# Modelling Structures of Terrain Surface Using GIS in Loess Plateau

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**Abstract:** Terrain is a combination of several scales of structures, with those different structures being sensitive to different landscape process and influenced by DEM (Digital Elevation Model) resolution in different ways. It is important to separate these structures to investigate their characteristics. In this research, the spatial structure of a terrain surface Loess Hilly areas in the Loess Plateau was analyzed using a 10 m resolution DEM. A geostatistical model named Independent Structures Model (ISM) was built and used to model the semi-variance of different terrain structures with different spatial frequencies. Surface of each terrain structure was mapped by kriging. The result showed that: 1). The spatial components for elevation surface could be modelled through the modelling of semi-variance. In the study area, the elevation surface could be modelled to be three components with range of 82.5 m, 655.4 m and 1974.2 m and one trend component. The third component was the most important because the sill value was larger than the other two components. 2). The three components in the model could be shown to be consistent with half width of catchments with minimum catchment area of 0.1 km<sup>2</sup>, 1 km<sup>2</sup> and 10 km<sup>2</sup>. The result of this work are relevant for research into the scaling effect of terrain parameters and the relationship between terrain and soil erosion modelling, hydrology analysis and related fields.

Keywords: Independent structures model, spatial structure, terrain

# 1. INTRODUCTION

The landscape has a range of scales. These need to be investigated and modelled because different scales have varied characteristics and are sensitive to different processes. Terrain is one of the most important factors in many areas, including hydrology, geomorphology, and soil erosion (Moore et al. 1991, De Roo et al. 1996, Wu et al. 2008). Terrain surface scales are more structured by scales at the levels of catchments, rivers and hillslopes. Terrain factors (slope, aspect, etc.) are mainly extracted from coarser resolution DEMs at regional and global scales, and change with DEM resolution (Gallant and Hutchinson 1997). The relationship between terrain factors and DEM resolution have been previously studied (Wolock and Price 1994, Tang et al. 2003, Wu et al. 2008, Vaze et al. 2010, Wang et al. 2012). However, most of these studies are about the relationship between statistics of terrain factors (for example 'mean slope') and resolution. There is a lack on the mechanistic explanations which could be given by the modelling of terrain structures.

Here we use variograms (Chiles and Delfiner 1999, Webster and Oliver 2007) to model terrain structures. In many fields such as remote sensing modeling (Jupp et al. 1988, Jupp et al. 1989), land cover (Oliver et al. 2005) and soil moisture (Western and Blöschl 1999), researchers modelling structures by modelling semi-variogram of certain natural features. Semi-variogram modelling is important for parameters in Kriging mapping. The calculation of semi-variogram is based on sampled point data sets and is more difficult for grid DEM data because the quantity of data pairs at most lag steps is huge. In this research, the authors calculated semi-variograms based on grid DEM data by developing an IDL program in ENVI 5.2.

# 2. METHODS

# 2.1. Study area

The study area is located in the Hilly area of the Loess Plateau (E109° 46′  $\sim$ 109° 59′ , N39° 50′  $\sim$ 40° ; Fig 1). It is a square of side 18km with an average altitude of 1422m. It is a typical hilly landform in the Loess Plateau with crossing gullies. The average slope is 6°.



Figure 1. Location and surface of study area

# 2.2. Base data and data processing

The base data is a topographic map at 1:50,000 scale issued by China's National Bureau of Surveying and Mapping with a contour interval of 20m. The data processing includes topographic map digitization, projection transformation, elevation values, river direction and lake boundary checks. The projection for the base data is Gauss-Kruger. A DEM with square cells of resolution of 10 m was built using the ANUDEM algorithm (Hutchinson 1989, Hutchinson 2011).

# 2.3. Modeling of Structures of Terrain Surface

In this paper, the structures of terrain surface were modelled based on the theory of Geostatistics through the modelling of semi-variograms. The model is named "Independent structures model" (ISM). The ISM is related to the "Nested model" in Geostatistics. However Serra (1982) suggests that "Nested" models would be a more appropriate description for a hierarchical model rather than for a sum of independent semi-variograms (Serra 1982) used in the ISM.

The mathematical expression for covariance and the semi-variance function is as follows:

$$C(h_x, h_y) = E((Z(x + h_x, y + h_y) - m)(Z(x, y) - m)) \qquad \gamma(h_x, h_y) = \frac{1}{2}E((Z(x + h_x, y + h_y) - Z(x, y))^2 \qquad \text{Where}$$

 $C(h_x h_y)$  refers to the covariance function and  $\gamma(h_x, h_y)$  refers to the semi-variance function; (x, y) stands for the spatial coordinates of the tested point of the slope; Z(x, y) stands for the data of the tested point;  $h_x$  and  $h_y$  stands for the interval in x and y direction between two tested points (in 1D cases  $h = (h_x^2 + h_y^2)^{1/2}$ ), *m* is the mean value over the image. We will assume that the covariance is stationary and the mean (*m*) is a constant over the image.

33.71

In this case the relationship between the two expressions is:

$$\gamma(h_x, h_y) = C(0,0) - C(h_x h_y)$$
  $C(0,0) = \sigma^2$ 

 $\sigma^2$  is the variance of the image data which needs to be spatially stationary (Webster and Oliver 2007). In this paper, we calculated elevation semi-variance in IDL program based on grid DEM.

In the Independent structures model the original field Z(x, y) is considered to be composed of N "independent" fields, the covariance between the N fields is zero.

$$Z(x, y) = \sum_{j=1}^{n} \sigma_j Y_j(x, y) \quad \sigma_Z^2 = \sum_{j=1}^{n} \sigma_j^2$$

In the "Independent Structures" Model, the covariance function and semi-variogram fuction for Z is given by:

$$C_{Z}(h_{x},h_{y}) = \sum_{j=1}^{N} \sigma_{j}^{2} c_{j}(R_{j};h_{x},h_{y}) \gamma_{Z}(h_{x},h_{y}) = \sum_{j=1}^{N} \sigma_{j}^{2} \gamma_{j}(R_{j};h_{x},h_{y}) = \sum_{j=1}^{N} \sigma_{j}^{2} (1 - c_{j}(R_{j};h_{x},h_{y})) \gamma_{Z}(h_{x},h_{y}) = \sum_{j=1}^{N} \sigma_{j}^{2} (1 - c_{j}(R_{j};h_{x},h_{y})) \gamma_{Z}(h_{x},h_{y}) = \sum_{j=1}^{N} \sigma_{j}^{2} \gamma_{j}(R_{j};h_{x},h_{y}) = \sum_{j=1}^{N} \sigma_{j}^{2} (1 - c_{j}(R_{j};h_{x},h_{y})) \gamma_{Z}(h_{x},h_{y}) = \sum_{j=1}^{N} \sigma_{j}^{2} \gamma_{j}(R_{j};h_{x},h_{y}) = \sum_{j=1}^{N} \sigma_{j}^{2} (1 - c_{j}(R_{j};h_{x},h_{y})) \gamma_{Z}(h_{x},h_{y}) = \sum_{j=1}^{N} \sigma_{j}^{2} \gamma_{j}(R_{j};h_{x},h_{y}) = \sum_{j=1}^{N} \sigma_{j}^{2} (1 - c_{j}(R_{j};h_{x},h_{y})) \gamma_{Z}(h_{x},h_{y}) = \sum_{j=1}^{N} \sigma_{j}^{2} \gamma_{j}(R_{j};h_{x},h_{y}) = \sum_{j=1}^{N} \sigma_{j}^{2} (1 - c_{j}(R_{j};h_{x},h_{y})) \gamma_{Z}(h_{x},h_{y}) \gamma_{Z}(h_{x},h_{y}) = \sum_{j=1}^{N} \sigma_{j}^{2} (1 - c_{j}(R_{j};h_{x},h_{y})) \gamma_{Z}(h_{x},h_{y}) = \sum_{j=1}^{N} \sigma_{j}^{2} (1 - c_{j}(R_{j};h_{x},h_{y})) \gamma_{Z}(h_{x},h_{y}) \gamma_{Z}(h_{x},h_{y}) = \sum_{j=1}^{N} \sigma_{j}^{2} (1 - c_{j}(R_{j};h_{x},h_{y})) \gamma_{Z}(h_{x},h_{y}) \gamma_{Z}(h_{x},h_{y}) = \sum_{j=1}^{N} \sigma_{j}^{2} (1 - c_{j}(R_{j};h_{x},h_{y})) \gamma_{Z}(h_{x},h_{y}) \gamma_{Z}(h_{x},h_{y}) \gamma_{Z}(h_{x},h_{y}) = \sum_{j=1}^{N} \sigma_{j}^{2} (1 - c_{j}(R_{j};h_{x},h_{y})) \gamma_{Z}(h_{x},h_{y}) \gamma_{Z}(h_{x}$$

 $R_i$  refers to the ranges of the component semi-variograms and:

$$0 < R_1 < R_2 < R_3 \dots < R_N$$

In this way, the first component is the one with greatest "roughness" or high spatial frequency content effect and the last is the one with greatest low frequency (regional) effect.

In this paper the authors assume that the base semi-variogram model is the radial 2D Gaussian, the covariance for each component is:

$$c_j(h) = \sigma_j^2 e^{-(h/R_j)^2}$$

The radial distance is  $h = \sqrt{h_x^2 + h_y^2}$ ;  $\sigma_j^2$  is the variance of the component j; the quantity  $R_j$  is taken as the range of component j and the component has the form of a correlation function.

#### 2.4. Indicative Goodness of Fit

In this paper, the Indicative Goodness of Fit (IGF; Pannatier 1996) was used to evaluate the result of fitting the semi-variogram models. IGF is defined as follows.

$$\begin{split} IGF &= 100 \times \left( \frac{1}{N_{V}} \sum_{k=1}^{N_{V}} \left( \sum_{i=1}^{n(k)} \left( \frac{n_{ik}}{d_{k}} / d_{k}(i) \right) \sum_{j=1}^{n(k)} \frac{n_{jk}}{d_{k}} / d_{k}(i) \right) \left[ \frac{\gamma_{k}(i) - \hat{\gamma}_{k}(i)}{\sigma_{k}^{2}} \right]^{2} \right) \right) \\ &= 100 \times \left( \frac{1}{N_{V}} \sum_{k=1}^{N_{V}} \left( \sum_{i=1}^{n(k)} w_{ik} \left[ \frac{\gamma_{k}(i) - \hat{\gamma}_{k}(i)}{\rho_{k}^{2}} \right]^{2} \right) \right)^{1/2} \\ w_{ik} &= nl_{ik} / d_{k}(i) / \left( \sum_{i=1}^{n(k)} \left( \frac{n_{ik}}{\rho_{k}} / d_{k}(i) \right) \right) \left| \frac{1}{\sigma_{k}^{4}} \right|^{2} \end{split}$$

Where:  $N_{i'}$  is the number of semi-variograms included in the fit (indexed by k); n(k) is the number of lags in semi-variogram k (indexed by i);  $nl_{ik}$  is the number of pairs used in lag i of semi-variogram k;  $d_k(i)$ is the lag distance for lag i of semi-variogram k;  $\sigma_k^2$  is the variance for the semi-variogram k (not sill but an image estimate for it);  $w_{ik}$  is the combined weight for lag i of semi-variogram k;  $\gamma_k(i)$  is the semivariogram for lag i of semi-variogram k;  $\hat{\gamma}_k(i)$  is the estimated (model) semi-variogram for lag i of semivariogram k. In this paper k equals 1.

#### 2.5. Model validation

Range refers to the distance where the variance plateaus. For the variance of elevation, the variance between two points tends to become larger from valley to hilltop, and tends to plateau when two points are in different catchments. In this paper, the range of each component in the model will be shown to correspond with the half width of a certain size of catchment. The difference between range and half width of the catchment was

measured using the index D which is defined as

$$\mathbf{D} = \left(1 - \frac{|\mathbf{R} - \mathbf{h}|}{\mathbf{R}}\right) * 100\%$$

Where R refers to the measured half width of the catchment, and h is range in the model. D is from 0% to 100%. The model is more efficient if D is larger.

#### 3. RESULTS

#### 3.1. Experimental semi-variogram analysis and anisotropy analysis

The experimental semi-variogram of elevation was computed from the digital numbers of DEM with resolution of 10m for this study. The semi-variogram was computed to a maximum lag of 9 km (about half of the size of the images). The graphical representations of the semi-variogram in the four principal directions were as shown in Fig.2. There is clear evidence of anisotropy after lag distance 2km since the semi-variograms from the four directions were different. The variation in directions N-S is smaller which is in accordance with the elevation surface of the study area for the main river flows from south to north. Since the differences between variances in different directions are relatively small up to lag distance 2km,



the radial semi-variogram is only computed to a lag distance of 2km in the following analysis.

#### **3.2. ISM modeling of the radial average semi-variograms**

The elevation semi-variogram (Figure 3, Table 1) was modeled to be 4 components, labeled in increasing order as Y1, Y2, Y3, and Y4. Y4 represents longer wave-length information which could be treated as a trend component as it had not reached a sill before the maximum lag distance. The IGF value was 0.38 for the fit of the model. The range values for components Y1, Y2 and Y3 correspond with the half width of catchments with minimum catchment area of 0.1 km<sup>2</sup>, 1 km<sup>2</sup>, and 10 km<sup>2</sup> in the study area (Fig 4). The D values were also higher than 99% for Y1 and Y2 component, representing a good fit, but for Y3 it was 72.87%.

<b>Table I.</b> Sill and range values in the n
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Component	Sill (m <sup>2</sup> )	Rang (m)
Y1	41.0	182.5
Y2	68.7	655.4
Y3	177.6	1974.2
Y4	784.0	8784.8



Figure 3. Modeling result of semi-variograms



Figure 4. Catchments selected for validation

Table 2. D value for each component				
Minimum catchment area	Mean half width of catchment	Range for the model	D (%)	
(km <sup>2</sup> )	(m)	(m)		
0.1	180.7	182.5	99.0004	
1	655.5	655.4	99.985	
10	1552.9	1974.2	72.870	

# **3.3.** Mapping of the topographic components

It is useful to help identify the nature of the corresponding components in the landscape to identify the different scales of components in the DEM data. Ordinary kriging (Oliver, Webster et al. 2000) was used to extract estimates of the surface of each component (Fig.5).



Figure 5. Surface of each elevation component

#### 4. **DISCUSSION**

This research is valuable for the explanation of scaling effects of terrain parameters, helping understand the relationship between terrain surface and soil erosion, hydrology analysis, biology and related fields. The Gaussian model is used for each component because it is additive and simplifies the upscaling derivation process which is the next stage of this research. The geographic meaning for the parameter range in the model could be explained and has been shown to be half the width of certain catchment levels for this study area.

# 5. CONCLUSION

# We could conclude that:

1). The spatial components for elevation surface could be modelled through the modelling of semi-variance. In the study area, the elevation surface could be modelled to be three components with range of 82.5m, 655.4m and 1974.2m and one trend component. The third component was the most important component for the sill value was larger than the other two components.

2). The three components in the model could be proved to be consistent with half width of catchments with minimum catchment area of  $0.1 \text{km}^2$ ,  $1 \text{km}^2$  and  $10 \text{km}^2$ .

# ACKNOWLEDGMENTS

This study has been financially supported through the projects NSFC Project 41301284, NSFC in Shaanxi Province Project 41371274, Program for Key Science and Technology Innovation Team (Grant No. 2014KCT-27), Science and Technology Fund in Shaanxi Province 2013JQ5002 and National College Students Innovation Project 201410697039.

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