Making spatial soil erosion predictions – planning tool or hocus-pocus?

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Introduction

Soil erosion models are a widely used tool for policy making land use planning. The development of Geographic Information Systems (GIS) has facilitated the production of spatial predictions across a range of land uses, topographic and agro-climatic regions. The maps produced may look impressive, but how much confidence do we really have in the predictions they represent? Planners often prefer to ignore the uncertainties which are present in model output and may not wish to know that we have little idea as to how well our spatial predictions represent reality. This, of course, is further confused by the considerable uncertainties that exist in our spatial observations that we use to drive and assess model prediction performance. If erosion modellers are also oblivious to the validity or otherwise of their predictions, then are model simulations more hocus-pocus[1] than a true reflection of the spatial erosion rates within a landscape?

This paper sets out to answer the research question: what does a distributed model that performs well at simulating erosion responses at the catchment outlet tell us about the true nature of the spatial erosion rates within the catchment?

Experiment

To demonstrate the problems of developing confidence in spatially distributed predictions we will use a fictitious, small and highly erodible catchment (Figure 1), loosely based on a real catchment in Southern France. The catchment is a former mine and much of the surface is devoid of vegetation and the soils are of low permeability. The total area of the catchment is 17.8 ha and the slopes drain down towards a single outlet drain. The area has a mean annual rainfall of 725 mm and this falls over 80 days a year.

We wish to calculate mean annual soil loss from the catchment and to determine the relative contribution of different areas of the catchment. To do this we have divided the catchment based on information about soils, slopes and vegetation. The catchment divides into five areas (Figure 2). To determine the annual soil loss for each of these areas we applied the Morgan, Morgan, Finney (MMF) soil erosion model (Morgan *et al.*, 1984). The MMF model is a relatively simple process based model suitable for predicting annual soil losses from plots and small catchments and can easily be programmed in a spreadsheet environment.

[1] Hocus-pocus is defined as trickery by the Collins dictionary.

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To enable us to quantify the impacts of parameter uncertainty within the model on simulated predictions made with the model, we linked the model to a commercially available package, Crystal Ball®, which facilitates the use of Monte Carlo analysis in modelling. Monte Carlo analysis allows us to establish distributions, rather than single value estimates, of model inputs and parameters as well as observations used to evaluate the model. These distributions are based on measured data or distributions taken from the literature. The software then samples from these distributions and executes the model, storing the output information for each run. Once a large number of runs have been completed a distribution of outputs can be viewed, and interrogated to provide values of the model outputs at different levels of confidence. In this example we use 10 000 runs of the model. Had we applied the model in the traditional manner where we would have selected a single effective parameter for each element our run would only have represented one of the 10 000 combinations we ran using the Monte Carlo analysis.

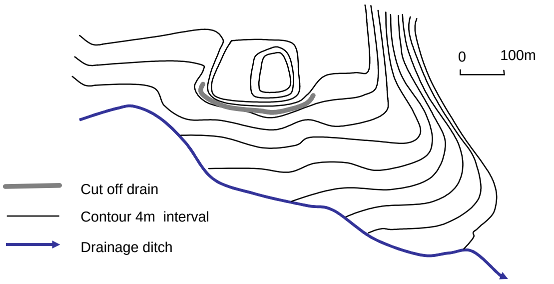

Figure 1. Topographic map of the study catchment.

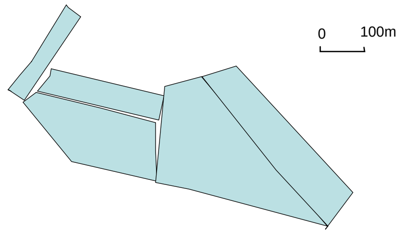

Figure 2. Elemental division of the catchment

Results

Figure 3 gives the distribution of total soil loss for the entire catchment. This is normally distributed around a mean value 786 t yr^{-1} with a maximum of 2503 t yr^{-1} and a minimum of 7 t yr^{-1}. 95% of the predictions lie below 1448 t yr^{-1}. The results from the different elements also have a large range (Table 1). We should not be disheartened by this as it has been shown previously (Quinton, 1997; Brazier *et al.*, 2000) that other erosion models such as EUROSEM (Morgan *et al.*, 1998) and WEPP (Nearing *et al.*, 1989) also suffer from considerable parameter uncertainty resulting in uncertain outputs.

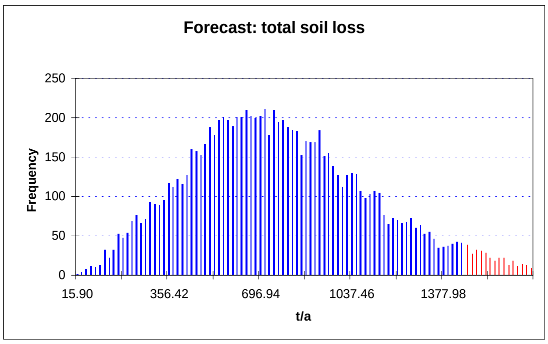

Figure 3. Distribution of soil loss from the study catchment after 10 000 simulations with the MMF model. 95% percentile indicated by a change in bar shading.

The data generated by the model also reveals information which is pertinent to our initial question. If we look more closely at Figure 3 we find that the mean is represented by over two hundred simulation results and over 200 different and equally possible parameter sets.

Table 1. Minimum and maximum soil loss (t yr^{-1}) for each of the catchment elements and the catchment outlet

	Element number					
	1	2	3	4	5	outlet
Minimum	0	0	0	0	0	7
Maximum	121	358	318	2012	858	2504

We took those simulations which produced between 780 and 790 t yr^{-1} total sediment loss from the catchment and looked at the distribution of soil losses for each of the elements. Figure 4 demonstrates clearly that knowing the soil loss at the outlet of a catchment is no guarantee that the contributions of the different elements within the catchment will be uniquely defined. For element 1 we can say that the soil loss will be below 100 t yr^{-1}. However, the contributions of the over elements vary widely. With some elements' contributions ranging from almost nothing to nearly the entire soil loss from the catchment.

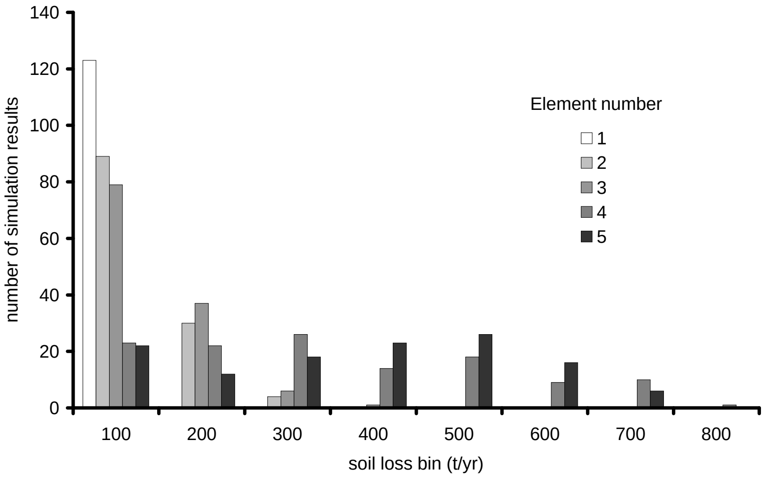

Figure 4. Number of simulations resulting in a soil loss value between the lower bin value and the bin value indicated on the axis for each element, where the a total catchment soil loss was between 780 and 790 t yr^{-1}.

Discussion and conclusion

The findings from this experiment indicate that if we calibrate or validate our erosion models at the catchment outlet we should not expect them to produce spatially accurate predictions. The calibration or validation at the outlet, simply demonstrates that the model can fit the outlet data and tells us nothing about spatially distributed soil erosion rates within the catchment. In our example it is only possible to identify only element which consistently behaves the same way (element 1) with the other elements all producing a wide range of soil losses.

This leaves us with a problem, because policy makers and land use planners are demanding spatially distributed predictions of soil erosion. If the soil erosion community is going to respond to this demand then it also has to consider how it will demonstrate confidence in spatial predictions. We make the following suggestions:

1. Modellers will need to demonstrate how their models perform at different scales and in different environments within an uncertainty framework, e.g. using Monte Carlo based techniques, such as performed in this study, or other uncertainty estimation techniques like GLUE (Beven & Binley, 1992; Beven & Freer, 2001)

2. Spatial models require a nested set of observations to be evaluated against, again within an uncertainty framework, ranging from how the model performs at a range of environments from the grid cell scale, to micro-catchments comprising a few grid cells and finally to larger catchments. Without this analysis we will not understand

which environments the model performs well in and whether or not the algorithms linking the grid cells perform well.

3. Models need to be tested on a range of environments from parameter data rich research catchments to parameter data poor catchments. Modellers then need to determine what these results mean in terms of our ability to robustly evaluate models and to quantify realistic prediction uncertainties. Furthermore better experiments need to be designed that try to capture not only the observed erosion rates, but also some understanding of the limitations and uncertainties in our ability to quantify those rates.

4. Policy makers and land use planners need to be trained to understand uncertainty and risk. The real world is highly variable and uncertain, expecting to quantify the impacts of policies in catchments with single values is no better than relying on hocus-pocus.

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