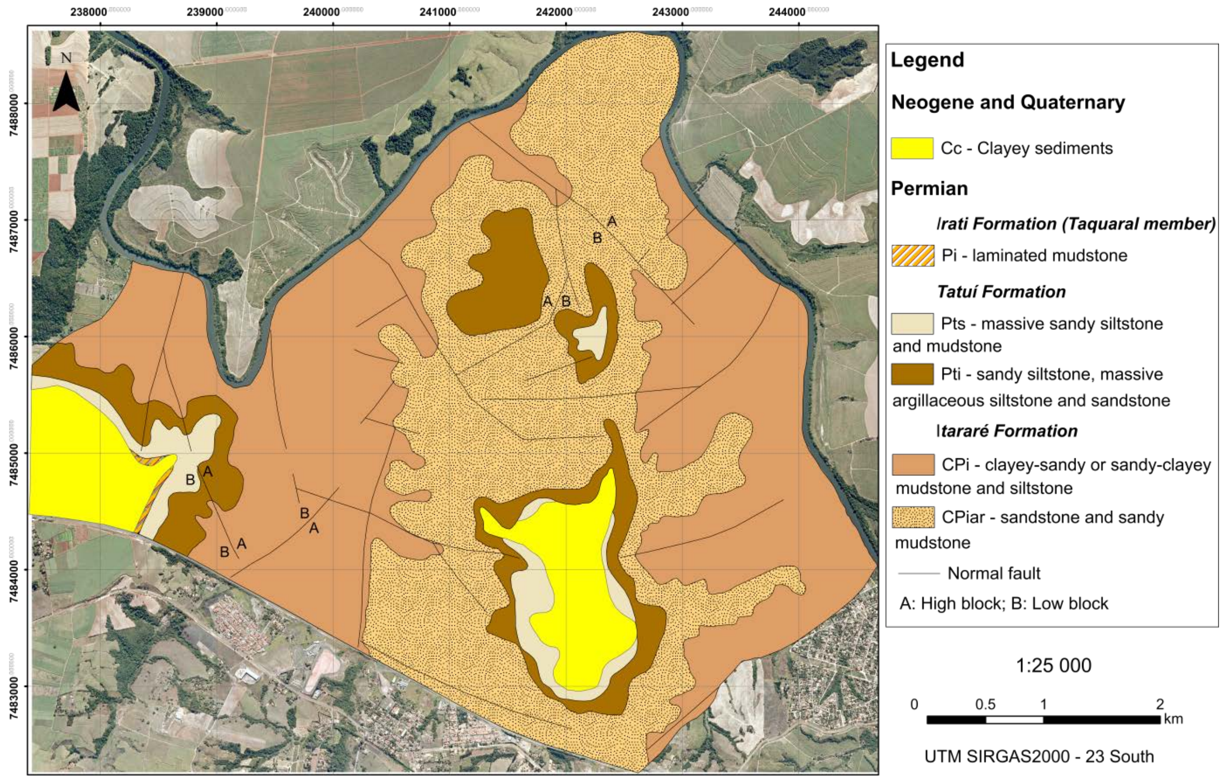

Figure 2. Geologic map of the study area (after Vidal-Torrado, 1994).

2.2 Digital segmentation of hillslope position at a detailed level by digital terrain analysis

Contour lines with 5-meter equidistance and specific elevation at some points were digitized from planialtimetric maps at the 1:10,000 scale obtained from the Geographic and Cartographic Institute of the São Paulo state. These data were interpolated to obtain a DEM with spatial resolution of 5 meters in GRASS GIS 7.0.4 (Geographic Resources Analysis Support System, 2015). The interpolation method used was the Regularized Spline with Tension, because it is considered to be the most suitable for vector data (Mitášová and Hofierka, 1993; Neteler and Mitášová, 2008).

The resulting DEM was used to obtain the following digital terrain derivatives: slope gradient and profile curvature with an analysis scale of 15 m (3x3 neighborhood) and 65 m (13x13 neighborhood), respectively (Miller, 2014), using the r.paramscale function in GRASS GIS. Relative elevation was calculated with the analysis scale at 435 m (87x87 neighborhood), using ArcGIS 10.3, per the equation proposed by Miller (2014). Instead of the 135 m analysis scale for relative elevation proposed by Miller (2014), the analysis scale was adjusted for this study based on comparison between field observations and the results obtained with different analysis scales for relative elevation. These digital terrain derivatives were selected and used because of their ability to provide a hillslope position segmentation based on their geometry and semantics, *i.e.* they express both the shape and the position of these elements in the landscape, and they are the most similar to the terrain variables used in pedologists' mental model in the field (Miller, 2014; Miller and Schaetzl, 2015a).

The hillslope position segmentation follows the DHP model of Miller and Schaetzl (2015a), in which hierarchical rules were used with the three digital terrain derivatives described above. The rules established in the decision tree started with slope gradient, subdividing it into: high (>6.4°), medium (1.4° - 6.4°), and low (<1.4°). Subsequently, the medium slope gradient was subdivided, considering the slope shape, into: convex (positive values) and concave (negative values). Likewise, the low slope gradient was subdivided by relative elevation into: high (positive values) and low (negative values) (Figure 3). The original DHP model was calibrated to landscapes in the Central Lowlands of the USA and had a threshold between medium to high slope gradients at 2.9º. To adapt the DHP model to the Brazilian landscape, the upper threshold of slope gradient was adjusted to 6.4º based on standard values used in the Brazilian soil survey. This adjustment was not necessary for the lower threshold, since it already corresponded to the one used in the Brazilian soil survey (Santos et al., 2015).

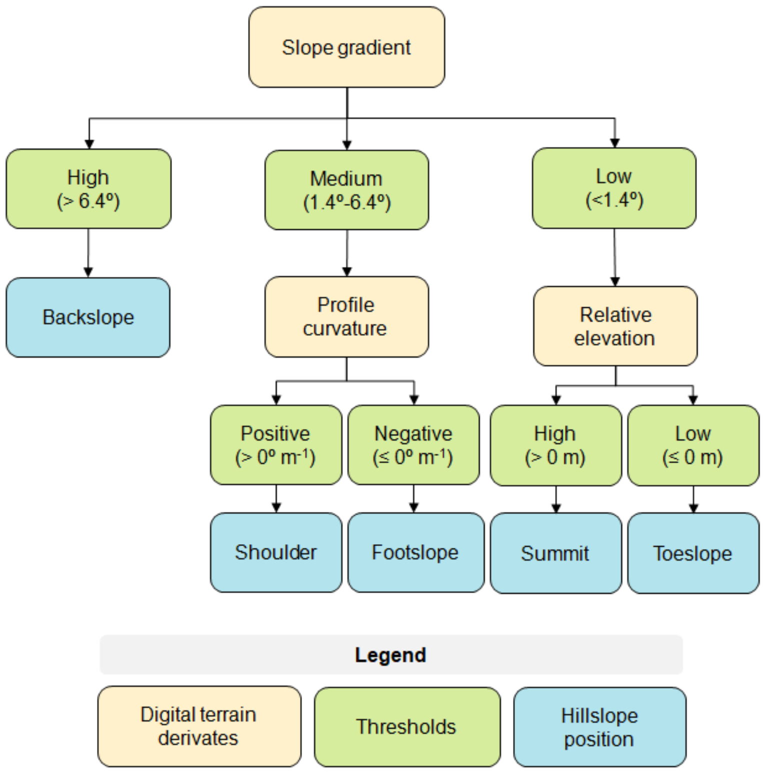

Figure 3. Decision tree used to segment the hillslope position through digital terrain derivatives (after Miller and Schaetzl (2015a).

The indicated sequence of the decision tree may not necessarily correspond to all aspects of the pedologist's thought process, since many of them can determine the hillslope position more by intuition than a stepwise decision process. However, Miller and Schaetzl (2015a) observed that this model performed consistently well in three different landscapes, supporting what King (1957) considered as the uniformitarian nature of hillslopes. Nonetheless, the need to calibrate the model in different landscapes cannot be ruled out. For example, this DHP model assumes that all areas with a slope gradient greater than 6.4° should be classified as a backslope, which is associated with linear curvatures. This may or may not be the case for different landscapes for multiple reasons, such as the possibility that physical properties of different parent materials may affect slope shape stability.

2.3 Validation of the hillslope position digital map

The validation of the hillslope position digital map was performed by the identification of the hillslope position through several field observations and their comparison with the user-calibrated model prediction. For this, a concordance analysis was performed, which includes the Kappa statistic (K) (Eq. 1) and its standard error, along with analyzing the confusion matrix that includes the global, producer's, and user's accuracy.

$$K = \frac{N\sum_{i=1}^{r} Xii - \sum_{i=1}^{r}(X_{i+} \ * \ X_{+i})}{N^2 - \sum_{i=1}^{r}(X_{i+} \ * \ X_{+i})} \qquad \text{Eq. 1}$$

Where: N is the total number of observations, r is the number of lines in the matrix, xii is the number of observations in the line i and row i, respectivelly, and x_{i+} and x_{+i} are the total quantity in the line i and row i, respectively.

The Kappa statistic is a measure of interobserver agreement that quantifies the degree of agreement beyond what would be expected by chance alone. This measure has a maximum value of 1, representing total agreement, and minimum values close to or below 0, which indicates no agreement or a level of agreement that would be expected by chance (Table 1) (Agrestini, 2007; Landis and Koch, 1977). A total of 191 field observations were recorded by GPS to carry out this validation, covering all the positions on multiple hillslopes and different lithologies.

Table 1. Values of the Kappa statistic for assessing the degree of agreement (after Landis and Koch, 1977).

Kappa statistic	Degree of agreement

<0.00	Poor
0.00 – 0.20	Slight
0.21 – 0.40	Fair
0.41 – 0.60	Moderate
0.61 – 0.80	Substantial
0.81 – 1.00	Almost perfect

2.4 Soil sampling and analysis

A total of 96 soil surface (0-20 cm) samples were collected with an auger on selected sites to cover both the five hillslope elements on multiple hillslopes and different lithologies present in the study area. Sample locations included 26 sites on summits, 28 on shoulders, 17 on backslopes, 17 on footslopes, and 8 on toeslopes. These soil samples were air-dried, sieved (2-mm mesh), and analyzed. Chemical analyses consisted of pH in water and exchangeable cations. Aluminum (Al^{3+}), calcium (Ca^{2+}), and magnesium (Mg^{2+}) were extracted by KCl solution 1 mol L^{-1}, which Ca^{2+} and Mg^{2+} were quantified by atomic absorption spectrophotometry and Al^{3+} by titration with NaOH solution 0.025 mol L^{-1}. Sodium (Na^{+}) and potassium (K^{+}) were extracted by Mehlich-1, which were quantified by flame photometry. Potential acidity (H + Al) was extracted by calcium acetate solution 0.5 mol L^{-1} at pH 7 and determined by titration with NaOH solution 0.025 mol L^{-1}. These analyses were performed according to current Brazilian Soil Survey methods (EMBRAPA, 2011). These results allowed calculating the cationic exchange capacity at pH 7.0 ($CEC = Ca^{2+} + Mg^{2+} + K^{+} + Na^{+} + H^{+} + Al^{3+}$), and base saturation ($V = [Ca^{2+} + Mg^{2+} + K^{+} + Na^{+}/CEC]*100$). Analysis of particle size by soil separates was performed according to Gee and Or (2002), where clay fraction (<0.002 mm) was measured by the hydrometer method, total sand fraction (2 - 0.05 mm) by sieving, and silt fraction (0.05 - 0.002 mm) obtained by the difference. The dispersing agent used was a mixture of sodium hexametaphosphate 0.1N and sodium hydroxide 0.1N. These soil analyses were selected because they are the primary tests used for soil classification according to the Brazilian Soil Classification System (EMBRAPA, 2013).

2.5 Evaluation of hillslope position’s effectiveness to identify detailed soil map units

The purpose for any kind of map unit is to express variation as appropriate to the map scale. Ideally, each map unit should have something different about it with respect to each of the other map units. Given the multi-dimensional characteristic of soil, it is reasonable for some soil map units to be similar or the same in some respects, but different in another. As long as respective map units are significantly different in one soil property of value to the map user, the division is worthwhile.

To evaluate the effectiveness of soil map unit identification based on the DHP calibrated in this study, we expect that samples in the respective DHP delineations should be significantly different for at least one measured soil property. Statistical significance was tested first by variance analysis (ANOVA) to assess if there were significant differences between any of the DHP-based map units for a given soil property.

Parent material is an important factor of soil formation and therefore areas differentiated by geologic map unit should also reflect differences in soil properties. Considering the hierarchy of phenomenon scale recognized by soil scientists, topographic units should sub-divide parent material units (Miller and Schaetzl, 2015b). In other words, topographic processes are modifying parent materials to contribute to the resulting soil pattern. To consider the interaction between parent material and topography, statistical analysis was also conducted on parent material map units and then the two together.

To further explore DHP as a useful subdivision of parent material for soil mapping, student's t-tests were performed iteratively across each hillslope position within a given parent material. To minimize the issue of too few samples in a map unit, this analysis focused on the Itararé Formation (CPi) parent material, where the majority of the soil samples were taken (n=52) because of its greater occurrence in the study area (Figure 2).

3. Results and discussion

3.1 Validation of the hillslope position map

Application of the customized DHP classification model to the study area presented many delineations of hillslope elements (Figure 4). This complexity in the landscape is likely related to the intense degree of dissection in the area, promoted by the proximity to its local base level, *i.e* the Piracicaba River. Local relief reaches approximately 120 meters.

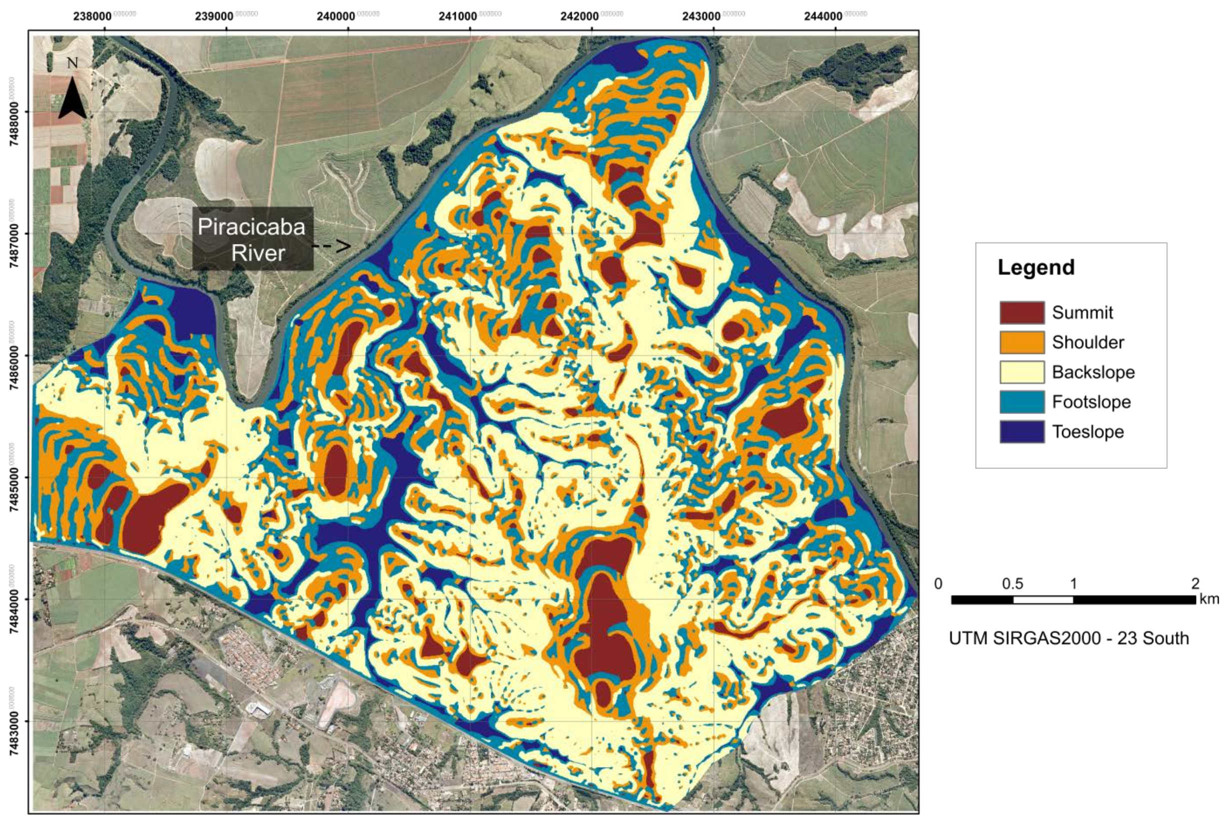

Figure 4. Digital map of the hillslope position obtained from the customized DHP classification model.

The digital segmentation of hillslope position showed a substantially high agreement with the field observations, with a Kappa of 0.7, and a global accuracy of 77% (Table 2). Miller and Schaetzl (2015a), using a similar model to segment hillslope position in Ottawa county, Michigan, USA, obtained a Kappa of 0.49 and global accuracy of 59%. The authors argued that disagreements between model prediction and field observations could be related to the combination of noise in the DEM, positional uncertainty, and the subjectivity associated with human judgment of hillslope position. It is worth noting that the variability in human judgment was reduced in this study by having a few soil scientists working together in the field. Indeed, Dikau (1989) and Williams et al. (2012) also pointed out that tacit and manual categorization of relief units is influenced by the individual's experience in landscape interpretation.

Table 2. Confusion matrix for the validation of the customized digital hillslope position model (Kappa = 0.7 and standard error = 0.04)

		Field observation					
	Hillslope position	SU	SH	BS	FS	TS	User's accuracy (%)
Digital model	Summit	52	1	0	1	0	96
	Shoulder	12	33	3	7	0	60
	Backslope	0	0	38	4	0	90
	Footslope	5	7	0	14	3	48
	Toeslope	0	0	0	1	10	91
	Producer's accuracy (%)	75	80	93	52	77	
	Global accuracy (%)	77					

SU: Summit, SH: Shoulder, BS: Backslope, FS: Footslope, and TS: Toeslope.

In the few places where there were discrepancies in the classification of hillslope position for the present study area (Figure 5), they were likely associated with the data source that generated the DEM. The elevation contour lines were obtained from old planialtimetric maps that were elaborated by an aerophotogrammetric restitution process. Errors may have occurred in this process where the soil surface was covered by some denser and taller vegetation. In these places, the change in the contour lines' value may have promoted errors in the generation of the DEM, which consequently influenced an erroneous calculation of the slope gradient. For example, where there are two extensive and almost flat summits, the slope gradient was erroneously calculated to be greater than 1.4°, due to differences of 5 to 15 meters in the DEM that were observed to not exist in the field (Figure 5). The existence of these false elevation changes in the DEM resulted in the model classifying part of these areas as shoulders or footslopes instead of summits, since the steeper slope gradient calculation moved the classification from the low to the medium slope gradient category (Figure 3).

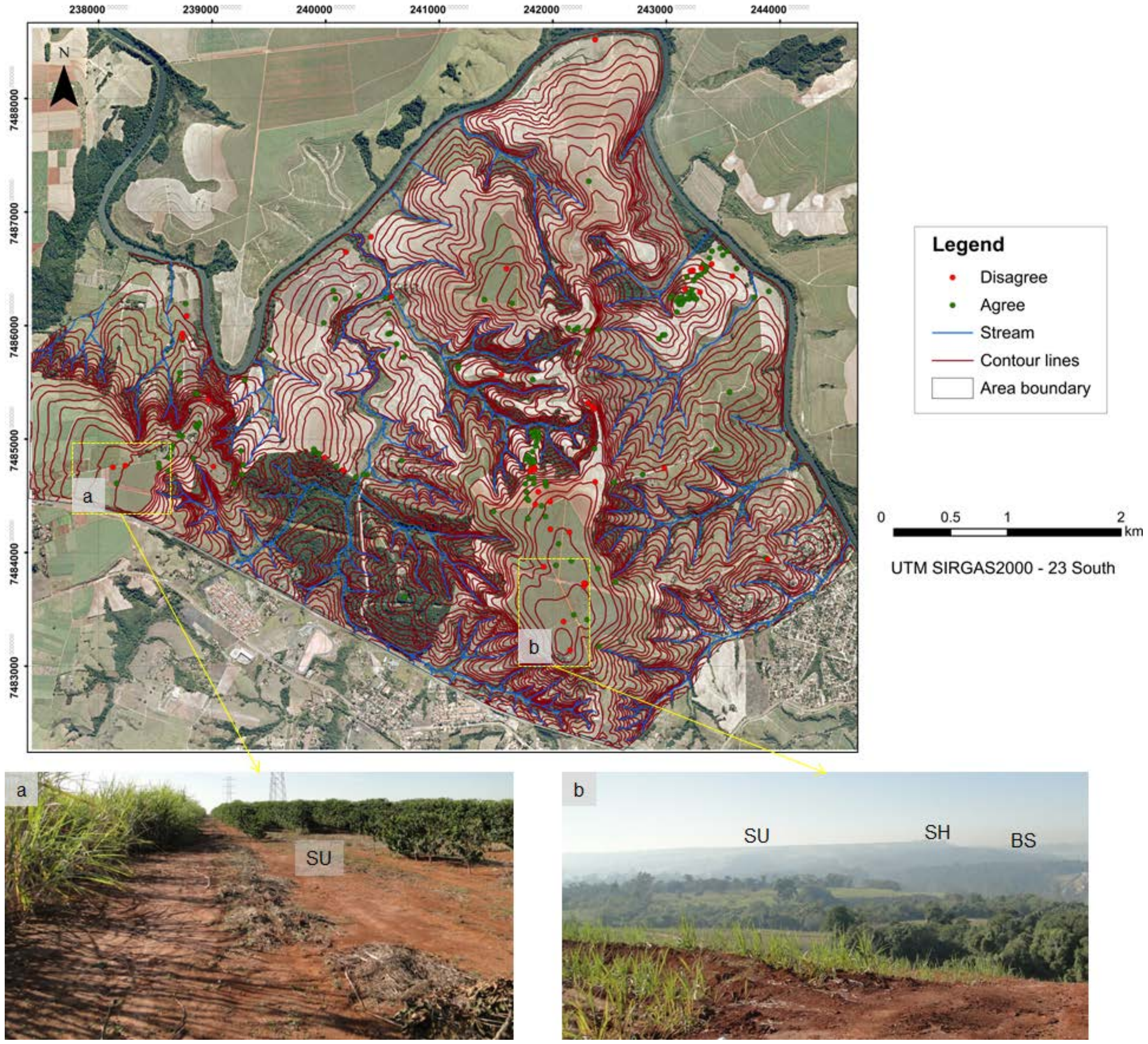

Figure 5. Examples of concordant and discordant points between observations of hillslope position in the field and determined by the DHP calibrated for this study. Several of the discordant points tended to coincide with areas on summits (a) that field observation revealed to not have the relief indicated by the DEM. The landscape in (b) shows that there is a smooth inclination towards the river, but not sufficient to change the type of hillslope element. SU: Summit, SH: Shoulder, and BS: Backslope.

The quality of the DEM depends mainly on the data used for its generation (Hutchinson and Gallant, 2000). Miller (2013) when using LiDAR data (with 3 m spatial resolution) for digital terrain analysis found some "noise" in the DEM such as striped patterns, which they attributed to the orientation of agricultural crop rows. Therefore, even using a DEM obtained from other sources and with higher spatial resolution, there may be other sources of interference for deriving the desired digital terrain attributes.

The DHP model classified some parts of the study area as shoulder and footslope alternations (Figure 4), which could not be confirmed explicitly in the field. These parts can be generically identified as being 'gently undulating' along the hillslope with slope gradients between 1.4 and 6.4º. On complex slopes, a 'gently undulating' relief would correspond to this type of alternation of hillslope elements based on the model of Ruhe (1960) (Figure 1). In this study, shoulders and footslopes were defined as having slope gradients between 1.4 and 6.4º and the difference between them being their profile curvature. As these elements occur subtly in the landscape, their identification in the field was very difficult, potentially resulting in their erroneous categorization from the human observation (Table 2). Nonetheless, the classification of the study area as having the pattern of complex hillslopes by the DHP model corresponds with understanding of the landscape. Although similar patterns could be produced from the influence of digitized contour lines from the topographic map, they do not directly coincide with the shoulder to footslope undulations.

In the hillslope position model described by Ruhe (1960) and Wysocki et al. (2011), the elements are interconnected and express the dominant surface process that act on each of them. In part, this is a question of analysis scale and sorting the effective size of topographic features needed to influence the distribution of soil properties. Also, the ‘gently undulating’ relief that was observed in the field was in both the profile and plan directions of the hillslope. Because hillslope position only describes the slope profile, it does not account for the full three-dimensional geometry of the hillslope (Santos et al., 2015; Young, 1980).

The classification metric of user's accuracy describes the inclusion of areas within a predicted class to which they do not belong in reality. The higher the user's accuracy value, the less inclusion in an improper class. User's accuracy values above 90% for summit, backslope, and toeslope were obtained (Table 2), which demonstrates that the model has a good ability to separate contrasting hillslope positions. However, for the identification of shoulders and footslopes, the user's accuracy was 60% and 48%, respectively, mainly because they were confused with summits and shoulders, respectively (Table 2). The model used for this study tended to classify more hillslope elements as shoulders and footslopes than those observed in the field. Miller and Schaetzl (2015a) obtained a user's accuracy of 33% and 8% for shoulders and footslopes, respectively, which suggests some challenges in defining those hillslope positions.

The producer's accuracy is the exclusion of areas for a class that should be included. The higher the producer's accuracy value, the lower the occurrence of this exclusion. The lowest value was obtained for the footslopes at 52% (Table 2). However, more areas were classified in the field as summits than detected by the model. These discrepancies may be related to the difficulty in separating them - both by the field observation and digital methods - where they present gradual limits in the landscape (Bathgate and Duram, 2003). For footslopes, there was a lower producer's accuracy due to field observations of this position often being classified as shoulders by the DHP model. Possible explanations of this discrepancy were previously discussed. Specifically, alternating shoulders and footslopes in the study area can occur subtly in the landscape, which hinders recognition in the field. Backslopes presented the highest producer's accuracy, with 93% (Table 2). Similar values were found for the user's accuracy of backslopes, which suggests a good capacity of the model for distinguishing this hillslope position.

3.2 Effectiveness of hillslope position to identify detailed soil map units

The pre-existing geologic map of the study area identified six map units (Figure 2). ANOVA of soil samples located within those respective parent material map units identified significant differences for all of the soil properties measured (Table 3). ANOVA performed on the same soil samples categorized by only DHP were not significant for all soil properties, but were significant for soil depth, pH, Mg^{2+}, H + Al, Al^{3+}, and clay content. Because both parent material and topographic factors can cause differences in soil properties, the significant differences between map units based on these factors individually suggests they are both reasonable criteria to identify detailed soil map units.

Table 3. Statistically significant differences between map units based on parent material (PM), this study's calibrated hillslope position model (DHP), and those two criteria combined (PM+DHP). Significance coded by *** = 0, ** = 0.001, * = 0.01, . = 0.05.

	Soil depth	pH	Na^+	K^+	Ca^{2+}	Mg^{2+}	Bsat	H + Al	Al^{3+}	CEC	Sand	Silt	Clay
PM	***	**	***	.	*	***	***	***	*	***	***	***	***
DHP	*	*				.		***	**				**
PM + DHP	***		**			*			*				***

Bsat: base saturation; CEC: cationic exchange capacity

Subdividing the available soil sample points by both parent material and DHP reduced the quantity of samples in the respective categories of comparison, which limited the conclusions that could be made by the statistical analysis. However, differences for the combined parent material and DHP map units remained statistically valid for soil depth, Na^{+}, Mg^{2+}, Al^{3+}, and clay content (Table 3). Ovalles and Collins (1986) also found relation of soil properties with both hillslope position and parent material. A relevant result to be noticed is that the clay content was highly significant for all three stratification criteria used. This soil attribute is one of the most important for soil mapping and it is sensitive to variation in soil formation factors.

The Itararé Formation parent material dominated the study area and contained sufficient soil samples to compare digitally classified hillslope positions within that parent material. Results from comparing each hillslope position with the other positions in that parent material map unit for the measured soil properties indicated multiple statistically significant differences (Table 4).

The summit hillslope position is the most geomorphically stable and least erosive part of a hillslope (Wysocki et al., 2011). The soil developed in this position tends to be deep, well-drained, dominated by vertical water movement, and have strong horizon development (Hall, 1983; Schoonover and Crim, 2015). Generally, soil in this hillslope position has low pH due to the intense leaching. However, in this study the pH was higher here than all the other positions (Table 4). This difference between what would be expected pedologically and the observed result may be related to the correction of acidity by liming. Flat areas in this region are more favorable for agriculture and are frequently managed for that purpose. Ovalles and Collins (1986) also related higher pH values in summit positions with agricultural use.

Table 4. Matrices of t-test results comparing hillslope positions within the Itararé Formation (CPi) parent material by measured soil chemical properties and soil particle size separates in the surface layer (0-20 cm).

pH					
1 tail: Col mean > Row mean?	Summit	Shoulder	Backslope	Footslope	Toeslope
Summit		no	no	no	no
Shoulder	p<.05		no	no	no
Backslope	p<.05	no		no	no
Footslope	p<.05	no	no		no
Toeslope	p<.05	no	no	no	

Na^+					
1 tail: Col mean > Row mean?	Summit	Shoulder	Backslope	Footslope	Toeslope
Summit		no	no	no	no
Shoulder	no		no	no	p<.05
Backslope	no	no		no	no
Footslope	no	no	no		no
Toeslope	no	no	no	no	

K^+					
1 tail: Col mean > Row mean?	Summit	Shoulder	Backslope	Footslope	Toeslope
Summit		no	no	no	p<.05
Shoulder	no		no	no	no
Backslope	no	no		no	no
Footslope	no	no	no		no
Toeslope	no	no	no	no	

Ca^{2+}					
1 tail: Col mean > Row mean?	Summit	Shoulder	Backslope	Footslope	Toeslope
Summit		no	no	no	no
Shoulder	p<.05		no	no	no
Backslope	no	no		no	no
Footslope	no	no	no		no
Toeslope	no	no	no	no	

Mg^{2+}					
1 tail: Col mean > Row mean?	Summit	Shoulder	Backslope	Footslope	Toeslope
Summit		no	no	no	no
Shoulder	no		no	no	p<.05
Backslope	no	no		no	p<.05
Footslope	no	no	no		no
Toeslope	no	no	no	no	

Al^{3+}					
1 tail: Col mean > Row mean?	Summit	Shoulder	Backslope	Footslope	Toeslope
Summit		no	p<.05	p<.05	p<.05
Shoulder	no		no	no	p<.05
Backslope	no	no		no	p<.05
Footslope	no	no	no		p<.05
Toeslope	no	no	no	no	

H + Al					
1 tail: Col mean > Row mean?	Summit	Shoulder	Backslope	Footslope	Toeslope

Summit		no	p<.05	p<.05	p<.05
Shoulder	no		no	no	p<.05
Backslope	no	no		no	no
Footslope	no	no	no		no
Toeslope	no	no	no	no	

Cationic exchange capacity

1 tail: Col mean > Row mean?	Summit	Shoulder	Backslope	Footslope	Toeslope
Summit		no	no	no	p<.05
Shoulder	no		no	no	p<.05
Backslope	no	no		no	no
Footslope	no	no	no		no
Toeslope	no	no	no	no	

Base saturation

1 tail: Col mean > Row mean?	Summit	Shoulder	Backslope	Footslope	Toeslope
Summit		no	no	no	no
Shoulder	p<.05		no	no	no
Backslope	no	no		no	no
Footslope	no	no	no		no
Toeslope	no	no	no	no	

Sand

1 tail: Col mean > Row mean?	Summit	Shoulder	Backslope	Footslope	Toeslope
Summit		no	no	no	no
Shoulder	no		no	no	no
Backslope	no	no		no	no
Footslope	no	no	no		no
Toeslope	no	p<.05	no	no	

Silt

1 tail: Col mean > Row mean?	Summit	Shoulder	Backslope	Footslope	Toeslope
Summit		no	no	no	no
Shoulder	no		no	no	no
Backslope	no	no		no	no
Footslope	no	no	no		no
Toeslope	no	no	no	no	

Clay

1 tail: Col mean > Row mean?	Summit	Shoulder	Backslope	Footslope	Toeslope
Summit		no	no	no	p<.05
Shoulder	no		no	no	p<.05
Backslope	p<.05	no		no	p<.05
Footslope	no	no	no		p<.05
Toeslope	no	no	no	no	

Shoulders are less stable and are subject to more erosion than summits because of their convex shape and greater slope gradient. Soil in this hillslope position tends to be similar to summit soil but is thinner and may appear to be vertically compressed or truncated (Wysocki et al., 2011). The shoulders in this study had lower Ca^{2+} and base saturation than summits and higher sand contents than toeslopes. Malo et al. (1974) also found the highest sand content on shoulders and they stressed that this hillslope position has more erosional activity than toeslopes, which effectively concentrates the coarse material by removal of the fines.

Backslopes experience greater surface runoff and erosional transport. Because of this, soil developed in this position are generally shallower than the other positions. Aluminum and potential acidity (H + Al) were higher in this position than summits, which may be related to the absence of management practices for improvement of acidic conditions. Agricultural management of backslopes in this area is not common because the steep slopes are not favorable for crops. Another notable difference of soil properties within backslopes was that clay content was lower than the summit soil, which we associate with the erosional potential of this position.

In footslope and toeslope positions, the decrease in slope gradient reduces the carrying capacity of flowing water and increases sediment accumulation. Footslopes merge downslope with toeslopes in the simple slopes models. The comparatively low slope gradient and low-lying position of toeslopes allows for the combined influence of sedimentation from upslope and alluvial processes from adjacent streams (Wysocki et al., 2011). Thus, soil in toeslope positions are highly variable and normally present clay content higher than all the other positions (Hall, 1983; Malo et al., 1974). In this study, toeslopes had significantly higher cation exchange capacity than the summits and shoulders as well as higher clay content than all other positions (Table 4).

It is probable that the pattern of processes operating on hillslopes and the pedologic reflection of those processes will exist on other landscapes under similar conditions. For example, we identified similar patterning of multiple soil properties in our study area as Ovalles and Collins (1986) identified in north central Florida and Malo et al. (1974) identified for a landscape in North Dakota with a closed drainage system. In Malo et al. (1974), the authors noted a degree of universality in the relationships between hillslope position and soil properties observed in studies conducted in Iowa, Angola, Russia, among others (Prill and Riecken, 1958; Dan and Yaalon, 1964; Walker, 1966; Dalrymple et al., 1968; Diniz and Aquiar, 1972; Guidilin, 1973; Spiridonov, 1973). While the DHP model offers a quantitative, repeatable approach for classifying hillslope positions, it was necessary to calibrate the model to the geomorphic geometry of the landscape examined in this research. Therefore, with proper calibration, the DHP model tested in this study could be a basis for predicting the spatial distribution of soil attributes in multiple landscapes. This study demonstrated the model’s potential to contribute to the detailed digital soil mapping of a tropical landscape.

4. Conclusions

When calibrated to local knowledge of the landscape, the model proposed by Miller and Schaetzl (2015a) allowed segmentation of hillslope position with high accuracy in this Brazilian study area. Summit, backslope, and toeslope were the hillslope elements best identified by the method used. There were some discrepancies in the shoulder and footslope identification, which was probably associated with issues in the DEM generated from inaccurate planialtimetric maps. Misclassifications occurred in limited areas that were prone to errors in the elevation data due to tall vegetation.

Variance analysis of soil samples located within the respective parent material map units identified significant differences for all the soil properties measured. When performed on the same soil samples categorized by only DHP, not all soil properties were significantly different. However, when differences in soil properties between hillslope positions were examined within a single parent material, at least one hillslope position was significantly different than the others for each soil property. These results suggest that the DHP map associated with geologic information can be useful for identifying detailed soil map units and to support future digital soil mapping.

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