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Digital modelling of landscape and soil in a mountainous region: A neuro-fuzzy approach

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ABSTRACT

Research on genetic relationships between soil and landforms has largely improved soil mapping. Recent technological advances have created innovative methods for modelling the spatial soil variation from digital elevation models (DEMs) and remote sensors. This generates new opportunities for the application of geomorphology to soil mapping. This study applied a method based on artificial neural networks and fuzzy clustering to recognize digital classes of land surfaces in a mountainous area in north-central Venezuela. The spatial variation of the fuzzy memberships exposed the areas where each class predominates, while the class centres helped to recognize the topographic attributes and vegetation cover of each class. The obtained classes of terrain revealed the structure of the land surface, which showed regional differences in climate, vegetation, and topography and landscape stability. The land-surface classes were subdivided on the basis of the geological substratum to produce landscape classes that additionally considered the influence of soil parent material. These classes were used as a framework for soil sampling. A redundancy analysis confirmed that changes of landscape classes explained the variation in soil properties ($p = 0.01$), and a Kruskal–Wallis test showed significant differences ($p = 0.01$) in clay, hydraulic conductivity, soil organic carbon, base saturation, and exchangeable Ca and Mg between classes. Thus, the produced landscape classes correspond to three-dimensional bodies that differ in soil conditions. Some changes of land-surface classes coincide with abrupt boundaries in the landscape, such as ridges and thalwegs. However, as the model is continuous, it disclosed the remaining variation between those boundaries.

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1. Introduction

The recognition that soil classes of similar characteristics usually occupy analogous positions on the landscape induced the application of geomorphology to support soil mapping. This opened a new field of research on soil-geomorphology (e.g. Conacher and Dalrymple, 1977; Elizalde and Jaimes, 1989; Daniels and Hammer, 1992; Gerrard, 1993; Birkeland, 1999; Schaetzl and Anderson, 2005; Zinck, 2013) and led to the production of comprehensive soil-landscape maps, which embody genetic relationships between soil and landforms (Zinck, 2013). However, this soil mapping approach has been criticized because conventional classification of landforms is usually based on a qualitative characterization of the configuration of the land surface (McBratney et al., 2003). This introduces subjectivity and biases with respect to selection of criteria for terrain segmentation and placement of boundaries (Bishop et al., 2012).

Nowadays, digital soil mapping (DSM) offers new options to model the spatial soil variation based on empirical relationships between soil properties and environmental covariates (McBratney et al., 2003; Scull et al., 2003; Dobos et al., 2006). The latter include some topographic and hydrological parameters computed from digital elevation models (DEMs) (e.g. altitude, slope, aspect curvature, relative position and the topographic wetness index) as well as values obtained from remote sensors (e.g. vegetation and soil indices). There are many successful examples of digital mapping of soil properties such as soil depth, pH, clay content, carbon content, A-horizon sand/clay content, Bt1-horizon sand/clay content, depth to Bt1-horizon, loess thickness, and depth to weathered bedrock (Penížek and Borůvka, 2006; Zhu et al., 2010; Sun et al., 2012). DSM basically consists in producing a predictive model of soil classes or individual soil attributes from a set of training data, by means of regression, classification or any other prediction method. The training data include a set of soil data recorded from sample points at known locations, and a set of environmental covariates. The prediction rules are fitted using the calibration data and subsequently applied at other locations where data on the environmental covariates are available. Usually, an independent set of soil data, known as a validation data set, is utilized to assess the certainty of predictions (McBratney et al., 2003; Scull et al., 2003; Dobos et al., 2006). The success of DSM requires: 1) sufficient predictor variables recorded in the whole area, 2) enough soil data points to fit a relationship with the environmental covariates, 3) predictive functions flexible enough to fit a nonlinear relationship,

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and 4) a strong soil–environment relationship (McBratney et al., 2003). Furthermore, it is desirable to have an even distribution of the sampling points over the mapped area to cover the whole variation of soil–environment relationships.

From the view of the research on soil–landform relationships, DSM has been criticized because it tends to see the soil as a surface instead of a three-dimensional body. Besides, the genetic relationships between soils and landforms and their effect on landscape evolution are not sufficiently reflected in the current digital approach (Zinck, 2013). In addition, the condition of having a large set of evenly distributed data points is not easily achieved where access is difficult, for example, in mountainous areas. On the other hand, DEMs have been utilized in geomorphological research to identify morphometric classes as elementary forms of terrain that can be recognized at the resolution considered (e.g. Burrough et al., 2000; Adediran et al., 2004; Bolongaro-Crevenna et al., 2005; Arrell et al., 2007; Minár and Evans, 2008; Ehsani and Quiel, 2008; Ehsani et al., 2010). Consequently, digital methods have created not only new opportunities for modelling soil variability and identifying elementary forms of terrain, but also new challenges to apply these methods to model genetic relationships between soil and landforms.

Relationships between environmental variables and soil properties tend to be complex and nonlinear, particularly over large areas and zones with irregular topography (Lark, 1999; Lagacherie and Voltz, 2000; Zhu, 2000; McBratney et al., 2003; Zhao et al., 2009; Ballabio, 2009). Hence, methods which allow modelling complex nonlinear processes and working with uncertain and noisy phenomena, seem useful for exploring these relationships. These methods include unsupervised classifications based on artificial neural networks (ANNs) (e.g. Zhu, 2000; Fidêncio et al., 2001; Zhao et al., 2009) and fuzzy sets (e.g. Lark, 1999; Zhu et al., 2001; Beucher et al., 2014; Akumu et al., 2015). Several researchers have used the ANN model known as self-organizing map or SOM (Kohonen, 1990) to produce unsupervised classifications of multidimensional data on phenomena related to earth sciences (e.g. Carniel et al., 2009; Das and Basudhar, 2009; Zhang et al., 2009; Ehsani et al., 2010). Schmitt et al. (2014) applied both SOM and fuzzy logic in a two-stage clustering approach to characterize a fluvial system by fuzzy signatures of hydromorphological drivers. First, they applied the neural network to derive a self-organizing map from a high-dimensional input data set. Then, they use the fuzzy c-means algorithm (Bezdek et al., 1984) to identify characteristic driver signatures from the neurons and thus to derive a hydromorphological classification of the entire fluvial network. Bezdek et al. (1992) integrated the SOM model with the fuzzy c-means algorithm in a single application. The resulting neuro-fuzzy approach, named the fuzzy Kohonen clustering network or FKCN (Bezdek et al., 1992), combines the advantages of a self-organized model of ANN with the optimization procedure of fuzzy c-means, and the capability provided by this algorithm to generate an output of continuous-values instead of hard clustering (Bezdek et al., 1992; Wu et al., 2004).

The choice of environmental covariates can become a key issue when a little known area is to be classified. According to Pike et al. (2009), three kinds of parameters can be derived from a DEM: 1) parameters describing the local morphology of the land surface, 2) those that reflect the potential movement of material over the land surface, and 3) those that relate geomorphometry to climatology or meteorology. In addition, some indices derived from remote sensing data can also be used. Most authors have utilized slope gradient as an input variable (e.g. Burrough et al., 2000; Adediran et al., 2004; Bolongaro-Crevenna et al., 2005; Arrell et al., 2007; Minár and Evans, 2008; Iwahashi and Pike, 2007; Ehsani and Quiel, 2008; Ehsani et al., 2010), but the use of other covariates varies between authors. A second problem to be faced when a new area is classified into fuzzy sets is to determine how many classes are required and the fuzziness of such classes. The latter is defined by the value of the exponent Φ of the fuzzy c-means algorithm. The number of classes and the value of Φ can be established on the basis of experience or intuition of the researcher. However, some authors have used indices calculated from the data to select the best combination of the number of classes and fuzzy exponent (e.g. McBratney and de Gruijter, 1992; Odeh et al., 1992; Fadili et al., 2001; Fridgen et al., 2004).

This study proposes an approach for digital modelling of soil–landscape relationships, based on the application of the neuro-fuzzy algorithm FKCN to identify land-surface classes from a DEM and remote sensing data. The proposal was appraised in a mountainous area with limited information in North-Central Venezuela. Given the little prior knowledge of the area, the research addressed the choice of environmental covariates, the number of classes and the degree of fuzziness of these classes. The results of the digital classification were analysed, along with complementary information on geology, to produce a geomorphological model of the studied area, which was used as a framework for soil sampling. The data recorded from the sampling sites were utilized as a basis to assess the relationship between soil attributes and the geomorphological model.

2. The study area

The study area covered 6760 ha in the mountain ranges of north-central Venezuela, at approximately 10°2′ North and 67°7′ West, (Fig. 1). The relief is mountainous, with an altitude ranging from 334 to 1405 m above sea level and a mean slope gradient of 40%. The average annual rainfall is 1100 mm and the average annual temperature is 22 °C. Recurrent fires and extensive grazing maintain a predominantly herbaceous cover, interrupted only by forest corridors along waterways and areas of evergreen forest on the highlands, above 900 m. Present along the area are two geologic formations: *El Chino–El Caño* metatobas (Vccn) and *El Carmen* metalavas (Vcca), which belong to metavolcanic and metasedimentary rocks of the *Villa de Cura* group (Urbani and Rodríguez, 2004). Vccn consists of metamorphosed basalts and associated volcanic sedimentary rocks while Vcca is made of mafic metalavas, interbedded with metasedimentary rocks and other metavolcanic rocks (Shagam, 1960). The area is part of an important watershed extensively affected by soil erosion; where there is an imminent need to implement programmes of sustainable management. However, land-use planning in such a watershed is restrained by the lack of reliable soil and geomorphological information.

3. Methods

3.1. Algorithm

The FKCN model is the result of an integration of the SOM neural network and the fuzzy c-means algorithm (Bezdek et al., 1992). The SOM model consists of two vector layers: input and output (Kohonen, 1990; Lin and Lee, 1996; Ehsani and Quiel, 2008). Each input vector contains the normalized values of the input variables at a given cell of the model. In the output layer a number of neurons, equal to the previously established amount of classes is arranged on a grid, so that each node is connected to all the others by specific topological relationships. Each neuron is described by a n-dimensional vector of weights, where n is equal to the number of variables in the input data. The weight vectors are initialized with random values and then the network is adjusted in an iterative and sequential manner. When a new input vector is presented to the network, the processing unit in the output layer computes the distance between the input vector and each of the weight vectors. The neuron at the shortest distance from the input vector is chosen as the winner node. Once this node is found, its weight vector and those of the nodes that belong to a predefined neighbourhood are updated, and thus moved closer to the input vector. This process is performed iteratively until the winning node remains the same, or a certain number of iterations is reached. The FKCN model adds a layer of memberships to the different classes, based on fuzzy-c-means, to the distance layer of

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