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78

The University of Manchester

79 Declan A. Valters

80 Doctor of Philosophy

81 Sensitivity of numerical landscape evolution models to the spatial resolu-
82 tion and complexity of precipitation

83 August 3, 2016

84

85 Write your abstract here: Remember, it must fit on this A4 page and should
86 describe contents of the thesis/dissertation. Here might also be a good place to indicate
87 what you have achieved in the thesis/dissertation and, in the case of a PhD, what new
88 results you have discovered. Note that for a PhD single-spacing is used throughout
89 the Abstract, including displayed equations as for the above example.

⁹⁰ Declaration

⁹¹ No portion of the work referred to in the thesis has been submitted in support of an application for another degree or qualification of this or any other university or other institute of learning.

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¹¹⁶ **Layperson's abstract**

¹¹⁷ An optional section suggested by the UoM thesis preparation guide.

¹¹⁸ Acknowledgements

¹¹⁹ Acknowledgements...

Chapter 1

Introduction

This chapter introduces the topic in a broad setting within the context of landscape evolution under different climatic conditions and meteorology (rainfall spatial patterns). The topic is discussed in its historic context as well briefly. It then goes on to clarify the topic of interest, and relates it to both topical research questions in landscape evolution theory and also the societal impact of intense, erosive rainfall events on the landscape.

128 Chapter 2

129 Modelling landscape evolution

130 *This is a general overview of landscape evolution models and the key concepts and*
131 *limitations they have.*

132 *In the next chapter, Chapter 3, there is a more focused review of the specific area*
133 *of Landscape evolution models that I am working on – i.e. rainfall representation in*
134 *LEMs. I only touch upon rainfall parametrisation here.*

135 This chapter could be based on the *Geomorphological Techniques* book chapter
136 (Valters, 2016).

Chapter 3

Rainfall representation in current landscape evolution models

3.1 Introduction

This chapter reviews how current landscape evolution models represent rainfall input into the landscape system. It is worth stating here what exactly is meant by rainfall input, in the context of the atmosphere–land-surface system as represented in numerical models. Perhaps equally as importantly, it is worth discussing what aspects of rainfall are *not* represented at all in any numerical models of landscape evolution, to clarify how geomorphologists conceptually think of meteorological processes acting on the landscape.

For most purposes, rainfall input in landscape evolution models is simply the quantity of water added to a surface cell or node, or to the whole model domain. In practise, no numerical models represent rainfall in the sense of it actually falling from the sky and hitting the ground. While this may seem a somewhat trivial point, the impact of individual rain drops on the land surface is known to be an important contributor to surface erosion. Rain-splash erosion, as it is termed, is a well-studied phenomenon [cite a review of rainsplash erosion, if there is one?]. The interaction of raindrops with the surface is complex; it depends on the size of raindrop, falling velocity, angle of attack, soil exposure, soil mineralogy, and cohesion of the soil surface. All of these factors could affect both erosion on the landscape hillslopes, as well as the route that water takes to runoff and reach the rivers, before fluvial erosion can happen.

159 If we briefly turn to physical analogue models of landscapes, rainfall representation
 160 implicitly accounts for some of the above factors in rainsplash erosion and runoff,
 161 because of the physical need to generate a rainfall source from above the model, such
 162 as through a fine-meshed sprinkler [CITE]. In fact, geomorphologists using physical
 163 analogue models of landscape evolution attempt a degree of rainfall realism by ensuring
 164 the raindrops they generate are reasonably well scaled to the size of their landscape
 165 analogue (Meyer, 1994). By contrast, numerical models of landscape evolution begin
 166 their representation of rainfall input at the surface – in effect rainfall input in most
 167 landscape evolution models has nothing to do with *falling* rain or its impact on the
 168 ground. Conceptually, rainfall input in numerical models is the amount of water that
 169 would be added at the surface from one or more (usually many more!) raindrops,
 170 once they have reached the ground. It ignores any effects from the physical collision
 171 raindrops make with the ground. This simple conceptual model of rainfall input is
 172 used throughout the rest of this chapter when referring to rainfall input in landscape
 173 evolution models.

174 3.2 Simple models and proxies for rainfall variation

175 3.2.1 1D models

176 Isolated aspects of landscape evolution and hydrology can be studied using 1D models
 177 of features such as hillslopes profiles and longitudinal river profiles, or storm hydro-
 178 graphs in the case of hydrology. Though the work in this thesis focuses on 2D models,
 179 it is useful to consider the work done by others investigating the feedback from rainfall
 180 variability on 1D models of landscape evolution, before progressing to full 2- or 2.5D¹
 181 models over an x, y model domain.

182 Roe et al. (2002) modify a simple 1D model for river profile evolution (Seidl and

¹Occasionally, the terms 2D and 2.5D are used interchangeably when referring to landscape evolution models, although in effect they both produce what looks like a ‘3D’ terrain surface from their output. The ‘third’ dimension (or extra 0.5D in 2.5D terminology) comes from the fact that the elevation variable can be used to reconstruct a 3D picture of the landscape based on the value for each grid cell or node. In practice, nearly all of the process models in landscape evolution models are 2D, e.g. water routing over the surface does not account for turbulent flow in x , y and z directions, such as in computational fluid dynamic models. Sediment transport does not account directly for 3D particle motion or collisions between particles. I use the term 2D landscape evolution model throughout the work.

183 Dietrich 1992; Howard et al., 1994; Whipple and Tucker, 1999) to incorporate a feed-
 184 back for orographic precipitation based on changing elevation along a steepening river
 185 profile. Their precipitation feedback model accounts for two precipitation regimes:
 186 the first typical of midlatitude, shallower, and narrower mountain ranges such as the
 187 West coast of North America, and one for broader and taller ranges such as the Sierra
 188 Nevada, European Alps or the Southern Alps of New Zealand. The former represents
 189 rainfall patterns that are dominated by the prevailing upslope winds, increasing pre-
 190 cipitation with distance upstream, whereas the latter represents environments where
 191 atmospheric moisture content exerts more control over precipitation, resulting in de-
 192 creasing rainfall at higher elevations, and a rainfall shadow on the leeward side of the
 193 range. In a later work (Roe et al., 2003) the 1D model incorporating orographic rain-
 194 fall feedback is extended to the 1D relief structure of mountain ranges. The maximum
 195 relief is found to be strongly dependent on the type of precipitation regime chosen -
 196 with the prevailing upslope wind regime favouring lower relief, symmetric mountain
 197 ranges, and the atmospheric moisture-limited regime favouring higher relief mountain
 198 ranges.

199 Further 1D models have been developed to determine the relative importance of
 200 rainfall variability compared to other boundary conditions, such as tectonic uplift or
 201 base level fall. The 1D river profile model of Wobus et al. (2009) uses a transport
 202 limited formulation of river profile evolution (Meyer-Peter and Muller, 1948) with a
 203 simple parameterisation of rainfall based on modifying the exponent to the discharge-
 204 area approximation given by:

$$q_w = k_q A^c \quad (3.1)$$

205 where q_w is the water discharge, k_q a dimensional coefficient, A the contributing
 206 drainage area, and c the exponent that relates which portions of the drainage basin
 207 contribute to gathering precipitation and converting it to water discharge. A decrease
 208 in c represents a shift to more rainfall being gathered in the upper reaches of the stream.
 209 An increase in c represents rainfall being gathered in the lower reaches. The situation
 210 where $c = 1$ implies rainfall input is equal along all sections of the river profile. The
 211 end result is perhaps intuitive – more rainfall input in the upper reaches of the stream
 212 (decrease in c) results in more incision in the headwaters. However, the study reveals

213 a key difference in the way that climatic and tectonic signals propagate along a river
214 channel. Numerical results show that rainfall-driven perturbations propagate from
215 the channel head downstream, whereas tectonic perturbations invariably propagate
216 from base-level upwards towards the channel head. The authors, however, reach this
217 conclusion without simulating the scenario where there is more contributing rainfall
218 from the lower reaches, i.e. the value of c is higher. Given the setting of the study
219 though, (streams draining a mountain front) it is perhaps reasonable to assume an
220 increasing precipitation gradient upstream towards the mountain range.

221 In the one-dimensional cases discussed, there is a key limitation, which is often
222 acknowledged by the authors. Channels profiles in 1D form are modelled with out
223 their tributary streams. The main stem of the channel is assumed to be representa-
224 tive of the entire catchment as a whole. This implies that tributary channels, and
225 hillslopes feeding the main channel, experience the same precipitation patterns, or
226 that differences between the main channel and its contributing water sources can be
227 ignored.

228 River channel profiles are not the only markers of landscape evolution, though they
229 do dominate the range of 1D modelling studies investigating sensitivity to the spatial
230 distribution of rainfall. Owen et al. (2010) address the sensitivity of hillslopes to aver-
231 age precipitation rates, although spatial variation of rainfall along hillslope profiles is
232 not considered. The study reveals hillslopes are most sensitive to average precipitation
233 rates when there is a lack of vegetation. Hillslope bedrock erosion decreases according
234 to a power law as mean rainfall rates decrease, from semi-arid to hyperarid environ-
235 ments. In general though, the study of hillslope sensitivity to the spatial distribution
236 of rainfall remains under-studied, particularly in the case of 1D profile evolution.

237 One-dimensional profile models are useful tools for exploring aspects of landscape
238 evolution. By their definition though, they restrict studies of rainfall spatial vari-
239 ability to a single dimension along the landform profile. Rainfall spatial variability
240 from tributary channels, or from runoff over hillslopes is lost, or ‘smeared-out’ (Roe
241 et al., 2002). The effects of water routing within a drainage network are also lost, and
242 interesting relationships between rainfall distribution, river network connectivity and
243 erosion are potentially overlooked. Complex parameterisations of rainfall production

are often reduced to a single number or exponent in an equation describing the evolution of the landform profile of interest. Rainfall spatial patterns are often complex over correspondingly complex terrain, and only 2D models may suffice to fully explore the sensitivity of landscape process and form to rainfall spatial distribution.

3.2.2 2D models

Early 2D numerical models of landscape evolution were often driven by single process laws of fluvial incision, and the topography that resulted from them was a product of the parameters in the fluvial incision laws. Simple fluvial incision laws, implemented in 2D numerical models resulted in topography broadly similar to the fractal patterns of river networks observed in nature [CITE Ahnert/Turcotte], with the hillslope features between neighbouring river channels been formed by what was ‘left behind’ from fluvial incision patterns. In other words, separate process laws were not implemented to describe the typically diffusive processes observed in hillslope formation. [Roerring, Hurst, citations from Hurst]

A typical form of the simple stream power law for fluvial incision takes the form:

$$E = KA^mS^n \quad (3.2)$$

where K is termed the coefficient of erodibility, and is a catch-all term for climatic processes (amongst others) including the role of rainfall on the fluvial incision process. The K term itself could be considered a proxy for rainfall variation over time, assuming all other factors remained constant. [are there studies that do this, I thought there were somewhere...not sure now?]

Another simple model is the excess shear stress model for fluvial incision, where the incision or erosion rate, E is given as a function of shear stress, τ above a threshold level, τ_c :

$$E = k_e(\tau^a - \tau_c^a) \quad (3.3)$$

With this simple model of landscape evolution, one of the first studies to study the 2D evolution of topography under varying climatic conditions was that of Rinaldo (1993). The study implemented a cyclic variation through time on the parameter of

critical shear stress, the threshold for erosion, τ_c . Since shear stresses driving incision are determined by river discharge, which in turn is controlled by rainfall input, the cyclical variation in critical shear stress, τ_c can be used a proxy for temporal variations in rainfall over the catchment at geological timescales. When the value of τ_c is low during the model this effectively represents a period of high rainfall intensity, and when τ_c is high this represents a period of lower intensity rainfall (Rinaldo, 1993). In the resulting topographies from these simulations, drainage density and fractal dimension were shown to increase in response to a decrease in critical shear stress, or an increase in rainfall input over time, assuming other factors such as uplift remain constant.

Other studies to expand on:

- CHILD (Tucker) - Precipitation Stochastic Model.
- Colberg and Anders (2003)
- Solyom and Tucker (2004) - is this distributed or not? Probably not because rainfall-runoff is a parameterisation.
- Solyom and Tucker (2007)

3.3 Distributed models

Distributed models² are grid-cell based (or based on a grid of ‘nodes’) and allow certain variables to vary spatially across the model domain, from cell-to-cell or node-to-node. The term is less frequently used with regards to landscape evolution modelling, but is useful to distinguish those models which represent a spatial variability in meteorological input from those that treat it through a proxy variable or another parameterisation. There are comparatively few landscape evolution models that allow spatially variable rainfall input to be distributed across the model domain, and some of the examples discussed here are from purely hydrological models. However, the principal of modelling spatially distributed rainfall remains the same and there are potential applications in hydrological modelling that can be extended to landscape evolution purposes.

²I borrow the term ‘distributed model’ here from hydrological modellers.

3.3.1 Hydrological models

In the world of hydrological modelling, distributed rainfall inputs are more commonplace. A range of meteorological input data sources have been used to drive distributed hydrological models. Three main sources of spatial rainfall data commonly used are dense-network rainfall-gauge data, precipitation radar, and precipitation outputs from numerical weather prediction models. Each one of these sources has a range of merits and demerits as a raw data source, but the discussion here focuses on their suitability as spatially heterogeneous rainfall datasets for numerical landscape evolution models, rather than an appraisal of their relative accuracies in reporting precipitation distribution.

Precipitation data generated by numerical weather prediction models has been successfully used in distributed hydrological models to make hydrological forecasts, as well as to analyse historic flooding events. Hay et al. (2006) use the MM5 model (mesoscale meteorological model)³ to generate gridded rainfall data over a five-year period. The rainfall data is used to drive the PRMS distributed hydrological model – the Precipitation Runoff Modelling System – over a corresponding five-year period. The numerical weather prediction model is run at grid cell spacings of 20km, 5km, and 1.7km, the finest of which resolves individual valleys and massifs, and captures the resulting rainfall patterns over the catchment at high resolution. The study also compares the way that rainfall input zones in the hydrological model are represented. In the hydrological model, different zones of rainfall input can be defined along natural topographic boundaries, which are termed *Hydrological Response Units*. These rainfall zone units tend to follow sub-catchment boundaries within the main catchment watershed. Alternatively, the catchment can be divided up more simply into rainfall input zones corresponding to a regularly spaced grid at a cell-spacing that matches the resolution of the input data. In general, increasing rainfall input resolution in the Hay et al (2005) study results in a greater accuracy when compared with observed river discharge values. Using irregular-shaped hydrological response units based on natural sub-catchments, rather than a regular gridding of input data, results in better agreement with observation. However, as resolution increases towards the 1.7km grid-cell spacing, the difference seen from using irregular shaped hydrological response units

³A precursor to the Weather Research and Forecasting model, WRF.

327 and regular grids of comparable resolution decreases.

328 A study that uses high resolution numerical weather prediction model data to drive
329 a hydrological model (Younger et al., 2007) tests the suitability of rainfall forecast
330 data for making hydrological predictions and improving flood forecasting. High reso-
331 lution (250m grid spacing) simulations using the United Kingdom Met Office Unified
332 Model are used to generate input rainfall data to drive a TOPMODEL-based (Beven
333 and Freer, 2001) hydrological model. The semi-distributed *Dynamic-TOPMODEL*
334 hydrological model groups topographically similar regions of the catchment and cal-
335 culates runoff-prediction for each of the these self-similar zones. The runoff calculation
336 is then assigned to each node in that particular zone (see Beven, 2002, for a full
337 explanation of the TOPMODEL concepts.) Computationally, this is more efficient
338 than performing runoff calculations for every single grid cell in the catchment do-
339 main. The Younger et al. (2007) study considers two events, a summer convective
340 rainfall-event and a winter stratiform rainfall event. Although the hydrological simu-
341 lation using the dense-network of rainfall gauge data produced outputs more closely
342 matched to discharge observations, simulations with the NWP rainfall forecast also
343 produce accurate results. The authors highlight the potential of using high-resolution
344 rainfall forecast data to improve flood-forecasting in the future, giving greater predic-
345 tion lead-in times compared to nowcasting from rainfall radar or real-time raingauge
346 measurements. Rainfall data from numerical weather prediction models lends itself
347 well to use as input data for hydrological modelling; it is typically written in a gridded
348 data output format, and if the user has control over both the generation of the NWP
349 output as well as the hydrological or landscape evolution model, generating compatible
350 data formats can be more straightforward.

351 A consensus has yet to emerge on whether distributed hydrological models are sen-
352 sitive to the spatial distribution of rainfall input. Nictoina et al. (2008), in a study
353 that assesses rainfall resolution in distributed hydrological models, note that several
354 studies are in disagreement, even when comparing catchments of similar sizes and
355 in similar environments. In terms of the peak discharge and the time to the peak
356 from the onset of heavy rainfall during a flood, modelling rainfall input as a spatially
357 heterogeneous boundary condition appears to have little impact on the predicted hy-
358 drographs. (Krajewski et al., 1991; Shah et al, 1996). It is noted that antecedent

conditions may determine some of the relative sensitivity in catchment hydrological response (Shah et al., 1996), but only when initial water saturation levels are low. The work by Shah, and that of Segond et al., (2007) indicate that variability in runoff production mechanisms are the dominant control on runoff response. Whether variability in rainfall heterogeneity also contributes to the runoff response depends on antecedent conditions, as catchments may be able to dampen spatial heterogeneities in rainfall (Segond et al., 2007). In the simulations run by Nicotina et al. (2008), the source of rainfall data is from a network of rain gauges. Rainfall resolution is varied by first interpolating the rain gauge data with inverse weighted kriging method to 100m resolution. The 100m resolution data is then upscaled to coarser grid-sizes of 10km and 50km, giving three sets of simulations. Their study uses two catchments of 1560km² and 8000km² in area. The authors select catchments of relatively large size compared to previous studies. Their choice of larger catchments is based on one their hypotheses being that smaller catchments are closer in size mesoscale rainfall features, and therefore less likely to experience truly heterogeneous spatial rainfall patterns. The results of the Nicotina study show small differences between flood hydrograph peaks, which is more pronounced for the larger (8000km²) catchment. A further set of simulations also compares a conservative upscaling of rainfall resolution to a non-conservative upscaling – i.e. the total volume of rainfall is not necessarily the same post-upscaling. The non-conservative upscaled rainfall resolutions display a greater difference in maximum flood discharge over the three rainfall resolutions than the conservative upscaling method. The authors assert that catchments are more sensitive to the total volume of precipitation than its spatial heterogeneity, although this is perhaps to be expected if the non-conservatively upscaled experiments simply add more water to the catchment at coarser rainfall resolutions. The authors' further experiments with different runoff-generation mechanisms show a much more marked sensitivity in hydrograph response, compared to rainfall spatial heterogeneity.

From a hydrological perspective, it would appear that getting the total rainfall volume and runoff-generating mechanisms accurately represented in a hydrological model are more important than the spatial pattern of rainfall (Gabellani et al., 2007; Nicotina et al., 2008). However, the approach of previous studies has been to focus primarily on the flood hydrograph during these simulations, which is essentially the water discharge

391 modelled (or measured) at a single point at the catchment outlet. Very few studies,
392 if any, have properly addressed the 2D spatial extent of floodwaters in response to
393 spatially variable rainfall inputs over a catchment. It seems an odd omission to inves-
394 tigate a boundary condition that is by definition spatially heterogeneous over three
395 dimensions (the areal spatial pattern of a rainstorm, as well as the storm depth or
396 intensity), and then to reduce the output to a modelled parameter at a single x, y
397 coordinate on the model domain. This could be remedied in future research projects.

398 Intuitively, one might expect that in a river catchment system with its well de-
399 fined boundaries and singular output point, that any mass-conserving model would
400 produce similar results given water inputs of equal volume (here, I am excluding the
401 non-conserving rainfall upscaling method used by Nicotina et al., 2008). The details
402 of interest may lie in what goes on inside the model domain, rather than what comes
403 out the outlet point. Nevertheless, the work done by the hydrological modelling com-
404 munity has laid some of the foundations for using spatially variable rainfall data in 2D
405 landscape evolution models. A range of data input sources, and interpolation meth-
406 ods that have been successful in hydrological modelling. Some of the basic findings
407 will also help guide the research in the later chapters, and development of an existing
408 landscape evolution model in Chapter 4.

409 3.3.2 Landscape evolution models

410 Few of the currently available numerical landscape evolution models explicitly allow the
411 user to vary the spatial distribution of rainfall across the model domain (Valters, 2016).
412 At longer timescales, it can be argued that spatial variation in climatic conditions
413 such as rainfall will eventually be averaged out over centuries and millennia, in effect
414 negating any variation in rainfall spatial patterns (Solyom and Tucker, 2007; Tucker
415 2010). However, this assumption only holds true if we believe that storm location
416 and rainfall patterns bear no relation to the underlying topography of a landscape or
417 river catchment. In other words, the assumption is that on the short term there is no
418 orographic influence, and on the longer term, that there is no link between evolving
419 topography and evolving weather patterns in a region. Only in recent years, and in
420 a select few studies, have geomorphologists begun to question this assumption. As
421 interest in this question has grown, models have evolved to accommodate this feature.

At the short term end of the landscape modelling spectrum (days to centuries), the latest releases of the CAESAR-Lisflood model (Coulthard et al., 2014) now allow for spatially variable rainfall input data.

Coulthard and Skinner (2016) In a sensitivity study that systematically varied the rainfall input data spatial resolution, Coulthard and Skinner (2016) assessed landscape evolution model sensitivity in terms of sediment and water flux, and the spatial distribution of erosion in a mid-sized upland catchment (415km²). Rainfall input data was sourced from precipitation radar, and rainfall data resolution is varied at 5km, 10km, 20km resolutions, as well as a ‘lumped’ input where rainfall is averaged spatially across the whole catchment. When the source data is upscaled to finer resolution, the total volume of rainfall is conserved (in contrast to the non-conserving upscaling methods used by Nicotina et al, 2008). The simulations are run with typical rainfall data that is extended over a 30 year period. Compared to the uniform (lumped) precipitation data, increasing the rainfall data grid resolution increases sediment flux from the catchment. In the case of the highest resolution rainfall simulation (5km), sediment flux increases by over 100% compared to the uniform rainfall case. Coulthard and Skinner’s study separates natural spatial variation in rainfall patterns by randomizing the rainfall cell ‘tiles’ from the precipitation radar data, in an attempt to remove any effects from orography in the catchment. In essence, their study is focused solely on the effects of rainfall data resolution alone, rather than the spatial patterns of rainfall in nature, which are often influenced by topography. The rainfall field randomising technique minimise biases from naturally occurring organisation in storm cells and orographic rainfall enhancement.

Von Ruette, et al (2014) So far in this chapter, the discussion has been on landscape evolution models and studies that focus on hydrological, fluvial, and hillslope erosional processes. Numerical models of whole-landscape evolution have a recognized bias towards temperate-humid landscapes (Pazzaglia, 2004; Tucker and Hancock, 2010; Valters, 2016) and tend to focus on a limited gamut of geomorphic processes: hydrology, fluvial erosion, hillslope evolution, and sediment transport. However, the sensitivity of other landscape processes may well be sensitive to the spatial distribution

of rainfall over a landscape. Landsliding is an often overlooked, yet important process in landscape evolution and frequently omitted in numerical models (Tucker and Hancock, 2010; Valters, 2016). Von Ruetten et al. (2014) investigate the sensitivity of shallow landslide initiation to the spatial distribution of rainfall in a catchment, using a physical based catchment-scale landscape evolution model designed specifically for investigating landslide triggering, the *CHLT* model (von Ruetten et al, 2013). In their modelling study, they examine the initiation of shallow landslides under spatially uniform rainfall and a coarse grid-based spatially variable rainfall input, from a real event occurring in 2002. The rainfall input data is a product of integrated rain gauge data and rainfall radar measurements. As the coarseness of the data is high relative to the size of the study catchment, the authors use an inverse distance weighting interpolation method⁴ to downscale the data to a 2.5m grid cell size, the same resolution as the digital elevation model data used in the study. The authors generate a further set of simulations with a set of artificial rainfall input grids at 500m grid cell size. In the model of landslide initiation in the authors' model, the main sensitivity is the rainfall intensity and the infiltration capacity of the soil. If rainfall intensity is too high, water will runoff before it can fully infiltrate the soil; there exists a sweet-spot where rainfall intensities are low enough that the soil will become saturated more readily, and more landslides will be initiated. In the simulations run with equivalent rainfall intensities, spatial heterogeneity exerts some control over the distribution of landslides, as certain grid cells experience high rainfall rates, whereas others experience lower rainfall rates, closer to the rainfall rate 'sweet-spot', and consequently more landslide initiation. The findings of the von Ruetten (2014) study are complex; sensitivity of landsliding initiation to rainfall spatial heterogeneity is dependent on a number of other conditions such as soil moisture capacity, infiltration rate, rainfall rate, and rainfall intermittency. Rainfall spatial distribution in a catchment exerts a control on whether these conditions will be optimal for landslide initiation, since it controls local rainfall intensities. Von Ruetten et al. conclude that both the spatial distribution of landslides and the total number of landslides triggered are sensitive to the spatial distribution of rainfall in a catchment, assuming other conditions such as infiltration capacity are near-uniform

⁴An interpolation that gives preferential weighting to points that are closer to each other. The measured values closest to the prediction point of interest have more weighting, which diminishes with distance from the point of prediction.

482 across the catchment.

483 Longer term landscape evolution

484 **Solyom and Tucker (2007)** Landscape evolution sensitivity to rainfall detail over
 485 much longer timescales, on the order of 100kyrs and greater, has been explored to a
 486 limited extent by a few studies. Solyom and Tucker (2007) investigate how limited
 487 storm size relative to the size and shape of the drainage basin, effects the evolution of
 488 landscape topography. In their model, storm cells are represented as circular patterns
 489 with peak rainfall intensities at the centre of the circle, decaying exponentially from
 490 the centre:

$$I = I_0 \exp(-L_s/L_0) \quad (3.4)$$

491 where I is the rainfall intensity at a given point in the storm cell, I_0 is the rainfall
 492 intensity in the centre of the storm, L_s is the distance from the centre of the storm to
 493 a given point in the storm cell and L_0 is a characteristic length scale associated with
 494 the spatial decline of rainfall intensity.

495 Orographic effects on rainfall enhancement are excluded in the model. In Solyom
 496 and Tucker's simulation, a set of idealised diamond-shaped catchments are varied in
 497 their elongation (length-width ratio), while being subjected to a steady non-uniform
 498 rainfall field described by the exponential decay function, centred at the middle of the
 499 diamond-shaped catchment. The exact implementation details in the model code is
 500 not revealed by the authors of the study. Their simulations reveal that in general non-
 501 uniform rainfall patterns introduce a catchment-shape sensitivity to rainfall-runoff
 502 production, which in theory should effect the size and distribution of geomorphic
 503 processes throughout the catchment as well. The authors do not present examples of
 504 topographies generated by the model, but instead show the total catchment discharge
 505 in non-dimensionalised form ($Q_p/A * I_0$) compared to non-dimensionalised catchment
 506 length (L/\sqrt{A} , where A is the catchment area). Their simulations indicate that the
 507 greatest sensitivity occurs when the size of the storm decline rate L_0 is about half of the
 508 catchment radius. Solyom and Tucker's interpretation of this is that if storm intensity
 509 declines very rapidly over space, i.e. the storm cell is small, then the majority of runoff
 510 production occurs in the vicinity of the storm cell, and is therefore insensitive to the

Parameter	Units
Initial cloud water column density	kg m^{-2}
Initial hydrometeor column density	kg m^{-2}
Time constant for conversion from cloud water to hydrometeors	seconds
Time constant for hydrometeor fallout	seconds
Wind speed	m s^{-1}
Mountain half width	metres

Table 3.1: User defined parameters in Han and Gasparini’s (2015) orographic rainfall model implemented in CHILD.

511 shape of the catchment (assuming the storm falls near the centre of the catchment.)
 512 If the storm intensity decline rate is small relative to the scale of the catchment then
 513 in contrast the catchment is relatively insensitive to catchment shape.

514 **Han and Gasparini (2015)** A more explicit look at the way topography is in-
 515 fluenced by spatial variation in rainfall patterns is found in the recent work of Han
 516 and Gasparini (2015). Building on earlier work by Roe et al. (2004), who found the
 517 geometry of river long profiles to exhibit sensitivity to an orographic rainfall feedback
 518 mechanism, they explore the sensitivity of the whole landscape over a 2D domain.
 519 Modifying the CHILD landscape evolution model (Tucker et al., 2001), they develop
 520 a parameterisation scheme for orographic rainfall based on the model of Smith and
 521 Barstad (2004). In their implementation of Smith and Barstad’s model, the user
 522 controlled variables governing rainfall production are given in Table 3.1. The model
 523 offers considerable control over many meteorological variables determining orographic
 524 rainfall. In a series of simulations under differing rainfall conditions, the authors find
 525 only a slight sensitivity of the concavity of the main trunk channels under spatially
 526 variable rainfall. They conclude that channel concavity is not generally sensitive to to
 527 orographic rainfall patterns, in contrast to the 1D profile model of Roe et al. (2002)
 528 which showed much greater sensitivity. The more revealing topographic metrics were
 529 found in planform study – both the hypsometric integral⁵ and the channel steepness
 530 index⁶ were found to be more strongly linked to the orographic rainfall gradient.

531 In the model domain, rainfall input values for each node are now calculated indi-
 532 vidually, rather than the uniform rainfall field used in standard versions of CHILD.

⁵A measure of the fraction of a catchment above a given elevation, describing the distribution of elevations over the catchment. See Brocklehurst and Whipple (2004); Cohen et al. (2008).

⁶A measure of channel steepness normalised to drainage area; See Wobus et al. (2006).

533 The calculation is based on a number of factors including the elevation of the current
534 grid node, the direction of the prevailing wind, and factors relating to water content
535 in the atmosphere. As the elevation of grid nodes can change as topography evolves
536 throughout the simulation, and rainfall inputs depend on the elevation of each node,
537 there is an explicit feedback mechanism between orographic precipitation and land-
538 scape evolution represented in the model.

539 3.3.3 Summary of current model capabilities

540 The capabilities of landscape evolution models have evolved in tandem with research
541 needs in a piecemeal fashion. As climate change has become an important factor in
542 driving research needs and interests, landscape evolution models have evolved them-
543 selves to cater for a range of climatic parameterisations at a range of time scales.
544 Two-dimensional⁷ numerical models are increasingly used for forecasting and predic-
545 tive purposes, as well as just answering theoretical research driven questions. Despite
546 their potential however, 2D models of landscape evolution are only beginning to be
547 developed to allow detailed spatial variation in many of the climatic variables, such as
548 rainfall. This is seen in the CHILD landscape evolution model work of Han and Gas-
549 parini (2015) as well of the development of CAESAR-Lisflood (Coulthard and Skinner,
550 2016) to simulate spatially variable rainfall input fields.

551 Recent advances in landscape evolution modelling have coupled hydrological model
552 components with the core erosional process modules to produce truly hydrodynamic
553 models that do not assume steady state discharge. For example the CAESAR-Lisflood
554 model (Coulthard et al., 2013), Landlab modelling framework (Tucker et al., 2015), and
555 tRIBS model [CITE] all contain forms of distributed hydrological models to simulate
556 the transfer of water as well as sediment between grid cells or nodes. At longer
557 timescales, the meteorological processes representing rainfall over a landscape have
558 been parameterised, though the detail of these parameterisation schemes can be quite
559 sophisticated (e.g. Han and Gasparini, 2015).

⁷Or 2.5-dimensional, if the elevation variable is considered a limited 3rd dimension, in the sense that elevation can go up or down in landscape evolution models, though the underlying process representation remains restricted two-dimensions in the x, y plane. For example water flow and sediment transport is not fully realised in 3D in any current landscape evolution model.

3.4 Research needs for landscape evolution modelling

The sensitivity of landscape evolutionary processes to the spatial details of climate and precipitation is still relatively unexplored. Though the subject is more advanced in purely hydrological studies (Krajewski et al., 1991; Smith et al. 2005; Segond et al. 2007; Nicotina et al. 2008), there is still a lack of agreement on when sensitivities to rainfall heterogeneities become most pronounced, given the dependence on other aspects of catchment hydrology. The role of runoff generating mechanisms, the influence of vegetation, the influence of groundwater routing pathways, are all affected by the spatial distribution of rainfall in a catchment, yet further investigations into these competing factors are required to reach more consensus among the hydrological community. Though some authors claim there is an insensitivity of hydrological processes to rainfall heterogeneity over a catchment (Krajewski et al. 1991; Smith et al. 2005), a key difference in landscape evolution modelling is that many erosional processes are threshold dependent. When rainfall is uniformly applied across a catchment model, the shear stresses generated by water runoff and river discharge tend to follow a uniform distribution as well. Findings by Coulthard and Skinner (2016) find a pronounced sensitivity to rainfall data resolution in term of sediment flux from a catchment (upto 100% increases), in contrast to the relatively small differences observed in purely hydrological models (e.g. Nicotina et al. 2008). Apart from the Coulthard and Skinner (2016) paper, no other studies have been found that systematically explore landscape evolution model response to rainfall data resolution. Studies have yet to explore the effect of different spatial patterns of rainfall on the geomorphic impacts of single severe storms.

With regards to data sources for rainfall input into landscape evolution models, the most typical source is rainfall gauge data, for single sites or sparse networks across a catchment. Rainfall radar has also been explored as a potential source offering higher spatial resolution than most rain gauge data typically available (Coulthard and Skinner, 2016). Other potential sources include output from numerical weather prediction (NWP) models, or the use of artificial weather generators. These two sources offer the potential to explore a variety of different spatial patterns of rainfall

data, without having to source them directly from historic events. High resolution rainfall radar data only goes back [XX] number of years [CITE] for example. With methods using NWP models to simulate idealised weather conditions, or using weather generators, researchers have the potential to explore sensitivity to the spatial patterns of rainfall for a variety of meteorological conditions, and the potential to systematically explore different distributions of rainfall on landscape evolution.

There is still a great deal of unexplored ground for developing landscape evolution models beyond their current capabilities. Developments are needed to accommodate further types of spatially variable climatic input data and their interpolation (e.g. von Ruetten et al, 2014; Coulthard and Skinner, 2016), to develop new feedback models between topography and rainfall generation (e.g. Han and Gasparini, 2015), new parameterisations of storm cell morphology (e.g. Solyom and Tucker, 2007), and to develop models to take advantage of high-performance computing facilities.

More on the research needs here...Perhaps an itemised summary of outstanding questions yet to be answered.

3.4.1 Technological advances

Landscape evolution modellers have in general been reluctant to take advantage of emerging technology or high performance computing systems to explore bigger problems, or to explore uncertainty in model output through ensemble simulations. By way of contrast, in fields such as meteorology, mineralogy, particle physics, and engineering, the use of high-performance compute facilities is commonplace. In part, this is due to many problems in landscape evolution modelling stemming from a lack of agreement over geomorphic process laws. There is still considerable uncertainty over which geomorphic ‘laws’ are best suited to represent certain natural processes, and the answer can be dependent on the environment being studied. As such, modelling simulations in landscape evolution have often focused on investigating the big-picture, broad-brushed questions about how landscapes evolve as a supplement to empirical field based studies. Geomorphologists, perhaps quite justifiably, have not yet required large-scale computing facilities used in other fields, for their questions can be answered satisfactorily with reduced complexity numerical models. This is especially true as a

621 large body of numerical landscape evolution modelling is used in an exploratory man-
622 ner (Tucker et al, 2010, some other citations tyo go here...and in this paragraph) –
623 geomorphologists have been accused by some (Hancock et al., 2003; Pelletier, 2015)
624 of being satisfied simply if their modelled landscape ”*looks about right...*” The era of
625 purely qualitative geomorphology has long since passed, and new quantitative methods
626 that can be applied such as the use of topographic metrics should employed. Return-
627 ing to the comparison with other fields and their use of high-performance computing
628 (HPC), these fields often suffer uncertainty that geomorphology does in the choice of
629 process law or parameterisation used in a numerical simulation. However, this does
630 not stop them from judicious employment of HPC. In fact, one of the strengths of
631 HPC facilities is the capability to assess many hundreds, if not thousands, of scenarios
632 in ensemble simulations – addressing the uncertainty in process laws and model pa-
633 rameters that have been noted by others in the modelling field (Tucker and Hancock,
634 2010; Pelletier, 2015). A drive towards making use of high performance computing
635 technologies is needed in geomorphology.

Chapter 4

Development of a numerical landscape evolution model for high-performance computing

4.1 Introduction

This chapter describes the development of a suitable numerical landscape evolution model for carrying out simulations of landscape evolution on the short term, on the order of hours to days. As reviewed in previous chapters, the current range of landscape evolution models available to the scientific community lack detailed representation of precipitation, especially regarding its spatial distribution.

Two aims of this thesis have driven the need to develop or extend an existing numerical model to address the questions of landscape sensitivity to the details of precipitation. One is the wish to explore uncertainty and sensitivity in model output through an ensemble of catchment simulations to varying spatial patterns of rainfall. Though ensemble analysis can be done on a standard desktop computer, repeated numerical simulations done serially, one after the other, would be time consuming. If each ensemble simulation could be done in parallel, at the same time, a considerable reduction in compute time could be achieved, given a cluster-type computer with sufficient resources. Since each would run the same program, but with a different set of parameters or input data, no modification to an existing landscape evolution model code would be necessary, so long as it was compatible with a supercomputing

environment. This type of parallel problem is referred to as *trivially* or *embarrassingly* parallel [CITE]– it requires no special endeavour other than ensuring the program is compatible with the intended computing platform to be used.

The second aim is a requirement to investigate the hydrogeomorphic response of the landscape at short timescales – during the passage of a single rainstorm. As reviewed in Chapter 2, and in Tucker and Hancock (2010), Valters (2016), most landscape evolution models assume a hydrological steady state. A common assumption, for example, is that water discharge at any given point can be approximated as a function of the upstream drainage area at that point. Given that the aim of the research is to look at spatial patterns of rainfall relative to a catchment, the assumption that all areas upstream of any point are wetted by rainfall can no longer hold true. Similarly, runoff generation and river discharge can not be assumed to be uniform over the catchment area, given a spatially heterogenous rainfall input. Therefore, the numerical model should capture the dynamics of runoff generation and water flow within the catchment, even if only to a simplified degree.

The research aims laid out in the introductory chapter include investigation of landscape evolution at a range of timescales, from single storms, to topographic evolution over millions of years potentially. Given the large discrepancy in timescales, a variety of modelling approaches will be needed. For short timescales, a hydrodynamic model would be ideal, as the water flux and sediment transport within a catchment can be explored in greater detail than a steady-state-hydrology landscape evolution model.

Are there currently available models that meet these criteria? The CAESAR-Lisflood model meets the requirement of being appropriate for simulation of short timescales (hours to days), and also has a non-steady-state hydrological component, based on the LISFLOOD hydrological model (Bates et al., 2010). However, it lacks compatibility with most cluster-computer systems, being a Windows-based program. The program code for CAESAR-Lisflood is open-source, which would normally lend itself to recompilation for a linux-based cluster computer. However, the source code for CAESAR-Lisflood is C# which is incompatible with most supercomputing services for a number of reasons: Firstly, compilers on supercomputers typically support only C/C++ or Fortran codes. Secondly, C# codes are usually reliant on Windows

operating system libraries¹. The typical supercomputing environment is Linux-based, and such libraries are not available. There is an open source implementation of C# for Linux environments available², however early attempts in the project to compile CAESAR-Lisflood using the Linux version of these software libraries were unsuccessful. In its present form, CAESAR-Lisflood is unsuitable for running on most supercomputing services, though it would serve as a useful base for further development.

4.1.1 Software design requirements

To summarise the previous section, the criteria for the landscape evolution model required for this research are:

- Allow the spatial variation of precipitation and use of spatially variable rainfall data.
- Be suitable for simulations at short timescales, to investigate landscape response during a single severe rainfall event.
- Adaptability to run ensemble simulations for sensitivity analysis, for example multiple simulations on a high-performance computing (HPC) facility, or similar cluster computer.
- Compatibility with a typical Linux-based supercomputer environment.
- Simulate a range of sediment transport and bedrock incision laws.

Since none of the existing landscape evolution models fully met the three key criteria above, a suitable model was developed instead. In particular, it was notable the none of the current models discussed in the previous chapters were particularly well suited to running on cluster computing facilities. The CHILD and CAESAR-Lisflood models came close to meeting these criteria, so it was decided to develop a new model based on one of these existing code bases. As discussed in the previous chapter, CAESAR-Lisflood was particularly suitable to simulating short-term landscape evolution, so this model was used as a starting point. The new model developed

¹The .NET framework

²The *Mono* project. The project is not yet fully compatible with all C# source code, however. In any case, further problems would have arisen trying to cross-compile suitable static binaries for the relevant cluster compute nodes, given that Mono is not generally available on HPC services.

715 and described in this chapter is an evolutionary progression from CAESAR-Lisflood
716 – many of the algorithms are reused in the new model’s development and the flow
717 structure within the program is similar in many respects.

718 4.2 Program description

719 It was decided to write the program in the C++ programming language³, given the
720 wide range support of compilers on supercomputing platforms, and the relative ease
721 of translating some of the existing algorithms from C# to C++⁴.

722 4.3 A module for rainfall-runoff generation and in- 723 terpolation

724 *This section describes the rainfall interpolation and runoff generation modules written*
725 *as part of the extensions to the CAESAR Lisflood model. It generates rainfall fields at*
726 *the same resolution as the topographic data supplied (DEM), either from rainfall radar*
727 *data supplied to it, or from an artificial storm generator, given some parameters for*
728 *rainfall intensity, storm morphology etc.*

³You might be wondering why I didn’t use C, given its widely supported status in supercomputing applications. I wanted to make use of the LSDTopoTools package, written in C++, which has tools for manipulating raster data and performing topographic analysis. The resulting software described in this chapter is tightly integrated with LSDTopoTools. C++ is increasingly well supported on supercomputing platforms.

⁴The syntax differences between the two languages are fairly minimal, compared to other widely-used language in numerical supercomputing, Fortran. Also, at the time, the author didn’t know enough Fortran...

Chapter 5

The hydrogeomorphic response of small catchments to rainfall radar resolution and patterns

5.1 Introduction

Landscape evolution at the catchment scale is punctuated by intense erosive episodes driven by flood events (Wolman and Miller, 1960; Newson, 1980; Costa and O'Connor, 1995) interspersed with periods of relative calm and little geomorphic change, an idea that harks back to the early ideas of geological ‘catastrophism’ (Cuvier, ?). It is these erosive events, driven by intense rainfall in temperate climates, separated by long periods of stasis, that cumulatively sculpt the landscape over geological time. The importance of these rare but formative events has been revisited by recent work such as Huang and Niemann (2006), looking at the long term implications of different geomorphically effective event discharges on fluvial incision; Gupta et al., (2007); Lamb and Fonstad (2010); and Baynes et al., (2015) where the amount of bedrock erosion during a single large flood event was quantified. Still, our understanding of catchment scale landscape evolution is far from complete - the role of individual events is highly variable. Anton (2014) report that rapid gorge formation can be driven primarily by small to moderate sized floods, rather than floods of extreme magnitude. Further, there was no observed relationship between flood magnitude and erosion rate. Turowski et al. (2011) report that streams within catchments can exhibit different

behaviour in response to the same flood event – some streams may erode during high flows, whereas others may deposit during high flows. During small–medium flows their respective behaviour is reversed. Wong et al. (2015) establish through numerical modelling that geomorphic changes in channel geometry during severe flood events are substantial enough to change hydrological response of a river catchment. Catchment-scale erosional dynamics are complex, and except in the simplest cases depend on other forcings other than the magnitude alone of single flood events. The understanding of hydrogeomorphic processes during single storm events is not only important for the long-term evolution of landscapes, but also for prediction of how catchments will respond to changing hydro-meteorological conditions that may accompany climate change (Kendon et al., 2014).

The focus in this paper is to quantify the sensitivity of catchment-scale erosional processes to the spatial distribution of rainfall during flood events. The assumption of uniform rainfall over a river catchment is argued to hold true for small catchments (Solyom and Tucker 2004; Tucker 2010), but even over small areas, mesoscale rainfall features, such as localized convective storm cells, can result in spatially and temporally uneven input of precipitation into the catchment. In the case of intense convective precipitation, individual storm cells can be as small as 10km^2 in areal extent (Weisman and Klemp, 1986; Von Hardenberg et al., 2003). Over larger catchments, or those with steep topographic gradients, precipitation is almost certain to vary spatially, due to orographic enhancement of rainfall (Roe, 2005). As such, rainfall-runoff generation, local river flow, and erosion rates may vary considerably within individual drainage basins.

Patterns of rainfall distribution across a catchment can affect hydrograph response, including the peak discharge and local water levels (Nicotina et al., 2008). As many geomorphic processes are threshold dependent (Schumm, 1979), such as fluvial incision into bedrock (Sklar and Dietrich, 2001; Snyder et al., 2003), there is potential for the spatial distribution of rainfall to control local erosion rates within a catchment. Non-linearity in geomorphic process laws (e.g. Coulthard et al., 1998; Phillips, 2003; Coulthard and Van de Wiel, 2007) should dictate that catchments are also geomorphically sensitive to the spatial distribution of rainfall.

Numerical models of landscape evolution usually omit a realistic distribution of

rainfall input in favour of uniform, homogenised precipitation across the landscape. When precipitation is ‘lumped’, either spatially or temporally in a catchment, local minima and maxima of precipitation are lost, and with discharge being a function of rainfall rate, this uncertainty propagates through to local discharges and erosion rates. The uncertainty in erosion rates is potentially exacerbated by the non-linearity and threshold dependence of erosive processes. The variability of precipitation is considered in many cases to be as important as total precipitation amount in determining erosional effectiveness (Tucker and Bras, 2000; Tucker, 2010). What is currently lacking in landscape evolution studies is a fuller understanding of how landscapes erode during individual storms, and in particular how erosional processes are sensitive to the details of precipitation across a catchment.

In numerical models of landscape evolution, resolving the precise temporal and spatial details of rain storms and the hydrological response is often computationally prohibitive, especially over long timescales, and as such modellers have taken to using simpler parametrisations of storm characteristics, such as using simple stochastic models to generate rainfall inputs and rainfall timeseries (Eagleson, 1978; Tucker et al., 2001). In studies of long term landscape evolution, the sensitivity of landscapes to the spatial distribution of rainfall has been investigated to some extent – particularly the imprint of orographic precipitation on landscapes (e.g. Roe 2002; Anders 2008; Han and Gasparini, 2015). Over the medium term, a study that systematically varied the resolution of rainfall input data in a decadal-scale catchment simulation (Coulthard and Skinner, 2016), local as well as catchment-wide sediment yields were predicted to increase by orders of magnitude as rainfall resolution increased. The study looked at the effects of rainfall data resolution alone, and not at the spatial distribution of rainfall itself, which was randomised for the simulations.

In contrast to previous studies, this paper looks at the effects of individual events and the distribution of rainfall during those events on catchment hydrogeomorphic response. The study investigates the sensitivity of catchment-scale erosion to the spatial details of severe rain storms – the agents of long term landscape evolution. Landscape response is investigated using a numerical landscape evolution model that incorporates a dynamic (non steady-state) water-routing component and a range of fluvial incision and sediment transport laws. A series of model experiments is presented

to test how sensitive real landscapes are to the catchment-scale details of precipitation during intense rainfall events. The simulations are each based on selected severe storms in Great Britain occurring in the past decade, which left significant flooding, damage, and geomorphic change in their wake.

The following questions are explored through the use of numerical modelling simulations;

- Are fluvial erosion and sediment transport processes sensitive to the details of precipitation at the catchment scale during single storm events?
- Does the choice of conceptual model representing the catchment influence sensitivity to rainfall patterns?
- What is the link between the spatial pattern of rainfall and spatial pattern of erosion and deposition in each storm–flood event?
- What are the implications of this for longer term landscape evolution?

5.2 Theory

In our conceptual model of landscape evolution, fluvial processes – erosion and deposition of sediment and bedrock by flowing water – are assumed to be the dominant geomorphic processes at work. The numerical model used to simulate these processes uses established hydrological and geomorphic process laws, which are briefly reviewed here in the following sections.

5.2.1 Rainfall-runoff and flow routing

From rainfall input, runoff is calculated using an adaptation of the Beven and Kirby (1979) TOPMODEL. Total surface and subsurface discharge is given by:

$$Q_{tot} = \frac{m}{T} \log \left(\frac{(r - j_t) + j_t \exp \left(\frac{rT}{m} \right)}{r} \right) \quad (5.1)$$

where T is the time step in seconds, r is the rainfall rate, j_t is a function that describes soil moisture store, and m is a parameter that controls the rise and fall of

this soil moisture store in j_t . These adapted TOPMODEL equations are given fully in Coulthard (2002), equations (1) and (2).

The amount of water partitioned between surface and subsurface flow is determined by a simple infiltration threshold, given by:

$$I_t = KS(Dx)^2 \quad (5.2)$$

where K is hydraulic conductivity, S is the slope, and Dx is the width of the grid cell or horizontal grid spacing. The infiltration threshold is subtracted from Q_{tot} to give the portion of water routed over the surface.

Surface water and channel flow is an important driver in catchment scale erosional processes. The amount and velocity of water flow is a variable in both the sediment transport and bedrock erosion laws. The water flow equations are based on a simplified form of the shallow water flow equations, a simplification first derived by Bates (2010) and incorporated into the landscape evolution model by Coulthard et al (2013). The flow between cells is calculated by:

$$Q = \frac{q - gh_{flow}\Delta T \frac{\Delta(h+z)}{\Delta x}}{1 + gh_{flow}\Delta t n^2 |q|/h_{flow}^{10/3}} \Delta x \quad (5.3)$$

where q is the water flux between cells from the previous iteration, g is acceleration due to gravity, h_{flow} is the maximum depth of flow between cells (m), t is time (s), h is depth of water, z is elevation, x is the grid well width, and n is Manning's roughness coefficient. The full implementation details are given in Coulthard (2013), and the derivation from the shallow water equations is given in Bates (2010).

5.2.2 Sediment transport

Transport of loose sediment is governed by the ? sediment transport model. The Wilcock and Crowe model represents transport of mixed sand/gravel fractions based on the surface sediment composition. The rate of sediment transport, q_i , is given as:

$$q_i = \frac{F_i U_*^3 W_i^*}{(s - 1)g} \quad (5.4)$$

where F_i is the fractional volume of sediment, for a given sediment fraction, i , U^* is the shear velocity, s is the ratio of sediment to water density. W_i^* is a function

relating fractional transport rate to total transport rate (see ? for a full derivation of this equation). The usage of this sediment transport model is extrapolated here to account for finer particles such as silts (?), as well as the sand-gravel mixture it was originally designed for.

5.2.3 Bedrock incision

A simple model of bedrock incision based on the excess shear stress model (Citations) is implemented in the numerical model. The rate of bedrock incision is determined by the amount of shear stress acting on the bedrock, above a threshold level of stress required to initiate substrate removal (e.g. Snyder (2003)). When bedrock material is removed, it is distributed amongst the sediment fractions according to the fractional proportions set by the user. The rate of bedrock erosion according to the excess shear stress model is given by:

$$\varepsilon = k_e(\tau_b - \tau_c)^{P_b} \quad (5.5)$$

where k_e is the bedrock erodibility coefficient, τ_b is the basal shear stress on the channel bed, τ_c , is the critical shear stress threshold, P_b is the shear stress exponent. (Cite Howard or Whipple?)

5.3 Experimental Design

Three upland catchments in the UK were selected to represent a range of catchment sizes and shapes. The catchments were also chosen on the basis that they had experienced a severe rain storm which could be used as a basis for the experiments, such that it could be considered ‘extreme’ in the typical return period of flooding events for each particular catchment. Peak discharges for each of the following flood events exceed the 99th percentile for their respective catchments. The catchments and respective severe rain events chosen were located in: Ryedale, North Yorkshire, 2005; Plynlimon, Mid-Wales, 2012; and Boscastle, Cornwall, 2004. An overview map of their locations is given in Figure ???. A table (Table 5.1) summarises the key features of each catchment and associated storm.

Catchment Name	Eden	Ryedale	Valency
Catchment Area	2286km ²	270km ²	18km ²
Catchment Type	Upland-Lowland	Upland, Moor/Peaty	Upland, Pasture
Storm Date	2005-01-07	2005-06-19	2004-08-16
Peak Rainfall			
Peak Discharge			
Meteorological Setting		Split-front, convective system	Quasi-stationary convective system
Return Period	(tbc)	(tbc)	1/200yr

Table 5.1: Table showing matrix of experiments carried out for each catchment

5.3.1 Meteorological setting

Boscastle, Cornwall storm 2004

The Boscastle storm took place on the 16th August 2004 leading to flooding within the River Valency catchment and the village of Boscastle. The extreme rainfall accumulations of up to 200 mm in the upper Valency catchment resulted from prolonged rainfall between the hours of 1200 – 1600 UTC. Rainfall rates were thought to have reached almost 400 mm hr⁻¹ (?), after correcting for under-reporting from rain gauges in the vicinity of the catchment. (Burt, 2006, same issue).

The meteorological conditions that enabled such prolonged heavy rainfall were a combination of large-scale synoptic conditions moving in from the Atlantic, with moist lower atmospheric layers readily forming convective cloud. Repeated initiation of convection along the north Cornish coast lead to what appeared to be relative stationary convective cells over the Valency catchment. Later authors refer to this type of convective storm as a 'Boscastle-type' or quasi-stationary convective storm (cite the reading person).

Ryedale, North York Moors storm 2005

The Ryedale storm occurred on 19 June 2005. Intense rainfall throughout the afternoon lead to total accumulated rainfall amounts of up to 89mm in the Ryedale valley, between the hours of 1400 – 1800 UTC. Peak instantaneous rainfall rates were estimated to have reached 32.5mm hr⁻¹ during the storm (Golding et al., 2005). The antecedent conditions had been dry for a prolonged spell, leading to cracking of the surface peat in the higher elevations of the catchment.

The meteorological conditions leading to such heavy rainfall was a combination of a cold, upper-level air mass advecting over a warm moist boundary layer, leading to unstable conditions that enabled a convective thunderstorm to develop in the late

913 afternoon. The instability was enhanced by a split-frontal system. [More? Too much
 914 met here?]. The conditions let to a particularly high amount of precipitable water
 915 present in the atmosphere which was subsequently washed out into the landscape
 916 during intense rainfall.

917 **Eden Valley, Carlisle, 2005**

918 **5.3.2 Numerical model set-up**

919 The landscape evolution model developed in Chapter 3 (Working name: HAIL-CAESAR)
 920 is used to carry out numerical simulations based on the three catchments and corre-
 921 sponding storm events. HAIL-CAESAR is a cellular automaton landscape evolution
 922 model based on the CAESAR-Lisflood model (Coulthard et al., 2013). The HAIL-
 923 CAESAR model simulates bedrock erosion according to a simple bedrock incision law
 924 based on critical shear stress. The equation describing the bedrock erosion model is
 925 described in section 5.2.3. The bedrock incision model is used in two of the three
 926 sets of simulations. The model also interpolates and downscales rainfall input data
 927 to higher resolutions and this feature is used in the group of simulations with the 5m
 928 interpolated radar rainfall data.

929 **Erosion model**

930 In order to address the uncertainty in choosing which erosion model applies for each
 931 catchment (Section ??), three variations of model set-up are used, with each one
 932 representing a different conceptual model of fluvial incision and sediment transport.
 933 These include: i) a purely sediment transport-limited model, ii) a detachment-limited
 934 bedrock incision model, and iii) a hybrid model incorporating sediment transport and
 935 bedrock incision. The equations describing the transport-limited and detachment-
 936 limited models are discussed in Section ??.

937 **Hybrid model** The hybrid model assumes a limited-depth sediment layer, overlying
 938 a bedrock layer. Figure ?? shows a typical cross section through a typical valley in the
 939 hybrid model set-up. In the initial model state (before the spin-up period), a channel
 940 is 'burnt-in' to the sediment-layer. Whenever bedrock becomes exposed during the
 941 hybrid simulation, the simple detachment-limited erosion law is applied. Material

removed from the bedrock layer is then apportioned between the various sediment fractions. At all other times, the sediment transport law applies to the sediment layer.

Rainfall spatial resolution

In order to assess the sensitivity of each erosional model to the spatial details of precipitation, three different spatial resolutions of rainfall input are used in each simulation. All three are based on the same original rainfall source data - the UK NIMROD radar data product. Only the spatial distribution and resolution of rainfall is assessed in this study – other studies have previously investigated the effects of the temporal resolution of rainfall data on discharge and erosion rates (e.g Nicotina et al., 2008; Coulthard and Skinner, 2015; Coulthard, 2013b). Three levels of rainfall detail are used:

- Uniform or 'lumped' precipitation – radar-derived rainfall rates across the catchment are spatially-averaged to produce a basin-wide average rainfall rate.
- Gridded rainfall input. The rainfall is input from a overlying gridded mesh of raincells, at the same resolution as the radar product (1km).
- Interpolated rainfall input. The radar data is interpolated to the same resolution as the topography grid (i.e. 50m). (*Interpolation method TBC - but see study by Tait et al (2006) and perhaps implement their method*)

The reason for running a simulation with an interpolated rainfall data set is to reduce the effect of harsh gradients between adjacent cells, as is sometimes apparent when using the rainfall data at its native resolution of 1km. Figure ?? gives an indicative illustration of this. A matrix of experiments is shown in Table ??.

Model spin-up

The HAIL-CAESAR model (Valters & Coulthard, 2016/7) initialises the model domain with a uniform distribution of sediment grain sizes across the catchment. This is physically unrealistic, so the model domain is 'spun-up' for a simulated time of 1000 days using typical rainfall data for each catchment. This ensures a heterogeneous distribution of sediment throughout the catchment prior to the detailed storm simulations.

970 5.4 Results

971 *(Probably separate sections for each)*

972 *I intend to discuss the spatial differences in erosion, as well as any differences in*
 973 *basin-wide average erosion rates, and explain these differences by referring back to the*
 974 *Theory section.*

975 5.4.1 Effect of rainfall detail on discharge and erosion

976 The discussion will be aided by figures showing (for each of the three rainfall input
 977 variations for each catchment):

- 978 • Total accumulated rainfall maps for each storm (Figure ??).
- 979 • Profiles of erosion along main channels in each catchment (Figure ??).
- 980 • Plots of the hydrographs and sediment yields for each storm (Figure ??).
- 981 • 2D Planform maps of distribution of erosion (and deposition if applicable).

982 *Indicative figures. Note these will change in the final version as I have decided to*
 983 *re-run some simulations after tweaking the model set-up.*

984 5.4.2 Implications for longer-term landscape evolution

985 *Some discussion on how these results scale-up to longer term landscape evolution. I.e.*
 986 *How many storms of similar magnitude would be needed to reach longer term erosion*
 987 *rates? Does this correspond to known longer term erosion rates of similar upland*
 988 *landscapes?*

989 5.5 Conclusions

990 Text.

991 5.6 Fixed parameters

992 *A table showing the other parameters used in the simulations (All of which remain*
 993 *fixed for each simulation)*

994 The following table lists the parameters that were held constant for all simulations.

995 Chapter 6

996 Sensitivity of landscape evolution
997 to the details of precipitation
998 patterns using NWP model data

999 Chapter 7

1000 A spatially-limited storm 1001 generation model for long-term 1002 landscape evolution modelling

1003 7.1 Intro

1004 In landscapes where fluvial processes are the dominant mechanism of sediment erosion
1005 and transport, several models of fluvial incision have been proposed that parameterise
1006 hydro-meteorological conditions – the transfer of water from the lower atmosphere to
1007 the land surface. Such models include the representation of rainfall input as discrete
1008 storm events, e.g. the Poisson pulse model of rainfall input (Tucker and Bras, 2000),
1009 models that incorporate the role of limited storm duration relative to runoff-time across
1010 the catchment (Solyom and Tucker, 2004), and the nature of orographic precipitation
1011 gradients the rainfall-runoff-erosion process (e.g. Anders and Roe, 2006; Han and
1012 Gasparini 2015).

1013 7.2 Hypothesis (mathematical model)

1014 **In short:** Rate of fluvial incision is dependent storm size, depth, and position of storm
1015 cell relative to the catchment. This applies to large catchments or small storm cells,
1016 where the ratio of storm coverage to total catchment size is less than one.

1017 **7.2.1 Catchment hydrology with limited storm cell sizes**

1018 For large catchments, or for small storm cells, the area of rainfall input, here termed
 1019 the catchment wetted area, will be less than the total catchment drainage area. (See
 1020 figure 1). This is denoted by the ratio: A_w/A , where A_w is the wetted area.

1021 Given a catchment with a smaller contributing storm cell, there can be variability
 1022 in the positioning of the storm relative to the catchment outlet point. This spatial
 1023 variation in storm cell positioning will influence the storm hydrograph for each storm
 1024 event. The total storm hydrograph time, T_h can be given by:

$$T_h = T_r + T_t \quad (7.1)$$

1025 Where T_r is the storm duration time, and T_t is the total runoff travel time from
 1026 the most distant wetted point in the catchment to the outlet. The total runoff travel
 1027 time is given by:

$$T_t = L_w/U_f \quad (7.2)$$

1028 where L_w is the longest wetted flow routing path in the catchment, U_f is the flow
 1029 routing velocity, assumed to be approximately spatially constant.

1030 **7.2.2 Deriving an approximation for discharge in storm-size** 1031 **limited catchments**

1032 Solyom and Tucker (2004) note that similar derivations for peak discharge approxi-
 1033 mation are needed for environments where storm size is limited relative to catchment
 1034 area, so I use their equations as a starting point.

1035 Starting with the simple case of Hortonian (infiltration excess) overland flow, the
 1036 discharge at a point in the river channel can be given by:

$$Q = (R - I)A_w \quad (7.3)$$

1037 where R is rainfall rate, I is infiltration rate, and A_w is the upstream wetted drainage
 1038 area. The total volume of water in a given storm is stated as:

$$V = (R - I)A_w T_r \quad (7.4)$$

1039 where T_r is the storm duration time. As per Solyom and Tucker (2004) the total
1040 flood hydrograph volume can be written as:

$$V = \int_0^{T_h} Q(t)dt \quad (7.5)$$

1041 The hydrograph can be non-dimensionalised by scaling with peak flow, Q_p , and
1042 time can be normalised by the total flood hydrograph duration, T_h (after Willgoose,
1043 1989):

$$Q'(t') = Q(t)/Q_p \quad (7.6)$$

1044 where

$$t' = t/T_h \quad (7.7)$$

1045 Then the non-dimensionalised flood-hydrograph volume can be written as such:

$$V = Q_p T_h \int_0^1 Q'(t')dt' \quad (7.8)$$

1046 Assuming constant rainfall, R , and infiltration rates, I , peak discharge can be
1047 written as a function of runoff rate, storm duration, storm wetted area, and wetted
1048 flow route length:

$$Q_p = \frac{V}{T_h \int_0^1 Q'(t')dt'} = \frac{1}{T_h} \frac{(R - I)A_w T_r}{F_{hs}} = \frac{(R - I)A_w}{F_{hs}} \frac{T_r}{T_r + L_w/U_f} \quad (7.9)$$

1049 where F_{hs} is a hydrograph ‘shape-factor’ equal to the integral in equation (8). F_{hs}
1050 goes to one for steady state run off conditions (i.e. a flat or rectangular hydrograph)

1051 According to equation 7.9, peak discharge will vary according to the catchment
1052 wetted area to wetted flow runoff length ratio, A_w/L_w , and the ratio of storm duration,
1053 T_r , to the total hydrograph duration. Also note that A_w and L_w are not independent
1054 of each other, and increasing A_w can increase L_w . (This is not true in the Solyom and
1055 Tucker (2004) application of this equation as rainfall is assumed to spatially uniform
1056 over the total catchment area.)

1057 7.2.3 Assumptions

- 1058 • Storm cell is stationary (does not track across the basin for the duration of the
1059 storm)

- 1060 • Storm cell is a single cell. (i.e. not multiple cells scattered across the basin)
- 1061 • Flow routing velocity is uniform. (Not entirely true assumption, routing time is
- 1062 slower on hillslopes, but the effect can be ignored if drainage density is relatively
- 1063 uniform (Solyom and Tucker (2004)).
- 1064 • Rainfall rate and infiltration rate constant for duration of storm.
- 1065 • Simple infiltration-excess (Hortonian) hydrological state.

1066 It may be possible to modify the model to account for one or more of these assumptions.

1067 **7.2.4 Fluvial erosion**

1068 (Deriving a similar expression for fluvial incision in a detachment-limited environment
 1069 here, incorporating the above non-steady discharge approximations for limited storm-
 1070 area cases)

1071 Chapter 8

1072 Co-evolution of rainfall patterns 1073 and landscapes

1074 *It would be nice to look at this if there was time (there probably won't be though!) I*
1075 *had a rough framework sketched out and partially implemented for how this would be*
1076 *done using CHILD and WRF together. Maybe one for the future instead.*

1077 Chapter 9

1078 Synthesis: Painting rainy 1079 landscapes with numbers

1080 And here is the final synthesis chapter bringing it all together...

1081 Bibliography

1082 Noah P. Snyder. Importance of a stochastic distribution of floods and erosion
1083 thresholds in the bedrock river incision problem. *Journal of Geophysical Re-*
1084 *search*, 108(B2):2117, 2003. ISSN 0148-0227. doi: 10.1029/2001JB001655. URL
1085 <http://doi.wiley.com/10.1029/2001JB001655>.

1086 Appendix A

1087 Code availability

1088 **Appendix B**

1089 **Key code and algorithms for the**
1090 **cellular automaton LEM**

1091 **Appendix C**

1092 **Key components and algorithms for**
1093 **the additions to the CHILD model**

1094 Appendix D

1095 Modifications made to the Weather 1096 Research and Forecasting model 1097 (WRF)

1098 **Appendix E**

1099 **Cluster computing simulations:**
1100 **set-up, compilation, and scaling**

1101 **Appendix F**

1102 **Paper off-prints may also be**
1103 **attached with a traditional-format**
1104 **thesis**

1105