~~The sensitivity of Landscape Evolution Models to DEM grid cell size~~ Testing the sensitivity of ~~of~~ the CAESAR-Lisflood Landscape Evolution Model to grid cell size

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Abstract.

Landscape evolution models (LEMs) are useful for understanding how large scale processes and perturbations influence the
10   development of planetary surfaces. With their increasing sophistication and improvements in computational power they are
finding greater uptake in analyses at finer spatial and temporal scales~~, however~~. For many LEMs, the ~~planetary~~ land surface is
represented by a grid of regularly spaced and sized grid cells, or pixels, referred to as a Digital Elevation Model (DEM), yet
despite the importance of the DEM to LEM studies there has been little work to understand the influence of grid cell size (i.e.
resolution) on model behaviour ~~and outputs~~. This is despite the choice of grid cell size being arbitrary for many studies, with
15   users needing to balance detail with computational efficiency. Using the global sensitivity analysis Morris Method, the
sensitivity of the CAESAR-Lisflood LEM to the ~~DEM~~ grid cell size is evaluated relative to a set of ~~key~~ influential user-
defined parameters, showing it had a similar level of influence as a key hydrological parameter and the choice of sediment
transport law. Outputs relating to discharge and sediment yields remained stable across different grid cell sizes until the cells
became so large that the representation of the hydrological network degraded. Although total sediment yields remained steady
20   when changing the grid cell sizes, closer analysis revealed that using larger grid resulted in it being built up from fewer yet
more geomorphically-active events, risking outputs that are 'the right answer but for the wrong reasons". These results are
important considerations for modellers using LEMs and the methodologies detailed provide solutions to understanding the
impacts of modelling choices on outputs.

1 Introduction

25   Landscape evolution models (LEMs~~S~~) simulate the morphodynamic change of landscapes typically over long time scales
ranging from decades to multi-millennia (van der Beek, 2013). Whilst ~~they have been~~LEMs were predominantly developed
for ~~predominantly~~ experimental purposes, such as to understand broad scale basin behaviours ~~over these~~ long time scales, the
increasing sophistication of the models, ushered~~ing~~ in an era of "second generation" LEMs~~S~~ (Coulthard et al., 2013)~~.~~ This~~,~~ has
seen ~~them~~LEMs increasingly used over shorter time frames with smaller grid cell sizes ~~and~~ for operational purposes ~~that could~~

30 ~~described as operational~~ or to support decision making (e.g. ~~(~~Environment Agency, 2021; Feeney et al., 2022; Ramirez et al., 2022; Wong et al., 2021). ~~Thise~~ This operationalisation of LEMs brings with it a need to ~~necessitates a deeper understanding o~~understand~~f~~ model limitations and uncertainties ~~where these might~~that may have a bearing over real-world decisions.

Landscape change is often simulated by applying process~~ ~~-based rules of hydrology, erosion and deposition to change the

35 elevation of cells in a regular grid, or ~~points~~ in an irregular mesh, that represents the land surface. The spatial resolution of this virtual surface is an important consideration due to two contrasting effects. Firstly, if it is too coarse (e.g. larger grid cells) it may smooth out the terrain too much and miss out key landscape features. Secondly, a finer of higher spatial resolution will better represent features but increases the number of cells and points for the area simulated that in turn increases the computation time (halving the grid cell size results in a square increase in the number of grid cells). Therefore, where high

40 resolution data is available, a compromise DEM grid cell size is used by LEMs that captures drainage basin and hillslope features whilst maintaining a low number of grid cells (Hancock, 2005; Hancock et al., 2016).

Unexpectedly, ~~in Landscape Evolution Modelling,~~ there are few studies that specifically address the impacts of ~~DEM~~ grid cell resolution ~~with~~on LEMs. ~~Though~~ Schoorl et al., (2000) used the LAPSUS model to simulate landscape development on a

45 series of artificial DEMs with varying grid cell sizes ~~of simple slopes and catchments~~ ~~with resolutions of 1, 3, 9, 37 and 81m respectively,. Schoorl et al., (2000) results showed~~ and showed that with larger grid cells total erosion or sediment yield from the simulations increased ~~and that this was~~ due to an in increase in erosion coupled with a decrease in sedimentation. They argued that the erosion increase was due to the model parameterisation, but that a ~~decrease~~ coarsening in the physical representation of the landscape with larger grid cells made sedimentation more difficult, concluding that it is important that

50 the extent of the landscape and its relief characteristics are realistically represented by the used DEM. ~~Pelletier, (2010) noted an impact of grid cell size in LEM's where using larger grid cells flow paths can become dominated by only being able to change direction by 45 or 90 degrees.~~

~~The lack of DEM resolution studies is someone surprising, considering there is research indicating the sensitivity of LEM's to~~

55 ~~the DEM used~~Where LEM studies have considered the influence of grid cell resolution, they have often demonstrated a sensitivity~~. For example,~~ Hancock, (2006) showed a sensitivity in LEM outputs to DEM's created with different kriging/interpolation methods. These changes in the representation can then have important cumulative impacts if the landscape is modelled as ~~Landscape Evolution Models~~LEMs may exacerbate, or deepen, concavities or other features ultimately leading to different shape topographies (Ijjasz-Vasquez et al., 1992; Willgoose et al., 2003). Hancock et al., (2016)

60 illustrated this by perturbating a DEM by different ranges of random values and simulating millennial timescale changes on the different surfaces using the SIBERIA LEM. They found that an increasing magnitude of random surface variability did not significantly alter total basin sediment yields, but greatly changed the temporal pattern or delivery of sediment output. Furthermore, after 10 000 years of simulation the alternative positions of initial random perturbations strongly influenced local

patterns of hillslope erosion and landscape evolution - although general landscape metrics were very similar. Hancock and

65   Evans (2006) looked at two small catchments in North Australia using 10, 20, 30, 40 and 50m grid cells to evaluate the impact

of ~~resoltuion~~resolution in determining channel head location and the area–slope relationship and cumulative area distribution

that is a key driver in the SIBERIA (Willgoose and Riley, 1998) LEM. Their findings showed a clear drop in the slope/area

relationship with larger grid cells – due largely to the smoothing and subsequent simplification of topography. ~~Finally,~~

Finlayson and Montgomery (2003) show a major degradation of DEM mean slope values when resampling from 30 to 90 to

70   900m – representing the smoothing of features and lowering of gradients~~.~~. Finally, Pelletier, (2010) noted an impact of grid

cell size in LEMs where using larger grid cells flow paths can become dominated by only being able to change direction by

45 or 90 degrees.

75   ~~Due to the paucity of LEM studies considering the sensitivity to grid cell resolution, we need to look wider at similar modelling~~

~~fields.~~ Looking outside the immediate LEM literature, with ~~In~~ cellular morphodynamic models (similar in many ways to

LEMs) Doeschl-Wilson and Ashmore (2005)~~,~~ examined the Murray and Paola (1994) braided river model and noted that the

model performance was strongly affected by the spatial scales at which the input topography were represented. They

demonstrated that when tested over a range of different spatial resolutions the model had a 'preferred' scale where it self-

80   adjusted to have a channel width with a certain number of cells (rather than a distance represented by a number of cells)

(Doeschl-Wilson and Ashmore, 2005). Possible reasons why there is a sensitivity to grid resolution in cellular approaches was

discussed by Nicholas (2005), who stated that this was a consequence of the water and sediment routing equations used in

simplified cellular models. For example, where sediment and water were routed in proportion to local bed slopes, the

calculations may become sensitive to very small variations in elevation as grid cell resolution changes (Nicholas 2005), that

85   also shows a weakness in using local bed slope to represent the energy slope. This is especially important in a LEM or

morphodynamic model where these elevations will be changing every iteration in response to erosion and deposition – this

effect will be amplified or reduced by grid resolution.

The two dimensional flow of water over landscapes is a key process in LEMs and for two dimensional hydraulic models of

90   flood inundation the effects of ~~DEM~~ gird cell resolution have been extensively studied (e.g. (Horritt and Bates, 2001; Savage

et al., 2016). Horritt and Bates, (2001) tested the LISFLOOD-FP inundation model against satellite derived flood inundation

extents over DEMs with gird cell resolutions ranging from 10 to 1000m. Overall, they showed a good comparison between

inundation area/extent over all resolutions (using the same model calibrations) though comparison of flood wave travel time

was notably different. Interestingly, this shows how ~~DEM~~ grid cell resolution was less important in spatial matches between

95   observed and modelled water extents, but certainly interfered with the equations determining where water went (travel times)

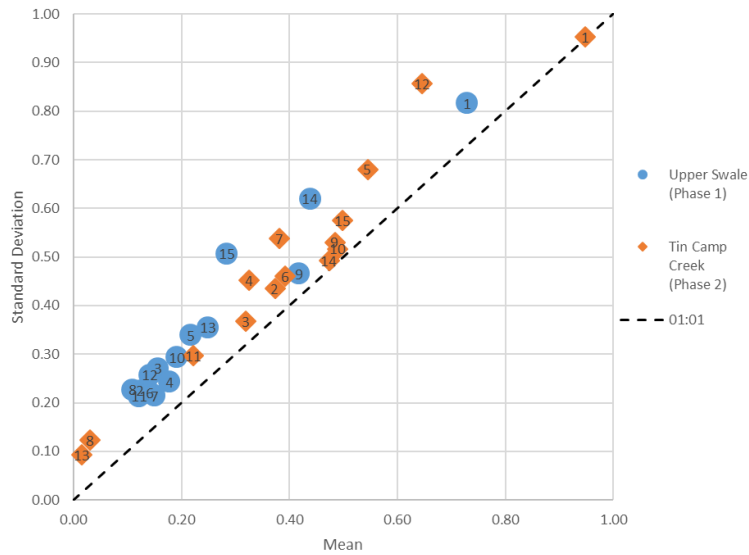
in effect simplifying them to a point where they did not perform adequately with respect to resolution. Claessens et al., (2005)

summarise these effects neatly: that the grid cell~~DEM~~ resolution acts to firstly simplify the topographic data, and secondly any

model processes or governing equations that operate below this resolution will therefore also be simplified. This can lead to apparent gains in accuracy due to greater process representation within the model being countered by the coarser model resolution (Claessens et al., 2005). Horritt and Bates, (2001) also described how changes in topographic detail with different resolution DEMs also affected floodplain storage. Similar topographic degradation affecting model behaviour was observed by Savage et al., (2016) where using LISFLOOD-FP to simulate inundation over a wide range of resolutions they noted that model performance degraded where grid cells were larger than 50m. This was due to the channel being poorly represented within the DEM leading to increased floodplain water depths – lower velocities that all affected negatively model performance. Importantly, Savage et al., (2016) also observed how model resolution affected *parameter sensitivity* a secondary affect aside from model performance. This was also a key finding of Lim and Brandt, (2019) using the hydraulic component of CAESAR-Lisflood LEM to examine any dependency between DEM resolution, Manning's *n* roughness coefficient*,* and model performance. Comparing model inundation extents and depths for flood events on two rivers to simulation results over ~~DEM grid cell~~ resolutions from 1 – 50m, they demonstrated that high-resolution DEMs performed better with higher Manning's *n* values whereas lower *n* values gave better outputs for lower resolution DEMs. Lim and Brandt, (2019) also showed that whilst coarser resolution DEMs generated better value performances according to their metrics, there were more discrepancies between known flooding and predicted water surface elevations illustrating a dependency on the metric used for assessment. Choice of metric for assessing model performance is also an important issue presently facing LEM studies, with metrics based on catchment outputs displaying different behaviours to those derived from changes within the catchment (Skinner et al., 2018).

In Computational Fluid Dynamics (CFD) where more complex numerical methods are used for hydraulic modelling, the effects of different grid resolutions or meshing methods are widely considered. Where CFD model simulations are applied to engineering solutions there are controls and standards for the verification of models (Vassiliadis et al., 2001) that are also reflected in the journal publication policies such as "*Solutions over a range of significantly different grid resolutions should be presented to demonstrate grid independent or grid-convergent results*" (Roache, 2019; Roache et al., 2009). Here grid independent (or grid independence) refers to whether errors or differences between different resolution simulations are sufficiently small. Hardy et al., (2003) provide a clear summary and example of methods for assessing grid independence using a 'Grid Convergence Index approach'. Nicholas (2005) comments that whilst grid independence is considered a key requirement of computational fluid dynamics (CFD) approaches – it may not be reasonable to use such approaches in cellular methods. A logical step might be to use methods from CFD grid independence testing on LEM models. However, grid independence tests are largely during steady flow conditions (e.g. Hardy et al., (2003)) measuring flow velocities in x, y, and z directions (for example) but sediment ~~transport~~ processes in LEM and morphodynamic models ar~~ei~~s highly episodic and non-linear even when averaged over medium time scales (Coulthard et al., 2010; Coulthard and Wiel, 2012). Therefore, the availability and choice of metrics to assess LEM performance is difficult.

This issue of which metrics to use to assess LEM model performance was considered by (Skinner et al., 2018) where they carried out a multidimensional sensitivity analysis on the CAESAR-Lisflood (Coulthard et al., 2013) LEM. Previously, such studies have been hampered by long model run times making Monte-Carlo style analyses difficult, but here Skinner et al., (2018) used the Morris Method (Morris, 1991) to analyse the sensitivity of 15 different model parameters on model performance. ~~(Figure 1).~~ Key to this study was the assessment of model behaviours across 15 model functions across four core behaviour groups: catchment sediment yields; internal geomorphology; catchment discharge; and, model efficiency. Skinner et al., (2018)'s work also provides ~~is with~~ a framework within which we could look at the impact of grid cell size on both overall model performance and in relation to the other model parameters tested. In effect providing us with a way of making a comprehensive assessment of the impact of grid cell size on LEM performance.

~~Usefully, Skinner et al., (2018) present us with a framework for assessing LEM model performance and this paper uses this methodology to comprehensively assess the relative sensitivity of grid-based LEMs to resolution of the grid cells used, in comparison to changes to important parameter values. It can help us determine whether there is a level of grid independence in LEMs. Importantly, the Morris Method framework also allows us to look at the non-linear influences of changing gird cell size on other key model parameters how the sensitivity of the model to individual parameters is non-linear, being influenced by the values of other parameters, and on how this further influences overall model behaviour and efficiency. Figure 1 shows how the Morris Method ranks parameters in order of relative influence on model behaviours, where higher values of the mean indicate greater relative influence, and higher values of standard deviation indicating greater dependency on the values of other parameters, i.e., non-linearity (Skinner et al., 2018).~~

~~Figure 1~~ ~~: Example of the Morris Method outputs for assessing the sensitivity of the CAESAR-Lisflood model to 15~~
~~different model parameters – over two different sized catchments after Skinner et al., (2018). This shows aggregated~~
~~scores for all Elementary Effects where: 1 = sediment transport formula (SED); 2 = maximum erode limit (MEL); 3 =~~
~~in channel lateral erosion rate (CLR); 4 = lateral erosion rate (LAT); 5 = critical vegetation shear stress (VEG); 6 =~~
~~grass maturity rate (MAT); 7 = soil creep rate (SCR); 8 = slope failure threshold (SFT); 9 = in/out difference (IOD); 10~~
~~= minimum Q value (MinQ); 11 = maximum Q value (MaxQ); 12 = slope for edge cells (SEC); 13 = evaporation rate~~
~~(EVR); 14 = Manning's n roughness coefficient (MNR); and 15 = grain size set (GSS).~~

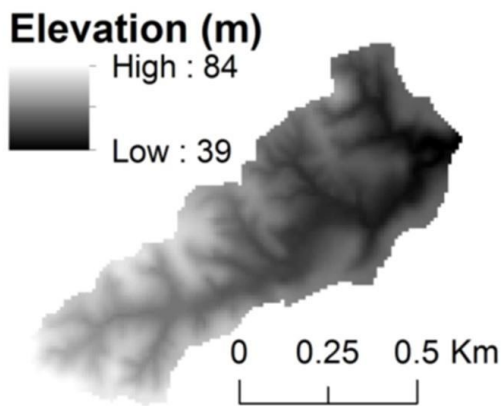
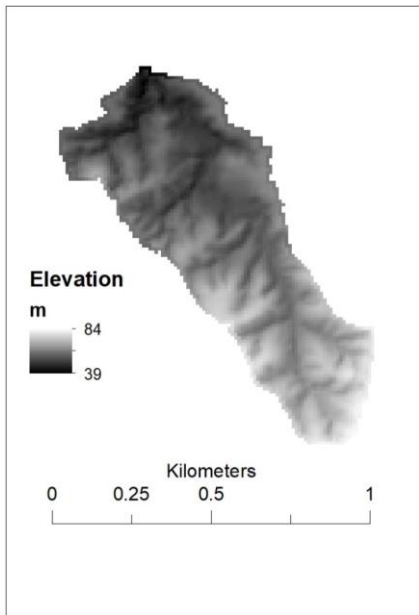
~~Whilst there are few studies addressing DEM resolution on LEM performance, I~~it is clear from the literature that small changes in the landscape (as represented by DEMs) can have an impact on LEM outputs. ~~Therefore, as the~~As T~~t~~he spatial resolution of a DEM affects the representation of topographic features, resolution *will* have an impact on model performance and output. LEMs may be especially sensitive to this as they typically use local gradients to determine erosion and deposition thus potentially generating a positive feedback if erosion and deposition increases local changes. ~~There are existing methods and frameworks for assessing hydrological and hydraulic model performance and grid independence, however, the chaotic and non-linear behaviour of LEM erosion and deposition patterns may make these methods unsuitable for LEMs. Prior to the use of the Morris Method we have no structure for assessing LEM sensitivity to DEM resolution – or importantly how model resolution affects the parameter sensitivity.~~~~This is a problem as, where high resolution data is available, the grid cell resolution used is a user choice, with the user needing to balance detail with efficiency, yet the user has no prior knowledge of how this~~

choice might influence model behaviour and results. If those results are to be used for real-world decision making, this lack of knowledge would make the use of the model inappropriate for such operational purposes.

In this paper we address these issues above and, by using the CAESAR-Lisflood LEM to simulate erosion and deposition over a wide range of spatial DEMgrid cell sizes resolutions. Outputs metricsfrom these simulations representing geomorphic, hydrological, and model performance are then assessed using the Morris Method to establish how DEM grid cell sizeresolution affects model results and performance and results; and importantly whether there are any parameter sensitivities to these resolutions. Our The focusaim is to understand how the hypothetical model sensitivitiesuser choice of grid resolution might influence outputs withover an operational use of the model, including catchment choice and the timescales simulated., which has influenced our choice of catchment and timescales simulated.

2 Methods

2.1 Study Catchment and DEM data

Testing of DEM grid cell resolution isThe model tests were carried out on a DEM of Tin Camp Creek in the Northern Territory, Australia (see Figure 12). Tin Camp Creek has a catchment area of 0.5km^2 and is located within a tropical climate, where its watercourse is ephemeral – rainfall in the wet season features small, intense convective events. It is a small sub-catchment of the wider Tin Camp Creek system and has been used previously for studies using LEMs (Hancock et al, 2010; Hancock, 2006; Hancock, 2012; Skinner et al, 2018). The DEM used is produced from high resolution digital photogrammetry and available at 2m grid resolution at its finest (as described by Hancock, 2012). For this study the 2m DEM was resampled using the Raster Resample tool in ArcMap v10.4.1 to grid cells sizes between 2 and 30m at 2m iterations and a final 50m grid resolution (see Appendix BA). The Cchoice of small area DEM is deliberate to reduce model run times – especially when using the smallest grid cell sizes. The 2m resolution proved to be too computationally expensive so was not used.

195   **Figure 2 1 – Digital Elevation Model of the Tin Camp Creek catchment shown at 10m resolution with hillshade.**

2.2 the CAESAR-Lisflood model

The LEM used wais the CAESAR-Lisflood model (Coulthard et al., 2013). 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

200 that can be lumped or spatially distributed (Coulthard and Skinner, 2016b). At each timestep the rainfall input is converted to surface runoff using TOPMODEL (Beven and Kirkby, 1979), and distributed across the catchment and routed using the LISFLOOD-FP component (Bates et al., 2010). The CAESAR component of the model drives the landscape development using sediment transport formulae based on flow depths and velocities derived from the LISFLOOD-FP component. Bed load is distributed to neighbouring cells proportionally based on relative bed elevations. This study has not used the suspended

205 sediment processes in the model. The model can handle nine different grain sizes, and information is stored in surface and sub-surface layers where only the top surface layer is 'active' for erosion and deposition. A comprehensive description of this process can be found in (Van De Wiel et al., 2007). The model has capability for bedrock erosion but the set up for this study does not include a representation of bedrock and is unlikely to be influential over the 30 year operational timeframe used. An initial soil layer is determined globally using the information within the Grain Size set parameter (see Table 1).

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CAESAR-Lisflood is freely available and since 1996 there have been 119 published studies using the model over a wide range of temporal and spatial scales (Skinner and Coulthard, 2022). Here we used CAESAR-Lisflood v1.9 with modifications to allow it to run in batch mode and to automatically collect information relevant to the behavioural functions (outlined below).

2.3 Morris Method

215 Our study used the Morris Method (MM) described in Ziliani et al. (2013), i.e. the original MM of Morris (1991), as extended by Campolongo et al. (2007), and applied the "sensitivity" package in the R Statistical Environment (Pujol, 2009) to generate the parameter sets for the Sensitivity Analysis (SA). To set up the MM we selected a number of parameters to be assessed, specifying a minimum and maximum range for each, plus a number of iterative steps. The parameter values are equally spaced based on the range and number of steps – for example, a parameter with a range of 2 to 10 and 5 incremental steps would have

220 available values of 2, 4, 6, 8, and 10. This was carried out for each parameter and where possible the same number of incremental steps were used for each. For a full description of the MM applied to CAESAR-Lisflood see Skinner et al., (2018) and a summary is provided below.

The MM uses a system of *repeats* to sample the global parameter space. For each parameter, the user defines minimum and

225 maximum values and the number of incremental steps within that range to choose values from (e.g., with a minimum value of 2, a maximum value of 10, and five incremental steps, the values of 2, 4, 6, 8, and 10 would be available). The first test in each repeat uses a randomly selected set of parameters determined from the whole available parameter space. The second test in the

repeat uses the same parameter set yet varies a single randomly determined parameter to a different randomly determined value from those available. That parameter would then be excluded from selection for change for the rest of this repeat, with the
230 process continuing until all parameters have been changed once.

The sensitivity of the model to changes in parameter values is evaluated by the changes of objective function values between sequential tests within repeats, relative to the number of incremental steps the parameter value has been changed by (e.g., where for thea set of values 2, 4, 6, 8, and 10, a switch from an initial value of 4 to either 2 or 6 is one step, a change to 8 is
235 two steps, and 10 is three). The change in objective function score between two sequential tests divided by the number of incremental step changes is an elementary effect (EE) of that objective function and the parameter changed (Equation 1). After all tests for each grid resolution have been performed, the main effect (ME) for each objective function and parameter is calculated from the mean of the relevant EEs – the higher the ME the greater the model's sensitivity. Alongside the ME, the standard deviation of the EEs is also calculated as this provides an indication of the non-linearity within the model.
240

Equation 1

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

where d_{ij} is the value of the jth EE ($j = 1, \ldots, r$; where r is the number of repetitions (here $r = 100$)) of the ith parameter (e.g.
245 $i = 1$ refers to sediment transport formula, see Table 1), x_i is the value of the ith parameter, k is the number of parameters investigated (here 7), $y(x_1, x_2, \ldots, x_k)$ is the value of the selected objective function, and Δ_i is the change in incremental steps parameter i was altered by.

250 In Skinner et al., (2018) a MM test was applied to a DEM of the same Tin Camp Creek basin used for this study, using a single 10m grid cell size (see Figure 12). That test used a sub-set of 15 parameters and 100 repeats, producing 1600 tests in the total. Here we are testing 15 different resolutions so the same level of scrutiny of parameters and repeats would result in 24,000 tests to be required. To reduce the computational expense, we reduced the 15 parameters to the 7 that exhibited the greatest impacts on model behavior in Skinner et al., (2018). In addition, the number of repeats was reduced to 10 in line with the minimum
255 number suggested by Ziliani et al., (2013). This reduced the total number of tests to 80 for each DEM resolution and 1,200 in total. The only difference in the parameter value ranges to Skinner et al., (2018) is the inclusion of Meyer-Peter Muller (Meyer-Peter and Muller, 1948) as an additional sediment transport law, with changes between any of the sediment transport laws being counted as a single iterative step change. Meyer-Peter Muller was included as this formula had been added to version 1.9d of CAESAR-Lisflood since the Skinner et al., (2018) analysis and enabled a greater number of 'steps' to be included in
260 the sediment transport component. The parameters and their values are shown in Table 1.

Table 1 – Parameters selected for the MM test, the number of iterative steps applied, and the values used for each iterative step. A description of the role of these parameters within the model is provided in Appendix A.

Code	Parameter	Steps	Tin Camp Creek
(1) SED	Sediment Transport Formula	3	1 Wilcock & Crowe / 2 Einstein / 3 Meyer Peter Muller
(2) GSS	Grain Size Set	5	Set 1; Set 2; Set 3; Set 4; Set 5
(3) MNR	Manning's n Roughness	5	0.03; 0.0325; 0.035; 0.0375; 0.04
(4) TOPN	m value used by TOPMODEL	5	0.005; 0.0075; 0.01; 0.0125; 0.015
(5) VEG	Vegetation Critical Shear Stress (Pa)	5	2; 3.25; 4.5; 5.75; 7
(6) MAT	Grass Maturity Rate (yr)	5	0.5; 0.875; 1.25; 1.625; 2
(7) MEL	Max Erode Limit (m)	5	0.001; 0.0015; 0.002; 0.0025; 0.003

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In Skinner et al., (2018) a model function approach to evaluating MM was developed and tested using the CAESAR-Lisflood model. The main purpose of the model function approach was to mitigate for the fact that there is almost always a lack of suitable observation data to use in evaluating the performance of LEMs via an objective function approach (an objective

270 function being the error score between modelled and observed data). Instead, Skinner et al., (2018) proposed a series of metrics that would assess key behaviours in the model relating to its outputs and assess MM against changes in the model's behaviour. Here we use the same 15 model functions as Skinner et al (2018) and these are shown in Table 2. To summarise the large amount of information produced, the ME of each parameter and model function combination was normalised based on the proportion of the ME for highest ranking parameter for that model function – therefore the highest ranked parameter for each

275 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 further sub-divided into core behaviour groups (Table 2) and the scores aggregated again for each core behaviour. The same was also done, separately, for the standard deviations of each parameter and model function.

280 **Table 2 – Core behaviours of the model and the Model Functions adopted to assess changes to these (from Skinner et al, 2018).**

Core Behaviour	Model Function
Catchment Sediment Yield	Total Sediment Yield
	Mean Daily Sediment Yield

	Peak Daily Sediment Yield
	Time to Peak Sediment Yield
	Days when Sediment Yield > baseline
Internal Geomorphology	Total Net Erosion
	Total Net Deposition
	Area with > 0.02m Erosion
	Area with > 0.02m Deposition
Catchment Hydrology	Total Discharge
	Mean Daily Discharge
	Peak Daily Discharge
	Time to Peak Discharge
	Days when Discharge > baseline
Model Efficiency	Total Model Iterations

The same set of repeats and parameter changes were used for each grid cell size to allow direct comparison. Finally, using the full set of results across all of the grid cell sizes a further analysis was performed with grid cells size as an additional parameter to assess its relative influence on the model compared to the other 7 parameters. This was done by using 5 steps (4, 8, 12, 16, and 20m resolution) and randomly selecting the starting grid cell size for each repeat, the position in the sequence it is changed, and the change in steps.

Each individual test within the repeats consisted of 30 years of simulations using the same input rainfall. The rainfall was produced by using 23 year observation record from a single raingauge at Jabiru Airport, with the first 7 years repeated for the full 30 year input. This was applied as a lumped input at a 1h timestep.

2.4 Stream network analysis

To examine how stream network metrics changed with DEM resolution, the Hydrology tools in ArcMap 10.4.1 were used to extract stream networks and stream orders for each resolution with the Strahler (1957) and Shreve (1966) methods. Both methods are top-down approaches to stream ordering in that they start from the source and increase in value towards the outlet. The Strahler method (Strahler, 1957) calculates the depth of the drainage network – a 2nd order stream begins only where two or more 1st order streams meet, and a 3rd order only where two or more 2nd order stream meet, and so on. As such the maximum stream order number does not provide information on the number of individual streams within the network. The Shreve method (Shreve, 1966) assigns stream values cumulatively, so where two streams with a value one meet, the downstream becomes 2, and unlike the Strahler method, lower order tributaries are including in the ordering, so where a stream with value 1 joins with

a stream with value 2, the downstream section is assigned a value of 3. Therefore, the stream number at the outlet provides information on the number of streams in the system. In ArcMap a stream identification threshold (in effect delineating 1st order streams) was set at 1000m^2 - rounded up to the nearest whole pixels. The total number of 1st order streams calculated by the

305 Strahler method was estimated by converting the raster output to a polyline and selecting only 1st order streams. With the exception of the 2m resolution, the analysis was performed on the post-test DEM for Test 1 of each resolution test to allow a drainage network to be established on spun-up into the DEM surface – this negated the need to pit fill the DEM before the network analysis.

3. Results

310 **3.1 Influence of grid cell size on model outputs (Model Functions)**

The ME for each of the 15 model functions were calculated for each of the grid cells sizes and the patterns observed for each Model Function are summarised in Table 3. The box and whisker plots of Figure 2̶3̶ highlights these patterns for four of the Model functions (plots for all of the Model Functions can be viewed in the Appendix B̶C̶). Figure 2̶3̶ shows that the mean total erosion and sediment yields output by the model remain similar for grid resolutions up to 24-30m, although the spread of

315 values across the 80 tests vary more with larger grid cells. However, the peak daily sediment yields increase with larger grid cells, whereas there is a decrease in the number of days where sediment yield is over the baseline. This indicates that with larger grid cells there are less events that produce erosion and sediment outputs offset by an increase in erosion and sediment outputs during larger events.

320 **Table 3 – Visual interpretation of influence of grid resolution on the 15 model functions.**

Model Function	Pattern with Coarse Grid Resolution	Resolution where Patterns breaks down
Total sediment yield	little change	>22m
Mean daily sediment yield	little change	>22m
Peak daily sediment yield	increase	>24m
Time to peak sediment yield	little change	>26m
Days when peak sediment yield > baseline	decrease	-
Total net erosion	little change	>22m
Total net deposition	decrease	>10m
Area with > 0.02m erosion	decrease	-
Area with > 0.02m deposition	little change	-
Total discharge	decrease	-

Mean daily discharge	decrease	-
Peak daily discharge	little change	>20m
Time to peak discharge	increase	>20m
Days when discharge > baseline	decrease	-
Total model iterations	decrease	>12m

325

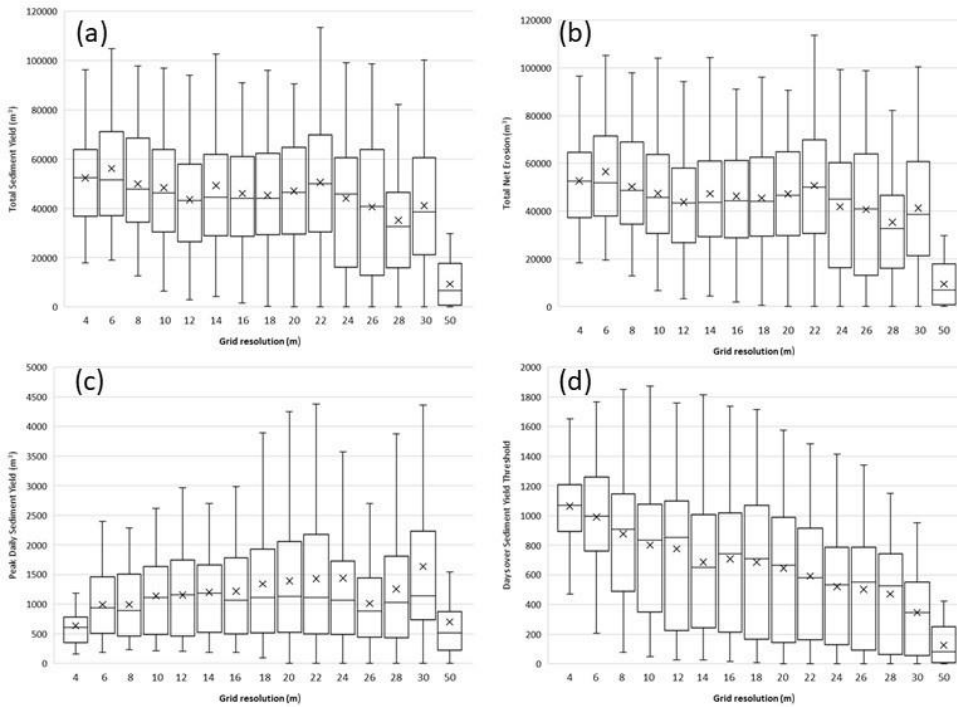



Figure 3 2 – Box and whisker plots showing the mean and spread of model outputs at each grid resolution, for (a) Total Sediment Yield, (b) Total Net Erosion), (c) Peak Daily Sediment Yield, and (d) Days over Sediment Yield Threshold.

330

The box and whisker lots in Figure 2 3 aggregate the results of 80 tests and could conceal a range of varying model behaviours when using the same parameter set across the different grid cell sizes. To check this, 5 parameter sets, or tests (numbered as

the order they appear in the MM), were randomly selected and plotted in Figure 34. This shows that the individual tests follow the overall trends displayed in Figure 23.

335

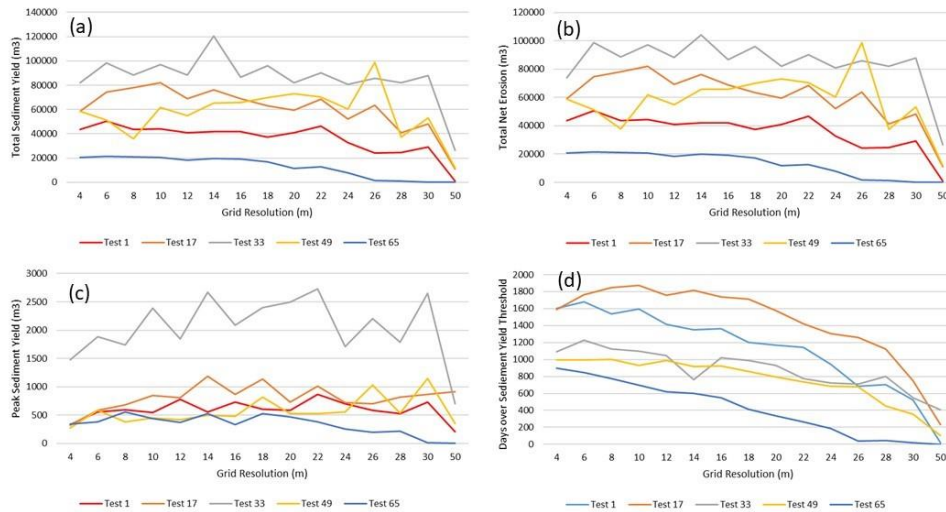



Figure 4 3 – Output values for five randomly selected test numbers at each grid resolution, for (a) Total Sediment Yield, (b) Total Net Erosion, (c) Peak Sediment Yield, and (d) Days over Sediment Yield Threshold.

340 **3.2 Influence of grid cell size on model behaviour (summary of MM)**

The mean aggregated ME scores, measuring the overall relative influence of each parameter across all of the model functions, are shown in Figure 45. Although there is variation between the grid cells sizes, the relative influence of each parameter remains fairly consistent across DEM resolution. The clear exception here being the Sediment Transport Law, that whilst remaining the most influential parameter for the majority of resolution, its relative influence decreases as the grid coarsens,

345 until for the coarsest of grids the TOPMODEL M replaces it as most influential (at 28m and 50m). It appears that it is an increase in influence of the TOPMODEL M that drives the decrease below 26m, beyond which all the other parameters increase in influence as Sediment Transport Law further decreases.

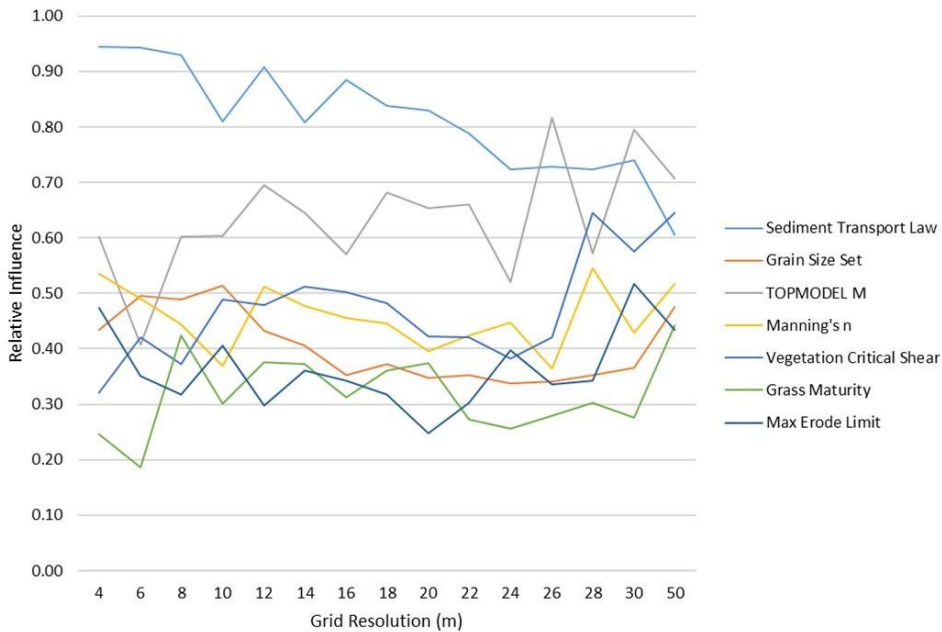



Figure 5 4 - Mean ME scores aggregated for all Model Functions for each parameter and each grid cell size.

3.3 Stream network analysis

The numbers of stream orders calculated is shown in Figure 56. The maximum number of stream orders calculated by the Strahler method remained consistent throughout, dipping to three orders at 28m resolution, and three again at 50m. The Shreve and Strahler first order counts steadily decreased as grid cells become larger. This shows that the depth of the drainage network does not reduce until the largest grid cells are used. However, the detail within the network is being lost with less 1st Strahler orders, and lower Shreve numbers, with larger grid cells. The disparity between the Shreve number and the number of 1st Strahler order streams is due to disconnection of part of the drainage channel to the main network, therefore these streams are not contributing to the Shreve number. This disconnection was not consistent through the resolutions, with some coarser resolution displaying a better connected network than others.

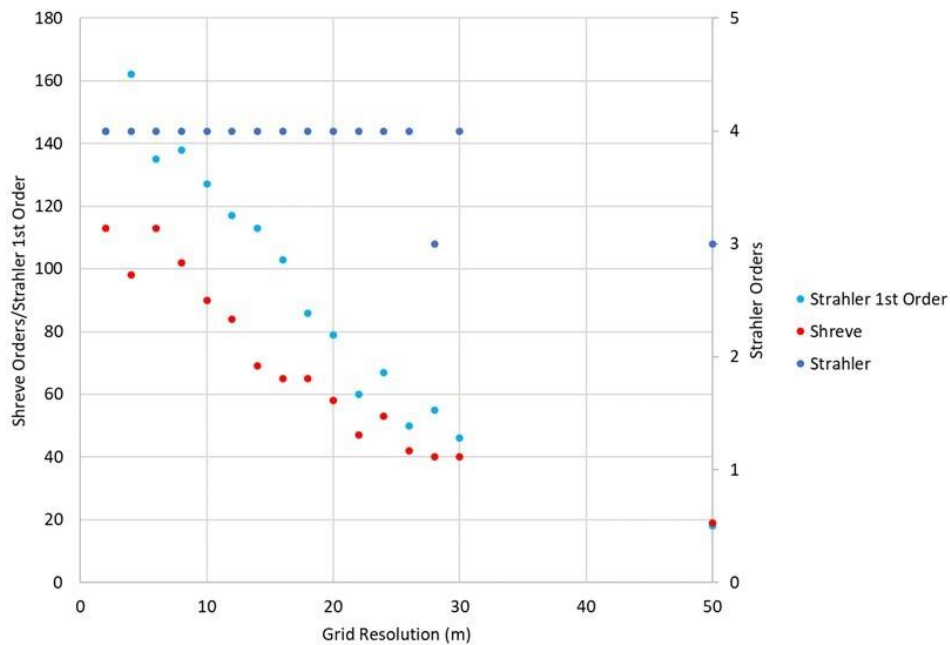
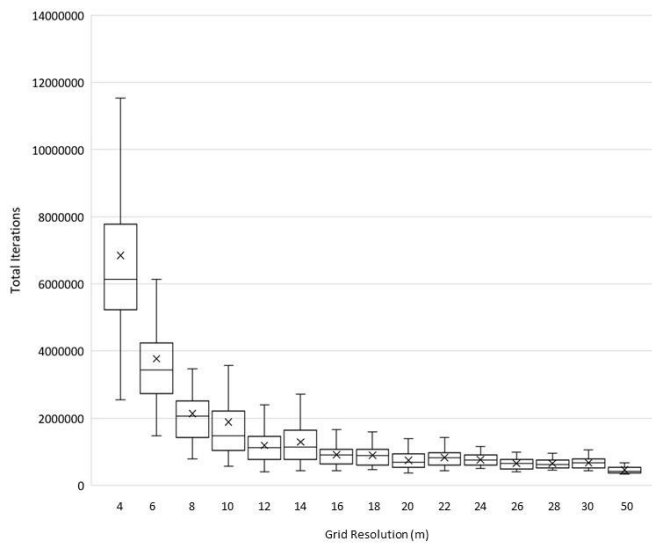



Figure 6 5 – The maximum number of stream orders calculated at each grid resolution using both the Strahler and Shreve methods. The total number of 1st Order stream cells calculated by the Strahler method is also shown.

3.4 Model performance

Figure 67 shows the changes in the number of iterations required by the model with each grid cell size. The iterations represent the number of calculations required by a test and is a useful proxy for model efficiency that is independent of the specification and performance of individual machines. There is a visible rapid drop off in the number of iterations required between 4m and 12m resolutions, yet little change with increasing coarseness beyond 12m, suggesting there are only marginal computational efficiency gain to be made using DEM resolutions coarser than 12m (the spread of the total number does decrease beyond 12m still).

375 **Figure 7 6 – Box-Whisker plots showing the spread of total number of model iterations required at each grid resolution.**

3.5 Relative influence of grid cell size

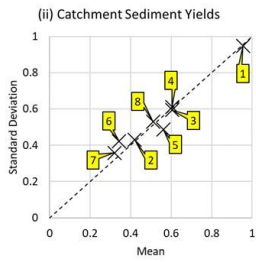
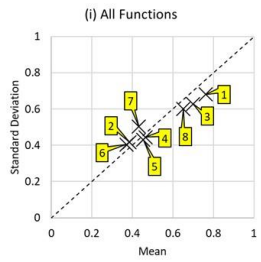
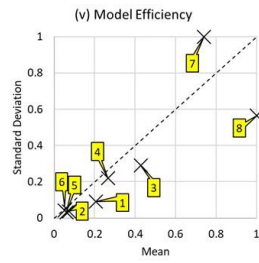
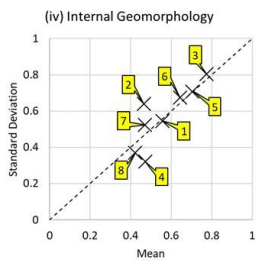
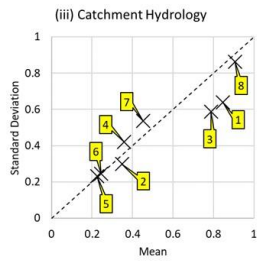
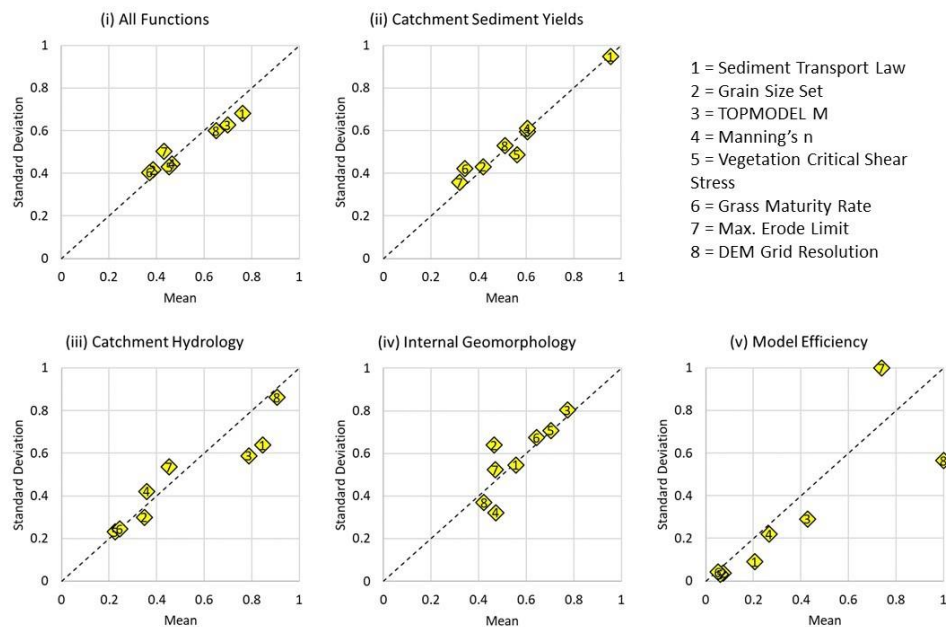
The results of from the MM tests for each grid cell size were further used to simulate a MM run where the DEM grid resolution could be considered a parameter itself. Figure 7 8 summarises the results and reveals the relative importance of grid cells size when compared to the key parameters in the model. Overall, it has a similar level of influence over all core behaviours as the
380 Sediment Transport Law (i) and the TOPMODEL M. Broken down, this is skewed by the Catchment Hydrology (iii) and Model Efficiency (v) core behaviours where it is the most influential parameter, whilst it has relatively low relative influence on the Catchment Sediment (ii) and Internal Geomorphology (iv) behaviours.

1 = Sediment Transport Law
2 = Grain Size Set
3 = TOPMODEL M
4 = Manning's n
5 = Vegetation Critical Shear Stress
6 = Grass Maturity Rate
7 = Max. Erode Limit
8 = DEM Grid Resolution

385

Figure 8 7 - Mean and Standard Deviation of relative MEs for the seven parameters and DEM Grid Resolution for all Model Functions aggregated by Core Behaviours (see Table 2).

4. Discussion

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4.1 Model robustness to grid resolution

Certain aspects of ~~CL's~~ CAESAR-Lisflood's performance are relatively robust to changes in grid cell size. However, this behavior can conceal important differences. As shown in Table 3 and Figures 2 3 and 3 4, important factors including Total

395 Sediment Yield and Total Net Erosion display little change until grid cell sizes >22m. However, whilst these output metrics remain relatively constant, related factors Peak Daily Sediment Yield increase, and Days When Peak Sediment Yield is > Threshold decrease. Despite long term sediment yields being similar this demonstrates a change in model behaviour, where with larger grid cells the sediment delivered from the catchment is doing so in fewer yet larger bursts. This can be explained

by a loss of the granularity of the drainage network as grid cell size increases, as shown in Figure 89. In particular, 1st Order streams are lost with larger grid cells (see Figure 56). With smaller grid cells there is a more detailed channel network, so when summed across the whole basin the process of channels geomorphically 'switching on and off' is smoother. With larger grid cells, there are less channels meaning the switching on and off response is more step like and thus more spikey. This also illustrates one of the weaknesses and difficulties of using a lumped parameter such as basin sediment yield to describe both model performance and basin geomorphology. There was also a decrease in Total Net Deposition with larger grid cells, consistent with the findings of School et al, (2000) that using larger grid cells makes the conditions needed for sedimentation less likely to occur. We did not see any of the larger grid- dependent erosion fluctuations demonstrated by Nicholas (2005) with their braided river model, that can be explained by CL using the flow velocity derived from water surface slope to calculate bed shear stress and thus sediment transport rather than bed slope. In other LEM's based on bed slope this sensitivity may therefore remain.
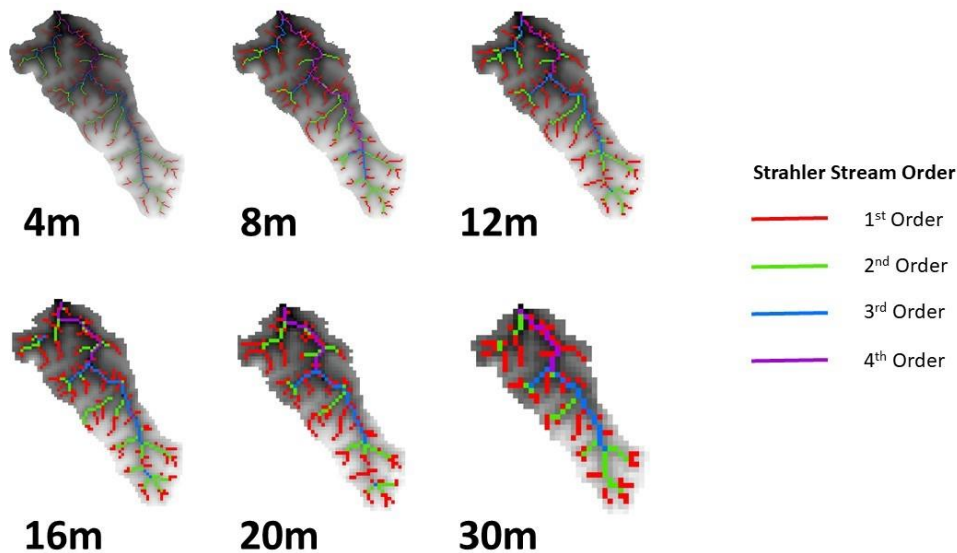
Figure 89 – Illustration of the loss of granularity in the representation of the stream network (shown is red) with increasingly large grid cell sizes.

4.2 Model behaviour with grid resolution

The behaviours of the model are captured by the relative influence of parameters on the Model Functions and Core Behaviours, with changes in the relative influence being taken as a change in behaviour. The relative influence of the 7 parameters tests on the Core Behaviours when using different grid cell sizes is summarised in Figure 45 and suggests a similar story to the changes in factors that would indicate model robustness. Although there is some noise, the relative importance of the different parameters remains relatively unchanged below the coarsest resolutions > 22m. However, there is also a general trend of waning influence of the choice of Sediment Transport Law that appears to begin at 10m resolution and continues throughout. This indicates that the coarsening of the grid resolution is resulting in some key behavioural shifts in the simulations that are most likely related to the loss of detail in the drainage network discussed in 4.1.

Relative to the 7 parameters used in the MM tests, grid cell size showed a mixed degree of influence on the model behaviours (see Figure 78). It had the greatest influence on the Model Efficiency, which also had a relatively low standard deviation ME suggesting this was non-linear and other parameter values did not affect this. This is exactly as would be expected as halving the grid cell size increases cell number by four, which also increases the number of iterations required by a same degree. Grid cell size had the greatest influence over the Catchment Hydrology behaviours, which is consistent with the loss of detail in the drainage network discussed in 4.1, and also the findings of Savage et al (2016) that grid resolution influences the sensitivity of hydraulic models to parameter values. It had relatively less influence over the Catchment Sediment and Internal Geomorphology behaviours but still influential enough to require consideration. Overall, grid resolution was shown to be the third most influential parameter, to a similar degree as the Sediment Transport Law and TOPMODEL M.

4.4 Implications and suggestions

This work has only simulated the influence of grid cell size on a single LEM and on a single, relatively small, catchment. The role of the loss of detail in the drainage network with larger grid cells is a physical effect applicable across all models using a regular grid of elevation and to any catchment, regardless of size or situation. However, the relative impact will change with different size basins – at different resolutions – and quite possibly when experiencing a different range or magnitude of driving events. Therefore, the generic finding of our study – that the degradation of a model DEM (larger grid cells) conceals topographic details that may be important to model outcomes – is important. But, the actual impact on individual studies will be specific to the catchment modelled and the resolution chosen.

This study has further highlighted the need for operators to better understand the sensitivities of their models to both internal and external factors before embarking on landscape evolution studies. Here, we have demonstrated that DEM grid resolution is a controlling external factor of the behaviours simulated in the system, with larger grid cells resulting in fewer yet more

extreme erosion producing events, which although overall produces similar total sediment yields does so over a smaller contributing area. Grid cell size was also shown to be the third most influential parameter out of those tested. This suggests that it is important that when making model choices, operators should aim to use the finest resolution available to them and that model efficiency will allow. Where model efficiency is a concern, a compromise can be made by selecting a resolution where coarsening further results in lower levels of benefits - in this study that would appear to be around 12m (Figure 67), close to the default 10m used for the same catchment in Skinner et al., (2018). Importantly – this choice is catchment specific.

The use of MM to assess the model's sensitivity to an external factors (e.g., grid cell size) relative to the sensitivity to internal parameters presents opportunities and a powerful tool. This allows for a more comprehensive consideration of the sensitivity of the model to choices of the modeller and enable them to evaluate on what areas to focus on improving, for example, the tests here tell the modeller that work to increase the resolution and detail of the DEM grid would yield greater benefits than work to reduce the uncertainty in the grain size parameters. Performing this type of analysis to inform model choices will increase the robustness and confidence in model outputs, crucial if LEMs are going to be used operationally and for decision making. Additionally, the same methods can be applied to other modelling fields, including hydrological and hydraulic modelling.

4.5 Limitations

Whilst this study has highlighted the influence that grid cell resolutionsize can have on model behaviour and outputs it is also limited by the narrow set of conditions tested. We have only considered a single LEM and. We have looked at only a single small catchment with its own unique set of conditions. Therefore, whilst many of our findings can reasonably be ported to different models with similar parameaterisation and operation we acknowledge that the findings are not generic. Equally, whilst we believe many of our findings are directly relevant to other applications of CEASAR-Lisflood to different catchments, Of particular note is the paucity of Tin Camp Creek has few depositional zones (e.g. floodplains or alluvial fans) so the deposition that occurs within the catchment itself, with the majority of eroded sediments leaveing the catchment entirely. We have deliberately used a short timescale of simulationonly use a single timescale of simulation – the timescale used, just 30 years, that is short by the standards of LEMs but analogous to operational uses of the models to aid decision making. The applicability of the detailed results of this study to other models, catchments, and timescales is unknown but the implications remain, that being the sensitivities of models to grid cell resolutions should be understood as part of any study using LEMs. This is particularly pertinent when they are being used operationally.

5. Conclusions

This research has explored the influence DEM grid cell size has on the water and sediment outputs of a LEM (CAESAR-Lisflood) using the Morris Method sensitivity. We found simulated basin sediment yields and hydrological outputs totalled over the model duration, were largely unchanged as grid cells sizes increased, up to a point where the grid cell size started to
485   degrade the extent and shape of the drainage network. It is likely that the impact of this network degradation will be dependent on the size of the basin, with the results being lessened on larger basins for the same grid cell size.

However, when the model results are analysed over event scale timescales it became clear that the lumped output grid scale independence masked important changes with resolution. As grid cell sizes increased, the similar sediment yields were
490   produced by fewer, larger events. It is important, therefore, to note this sensitivity in the models application or risk a 'right results for the wrong reasons' set of outputs.

These findings are important because the resolution of the DEM used in LEM studies is often an arbitrary choice, often driven by the need to balance including as much detail as is available with model efficiency. The approach presented in this paper
495   demonstrates the feasibility of using a screening sensitivity analyses to identify key influences on model behaviour, for grid cell size and parameter choices, which will help modellers identify the optimal grid cells size for their study.

Appendix A - Description of Parameters

Code	Parameter	Description
(1) SED	Sediment Transport Formula	Relationship between properties of flow and the volume of sediment entrained, often determined via field and laboratory observations.
(2) GSS	Grain Size Set	The proportion of sediment within different size classes distributed uniformly across the model domain at the start of each simulation.
(3) MNR	Manning's n Roughness	A coefficient related to how much resistance the land surface presents to flows.
(4) TOPN	m value used by TOPMODEL	A parameter that controls the flashiness of hydrograph response to rainfall.
(5) VEG	Vegetation Critical Shear Stress (Pa)	A shear stress threshold above which vegetation is removed from the land surface by flows.
(6) MAT	Grass Maturity Rate (yr)	The amount of time it takes new vegetation to grow to full size.
(7) MEL	Max Erode Limit (m)	A limit to the amount of sediment that can be eroded in a cell each time step used to maintain stability.

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Formatted Table

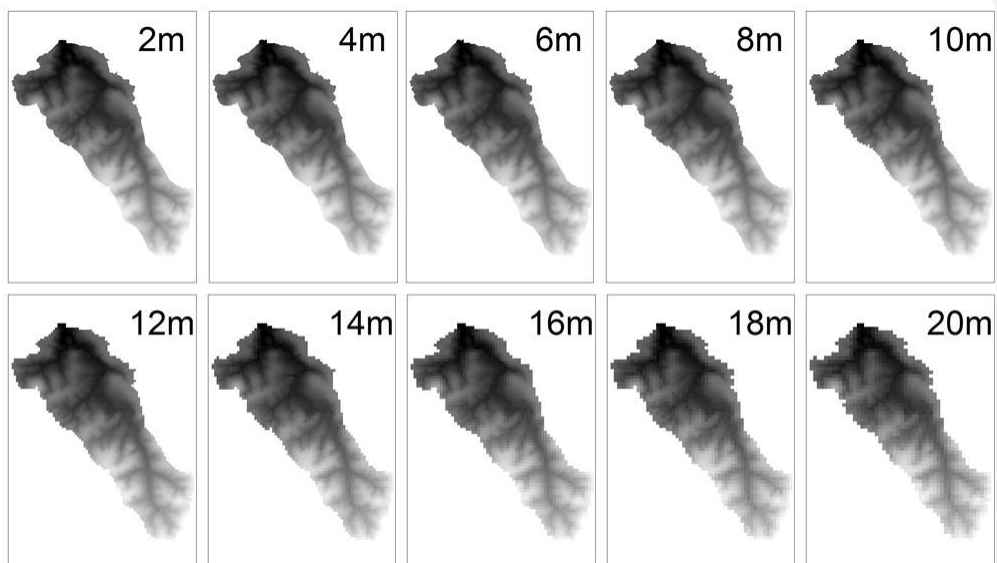
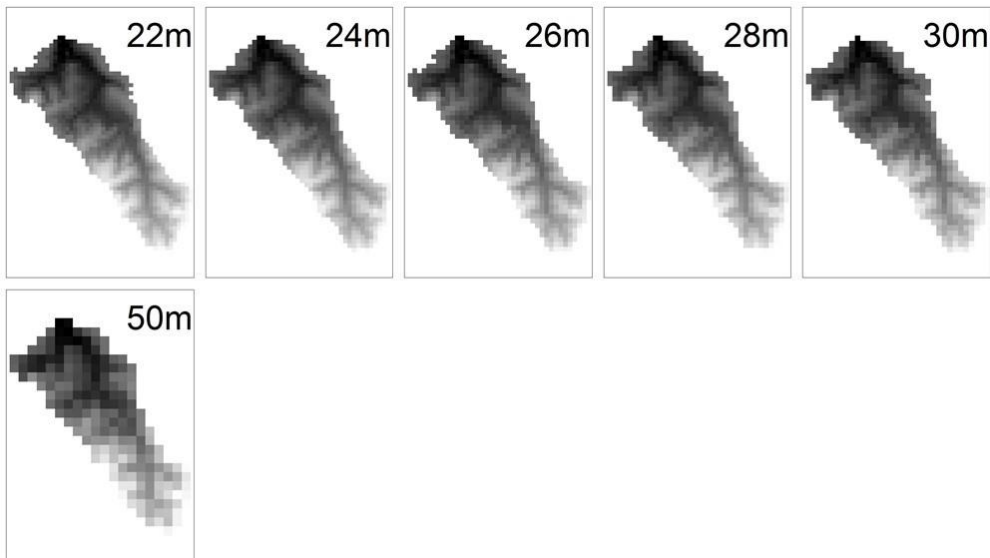
Appendix BA - DEMs at different grid resolutions

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Figure A1 - Illustrations of the Tin Camp Creek DEM resampled at 2m increments, from 2m grid resolution to 30m, plus 50m.

Appendix CB - Box and whisker plots

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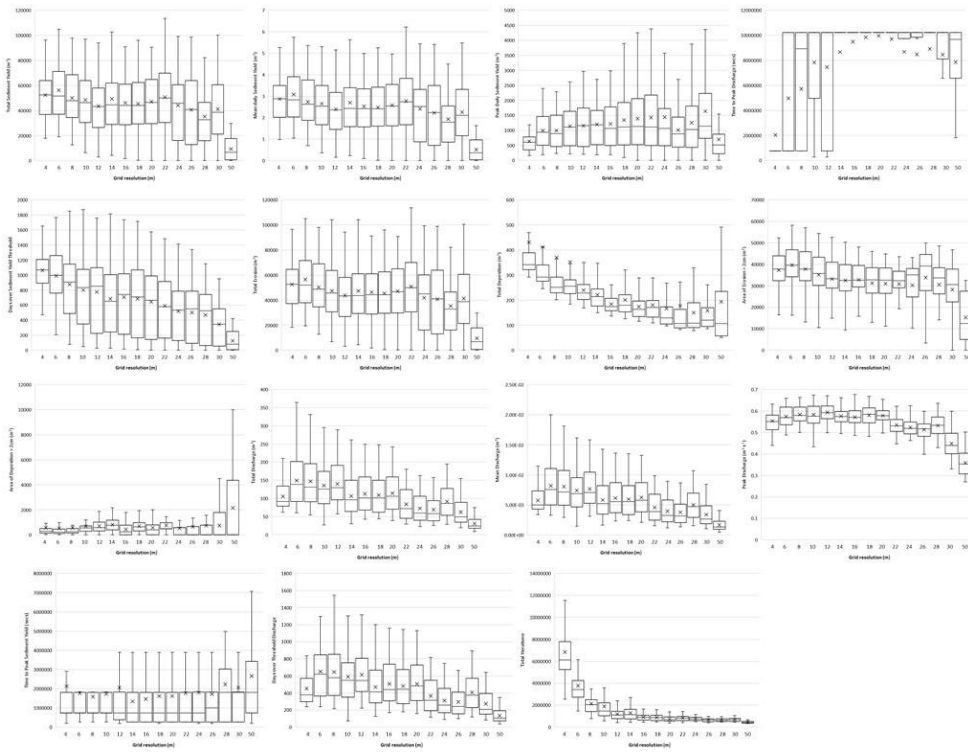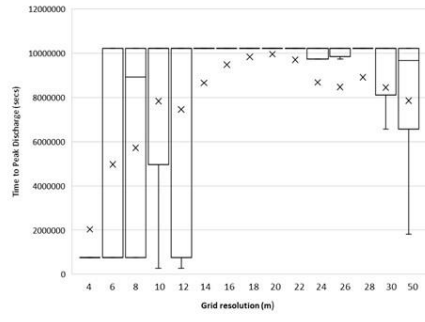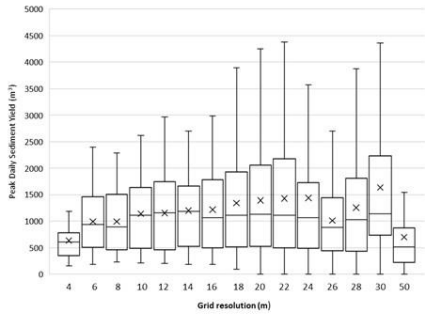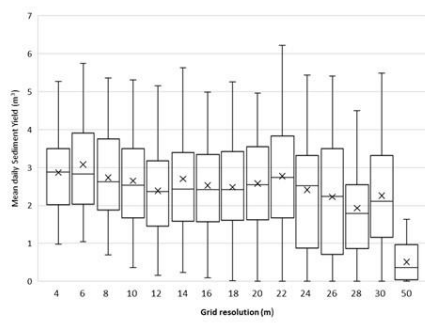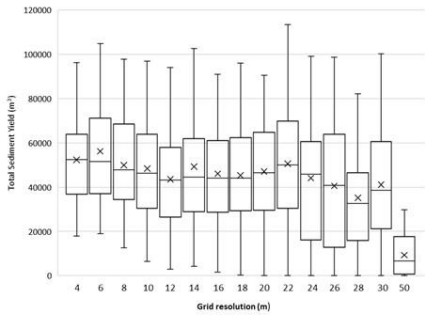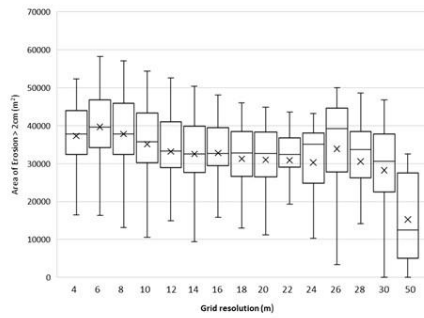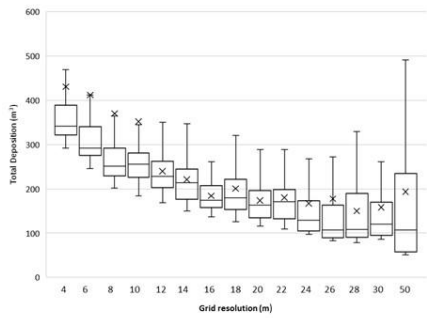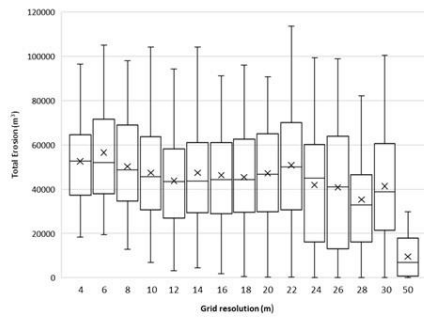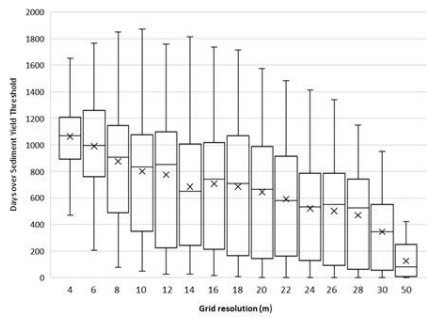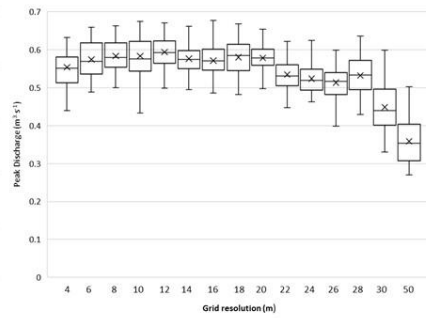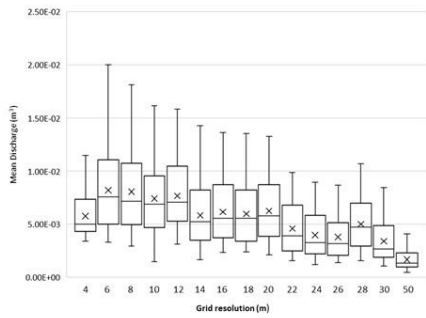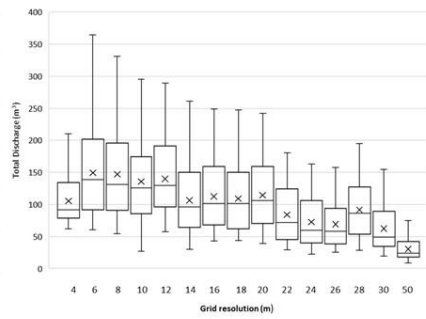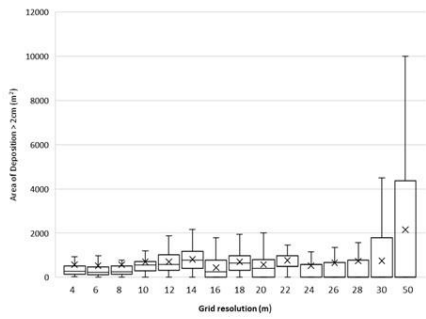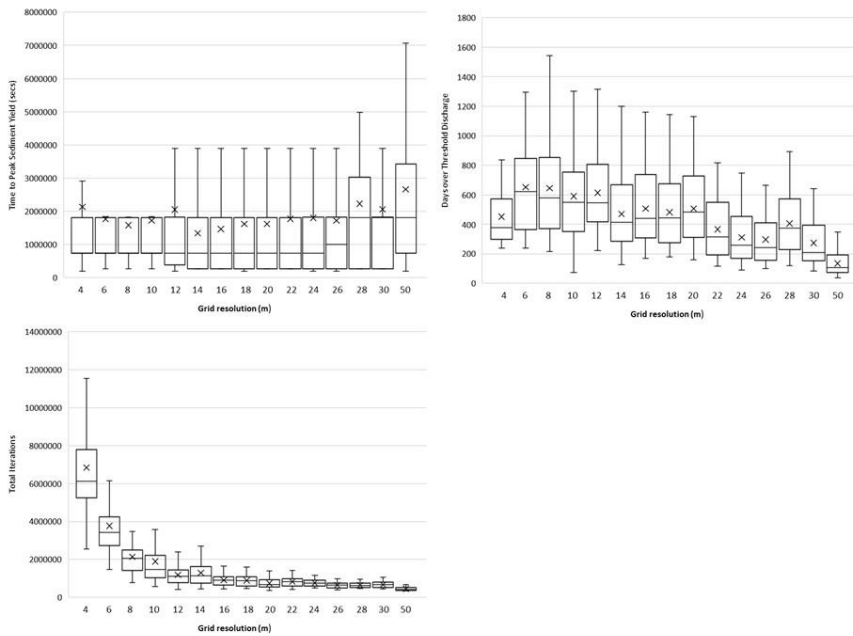
515 **Figure B1 - Box and whisker plots showing the spread of model outputs, and the means at each grid resolution.**

Acknowledgements

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520 **Author Contributions**

CS and TC conceived and designed the project. CS set up the tests and performed the model runs. CS and TC analysed the results, wrote, and edited the manuscripts.

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