TRANSIOGRAMS FOR CHARACTERIZING SOIL TYPE SPATIAL VARIABILITY

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1. Introduction

Soil types may be one of the most typical multinomial discrete geographical variables that are composed of multiple nominal classes. Soil types normally exhibit complex interclass dependences. To describe the auto-dependence of each soil type and the interdependence between different soil types, we need theoretically sound and practically verified spatial continuity measures. Conventionally, we use indicator variograms to describe the correlations of discrete variables. The constraints of indicator variograms are that cross-variograms cannot detect the directional asymmetry of class occurrence sequences and effectively represent the juxtapositional relationships of classes. This study uses a new spatial continuity measure – transiogram, as an alternative to characterize the spatial variability of soil types.

One-dimensional Markov chains have long been used to describe spatial sequences of discrete variables in geosciences (Li et al., 1997, 1999). Recently, multidimensional Markov chain methods for conditional simulation emerged for simulating lithofacies (Lou, 1996; Elfeki and Dekking, 2001), soil types (Li et al., 2004) and land cover classes (Zhang and Li, 2004, 2005). Conditional Markov chain simulation models normally use one-step transition probabilities as model parameter inputs and calculate multi-step transition probabilities from one-step transition probabilities under the first-order Markov chain assumption. Such an approach has many limitations. Transition probabilities with different numbers of spatial steps (or lags) actually can form a continuous one-dimensional transition probability diagram, which is denominated "*transiogram*" by W. Li. Directly using transiogram, not one-step transition probability, as an independent spatial continuity measure and tool for describing spatial variation structure of discrete variables will provide great conveniences for estimating transition probabilities from various kinds of data, visually displaying the spatial class/interclass dependence in the Markov chain framework, incorporating expert knowledge, and accounting for the high-order Markovian effect of discrete data. Markov chain models can thus directly draw needed transition probabilities at any lag from transiograms in a simulation. Therefore, transiogram will play the similar role in Markov chain geostatistics as indicator variogram does in kriging geostatistics.

2. Transiograms

According to W. Li, a transiogram is defined as a continuous transition probability diagram over the continuous distance, that is, $p_{ij}(h)$. Here p_{ij} is the transition probability of random variable Z from class i to j over a constant distance or lag h. With increasing h from zero to a further distance, $p_{ij}(h)$ forms a continuous curve. $p_{ii}(h)$ represents the auto transiogram of class i

and $p_{ij}(h)\,(i ? j)$ represents the cross transiogram from class i to j. Compared with indicator variograms, transiograms are direct probability representations of spatial change of classes; therefore they are physically meaningful, easy to understand and interpret.

3. Material and Methods

In this study, we apply the transiogram theory to describe the spatial variability of soil types at a watershed scale. We choose a large piece of the soil survey map of the Iowa County, Wisconsin, to serve as the study area. The soil map is about 9656m × 9656m, containing 48 different soil types (soil series). We use raster data (for working with GIS) to estimate transiograms by discretizing the soil map into a raster with a pixel size of 20 × 20m. We estimated a large number of unidirectional real transiograms from the exhaustive soil map, and examined their characteristics. By comparing real transiograms with the transiograms derived from one-step transition probability matrices, we examined the high-order Markovian effect of soil type data. We thinned the soil map into a sparse dataset and estimate experimental transiograms from the sparse data. The experimental transiograms are fitted with basic transiogram models.

From the transiograms estimated from a soil map (Figure 1) and a sparse dataset, we attempt to explain the following spatial variation characteristics of individual soil types and spatial relations between different soil types in the study area: proportions, parcel mean lengths, juxtaposition relationships, directional asymmetries, auto/cross correlation ranges, occurrence periodicities, common shapes of transiograms, and high-order Markovian effect. Based on the analysis, we suggest a set of suitable transiogram models for representing the spatial variability of soil types.

4. Results

Transiograms estimated from the soil type map show that (1) their sills are close to the proportions of corresponding soil types in the study area as expected, (2) auto-transiograms of soil types are normally close to exponential curves, and (3) cross-transiograms of soil types are mostly close to exponential or spherical curves, however, with apparent irregular periodicities, which represent a reflection of irregular change of natural landscape. Transiograms derived from one-step TPMs are mostly smooth exponential curves, with some of cross ones having a peak. While a TPM-derived transiogram only represents a first-order transition probability model, transiograms estimated from data apparently contain more information than that a first-order transition probability model can capture. The extra features of real transiograms are essentially a reflection of the high-order Markovian property of the data. Using one-step TPMs to derive transiograms provides a simple and cheap way in transiogram estimation and in Markov chain simulation but its application is limited because of the difficulty in acquiring reliable one-step TPMs and its inability in reflecting the high-order Markovian effect of data. By model fitting of experimental transiograms, the high-order Markovian effect of data may be incorporated into a simulation.

Because transiograms can provide continuous transition probabilities at any lag needed in a Markov chain simulation and have the flexibility of incorporating high-order Markovian effect and expert knowledge, their introduction will also promote the capacity and application scope of Markov chain models and algorithms. For example, with this transition probability estimation approach, Markov chain geostatistical algorithms, such as the 2-D Markov chain algorithm introduced by Li et al. (2004), will be ready to be extended for working with point data. For another example, by fetching transition probabilities from transiograms, even 1-D Markov chain models may incorporate more spatial variation characteristics into a conditional simulation. Given the significance of cross-transiograms in incorporating interclass dependence, transiograms will provide a potentially powerful tool for characterizing spatial variation structures of discrete variables.

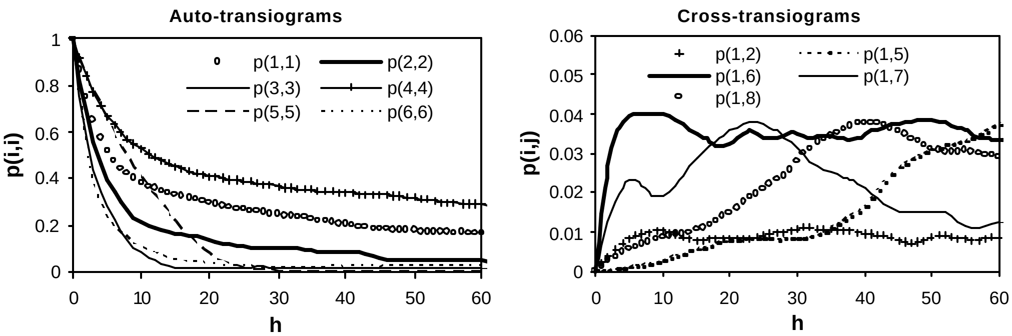

Fig. 1. Some transiograms estimated from a soil type map in the west-east direction. p(i,j) in legends means a transiogram from class *i* to *j*. Scales along the *h* axis are numbers of grid units in the direction.

5. Conclusion

Though facing lots of challenges, the Markov chain geostatistics is emerging. This new geostatistics is a non-covariance and non-kriging approach. Its major power is the ability of incorporating interclass dependences and dealing with many classes. Therefore, it is potentially very suitable for simulating complex categorical variables such as soil types. Accompanying this geostatistics is the herein introduced new spatial measure – transiogram.

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