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The analysis of ranked observations of soil structure using indicator geostatistics

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Abstract

Structure is an important physical feature of the soil that is associated with water movement, the soil atmosphere, microorganism activity and nutrient uptake. A soil without any obvious organisation of its components is known as apedal and this state can have marked effects on several soil processes. Accurate maps of topsoil and subsoil structure are desirable for a wide range of models that aim to predict erosion, solute transport, or flow of water through the soil. Also such maps would be useful to precision farmers when deciding how to apply nutrients and pesticides in a site-specific way, and to target subsoiling and soil structure stabilization procedures.

Typically, soil structure is inferred from bulk density or penetrometer resistance measurements and more recently from soil resistivity and conductivity surveys. To measure the former is both time-consuming and costly, whereas observations made by the latter methods can be made automatically and swiftly using a vehicle-mounted penetrometer or resistivity and conductivity sensors. The results of each of these methods, however, are affected by other soil properties, in particular moisture content at the time of sampling, texture, and the presence of stones. Traditional methods of observing soil structure identify the type of ped and its degree of development. Methods of ranking such observations from good to poor for different soil textures have been developed. Indicator variograms can be computed for each category or rank of structure and these can be summed to give the sum of indicator variograms (SIV).

Observations of the topsoil and subsoil structure were made at four field sites where the soil had developed on different parent materials. The observations were ranked by four methods and indicator and the sum of indicator variograms were computed and modelled for each method of ranking. The individual indicators were then kriged with the parameters of the appropriate indicator variogram model to map the probability of encountering soil with the structure represented by that indicator. The model parameters of the SIVs for each ranking system were used with the data to krige the soil structure classes, and the results are compared with those for the individual indicators. The relations between maps of soil structure and selected wavebands from aerial photographs are examined as basis for planning surveys of soil structure.

Keywords: Aerial photographs; Soil structure; Indicator variograms; Sum of indicator variograms; Kriging; Sampling

1. Introduction

Structure is an important physical feature of the soil that affects the nature and distribution of pores, which hold water, air and allow roots to penetrate. It is also plays a crucial role in the transport of water, gases and solutes in the environment, and in microorganism activity and nutrient uptake. A soil without any obvious organisation of its components is known as apedal. This can be single grain where the mineral material is almost surrounded by a continuous pore phase (usually sandy soil), or massive where the mineral material is continuous and the pores are discontinuous (usually clayey soil). Bronick and Lal (2005) present a comprehensive review of the processes that cause and disrupt soil aggregation and also consider the advantages and disadvantages of various methods of managing soil structure.

Accurate maps of topsoil and subsoil structure are desirable for a wide range of models that aim to predict soil erosion, solute transport, or flow of water through the soil. Also such maps could be used as a guide for farmers when applying nutrients and pesticides variably, or to target subsoiling or stabilization of soil structure. The designation of nitrate vulnerable zones in England and Wales in 1996 (Evers et al., 2001) for example, means that farmers now need to consider soil structure and

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texture, as well as crop needs, when applying nitrogen fertilizers to the soil. Where soil structure allows preferential flow of water and solutes through macropores in the soil there is a greater need to limit nitrate and pesticide applications. Typically, when mapping the spatial variation in soil structure for such purposes it is inferred from bulk density (Horn et al., 2003; Dexter and Birkas, 2004; Bartoli et al., 2005) or penetrometer resistance measurements (Perfect et al., 1990; Grunwald et al., 2001; Munkholm et al., 2003). Measuring bulk density is time-consuming and costly, whereas penetrometer resistance can be measured automatically and swiftly using a vehicle-mounted penetrometer. However, the results of both methods are affected by many properties of the soil that vary spatially, in particular the moisture content at the time of sampling, soil texture, and the presence of stones. Thus, pedotransfer functions (To and Kay, 2005; Grunwald et al., 2001) developed to aid the interpretation of such measurements are likely to be useful only very locally. An additional problem is that both methods have linear scales related to soil compactness (ratio of soil weight to volume) and strength, respectively, whereas structure is a non-linear set of ranks. This is because the types of structure regarded as good and poor depend on soil texture. Bulk density and penetrometer measurements can provide insight into the spatial variability of soil structure where the texture is reasonably constant, but if the texture varies laterally and with depth such measurements become less reliable. Therefore, soil texture needs to be recorded for each location where bulk density and penetrometer resistance are made, which is expensive. Furthermore, these methods cannot be used to infer soil structure in stony soil.

Recently, soil resistivity and conductivity surveys (Tabbagh et al., 2000; James et al., 2003; Besson et al., 2004) have been used to infer soil structure, however, as for bulk density and penetrometer resistance there are difficulties in interpreting the results as the relations with other properties can change even within fields. Therefore, we suggest a return to traditional methods of observing soil structure and the application of geostatistical methods for mapping it. Indicator kriging has been used successfully to map nominal data, such as water table class (Bierkens and Burrough, 1993), notions of soil quality (Smith et al., 1993), and soil degradation (Diodato and Ceccarelli, 2004). Therefore, it seems an appropriate approach for mapping soil structure.

Traditional observations of soil structure are made by noting the type of ped and its degree of development (Hodgson, 1974). Peerlkamp (1967) and Hodgson (1976) have developed methods for ranking such observations for soil types with different textures to indicate what constitutes 'good', 'medium' and 'poor' structure for agricultural purposes. Such methods of ranking structure can also be used by those wanting to model soil processes, for example to determine its influence on other soil properties, such as hydraulic conductivity. This paper evaluates the merits of four methods of ranking structure on different parent materials using geostatistics, and suggests an approach for mapping soil structure that economizes on the number of observations required. Kerry and Oliver (2003) showed that intensive ancillary data, such as those from digitized aerial photographs, could be used to guide sampling in the absence of existing variograms of soil data for a site.

1.1. Theory: the indicator approach

An indicator variable is essentially a binary variable; it takes the values of 1 or 0 only, i.e. presence or absence, respectively (Webster and Oliver, 2001). Soil structure is a multi-state character that generally has more than two classes. This type of random variable is described as discrete or categorical (Goovaerts, 1997). It can be converted to indicators by coding each class as present or absent for a given sampling point. If there are three classes of soil structure, i.e. $K=3$ for example, there would be one binary variable for each class and each one would be coded as 1 or 0 in turn. The K classes of structure are mutually exclusive and only one of the three would be coded 1 and the other two would be 0 at a given site.

Let $S(\mathbf{x})$ denote a discrete random variable at a site $\mathbf{x}$. The relation between a categorical variable at two sites separated by a lag, $\mathbf{h}$, can be determined by considering the probability, $p(\mathbf{h})$, that they belong to different categories of soil structure, S (Goovaerts, 1994). The probability is defined by

$$p(\mathbf{h}) = \Pr[S(\mathbf{x}_i) \neq S(\mathbf{x}_i + \mathbf{h})], \tag{1}$$

and it describes how the probability that the soil structure observed at two sites changes with distance. For a set of observations, an estimate of $p(h)$ can be obtained by computing

$$\hat{p}(\mathbf{h}) = \frac{1}{N(\mathbf{h})} \sum_{i=1}^{N(\mathbf{h})} \Omega[S(\mathbf{x}_i) \neq S(\mathbf{x}_i + \mathbf{h})], \tag{2}$$

where $N(\mathbf{h})$ is the number of paired comparisons and $\Omega[S(\mathbf{x}_i) \neq S(\mathbf{x}_i + \mathbf{h})]$ is an indicator function defined as

$$\Omega[S(\mathbf{x}_i) \neq S(\mathbf{x}_i + \mathbf{h})] = \begin{cases} 1 \text{ if } S(\mathbf{x}_i) \neq S(\mathbf{x}_i + \mathbf{h}) \\ 0 \text{ otherwise} \end{cases}. \tag{3}$$

Let $I(\mathbf{x};S_k)$ be an indicator variable for soil structure class k, $k=1,\dots, K$, defined as

$$I(\mathbf{x}; S_k) \quad \begin{cases} 1 \text{ if } \mathbf{x} \subset S_k \\ 0 \text{ otherwise} \end{cases}. \tag{4}$$

The indicator variogram for class k is the variogram of Eq. (4)

$$\gamma_I(\mathbf{h}, S_k) = \frac{1}{2} \operatorname{Var}[I(\mathbf{x}_i; S_k) - I(\mathbf{x}_i + \mathbf{h}; S_k)] \tag{5}$$

The function $p(\mathbf{h})$ above is equivalent to the sum of the individual indicator variograms, $\gamma_I(\mathbf{h};S_k)$, as described by Goovaerts and Webster (1994). The sum of indicator variograms (SIV) is given by

$$\begin{aligned} p(\mathbf{h}) &= \sum_{k=1}^{K} \gamma_I(\mathbf{h}; S_k) \\ &= \frac{1}{2} \sum_{k=1}^{K} \operatorname{Var}\ [I(\mathbf{x}_i; S_k) - I(\mathbf{x}_i + \mathbf{h}; S_k)]. \end{aligned} \tag{6}$$

When an individual indicator is kriged, the values are between zero and one. This gives us the probability,