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Global Sensitivity Analysis of Parameter Uncertainty in Landscape Evolution Models

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Abstract

Landscape Evolution Models have a long history of use as exploratory models, providing greater understanding of the role large scale processes have on the long-term development of the Earth's surface. As computational power has advanced so has the development and sophistication of these models. This has seen them applied at increasingly smaller scale and shorter-term simulations at greater detail. However, this has not gone hand-in-hand with more rigorous verifications that are commonplace in the applications of other types of environmental models- for example Sensitivity Analyses.

This can be attributed to a paucity of data and methods available in order to calibrate, validate and verify the models, and also to the extra complexity Landscape Evolution Models represent - without these it is not possible to produce a reliable Objective Function against which model performance can be judged. To overcome this deficiency, we present a set of Model Functions - each representing an aspect of model behaviour - and use these to assess the relative sensitivity of a Landscape Evolution Model (CAESAR-Lisflood) to a large set of parameters via a global Sensitivity Analysis using the Morris

Method. This novel combination of behavioural Model Functions and the Morris Method provides insight into which parameters are the greatest source of uncertainty in the model, and which have the greatest influence over different model behaviours. The method was repeated over two different catchments, showing that across both catchments and across most model behaviours the choice of Sediment Transport formula was the dominate source of uncertainty in the CAESAR-Lisflood model, although there were some differences between the two catchments. Crucially, different parameters influenced the model behaviours in different ways, with Model Functions related to internal geomorphic changes responding in different ways to those related to sediment yields from the catchment outlet.

This method of behavioural sensitivity analysis provides a useful method of assessing the performance of Landscape Evolution Models in the absence of data and methods for an Objective Function approach.

1. Introduction

Landscape Evolution Models (LEMs) investigate how the Earth's surface evolves over timescales ranging from hundreds to millions of years (Coulthard and Van De Wiel, 2012; Martin and Church, 2004; Pazzaglia, 2003; Tucker and Hancock, 2010; Van De Wiel et al., 2011). They represent the earth's surface with a regular or irregular mesh and simulate how the surface evolves over time as a function of tectonic processes, and erosion and deposition from fluvial, glacial, aeolian and hillslope processes. LEMs have proved to be very useful scientific tools to understand how Earth surface processes interact to shape the landscape.

More recently, LEMs have improved considerably in their ability to simulate the physical environment, and this has developed in parallel with improvements in computational efficiency and power. This allows LEMs to go beyond highly simplified models of landform development but to also incorporate

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increasingly complex processes such as pedogenesis (Vanwalleghem et al., 2013; Welivitiya et al., 2016) and periglacial processes (Andersen et al., 2015; Egholm et al., 2015). Other processes are now being handled in more detail such as hydrodynamic flow models and aeolian processes (Adams et al., 2017; Coulthard et al., 2013; Liu and Coulthard, 2017). These developments led to Coulthard et al. (2013) describing them as 'second generation' LEMs that extend previously explanatory and explorative models to be used for prediction of future changes in landscapes, such as for the mining industry (e.g. Hancock et al., 2017; Saynor et al., 2012).

However, more detailed physical representations of the processes that shape the Earth's surface involve a larger number of parameters that are typically not legitimated by theories but must be determined from empirical data or are incompletely known (Oreskes et al., 1994; Petersen, 2012). If LEMs are to be operationally used for prediction or as decision-making tools in the future, their outputs must be evaluated against the uncertainty in input parameters – a task that is increasingly difficult for a large number of parameters. Sensitivity analysis (SA) investigates how variations in the output of a numerical model can be attributed to its input factors (Pianosi et al., 2016), but has rarely been conducted for LEMs. The aim of this study is thus to conduct a SA of the widely used and highly parameterized LEM CAESAR-Lisflood (Coulthard et al., 2013) - in particular, we wish to be able to detect the parameters that have the greatest influence on the model. As model sensitivity may be influenced by different landscapes, we run the SA in two individual and distinct catchments.

1.1 Sensitivity Analysis and Landscape Evolution Models

The application of SA in environmental modelling has a history spanning four decades (Norton, 2008) and forms an important component of using models for decision-making, including model development, calibration and uncertainty analysis (Yang, 2011). SA addresses five key questions (Cariboni et al., 2007; Neumann, 2012; Song et al., 2012, 2015):

1. Which parameters have the greatest influence on the model?
2. If additional data could be used to reduce the uncertainty in a parameter, which would most reduce the model output variance?
3. Are there parameters with such low influence that their values could be fixed without impact on the model outputs?
4. If parameter values emerge as incorrect, how will they influence model outputs?
5. Which parameters influence model outputs in different regions (parameter space)?

Clearly, based on the above, an appraisal of model sensitivity is important to fully understand and apply model results. In a review of applications of SA in environmental models, Yang (2011) identified two common approaches to SA – local and global. Local SA are limited, considering only the impacts of factors on model outputs locally, whilst global SA typically utilise Monte-Carlo methods to assess the sensitivity of impacts across the whole parameter space (Yang, 2011). For complex models with non-linear behaviours, the use of Local SA can be highly biased as they neglect the non-linear interactions between parameters (Oakley and O'Hagan, 2004; Pappenberger et al., 2006; Yang, 2011). Global SA are more computationally expensive, but as the methods are more reliable, they are attractive to modellers (Yang, 2011).

However, for LEMs there are surprisingly few examples of SA being carried out. This can be explained by three inter-related issues: (i) LEMs typically have a large number of model parameters; (ii) long model run times can make multiple simulations for SA impractical; and (iii) model behaviour can he highly non-linear (e.g. Coulthard and Van De Wiel, 2007; Larsen et al., 2014; Van De Wiel and Coulthard, 2010), leading to potentially complex SA interpretations. Large numbers of model parameters and long run times, in particular, make Monte-Carlo methods extremely time consuming – and therefore often unviable.

There are several past studies investigating how LEMs respond to process changes and model parameters, including changes in climate variability and precipitation resolution (Armitage et al., 2017; Coulthard and Skinner, 2016a; Ijjasz-Vasquez et al., 1992; Tucker and Bras, 2000), channel widths (Attal et al., 2008), vegetation (Collins, 2004; Istanbulluoglu and Bras, 2005), and variations in initial conditions (Hancock, 2006; Hancock et al., 2016; Ijjasz-Vasquez et al., 1992; Willgoose et al., 2013). Yet few studies explicitly perform SA and most of the applications described above are exploring LEM sensitivity to processes, or changes in environmental conditions, and are more correctly referred to as exploratory tests (Larsen et al., 2014). On the other hand, investigations to ascertain the model's response to potential uncertainties (e.g from model parameterisation) can be deemed as true SA (eg, Armitage et al., 2017; Coulthard and Skinner, 2016a; Hancock et al., 2016).

The study by Ziliani et al. (2013) is another example of a LEM SA, seeking to spatially calibrate a reach-scale application of the CAESAR LEM to field observations. They performed a two-stage SA, utilising the Morris Method (MM) (as adapted by Campolongo et al., 2007) as a pre-screening before a more complex local SA was applied. The study investigated the model's sensitivity to 12 user-defined parameters, using MM to exclude those showing the least influence on performance measures from the subsequent SA and calibration. Whilst Ziliani et al. (2013) demonstrated the feasibility of applying MM as a global SA to a reach-scale LEM, it was applied as a pre-screening stage to identify parameters to focus model calibration on, and not to observe model behaviour.

1.2 Metrics for Landscape Evolution Model Assessment

An issue with the testing of LEMs is finding the field data and statistical tools that can actively discriminate between what is a good model and a bad model, and for parameterisation (Hancock and Willgoose, 2001; Hancock et al., 2016; Tucker and Hancock, 2010). As the models are designed to assess both short (annual to decadal) to long-term (geological time scale), the data and assessment methods require both a multi-dimensional approach. The application of SA to environmental models often assesses the impacts of factors based on variations in values of an objective function, which is often an error score between observed and simulated values – for example, a common approach in hydrology would to use the Nash-Sutcliffe score (Nash and Sutcliffe, 1970) as an objective function, and catchment discharges as a value. The objective function approach was used by Ziliani et al. (2013), matching the outputs of a reach simulation in CAESAR to observed patterns of wet/dry pixels, erosion/deposition, and vegetation. However, the objective function approach is generally not practical for LEMs due to a paucity of observed data to use as a value, so often the results from LEMs are assessed qualitatively, relying on visual interpretation of the final simulated landforms or cross-section profiles (eg. Hancock et al., 2010; 2015; Hancock and Coulthard, 2012; Coulthard and Skinner, 2016a).

The use of catchment outlet statistics, such as sediment yield time series, allow for comparison between simulations to indicate a catchment's response to perturbations (e.g. Coulthard et al., 2012; Coulthard and Skinner, 2016b; Hancock and Coulthard, 2012). However, although this provides some information about the catchment response as it gives an incomplete picture. Coulthard and Skinner (2016b) showed that simulations calibrated to provide equivalent sediment yields, to compensate for loss of spatial and temporal resolution in rainfall inputs, produced different landscape shapes. Statistics based on measurements from the catchment outlet cannot account for factors such as geomorphic equifinality, self-organised criticality, and autogenics, which act as a non-linear filter on the response (Coulthard and Van De Wiel, 2007, 2013; Hancock et al., 2016; Jerolmack and Paola, 2010; Van De Wiel and Coulthard, 2010).

Hancock and Willgoose (2001) reviewed statistical attempts to define catchment geomorphology, including width function, cumulative area distribution, area-slope relationship, and hypsometric

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curve, and used these as an objective function between physical experiments and numerical experiments using SIBERIA. However, although statistically similar, there were visually clear differences between the physical models and the simulations. Other methods employed include changes to mean elevations (Hancock et al., 2010, 2011), and Optimal Channel Network (Ibbitt et al., 1999). However, although visual difference may be observed between simulations, variations within these measurements have proved to be small for timescales of 1000 years and less (Hancock et al., 2010, 2011), so are limited in their scalability. There is, therefore, a clear need for more objective statistical methods for critically evaluating and comparing landscapes that can also be used for evaluating the accuracy/reliability (or otherwise) of LEMs. Field data at the catchment scale that includes erosion and deposition data, vegetation type and change as well as sediment transfer at critical points along the stream network is required. Such all-encompassing catchment scale data is currently not available.

1.3 A Global SA for a catchment LEM

This study demonstrates the first application of a Global SA to a catchment LEM (CAESAR-Lisflood), using MM to assess the model's sensitivity to user-defined parameters – in total 15 parameters are selected based on known importance to the model or because the model's response to the parameter is presently poorly understood. Although not all the parameters chosen are universal between LEMs, many LEMs have equivalents. A set of 15 model functions has been developed which reflects core behavioural responses of the model, and these will indicate whether the same parameters influence all behaviours, or whether the different behaviours respond to different parameters. The method is applied to two contrasting catchments (scale, environment and climate) to assess how transferable an individual SA is to different conditions.

2. Methods

The test applies the MM method to perform a global SA on the CAESAR-Lisflood model for two contrasting catchments – the Upper Swale, UK (medium sized, temperate, perennial), and Tin Camp Creek, Australia (small sized, tropical, ephemeral). For each catchment, 15 user-defined parameters are assessed against a set of 15 model functions. Finally, the changes in elevations across the catchments are assessed.

2.1 CAESAR-Lisflood

The LEM used is the CAESAR-Lisflood model (Coulthard et al., 2013). CAESAR-Lisflood is a second generation LEM, capable of simulations with greater physical realism than first generation models but also with increased complexity – the model features a large number of fixed, physically-based, or user-defined parameters. This additional complexity may result in an increased non-linearity and sensitivity to model parameters.

A full description of the CAESAR-Lisflood model can be found in Coulthard et al. (2013), and its core functionality is only summarised here. The model utilises an initial DEM built from a regular grid of cells, and in the catchment mode (as used in this model set up) is driven by a rainfall timeseries (Coulthard and Skinner, 2016b). At each timestep the rainfall input is converted to surface runoff using a version of TOPMODEL (Beven and Kirkby, 1979), and distributed across the catchment and routed using the Lisflood-FP component (Bates et al., 2010). The Lisflood-FP component generates flow depths and velocities, which are used by the CAESAR component to simulate fluvial erosion, transport and deposition, across 9 grain sizes, using an active layer system, and altering the elevation values of the grid (Van De Wiel et al., 2007).

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CAESAR-Lisflood is freely available and since 1996 there have been 62 published studies using the model over a wide range of temporal and spatial scales (Skinner and Coulthard, 2017). These previous studies provide useful background into model parameter interactions helping to inform the choice of the user-defined parameters used for the SA as described in Section 2.4. Some studies have also investigated the model's sensitivities to external factors - for example, Coulthard and Skinner (2016) investigated the sensitivity of the CAESAR-Lisflood model to the spatial and temporal resolution of precipitation. Other studies have investigated the influence of processes which could be described as both SA and an exploratory test with, for example, Coulthard and Van De Wiel (2017) examining how the use of a spatially variable 'm' parameter, representing the land use of an area, could influence the outputs of the model.

2.2 Morris Method

Hydrological models faced similar issues to LEMs in the past, in regards to model complexity and resulting processing times when applying SA. To overcome them, hydrologists have used the method of Morris (1991). The MM can be regarded as a global SA, although it actually performs multiple local SA sampled from across the full parameter space – this produces a series of local evaluations, the mean of which is an approximation of the global variance (Saltelli et al., 2000; van Griensven et al., 2006; Norton, 2009). The main strength of the MM is its computational efficiency. Herman et al. (2013) showed that the MM could estimate similar variance in model outputs to the Sobol' Variance-based global SA method (Sobol', 2001), yet required 300 times less evaluations, and significant less data storage for an application to a distributed catchment hydrological model. The robustness of this approach has been further shown by numerous workers (e.g. Brockmann and Morgenroth, 2007; Pappenberger et al., 2008; Yang, 2011). However, the MM cannot provide a full quantitative assessment of parameter sensitivity and is dependent upon the user-defined bounds to the parameter space. It can successfully rank parameters between the least and most influential to model outputs,

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but cannot determine parameters' exact relative influence (Brockmann and Morgenroth, 2007). This combination of advantage and limitation has seen it used extensively as a pre-screening stage, isolating the most influential parameters for further SA with quantitative, yet more computationally expensive, methods (e.g. Ratto et al., 2007; Song et al., 2015; Yang, 2011; Ziliani et al., 2013).

This paper uses the MM described in Ziliani et al. (2013), i.e. the original MM of Morris (1991), as extended by Campolongo et al. (2007). The Design of Experiment (DOE) used the R Statistical Environment and the "sensitivity" software package (Pujol, 2009). A full description of the method can be found in these papers, but a summary is provided here.

MM operates as a series of local SA starting with a stochastically selected set of initial parameters drawn from the global parameter space. For each parameter, a defined boundary of available values is set and divided into a series of equal incremental steps - each parameter is subsequently altered one-at-a-time (OAT) by a number of incremental steps, until each parameter has been altered once. The change in the model output measures, or model factors, is observed between each test – these are the Elementary Effects (EE). This process is repeated a number of times and the mean and standard deviations of the EE for each parameter is calculated – the Main Effect (ME). The higher the mean ME for a parameter shows greater influence of that parameter on the factor, and a higher standard deviation indicates greater non-linear relationships with other parameters. The calculation of an EE can be summarised as in Equation 1 –

$$d_{ij} = \left| \frac{y(x_1 x_2 \dots, x_{i-1}, x_i + \Delta_i, x_{i+1}, \dots, x_k) - y\,(x_1 x_2 \dots, x_{i-1}, x_i, x_{i+1}, \dots, x_k)}{\Delta_i} \right|$$

where, d_{ij} is the *j*th EE of the *i*th model output measure (eg, *i* =1 refers to Sediment Transport Formula, see Table 1), *k* is the number of parameters investigated (here 15), $y(x_1 x_{2,\dots,} x_k)$ is the value of the model output measure, r is the number of repetitions (here r = 100), and Δ_i is the change in incremental steps parameter *i* was altered by.

2.3 Study Basins

2.3.1. Upper Swale, UK

The Swale catchment, UK, is a medium sized basin (181 km^2) with 500 m of elevation drop (Figure 1). It has been used extensively in previous CAESAR/CAESAR-Lisflood applications (Coulthard et al., 2012; Coulthard and Macklin, 2001; Coulthard and Skinner, 2016a; Coulthard and Van De Wiel, 2013). For this SA, it represents a medium basin in a temperate climate. All simulations on the Swale are based on a 50 m resolution DEM and 30 years in duration. Precipitation inputs are 10 years of NIMROD composite RADAR rainfall estimates (Met Office, 2003) (1 h – 5 km resolution) repeated.

2.3.2. Tin Camp Creek, Australia

The Tin Camp Creek catchment is a small sub-catchment (0.5 km^2) of the full Tin Camp Creek system (Hancock et al., 2010; Hancock, 2006) (Figure 1). The basin has a 45 m of elevation drop and is in the tropical region of the Northern Territory, Australia. Contrasting to the Swale, Tin Camp Creek is much smaller and the region has pronounced wet and dry seasons, with short intense rainstorms a feature of wet season precipitation. The DEM is at 10 m grid cell resolution, and like the Swale simulations are 30 years in length. The rainfall input is taken from observations from a single raingauge at Jabiru Airport, providing a 1 h – lumped resolution timeseries for 23 years, which was looped to create the 30 year record required.

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For both basins the changes in the mean elevation across different areas of the catchment will be assessed as a representation of changes in the geomorphology. Each basin was sub-divided into regions corresponding to the watersheds of five stream orders based on the proportion of the catchment drained – 1st = < 1 %; 2nd = > 1 %; 3rd = > 10 %; 4th = > 25 %; 5th = > 50 % (see Figure 1).

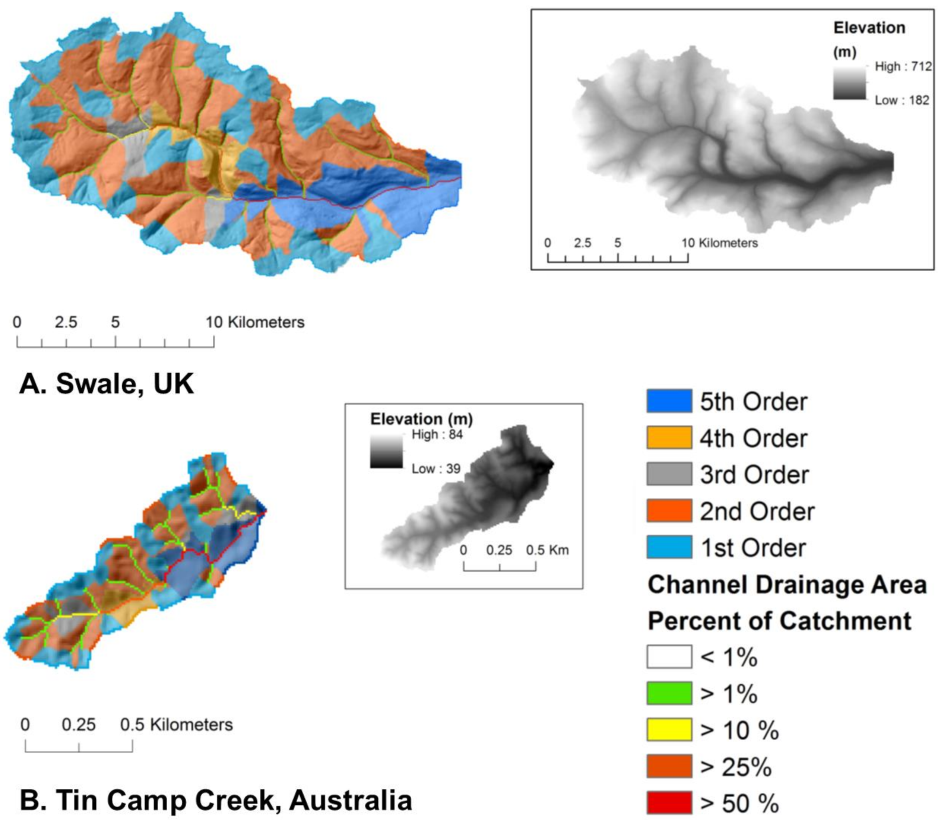

Figure 1 – Elevation map for the Upper Swale catchment, UK (top), and Tin Camp Creek catchment, Australia (bottom). Each catchment is sub-divided into watersheds of five stream orders based on the proportion of the catchment drained.

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2.4 User-Defined Parameters

Table 1 – User-defined parameters used and the min-max values for the two study catchments.

Code	Parameter	Steps	Upper Swale	Tin Camp Creek
(1) SED	Sediment Transport Formula	2	1 Wilcock & Crowe / 2 Einstein	1 Wilcock & Crowe / 2 Einstein
(2) MEL	Max Erode Limit (m)	5	0.01; 0.015; 0.02; 0.025; 0.03	0.001; 0.0015; 0.002; 0.0025; 0.003
(3) CLR	In Channel Lateral Erosion Rate	5	10; 15; 20; 25; 30	10; 15; 20; 25; 30
(4) LAT	Lateral Erosion Rate	5	$2.5e^{-6}$; $3.75e^{-6}$; $5e^{-6}$; $6.25e^{-6}$; $7.5e^{-6}$	$1.5e^{-6}$; $2.25e^{-6}$; $3e^{-6}$; $3.75e^{-6}$; $4.5e^{-6}$
(5) VEG	Vegetation Critical Shear Stress (Pa)	5	10; 15; 20; 25; 30	2; 3.25; 4.5; 5.75; 7
(6) MAT	Grass Maturity Rate (yr)	5	0.5; 0.75; 1; 1.25; 1.5	0.5; 0.875; 1.25; 1.625; 2
(7) SCR	Soil Creep Rate (m/yr)	5	0.00125; 0.001875; 0.0025; 0.003125; 0.00375	0.00125; 0.001875; 0.0025; 0.003125; 0.00375
(8) SFT	Slope Failure Threshold (°)	5	40; 42.5; 45; 47.5; 50	40; 42.5; 45; 47.5; 50
(9) IOD	In/Out Difference ($m^3.s^{-1}$)	5	2.5; 3.75; 5; 6.25; 7.5	0.1; 0.175; 0.25; 0.325; 0.4
(10) MinQ	Min Q Value (m)	5	0.25; 0.375; 0.5; 0.625; 0.75	0.025; 0.0375; 0.05; 0.0625; 0.075
(11) MaxQ	Max Q Value (m)	5	2.5; 3.75; 5; 6.25; 7.5	2.5; 3.75; 5; 6.25; 7.5
(12) SEC	Slope for Edge Cells	5	0.0025; 0.00375; 0.005; 0.00625; 0.0075	0.0025; 0.00375; 0.005; 0.00625; 0.0075
(13) EVR	Evaporation Rate (m/d)	5	0.00067; 0.001005; 0.00134; 0.001675; 0.00201	0.0025; 0.004375; 0.00625; 0.008125; 0.01
(14) MNR	Manning's n Roughness	5	0.03; 0.035; 0.04; 0.045; 0.05	0.03; 0.0325; 0.035; 0.0375; 0.04
(15) GSS	Grain Size Set	5	Set 1; Set 2; Set 3; Set 4; Set 5	Set 1; Set 2; Set 3; Set 4; Set 5

The MM varies the value of each parameter tested once per repeat, and here we use 100 repeats. Therefore, careful consideration was required in the selection of parameters as each parameter tested added 100 model runs to the test – there are 49 user-defined parameters in the version of CAESAR-Lisflood model used (v1.8), and even excluding parameters associated with dune and soil development, there are still 35 user-defined parameters. To test each would require 3600 model runs for each catchment, yet the inclusion of some parameters is likely to add little value. Therefore, in

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total, 15 user-defined parameters were tested (Table 1) and the selection was based on prior knowledge of the importance of these parameters, or due to a lack of previous knowledge of the influence of the parameters on the model – full justification of the selection of parameters can be found in Supplement S1 of the Supplementary Material.

The Morris Method is a qualitative method and the results are subjective on the range of values and number of iterative steps set by the user. Therefore, it is necessary to set each parameter's range to be broadly equal to the others. Whilst it is difficult to define what this means it is also difficult to estimate without prior knowledge - something this study is attempting to address. Here, as a general rule, we have used a default value taken from past calibrations and varied this by +/- 25 % and +/- 50 %. There are some instances where this was not appropriate, and instead a minimum and maximum bound was set instead, and 5 iterative steps of equal distance determined (for example, the Manning's n Roughness for Tin Camp Creek).

The Sediment Transport Laws employed for SED were Einstein (Einstein, 1951) and Wilcock & Crowe (Wilcock and Crowe, 2003). This was applied as a binary two-step, switching from one Law to the other.

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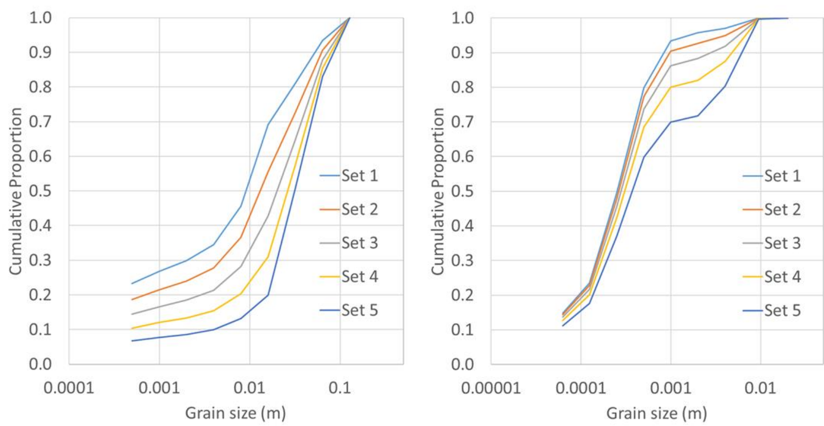

Figure 2 – Sediment grain size distribution sets for the Upper Swale (left) and Tin Camp Creek (right), showing the cumulative proportions.

Grain size distribution has been shown to influence erosion patterns and erosion rate(Hancock and Coulthard, 2012)). It is more difficult to define iterative steps for the sediment grain size sets which include 9 different grain sizes and proportions in each. Instead, these were skewed by altering the proportions of the five smallest grain sizes +/- 25 % and 50 %, and the opposite to the four largest grain sizes, before adjusting the final proportions to equal one based on the relative values. This produces two sets biased for smaller grain sizes (Sets 1 and 2), and two sets biased for larger grain sizes (Sets 4 and 5), as well as the default grain size set (Set 3). The grain size distributions can be seen in Figure 2.

2.5 Model Functions

The common method of assessing a model's sensitivity to parameters values via SA is to observe the variations to objective function measures, yet as discussed in Section 1.3 the use of objective functions

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is often not feasible or appropriate when simulating using LEMs. Also in Section 1.3, previous attempts to quantify changes to the geomorphology of catchments were discussed, showing that no statistical methods, whether based on catchment outlet or some feature of the landscape within the catchment, fully captured or reflected the geomorphic change. The methods reviewed in Hancock and Willgoose (2001) have also been shown to be of little value for simulations of 1000 years and less.

Table 2 – Model Functions and the associated core behaviours.

Model Function	Core Behaviour
Total Sediment Yield (m^3)	Catchment Sediment Yield
Mean Daily Sediment Yield (m^3)	
Peak Daily Sediment Yield (m^3)	
Time to Peak Sediment Yield (s)	
Days when Sediment Yield > Baseline (d)	
Total Net Erosion (m^3)	Internal Geomorphology
Total Net Deposition (m^3)	
Area with > 0.02 m Erosion (m^2)	
Area with > 0.02 m Deposition (m^2)	
Total Discharge (m^3)	Catchment Discharge
Mean Daily Discharge (m^3)	
Peak Daily Discharge (m^3)	
Time to Peak Discharge (s)	
Days when Discharge > Baseline (d)	
Total Model Iterations (calculations)	Model Efficiency

The method we have used is to abandon the objective function approach and instead assess the model against a series of Model Functions designed to reflect some of the core behaviours displayed in the model. It should be noted that this is a philosophical difference to traditional applications of SA – here we are not testing the model against its skill in simulating the physical environment, but rather how the model responds behaviourally to the uncertainty in the user-defined parameters detailed in Section 2.4 – in this sense it also differs from methods of assessing parameter uncertainty, such as the Generalised Likelihood Uncertainty Estimation (GLUE) of Beven and Binley (1992), yet is an important step towards the adoption of such techniques with LEMs. The 15 model functions (Table 2) are simple, scalable and transferable between different catchment types, and can be applied to simulations of

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different timeframes. The model functions are based on outputs which are not unique to CAESAR-Lisflood, so can be applied to other LEM and geomorphic models.

The ME of each parameter versus each model function was normalised based on the proportion of the ME for highest ranking parameter for that model function – therefore the highest ranked parameter for each model function always scored 1. The scores for each parameter were aggregated for across all model functions based on the mean of the scores. The model functions were sub-divided into core behaviour groups (Table 2), and the scores aggregated again for each core behaviour. LEMs are subject to transient model behaviour (an internal model adjustment), as the model reacts to effects of the initial DEM surface and the global grain size distribution. During the initial period of model simulation this results in accelerated sediment processes as the model removes uneven surfaces and noise, and easily mobilises smaller grain sizes in the channel. This is commonly accounted for by allowing the model to run for a 'spin-up' period before the simulation begins. It is possible that small differences in the model could be exaggerated during this period, therefore the first 10 years of each simulation has been discounted for the calculation of the model functions.

3. Results

3.1 All Model Functions

Figure 3 shows the spread of parameter influence for both catchments, where the higher the mean of the aggregated MEs indicates greater sensitivity in the model to that parameter, and the higher standard deviation shows greater non-linearity to other parameters. Table 3 shows the parameters ranked for both catchments, based on the aggregated mean ME values. The most influential parameter is SED (see Table 1 for full description of parameter abreviations), ranked top for both and also being most influential by a reasonable margin, having an aggregated mean of at least 0.2 higher

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than the 2nd ranked parameter. Other parameters, such as VEG, IOD, MNR, MinQ and GSS, rank highly or mid-range. There is a visually close correlation between the most influential parameters and those which display the most non-linearity.

Table 3 – Parameters ranked by means for each catchment from the aggregated scores for all Elementary Effects.

Rank (by mean: 1 = most influential)	Upper Swale	Tin Camp Creek
1	SED	SED
2	MNR	SEC
3	IOD	VEG
4	GSS	GSS
5	EVR	MinQ
6	VEG	IOD
7	MinQ	MNR
8	LAT	MAT
9	CLR	SCR
10	SCR	MEL
11	SEC	LAT
12	MAT	CLR
13	MEL	MaxQ
14	MaxQ	SFT
15	SFT	EVR

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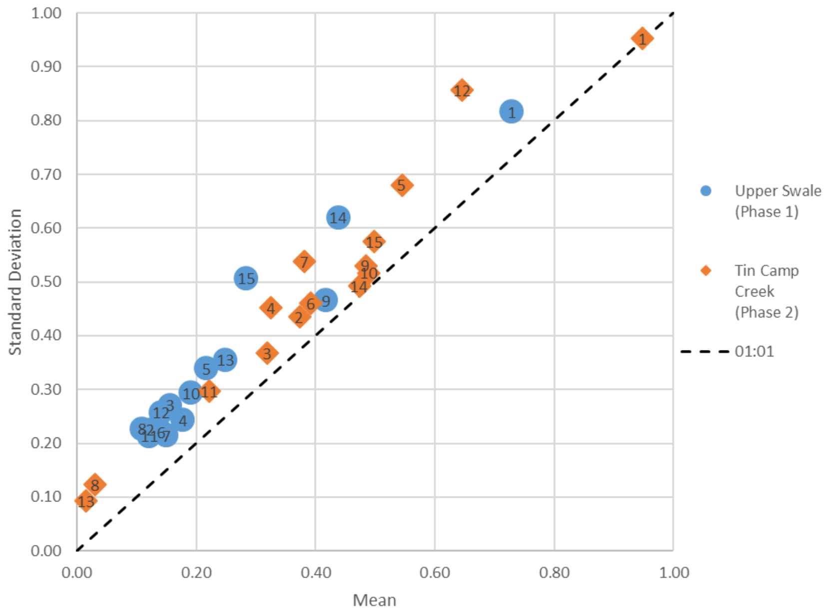

Figure 3 – Aggregated scores for all Elementary Effects where: 1 = SED; 2 = MEL; 3 = CLR; 4 = LAT; 5 = VEG; 6 = MAT; 7 = SCR; 8 = SFT; 9 = IOD; 10 = MinQ; 11 = MaxQ; 12 = SEC; 13 = EVR; 14 = MNR; and 15 = GSS.

3.2 Catchment Sediment Yield Vs Internal Geomorphology

The core behaviours of Catchment Sediment Yield and Internal Geomorphology show a different response to the changes in parameter values, as can be seen in Figure 4, and also the rankings in Table 4. For both catchments, SED is ranked as most influential for Catchment Sediment Yields. For influence on the Internal Geomorphology, SEC ranks higher in the Tin Camp Creek catchment. The Upper Swale catchment displays a similar response with both behaviours, with SED and MNR most influential and by similar amounts, although GSS has less influence on Internal Geomorphology. The change in response for Tin Camp Creek is more varied – SED is less influential on Internal Geomorphology, and SEC is the most influential with a higher aggregated mean. GSS is slightly less influential, and MNR slightly more, and VEG is more influential on the Internal Geomorphology than it is on Catchment

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Sediment Yield. For both model functions, there again is a strong visually correlation between those parameters showing the most influence and those showing the most non-linear behaviour.

Table 4 – Parameters ranked by means for each catchment from the aggregated scores for Catchment Sediment Yields (SY) and Internal Geomorphology Elementary Effects (IG).

Rank (by mean: 1 = most influential)	Upper Swale		Tin Camp Creek	
	SY	IG	SY	IG
1	SED	SED	SED	SEC
2	MNR	MNR	SEC	SED
3	GSS	GSS	GSS	VEG
4	LAT	VEG	MinQ	MNR
5	VEG	CLR	VEG	MinQ
6	EVR	LAT	MNR	GSS
7	MinQ	MinQ	IOD	SCR
8	SCR	MaxQ	MAT	MAT
9	IOD	EVR	SCR	IOD
10	SEC	IOD	MEL	LAT
11	MAT	MAT	CLR	MEL
12	SFT	SEC	LAT	CLR
13	CLR	SCR	MaxQ	MaxQ
14	MEL	MEL	SFT	SFT
15	MaxQ	SFT	EVR	EVR

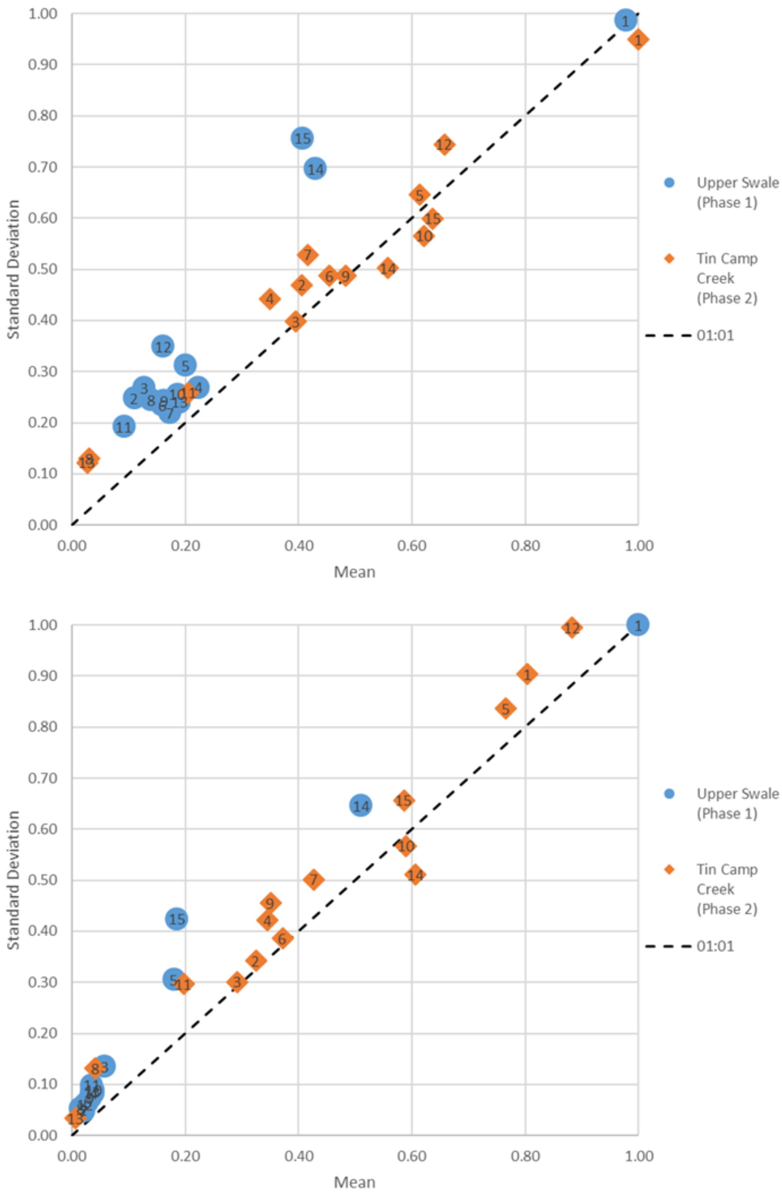

Figure 4 – Aggregated scores for Sediment Yield Elementary Effects (top) and Internal Geomorphology (bottom) where: 1 = SED; 2 = MEL; 3 = CLR; 4 = LAT; 5 = VEG; 6 = MAT; 7 = SCR; 8 = SFT; 9 = IOD; 10 = MinQ; 11 = MaxQ; 12 = SEC; 13 = EVR; 14 = MNR; and 15 = GSS.

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3.3 Changes in the Mean Elevations

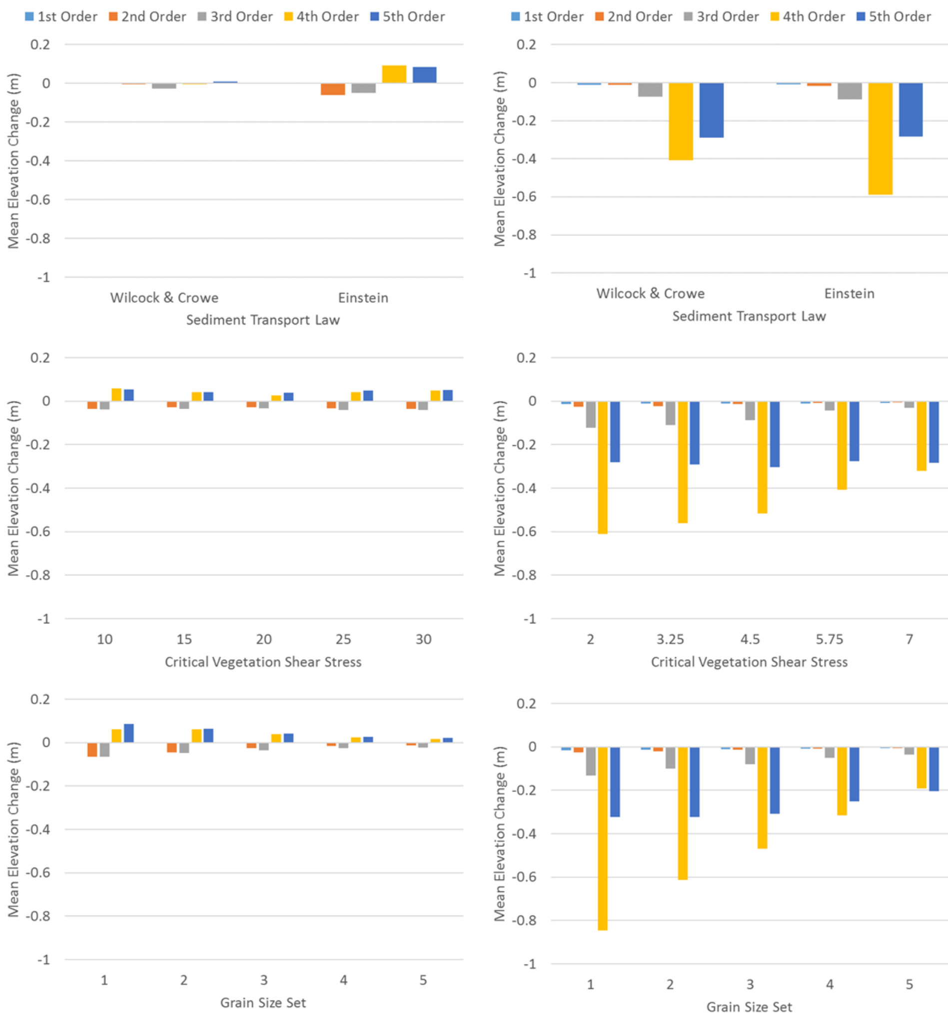

Figure 5 – Changes in the mean elevations for Upper Swale (left), and Tin Camp Creek (right) for the tests split by SED (top), VEG (middle), and GSS (bottom). The catchment is sub-divided into watersheds of five stream orders, based on proportion of catchment drained.

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The test results were binned by the parameter values used, and the mean changes in the mean elevations across the 5 stream orders calculated – Figure 5 shows the changes in each catchment for parameters SED, VEG and GSS. In general, the patterns of changes remain similar despite changing parameter values, yet rates of change do vary – for example, for GSS, the mean reduction in elevations decreases across the catchments using grain size sets biased towards larger grain sizes. In both catchments, the largest variations are observed in the 4th and 5th stream orders.

4. Discussion

The SA has been applied here to a single LEM, CAESAR-Lisflood, and the implications for that model have been discussed above. Yet the results also reveal some important insights concerning metrics, transferability, sediment transport laws, and full uncertainty analysis, which are relevant to all LEMS.

1. Metrics

Interestingly, the findings show that different metrics provide us with different indications of model sensitivity. This has important implications for how to measure LEM performance – and more widely how to quantify and assess geomorphic change within a basin. For example, Figure 4 and Table 4 show that the model has different responses when assessed using sediment yield model functions (calculated from the catchment outlet) to when using the internal geomorphology model functions (based on spatial measures from within the catchment). Whilst at-a-point sediment yields are straightforward to extract from simulation data and easily related to field measurements (e.g. gauges), similar or identical yields may conceal very different behaviours within the basin. This is important for users to realise that when calibrating LEMs, changes in sediment yields from a catchment outlet only provide partial information of what is changing internally. We therefore argue that metrics incorporating *spatial* changes in the basin (as well as bulk figures) are vital for assessing LEM performance. (i.e. a nested set of flumes within a catchment to quantify discharge and sediment

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output) This is especially important as the shape of the landscape – where material has been eroded and deposited – is effectively the basins geomorphic memory and will directly influence subsequent model performance. For other basin scale models (e.g. hydrological models) this aspect is possibly not so important given the limited memory of basin antecedence.

2. Transferability

For environmental models, a single selection of calibrated parameter values is not transferable between catchments as the conditions are different. The same is true for SAs and here we have clear different behaviours between the two catchments tested – some of this can be attributed to the different conditions in each catchment and associated data, but also to the choice of parameter values used in the SA (ie, the minimum and maximum bounds set). The bounds of the parameter values are chosen to be appropriate to the catchment they are applied to. Hence, SA are not transferable between catchments, and should be performed as a preliminary phase for any new investigation. Another consideration is that a single calibrated parameter set is also likely to be non-stationary, especially when factors such as climate and land-use are also non-stationary, and similarly this may impact on model behaviour over time.

3. Sediment Transport Formulae

Our SA shows that the choice of sediment transport formula (SED) had a very strong impact on the model functions, and as sediment transport formulae are also integrated into other LEMs and geomorphic models they will affect their outcomes too. This is, however, to be expected as previous studies have shown that erosion thresholds in sediment transport for LEMs have a significant impact on a model's sensitivity to climate forcings (Tucker, 2004). Looking at sediment transport formulae themselves, Gomez and Church (1989) tested 11 different sediment transport formulae to the same data sets and showed widespread variation in predictions – in some cases over orders of magnitude. The variation in the model performance can be explained by the derivation of the sediment transport formulae themselves, that are often empirically based on limited laboratory and field data, sometimes representing temporal averages over equilibrium conditions (Gomez and Church, 1989). The formulae do not, and were likely never intended to, represent the full variation of flow conditions Therefore, when applied to different situations, they can be wrong (Coulthard et al., 2007a). This, however, presents researchers using LEMs with a considerable problem, as it is highly likely that the sediment transport formula to be used was not designed or calibrated for that particular application. The SIBERIA model (Hancock et al., 2010; 2016; 2017; Willgoose et al., 2003) overcomes this issue by having a version of the Einstein (1950) sediment transport law that is calibrated or tuned to field data on erosion rates. However, even when calibrated, LEMs (and their sediment transport formulae) face another hurdle with the non-stationarity of basin sediment yields. For example, a calibrated LEM will be adjusted to perform for a set of observed sediment outputs or erosion and deposition patterns. If, due to climate change for example, rainfall and channel flows significantly increase then the initial calibration may no longer be valid (Coulthard et al., 2007b). The issue of non-stationarity has been a considerable focus of the hydrological community in recent years. However, despite all the above limitations, LEMs – when applied correctly – have generally been found to compare well with available field data. Nonetheless, the issue of the scaling of parameters for different catchments and even more importantly DEM grid size is an issue that remains to be addressed.

4. Full Uncertainty Analysis

It is important to note that the MM does not provide an absolute value of sensitivity, but ranks each factor based on its relative influence on the model. This means it can be used to assess the main sources of uncertainty on a particular model set up. The next step would be to establish how the uncertainty caused by model parameters (e.g. the choice of sediment transport formula) compares to other identified sources of uncertainty, such as rainfall input uncertainty, DEM observation and resolution uncertainty, and length of spin-up period. For example, it may be that the choice of sediment transport formula may only be a minor source of uncertainty compared to the DEM resolution, or equally, it might be the most significant source of uncertainty in LEMs.

Importantly, whilst the simulation of long-term development of landscapes may be somewhat resilient to uncertainty (Hancock et al., 2016), any attempt to reproduce, predict or forecast physical changes, especially if there is a decision-making element, should have the same appreciation of uncertainty and rigorous testing that has been applied to models such as Lisflood-FP. For example, the Lisflood-FP has been rigorously tested and benchmarked for decision-making purposes (Hunter et al., 2005; Neelz & Pender, 2013), and the use of SA to assess model response and uncertainty is standard practise (Di Baldassarre et al., 2009; Fewtrell et al., 2008, 2011; Hall et al., 2005; Horritt and Bates, 2001, 2002; Hunter et al., 2008; Neal et al., 2011; Sampson et al., 2012), often as a stage of calibration using the GLUE method (Aronica et al., 2002; Bates et al., 2004; Horritt et al., 2006; Hunter et al., 2005; Pappenberger et al., 2007; Wong et al., 2015). Uncertainty in model predictions can be accounted for by utilising probabilistic measures and uncertainty cascades (for example, Pappenberger et al., 2005; Stephens et al., 2012). This is not considered unique to CAESAR-Lisflood, and any application of an LEM or other geomorphic model for operational, decision-making or forecasting applications should make full consideration of all associated uncertainties.

5. Limitations

There are limitations to the methodology presented here. The MM should not be considered a quantitative assessment of sensitivity – it is designed to be an efficient pre-screening method to isolate key parameters for further assessment or for calibration, and ranks parameter values based only on their relative influence of the model. It is also subjective in the sense that the user defines the parameter space explored by setting minimum and maximum values. The range of these values and

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the number of iterative steps between them will have an influence on the relative influence shown – here, the fact that SED was binary, with no intermediate steps, whereas most other parameters had five equal and iterative steps, will have affected its overall relative influence. Reducing the number of iterative steps would likely increase the EEs calculated, and increasing would reduce them, and shift the other parameters' relative influence against that for SED. This is acknowledged here, but the range of parameter values and the steps used were appropriate to represent the possible uncertainties in the model (i.e., they were based on proportional deviations from previous calibrated parameter sets). An obvious limitation to this exercise is computational resource. This test incorporated 1600 individual model runs to test the behavioural response of the model to 15 parameters, in just two catchments, and this partly influenced the choice to limit the simulation periods to 30 years. We used a batch mode functionality of CAESAR-Lisflood to run simulations of each repeat (16 model runs each) consecutively, and distributed batches across different machines – this is feasible for the model set ups described. However, for long-term simulations for catchments the size of the Upper Swale, individual model runs can take several weeks and running several runs consecutively becomes prohibitive. One solution would be to distribute the jobs on High Performance Computing (HPC) facilities, where the time for a single model run would not significantly decrease, but several hundred, even thousands, of individual model runs can be performed coincidently.

The methodology has only been applied to the CAESAR-Lisflood model, and although some of the findings will have implications to other LEMs, most will be unique to CAESAR-Lisflood and the model set ups presented. The methodology should serve as a tool for users to determine the behaviour of each model set up prior to calibration and simulation. For CAESAR-Lisflood itself, future SA should analyse more catchments of different sizes and environmental conditions. The two model set ups used here should be analysed again but using a long-term timeframe to understand how the model behaviour might evolve over longer simulations.

5. Conclusions

The feasibility of performing global SA to a highly parameterised catchment LEM has been demonstrated through the application of the MM to the CAESAR-Lisflood model. The test was repeated over two different catchments suggesting some model behaviours are universal, and others vary depending on the catchment characteristics providing crucial information to inform future model developments. This analysis confirms that the sediment transport formulae are a significant source of uncertainty in LEMs, and in the CAESAR-Lisflood model the use of one formula over another can result in an order of magnitude differences in sediment yields when all other factors are kept constant.

In addition to the above, the results reveal the parameters in CAESAR-Lisflood which exert the greatest influence, and whilst we can only apply this to the CAESAR-Lisflood model itself, it is likely that LEMs with comparable parameters will display similar behaviours. Some of the most influential parameters, like MNR, GSS and VEG are physically-based, so any uncertainty can be reduced by gathering data from the field – in these tests each of these parameters utilised global values initially, so more detailed field measurements could be utilised to provide spatially distributed values and further reduce uncertainty. The parameters which are most likely to be an issue for operators are those which have a medium influence and are set based on data characteristics for numerical efficiency – these include IOD, MinQ and MaxQ. For example, the typical and recommended value for MinQ is 1/100 of the DEM resolution and here, by varying the value yet keeping resolution the same, some variation was observed in the results – it is not yet determined whether any difference in model results at different resolutions are due to changes in values of MinQ and MaxQ, or the grid resolutions, or a combination of the two, and this will be a focus for future work.

The application of a global SA should become a vital step in any investigation using LEMs. This paper has demonstrated that the use of the MM is efficient for this purpose and yielded some useful insights into model behaviour that can be fed back into the model set up, and future model development.

Model and Data Availability

The data produced by this study is made available on request from the corresponding author. The CAESAR-Lisflood model used in this study is freely available under a GNU licence from http://www.coulthard.org.uk

Competing Interests

The authors declare that they have no conflict of interest.

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