# Modelling Erosion On Conditionally-Simulated Dems Of Bare Soil Surfaces

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## Biography Of First Author

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## Introduction

Soil erosion by water is a major present-day environmental problem: to manage its impacts, quantitative modelling is an important tool. The present-generation of erosion models have difficulties in predicting the spatial patterns of erosion, however. Thus a model (‘RillGrow 2’) was developed (Favis-Mortlock, 1998; Favis-Mortlock et al., 2000). The modelling approach considers that the movement of runoff is conditioned by microtopography, which is itself modified by the passage of erosive flows. This iterative relationship constitutes a self-organising complex system: networks of erosional channels (‘rills’ and ‘microrills’) develop as emergent features of this system. In a series of validation studies, DEMs of the microtopography of real soil surfaces were used as inputs to the RillGrow model. Simulated rill networks were compared with those which developed on these surfaces during laboratory and field experiments. Results from these studies (Favis-Mortlock et al., in preparation) demonstrate that, given suitable information on initial conditions including microtopography, the RillGrow model is able to realistically predict the eventual pattern of erosion’s impacts on small hillslope areas.

However, if the approach is to be used practically, e.g. to simulate rill networks on a larger hillslope area under some future conditions of rainfall or tillage, then a method is needed for generating synthetic DEMs of soil surface microtopography which are statistically similar to those of real soil surfaces. These may then be superimposed on a more coarsely-gridded DEM of the hillslope area. Multiple runs of the RillGrow model could then be carried out, each with a different simulated realisation of the microtopography. This would enable a probabilistic description of the spatial occurrence of erosion to be created, for a particular hillslope under a particular set of conditions.

In this research, sequential Gaussian simulation (SGS) was used to generate multiple equally-probable realisations of microscale bare soil surfaces from a sparse grid. The different realisations were each input into RillGrow 2. Variations in outputs from RillGrow 2, given the different simulated inputs, were explored. The importance of uncertainty in inputs (i.e., simulated realisations) on the form of the outputs was examined.

## Conditional Simulation

Kriging predictions are weighted moving averages of the available sample data. Kriging is, therefore, a smoothing interpolator. Geostatistical simulation (also called stochastic imaging) is not subject to the smoothing associated with kriging (conceptually, the variation lost by kriging due to smoothing is added back) as predictions are drawn from equally probable joint realisations of the random variables (RVs) which make up a random function (RF) model (Deutsch and Journel, 1998). That is, simulated values are not the expected values (i.e., the mean) but are values drawn randomly from the conditional cumulative distribution function (ccdf): a function of the available observations and the modelled spatial variation (Dungan, 1999). SGS, and related approaches, reproduce the histogram and variogram. Simulated realisations represent a possible reality whereas kriging does not. The simulation is considered "conditional" if the simulated values honour the observations at their locations (Deutsch and Journel, 1998). Simulation allows the generation of many different possible realisations that may be used as a guide to potential errors in the construction of a map (Journel, 1996). Multiple realisations encapsulate the uncertainty in spatial prediction.

Probably the most widely used form of conditional simulation is sequential Gaussian simulation (SGS), applied in this paper. With sequential simulation, simulated values are conditional on the original data and previously simulated values (Deutsch and Journel, 1998). In SGS the ccdfs are all assumed to be Gaussian.

## Analysis

Two data sets were available in this study: (i) observations on a cm-scale grid covering the entire area of interest and (ii) observations on a finer mm-scale grid covering only a part of the study area.

Spatial variation in both data sets (i) and (ii) was characterised using experimental variograms to which models were fitted. The variogram models were then used to predict from data set (ii). Following this, the coefficients of models fitted to the two variograms were used to inform SGS to generate two sets each of 50 realisations. The mean and variance at each location for the two sets of realisations were then estimated to give an idea of the uncertainty in the realisations. The histogram and variogram of each of the realisations were estimated to assess the degree to which the sample data histogram and variogram were reproduced. A selection of the SGS realisations was then input into RillGrow 2.

The outputs from RillGrow 2 were compared in various ways. Regression was used to provide a very simple comparison of co-located values in different outputs. The form of rills formed was compared by examining profiles cut orthogonal to the direction of the rills. These comparisons provided only a limited means of assessing differences in outputs, but they did indicate that it is necessary to consider uncertainty in inputs to the model given differences in the outputs derived using each realisation. One specific objective was to assess if SGS using the variogram of data on the fine grid provides significantly different outputs than SGS based on the variogram of the data on the coarse grid.

## Summary

This research explored the relationship between changes in short range variation of inputs to RillGrow 2 and the form of outputs from the model. In this way, the sensitivity of RillGrow 2 to variations in inputs was assessed.

## References


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