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Multiscale contextual spatial modelling with the Gaussian scale space

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ABSTRACT

We present a contextual spatial modelling (CSM) framework, as a methodology for multiscale, hierarchical mapping and analysis. The aim is to propose and evaluate a practical method that can account for the complex interactions of environmental covariates across multiple scales and their influence on soil formation. Here we derived common terrain attributes from multiscale versions of a DEM based on up-sampled octaves of the Gaussian pyramid. Because the CSM approach is based on a relatively small set of scales and terrain attributes it is efficient, and depending on the regression algorithm and the covariates used in the modelling, the results can be interpreted in terms of soil formation. Cross-validation coefficient of determination modelling (R^2), for predictions of clay and silt increased from 0.38 and 0.16 when using the covariates derived at the original DEM resolution to 0.68 and 0.63, respectively, when using CSM. These results are similar to those achieved with the hyperscale covariates of ConMap and ConStat. As with these hyperscale covariates, the multiscale covariates derived from the Gaussian scale space in CSM capture the observed spatial dependencies and interactions of the landscape and soil. However, some advantages of CSM approach compared to ConMap and ConStat are i) a reduced set of scales that still manage to represent the entire extent of the range of scales, ii) a reduced set of attributes at each scale, iii) more efficient computation, and iv) better interpretability of the important covariates used in the modelling and thus of the factors that affect soil formation.

1. Introduction

The universal model of spatial variation (Matheron, 1971) recognizes that all types of soil variation can be described, and modelled, in terms of a deterministic component and a stochastic component (Eq. 1).

$$Z(s) = Z^{*}(s) + \varepsilon'(s) + \varepsilon' \qquad (1)$$

Where $Z(s)$ is the soil property value, $Z^{*}(s)$ is the deterministic part of the model describing structural variation, $\varepsilon'(s)$ is the stochastic part of the model consisting of (apparently) random variation that may be spatially correlated and ε' is the spatially uncorrelated random noise component.

Initial efforts in digital soil mapping (DSM) typically modelled either the deterministic component using some form of regression against environmental covariates, or the stochastic component using some form of kriging. DSM largely adopted the *CLORPT* concept based on Jenny (1941) in which soil properties were expected to be predictable in terms of values for environmental covariates that represented the five factors of soil formation (climate, organisms, relief, parent material and time). McBratney et al. (2003) proposed the *scorpan* model for soil mapping as an extension to CLORPT by explicitly accounting for space (or location, *n*), to account for spatial dependency in the theoretical framework. Two hybrid approaches, Regression Kriging (RK) (Neuman and Jacobson, 1984) and Geographically Weighted Regression (GWR) (Brunsdon et al., 1996) permit joint modelling of environmental correlation and spatial dependency. While Kriging is commonly used to deal with spatial autocorrelation, GWR was developed to handle spatial non-stationarity.

Landscape processes, and thus spatial dependence, result from complex interactions of different soil forming factors, which are connected with each other in nested hierarchies (MacMillan et al., 2004). Consequently, pedogenesis is influenced by interactions between landscape and environmental processes across multiple scales (Pike, 1988; Gerrard, 1981; Hole, 1978; Behrens et al., 2010a; Kerry and Oliver, 2011; Viscarra Rossel, 2011). Because the geomorphic settings interact with for example climate or parent material, or are the result of other processes such as tectonics, the "geomorphic signature" of a landscape (Pike, 1988) can often serve as their proxy. That is, surface shape and context can be an indicator for parent material; elevation and

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aspect can indicate differences in temperature, precipitation and solar insolation.

Due to the multiscale nature of environmental interactions of the different processes, it is important to cover important ‘process scales’ in spatial modelling (Behrens et al., 2010a; Behrens et al., 2014). For instance, Viscarra Rossel (2011) produced fine spatial resolution digital mapping of clay minerals across Australia and suggested that the detailed expression of the minerals at different spatial scales was possible because the different covariates used in the modelling exerted their influence at the dominant scales that they represent. When all relevant environmental covariates, which cover the process scales, are included in the model, the stochastic component ($\varepsilon'(s)$) of the residuals can be insignificantly small or spatially uncorrelated (Moran and Bui, 2002; Behrens et al., 2010a; Behrens et al., 2014; Viscarra Rossel et al., 2015; Hengl et al., 2017). This could be related to the (regression) algorithm used, the availability and quality of the covariates, how well they represent the processes of soil formation and the complexity of the soil.

In many cases, not all relevant covariates covering the process scales are available. However, additional relevant information can be derived from the original covariates. One example is using a digital elevation model (DEM) to derive terrain attributes. However, it is important to extract descriptors at multiple scales and not only at the original local scale, since there can be a mismatch between the spatial dependency of a soil property or the scale of generalization of soil units and the terrain attributes derived at a specific resolution (Bui et al., 1999).

Scaled versions of environmental covariates are typically extracted using expanding convolution kernels, e.g. by increasing the spatial neighborhood to derive terrain or by applying low-pass filter attributes, or by reducing the resolution of covariates (e.g. Huber, 1994; Fels and Matson, 1996; Wood, 1996; Behrens et al., 2010b). Both approaches have been widely used and tested for DSM (e.g. Moran and Bui, 2002; Grinand et al., 2008; Behrens et al., 2005; Behrens et al., 2010b; Smith et al., 2006; Zhu et al., 2008; Drăguţ et al., 2011). However, these multiscale mapping approaches typically only cover a relatively small range of spatial scales and thus the relevant geomorphic signature might not be fully derived. This limited range of scales used may be due to a high computational demand for filter-based approaches with large neighborhoods or to the production of visual artifacts related to different cell sizes.

Two previously described methods for deriving hyperscale covariates are ConMap and ConStat (Behrens et al., 2010a; Behrens et al., 2014). Both are designed to produce covariates that represent processes at spatial scales ranging from the local scale to the supra-regional scale. The covariates derived by ConMap are elevation differences from the center pixel to each pixel in a sparse circular neighborhood, while ConStat derives covariates that represent statistical measures of central tendency, dispersion, and shape of the distribution within growing sparse circular spatial neighborhoods. These hyperscale covariates are then used as predictors in random forest regressions, although other algorithms could also be used. Both ConMap and ConStat produce a very large number of scales and predictors computed for each grid location, which can easily grow to 100 scales and 1000 attributes per grid cell respectively.

Another group of approaches, which can be used to extract scales from covariates for DSM, consists of spectral analysis, wavelet transforms, and empirical mode decomposition (Pike and Rozema, 1975; Gallant and Hutchinson, 1996; Huang et al., 1996). Because, they allow the decomposition of covariate data into specific scales, the resulting scaled information can be used as additional predictors or as the basis to derive scaled versions of derivatives such as terrain attributes (Lashermes et al., 2007; Biswas et al., 2013b). In this respect, several studies used 2D wavelet decomposition to analyze soil spatial variation as well as to map soil properties based on covariates of different scales or resolutions (Lark et al., 2003; Lark and Webster, 2004; Lark, 2007; Mendonca-Santos et al., 2007; Taghizadeh-Mehrjardi et al., 2014; Biswas et al., 2013a; Biswas et al., 2013b; Sun et al., 2017). These studies either develop DSM models on single scales or resolutions, or across a relatively small range of scales comparable to the range of scales used in DSM approaches that employ expanding convolution kernels (e.g. Behrens et al., 2010b), and often only for small areas.

Another important aspect of spatial modelling in DSM is the interpretability of the models and the relevant pedogenetic processes (Walter et al., 2006), which may be interpreted from the deterministic modelling (Eq. 1) (cf. Jenny, 1941; Gerrard, 1981), particularly if the algorithms used lend themselves to interpretation such as approaches based on Decision Trees (Breiman et al., 1983; Quinlan, 1985). The autocorrelated part of residuals ($\varepsilon'(s)$) (Eq. 1), if it exists, is more difficult to interpret in terms of pedogenesis. Hence, the advantages of using decision tree methods with covariates that represent multi-scale processes are that only the pure noise part of the predictive model (ε') (Eq. 1) remains. The resulting deterministic models can be interpreted in terms of soil genesis using analysis of feature importance and other knowledge discovery tools (Behrens et al., 2014).

Good spatial modelling and mapping should i) capture and describe spatial dependency, ii) be interpretable, and iii) be efficient to compute. Here, we present a new contextual mapping and analysis approach that uses the Gaussian pyramid scale space (Burt and Adelson, 1983). The method creates a hierarchical pyramid of the covariate data (e.g. a DEM) of decreasing spatial resolution by downscaling and then upscaling back to the original resolution. The idea is to cover the range of scales available from the spatial extent of the covariate data and to use all scales simultaneously in the spatial modelling. Together, the scale specific terrain analysis and regression, enables variable importance analysis and interpretability with relation to soil formation. We tested the method with a small set of terrain attributes (slope, aspect and curvature) derived from scaled versions of the DEM. However, the method can be extended to include contextual information of other covariates.

2. Material and methods

2.1. The Gaussian scale space

A Gaussian pyramid is a hierarchical, multiscale representation of images, or gridded maps, based on smoothing and scaling (Burt and Adelson, 1983). It is used in many image processing algorithms such as image compression or in computer vision for scale-invariant feature detection (Burt and Adelson, 1983; Adelson et al., 1984; Lowe, 2004).

In a Gaussian pyramid, the resolution is successively reduced by half until only one pixel remains (Fig. 1). Hence, a matrix pyramid is a dyadic sequence $\{M_i, M_{i-1}, \ldots, M_0\}$ of gridded datasets, where M_i has the same dimensions and resolution as the original dataset. M_{i-1} is derived from M_i by reducing the cell count by one half. M_0 is a matrix of one pixel only (Sonka et al., 2014). This is accomplished by convolving the matrix with a Gaussian blur filter, to avoid aliasing effects, followed by a downscaling step where all even-numbered rows and columns are removed. Iterating this process constructs the levels or octaves of the pyramid. The finest scale corresponds to the resolution of the input dataset. As the pyramid scales down to one pixel there is no further coarser scale or octave possible. Hence, the coarsest scale is related to the extent of the dataset. Thus, the Gaussian pyramid covers the entire range of scales based on the extent of the dataset. This does not mean that all possible scales are derived but that the extremes are covered.

Upsampling in a Gaussian pyramid approach is commonly required to generate a Laplacian pyramid, which contains the relevant information for image compression and feature detection (Burt and Adelson, 1983; Lowe, 2004). Instead of building a Laplacian pyramid, we use upsampling to return the resolution of each Gaussian octave to the original resolution of the DEM (Fig. 1). The purpose is to avoid scale related artifacts in CSM, which would occur when combining maps of different cell sizes. Technically, upsampling is done by injecting even rows and columns into an octave. All new cells are set to zero. In a next

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