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Spatial filtering of a legacy dataset to characterize relationships between soil organic carbon and soil texture

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ABSTRACT

The spatial distribution of soil properties often displays complex and multiscale patterns of variation. It results from multiple soil processes acting simultaneously but at different scales. Hence, characterizing the influence of a given controlling factor on the soil property is made more difficult by the variation due to other controlling factors. In this context, separating the variation of the soil properties by spatial scales could allow disentangling the combined effect of controlling factors and would provide a qualitative and quantitative characterization of controlling factors separately. In this paper, geostatistical tools have been used to separate the scales of variation of two soil properties (i.e. SOC and texture) coming from a legacy dataset in the Belgian Loess Belt. Scale components were predicted separately and the relationships between soil properties were analyzed at different scales. Results illustrated that the contents of a given soil property in different depth layers were typically more correlated when only the long range components were compared. Similarly, the link between SOC and texture components was also clearer for the long range components. This means that soil processes acting at local or landscape scale influence soil properties differently according to their nature or to the depth considered. Eliminating the variation at this scale allows to better characterize the relationships between depth layers and soil properties. The study gives insights for further spatial mapping of SOC by focusing on more appropriate variables at specific spatial scales. Furthermore, we raise the interest of spatial filtering for detecting inconsistencies inside composite datasets.

1. Introduction

The spatial patterns of soil properties are scale dependent as different processes dominate at different scales (Heuvelink, 1998). This is well illustrated by the spatial variation of Soil Organic Carbon (SOC). At continental or global scale, the variation is high and largely follows the variation of latitude because of climatic control (Minasny et al., 2013). Geologic and pedologic properties play also a major role. In a global inventory, Batjes (1996) showed large differences of SOC content between FAO–UNESCO soil unit. In contrast, at the field or landscape scale, dominant processes are different and often of very diverse natures (Viaud et al., 2010). At a distance of a few meters, SOC variation is very large and can reach the same order of magnitude as the variation over a whole region (Goidts et al., 2009).

Soil models are generally developed to explain and to predict soil properties at a specific scale, so their transferability to other scales may not be guaranteed. The link between soil/environmental properties is typically scale-dependent. For example, the measured correlation between soil properties depends on the extent of the sampled area (Corstanje et al., 2007). Vasques et al. (2012) showed that both the spatial extent and the resolution of the input data had a substantial effect on the calibration parameters of a SOC predictive model. Therefore, using a model calibrated at a given extent (resp. resolution) to predict SOC at another extent (resp. resolution) generally dramatically decreased its performances and questioned its validity in this new context. Besides the fundamental influence of the spatial extent and resolution on the relative importance of controlling factors, the scale dependence of models may also be explained by the fact that rescaling also often modifies support and availability of model input data, and thus the quality and the potential of these data to represent specific processes (Heuvelink, 1998).

In the perspective of disentangling complex and interlaced soil processes, methodologies separating scales of variability could help to highlight individual processes controlling soil properties. The variation coming from secondary controlling factors could be filtered, and the relationship between the soil property and the main controlling factor would thus appear more clearly. For example, Biswas et al. (2013) separated soil water storage data along a transect in various scale components and showed, among others, that short range components were

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positively correlated to relative elevation, while it was not the case for the original data. Wieland et al. (2011) applied different methods to filter a digital elevation model and found that the correlation between topography and depth of carbonates was optimal when only components with a wavelength between 60 m and 380 m were considered.

Different techniques of spatial decomposition may be applied and the choice of the method may be influenced by (1) the density, location (e.g.: scattered vs. grid data) and support (e.g.: point for field sampling vs. pixel for remote imagery) of the variable of interest and auxiliary data, and (2) the objective of the study (e.g. to understand a particular process, or to maximize the spatial prediction accuracy). Increasing pixel size by aggregation and interpolating from scattered points to a regular grid are typical cases where small scale information is implicitly filtered out. Other methods decompose explicitly the mathematical space of the soil properties into a set of basis functions. These may be wavelets in the case of Multi Resolution Analysis (MRA, Mallat (2009)), or sinusoidal functions in the case of Fourier analysis (Butz, 2006). The empirical mode decomposition framework (Biswas and Si, 2011) also proposes to decompose the spatial variation in a set of mode function directly extracted from the data without any preliminary assumption.

In this study, we propose to spatially decompose soil properties using kriging filtering, also known as kriging analysis. This method was first described by Matheron (1982) as a component of a bigger methodology called factorial kriging analysis (FKA). Our objective is to test the hypothesis that filtering allows a better qualitative and quantitative description of relationships between soil properties. In some cases this could lead to a better understanding of the underlying processes.

2. Material and methods

2.1. Study area

To confirm our hypothesis, an analysis was carried out in the cropland of the Belgian Loess Belt in central Belgium (Fig. 1). The Belgian Loess Belt is an area of 9921 km^2 of which 43% is occupied by cropland under intensive cultivation. It is characterized by a rolling topography with plateaus, slopes and some incised rivers with generally well drained, dry valley bottoms. The climate is temperate oceanic with mild winters and cool summers. The geological substrate is a several-meters thick Pleistocene aeolian deposit of calcareous loess overlying tertiary sands, and in which Luvisols have developed. Forests, grassland and urban areas are typically located in the floodplains.

2.2. Dataset

Because of its large density of profiles for a regional dataset (2506 profiles across the whole study area, i.e. 1 profile every 4 km^2), we used the so-called legacy dataset “Aardewerk”. Profiles were originally sampled by horizon between 1949 and 1964 and the dataset was digitized in 1988 (Van Orshoven et al., 1988). SOC was analyzed using the Walkley & Black dichromate oxidation method. Texture fractions were determined after removal of organic matter and calcium carbonates (Van Orshoven and Vandenbroucke, 1993).

Since profiles were sampled by horizon, a method involving equal area quadratic splines was used to estimate the content of SOC and texture fractions for three distinct soil layers (0–30 cm, 30–60 cm, 60–90 cm) (Stevens et al., 2014). As soil material consists of aeolian loess deposits, spatial variations of soil properties are smooth and sharp transitions between different pedological regions are not expected, except at the lower limit of the plough layer. Therefore, the use of a method involving splines that smooths the profile but honors the mean values measured over each horizon is expected to yield more realistic contents of the soil properties in the three selected soil layers.

The dataset that was obtained after calculation of the values of soil properties in the three soil layers will be referred hereafter as AW. These values will also be denoted as the “raw values” in the remaining part of the paper, in contrast to the filtered values. A summary of available soil properties is shown in Table 1, and their main statistics are given in Table 2. The minimum of some variables is negative because of the spline method which has to respect both constraints on smoothness

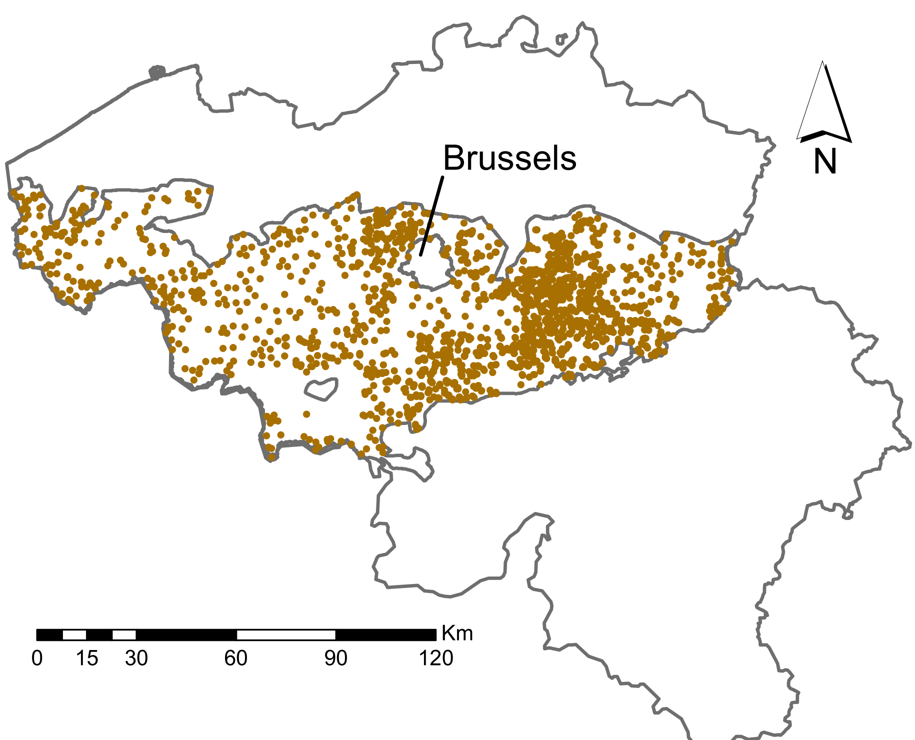

Fig. 1. The 2506 profiles of the dataset AW situated in the cropland of the Belgian Loess Belt were used in the study.