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Spatial modelling of soil hydraulic properties integrating different supports

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SUMMARY

Modelling soil–water interactions provides important outputs for agriculture management and environmental monitoring. Most of the existing models rely on soil hydraulic properties (SHP) as input data. Geostatistical approaches based on stochastic simulations provide the spatial distribution of SHP and the uncertainty attached to their estimates. Frequently, SHP are measured in different data supports thus one needs to guarantee the integration of these different supports to provide a coherent and reliable model. One possible solution is to use block sequential simulation (Liu and Journel, 2009). Our work presents an application of this algorithm to map and quantify the spatial uncertainty of total porosity. Based on the simulation outputs and on the comparison with direct sequential simulation that does not account for the multiple supports of the data, we concluded that block sequential simulation should be used to produce reliable input data to dynamic soil–water models.

1. Introduction

Intensive agricultural activities in many regions of Europe are affecting the quality of main environmental resources such as soil and groundwater. It is of crucial importance to identify these environmental problems and to propose solutions to minimise the potential risks for public health and the ecosystems. With this purpose, models are developed to design irrigation schemes and to describe soil–water regimes and nutrient dynamics useful for environmental monitoring (Verhagen, 1997; Alphen et al., 2001). Research on this subject has produced diverse models towards quantifying and integrating the most important physical, chemical and biological processes active in the unsaturated zone of soils. The application of these models is fully dependent on the availability and quality of input data (namely, soil hydraulic properties (SHP)) that will determine the accuracy of modelling results (Wösten et al., 2001). However, lack of easily accessible, representative and accurate SHP is recognised as a limitation to soil–water models reliability (Wösten et al., 1999). The reasons behind the lack of quality of soil hydraulic data are mostly related with the techniques used to obtain direct measurements of these properties. The majority of these techniques remain relatively time consuming and therefore costly (Schaap et al., 1998; Minasny and McBratney, 2002). The cost-effectiveness of obtaining SHP can be improved by using indirect methods to predict hydraulic properties using more easily, widely available, routinely, or cheaply measured properties (Minasny and McBratney, 2002). Methods developed for this purpose use the so-called pedotransfer functions (PTFs) (Bouma, 1989). By using regression or data-mining models, PTFs relate hydraulic properties to easier to measure soil attributes such as soil texture, organic matter content and/or other data routinely measured in soil surveys.

However, reliability of pedotransfer estimates should be carefully analysed since PTFs are based on general data sets and validation with 'true' field data is often lacking. Also, PTFs are specific for certain edafo-climatic conditions and soil family types, hence extrapolation to other areas beyond their geographical dataset should be regarded carefully (Minasny et al., 1999). Concerning the accuracy of SHP predictions, generally measured in terms of the uncertainty attached to the result, many PTFs have been developed without including any uncertainty calculation (McBratney et al., 2011).

One possible way to overcome PTFs limitations and to provide an accurate estimate for SHP is to use a spatial inference model

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able to integrate the spatial variability of SHP (Wösten et al., 2001). This can be implemented using geostatistical models. Geostatistical estimation of SHP, or any other soil property, is about predicting the attribute at unsampled locations. Few studies have previously adopted this approach for SHP mapping. The work by Sinowski et al. (1997) shows an example of how geostatistical estimation (kriging) can be used to generate maps of water retention curves (integrating PTF information). The results obtained are a good example of the advantages of using geostatistics for the quantification of SHP. Also, the benefits of using geostatistical models to predict any other soil property have been recognised by several authors (for example, Goovaerts (1999) and Webster (2000)).

In this paper we present a geostatistical approach that goes beyond previous studies in that it provides an estimate of the spatial distribution of SHP together with an evaluation of the uncertainty associated with the result, while accounting for the different data support.

When modelling uncertainty we face two main decisions: whether to model uncertainty locally or spatially, and how to account for the different supports of the data and of the model discretization.

Goovaerts (2001) recommends choosing the type of uncertainty modelling guided by practical criteria. Local uncertainty modelling is the most traditional approach and it amounts to assigning a confidence interval to the estimate, or, at most, to build a local uncertainty distribution from which to derive an estimate and its associated uncertainty. However, when the aim of the study is to use the estimates as input to another model for further prediction (such as would be the case here in which we propose to use the estimates as input to a subsurface water flow model) the combination of a map with local estimates and a map of local variances is of no use (Gómez-Hernández and Wen, 1998). For this reason, we opt for a stochastic approach to spatial uncertainty modelling by generating multiple, equally likely realizations of the SHP from their joint distribution. Later, the postprocessing of these realizations through the flow model will provide a model of uncertainty about the target result.

The SHP considered in this study is total porosity (Ptotal). The data available for our study consists in measurements of Ptotal made for samples collected in the same soil layer but not at the same depth hence the measured values are not reported for the same support. This usually happens when soil surveys are performed in different conditions such as different surveys or sampling protocols. Commonly, the different data supports are ignored and all data are treated as point data. Alternatively, a change of support can be applied to obtain an interpolated value for a larger support, a method largely applied in geostatistics and known as point-to-area interpolation or block kriging (Isaaks and Srivastava, 1989); or measurement values can be considered as average SHP values that should be downscaled to a smaller support. Several authors (Gotway and Young, 2002, 2005; Kyriakidis, 2004; Goovaerts, 2008) have proposed to use kriging to predict point values from block data, an approach referred to as 'area-to-point' kriging.

We wish to account for the data at their sampling support without the need for upscaling or downscaling. This can be accomplished using block sequential simulation (BSSIM) as proposed by Liu and Journel (2009). In sequential simulation, each realization is generated by sequentially visiting each node and generating a value at each location. At any given location, a local probability distribution function is built after solving a kriging system. This probability distribution must account for the conditioning data and for previously simulated values. BSSIM is able to incorporate block data, as well as point data, as conditioning data, by using point-to-point, area-to-point, point-to-area and area-to-area covariances. In addition, BSSIM uses the DSS algorithm (Journel, 1994; Soares, 2001) to build the local probability distribution in original space of the variable without the need of any transformation, and it is free of any distribution assumption on the attribute.

In this paper we demonstrate how to spatially characterize the uncertainty of SHP accounting for different supports using BSSIM. In order to show the importance of properly accounting for the different data supports, the BSSIM results are compared with those resulting from the application of direct sequential simulation considering all data as point values.

2. Materials and methods

2.1. Soil database and study area

The soil data used in this work was extracted from a Portuguese database (*PROPSOLO*, Ramos et al., 2007) comprising 347 georeferenced (Lisboa Hayford Gauss IGeoE projection with datum Lisboa Hayford) soil profiles, collected in several locations across Portugal, from 1977 to 2011. During this 30-year period, profiles were collected for different public and private projects conducted by EAN (Estação Agronómica Nacional), a Portuguese research centre for agriculture and soil science development. Some of the data included in *PROPSOLO* were provided to HYPRES (Hydraulic Properties of European Soils; Wösten et al., 1999), a European database for soil hydraulic data.

Each sampling campaign complied with Portuguese and international procedures (Cardoso and Fernandes, 1972; FAO, 2006). For each soil profile, a qualitative description was made, each horizon was sampled, and soil properties were determined in the laboratory. All soil hydraulic properties were measured on undisturbed soil cores collected in the soil horizons/layers of the different soil profiles included in the database (Ramos et al., 2006).

For this paper, 46 soil profiles were chosen in an area located in the South of Portugal, with circa 3800 km^2 (Fig. 1). The major soil groups in this area are predominantly Luvisols, Cambisols, and Vertisols. The criteria for selecting these soil profiles included the number and the proximity of sampling points as well as the homogeneity of soil type and land use. The selected area was converted from rainfed agriculture to irrigation over the last two decades. To sustain the irrigation projects a greater number of soil profiles were collected than in other Portuguese regions.

For our study, we selected only the topsoil layer for each location. Topsoil depths varied between 10 cm and 48 cm.

Total porosity (Ptotal) was obtained from the maximum holding capacity of 100 cm^3 undisturbed soil cores in volumetric basis. Several 100 cm^3 samples were taken from each core, and their average value was provided as Ptotal for the given core. For the 46 topsoil samples collected in the study area, the measured Ptotal varies between 0.33 cm^3/cm^3 and 0.64 cm^3/cm^3, its histogram is shown in Fig. 2. The spatial distribution of Ptotal is displayed in Fig. 1.

The variability observed for Ptotal can be explained by the effects of local soil texture, soil structure, organic matter content, particle dispersion, soil crusting, changes in the concentration and ionic composition of the soil solution, microbiological activity, and the loading (stress) history on the soil profile (van Genuchten and Šimůnek, 1996; Gupta et al., 2006; Strudley et al., 2008).

In the next sub-section, we describe the geostatistical approach proposed not only to estimate Ptotal but to address two issues: how to deal with different sampling supports and how to provide an uncertainty measure regarding the variability of Ptotal in the study area and not only at specific locations.

2.2. Block sequential simulation

The geostatistical model proposed in our work uses the block sequential simulation (BSSIM), an algorithm included in the BGeost