NbS-TISE: Nature-based Solutions Tool for assessing the full Impact of Soil Erosion

NC-International Integration project for Theme 2: Assessing Net Zero Plus trade-offs.

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NATIONAL CAPABILITY FOR GLOBAL CHALLENGES
International science for net zero plus

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Executive Summary

Soil erosion is one of the main drivers of land degradation, reducing the resilience of terrestrial ecosystems to future climate change and threatening food security worldwide. Sub-Saharan Africa (SSA) is one of the most adversely affected regions, with 60-80% of people working as smallholder farmers reliant on local agriculture for their livelihoods as well as their direct food supply. Nature-based Solutions (NbS) are often cited as important strategies to mitigate the impacts of global environmental change on land degradation and its impacts. However, their efficacy relies on building an accurate evidence base of likely co-benefits and trade-offs to environment and society (e.g. economic costs, food security and biodiversity conservation).

For this pilot project, we developed a new tool called *NbS-TISE* (Nature-based Solutions Tool for assessing the full Impact of Soil Erosion). This new tool allows us to efficiently integrate processes of weather and climate, land use change and surface runoff to make robust estimates of soil erosion rates over space and time. The tool was developed through integration of work packages 1B and 2C in the NC-International programme under Theme 2 (assessing Net Zero Plus trade-offs), combining expertise on the *JULES* land surface model with experience applying the *RUSLE* soil erosion model in SSA.

Soil erosion routines based on the *RUSLE* model were coded as a post-processing workflow based on outputs from the *JULES* model. Because *JULES* also has existing code structures that can predict the spatial occurrence of surface runoff, this makes it possible to simulate a wider set of erosional processes and sediment transport over the land surface. The model and workflow were then tested over two small catchment areas in South Africa’s Western and Eastern Cape regions where there is an extensive knowledge base of NbS from staff at the African Climate & Development Initiative (ACDI; University of Cape Town). In addition, the *InVEST* Sediment Delivery Ratio (SDR) model, which uses *RUSLE*, was used to simulate erosion in these same catchment areas to provide both a comparison against *JULES* simulation results and additional outputs including the role of land cover and management in inhibiting further erosion and sediment delivery to rivers.

Patterns of soil erosion and sediment yield from existing third-party datasets indicate that soil erosion is generally most severe towards the Eastern Cape and steeper sloping areas in the Western Cape. Our modelling appears to reflect this, albeit, with some subtly different spatial patterns and higher predicted values compared to the South African national *RUSLE* map from 2008, which most likely stem from our simplified estimates of rainfall erosivity, land cover and management, and the lack of adequate consideration of agricultural and conservation practices in the region, due to a lack of spatially explicit data on these practices. SDR model results highlight that a large proportion of potential soil erosion (assuming a landscape completely bare of vegetation cover) is mitigated by existing land cover and management factors, which will be useful for informing future NbS strategies in the region. Results from the

JULES model, conversely, draw attention to additional factors, such as the occurrence of runoff-based erosion in topographic valleys where rainfall is non-negligible.

Through further development and application, the new *NbS-TISE* tool will be able to provide valuable decision-support information to directly inform on two aspects of Net-Zero-Plus: maintaining a healthy and productive environment and adapting and building resilience to a changing climate. We suggest several key areas to work with other work packages within NC-International and international partners to apply this tool elsewhere, including:

- Across a wider set of catchments in Sub-Saharan Africa, linking with ongoing work in East Africa (WP2C) as well as West Africa (WP3C).
- Within Malaysia and Indonesia (linking with WP2B) to assess the vulnerability of oil palm plantations to soil erosion and flash flooding, particularly the scale of the increased risk compared to naturally forested conditions.

Furthermore, we would look to develop soil erosion capabilities that are more sophisticated than *RUSLE* alone and include runoff-based processes. This would allow us to address erosion following short, high magnitude weather events (e.g. floods and wildfires) as well as consider additional important processes including river channel changes and gullying. Potential future directions include:

- Integrating *MUSLE* (a version of *RUSLE* that uses daily surface runoff instead of long-term rainfall erosivity estimates).
- Integrating a wider ensemble of daily time-stepped erosion models to allow for more robust scenario modelling in future.
- Experimenting with channel erosion modelling routines that can capture processes like riverbank erosion and gullying.

1. Overview of 2024 pilot project

1.1 Context & rationale for the pilot project

In Sub-Saharan Africa (SSA), soil erosion is the single most important threat to the livelihoods of most people. In SSA, 60-80% of people are smallholder farmers, relying on agriculture for their livelihoods and direct food supply (FAO & ITPS, 2015). Therefore, when agricultural outputs decline, the income and food supply of the region's 700 million smallholder farmers is also degraded.

Globally, Nature-Based Solutions (NbSs), which use nature to address climate change impacts (e.g. hydro-climate risks), biodiversity loss and human health, have been widely implemented to mitigate anthropogenic impacts on sediment and nutrient losses. However, their effectiveness depends not only on their success in delivering benefits to human populations: it depends also on minimisation of associated costs, e.g. local effects on surface hydrology, soil erosion, nutrient dynamics, and soil loss.

Over the past decade, the African Climate and Development Initiative (ACDI) has been engaging with stakeholders across Africa specifically in order to identify scenarios for NbS in Africa (Holden, et al., 2022), most recently through the project *Towards Equitable & Sustainable Nature-based Solutions* (TES-NbS) at the University of Cape Town (see https://www.tobymarthews.com/tes-nbs.html). The ACDI has become a world-leader in this area, introducing quantitative assessments of the impact of NbS e.g. for climate change mitigation potential (carbon sequestration potential) or effects on global temperatures (Holden, et al., 2024).

Because some NbSs promote increasing tree cover (e.g. reforestation), but others involve reducing it (e.g. removal of invasive species) (Holden, et al., 2022; Holden, et al., 2024), the impact of an NbS on surface hydrology and soil erosion is not straight-forward either to assess or predict. Potential erosion or degradation of soil as a result of NbS would significantly reduce the overall benefits of any tree-planting or ecological-restoration project in SSA (FAO & ITPS, 2015).

The NC-International project initiated at the UK Centre for Ecology & Hydrology (UKCEH) in 2023 has already been collecting data relevant to these issues and thereby presents a unique opportunity. Current work in East Africa has produced novel data and techniques for estimating soil erosion (Feeney, et al., 2023) and also assessments of the impact of some afforestation NbSs (Feeney, et al., 2023), all following the broad approach of the *InVEST* framework (Hooftman, et al., 2023). Meanwhile, work in the SE Asian arm of the project has been applying the *JULES* land surface simulation model to predict other aspects of environmental impact such as the socio-economic impacts of oil palm cultivation.

1.2 Aim & objectives

In this project, we aim to assemble a new tool called ***NbS-TISE*** for assessing the full impact of NbS projects on soil and water resources (**Error! Reference source not found.**). Working from data beginning to become available through the NC-International project, *NbS-TISE* will reveal the mechanistic linkages between the drivers of soil degradation (e.g. precipitation, land use change) and their impacts on the success of NbS projects. This approach integrates recently acquired knowledge of regional soil erosion rates (Feeney, et al., 2023) with the mechanistic approach of a land surface model JULES (Land Surface Science Group, UKCEH, https://jules.jchmr.org).

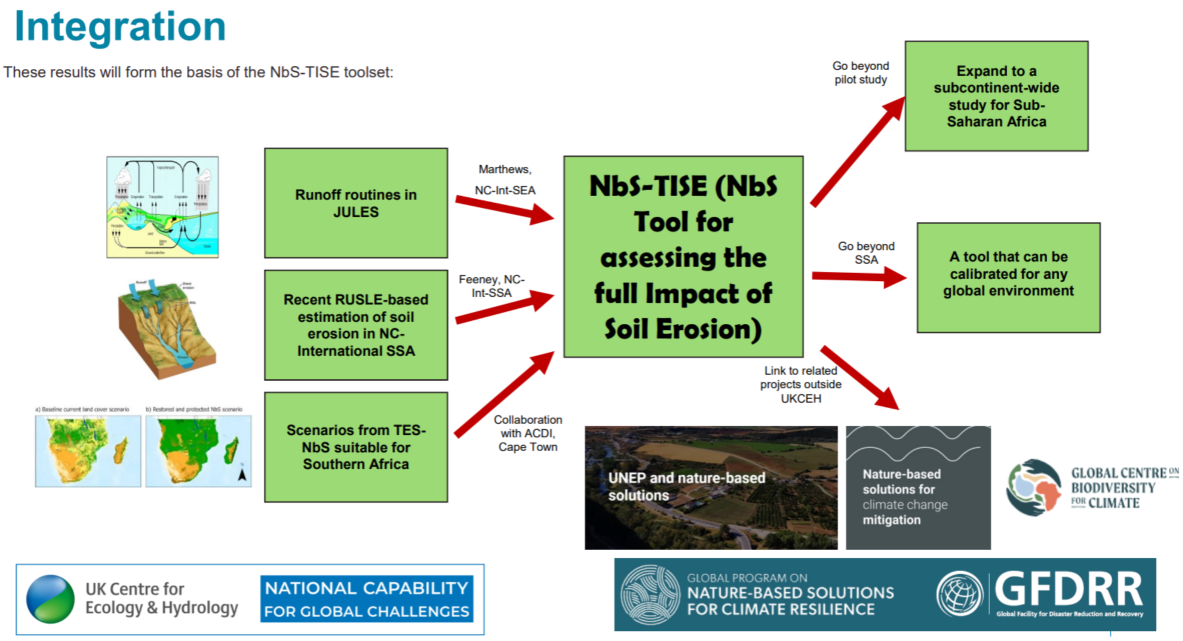


Figure 1: Project overview, integrating NC-International WP1B, WP2C and ACDI (University of Cape Town) staff from the TES-NbS project.

In order to assemble the ***NbS-TISE*** assessment tool, we need to be able to quickly integrate the effects of weather and climate (e.g. precipitation), land use change (e.g. NbS scenario) and surface hydrology and make robust estimates of changes in impact variables (e.g. soil erosion rates). This will require a mechanistic approach (i.e. land surface model simulations using JULES) combined with other methods, notably the application of the Revised Universal Soil Loss Equation (RUSLE, Table 1).

The RUSLE (Renard, Foster, Weesies, McKool, & Yoder, 1997) is calculated as follows:

$$RUSLE = K \times C \times P \times LS \times R \qquad \text{(eqn1)}$$

where *RUSLE* = Mean annual soil loss (t ha^{-1} yr^{-1}), *K* = Soil erodibility factor (t J^{-1} mm^{-1}), *C* = Cropping – Management factor (dimensionless 0-1), *P* = Erosion control practice factor (dimensionless 0-1), *LS* = Combined slope and length of slope factor (dimensionless) and *R* = Rainfall and runoff erosivity index (MJ $mm.m^{-2}$ h^{-1}). Note that C may be estimated from the standard crop parameters already encoded within the *JULES* model. *RUSLE* and other modelling approaches are summarised (Morgan & Nearing, 2010). We note that there are extensions of the *RUSLE* available (Dabney, Yoder, Vieira, & Bingner, 2011), but at least in the pilot phase of this study we will use only *RUSLE*.

Table 1: Processes contributing to soil erosion by water in non-glaciated, natural ecosystems (i.e. excluding urban areas).

Process	Description	Model representation
RAINDROP EROSION (SPLASH EROSION)	Detachment and displacement of soil particles by raindrop impacts (non-vegetated areas).	Included in the *RUSLE*
SHEET EROSION (WASH-OFF EROSION)	Detachment and transportation of soil particles by flowing rainwater.	Included in the *RUSLE*
RILL EROSION	Finger-like rivulets (rills) appear on the land surface after it has undergone sheet erosion.	Included in the *RUSLE*
GULLY EROSION	The removal of soil along drainage lines by surface water runoff	Excluded from *RUSLE* (which estimates only *in situ* processes) and also cannot easily be addressed by *JULES* (which includes processes only at larger spatial scales).
RUNOFF-BASED EROSION	Larger-scale erosion as a function of land surface runoff	Excluded from *RUSLE* (which estimates only in-situ processes). To be estimated using *JULES*

Figure 2: Map of the study region for this report, showing the Berg & Breede rivers in the Western Cape (West Region) and the Umzimvubu river system in the Eastern Cape (East Region).

The RUSLE will provide a robust estimate of water-mediated soil erosion by splash, sheet and rill processes. JULES will be used to provide an estimate of larger-scale processes based on the lateral movement of water across the land surface (Table 1). Because gully erosion is usually assumed to be included in runoff-based erosion (Table 1), this combination will provide the project with a best estimate of total soil erosion from most sources. The focus of our modelling will be on 2 contrasting South African catchment systems: the Western Cape including the Berg-Breede rivers, and the Eastern Cape centred around the Umzumvibu system (Figure 2).

2. Data & methods

2.1 Datasets

RUSLE-based soil erosion models require a small number of raster spatial layers to be used, each representing one of the factors that make up the *RUSLE* model (see Section 1.2). Additionally, a vector spatial layer representing river catchment boundaries is used to both constrain simulations to a region of interest and allow for sediment transfers to water to be calculated (usually using a simple connectivity index). Requirements for each RUSLE factor are as follows (symbols are as used in eqn1):

- **K**: Soil erodibility factor (t ha h ha^{-1} MJ^{-1} mm^{-1}): Typically derived from digital soil maps covering several physical soil properties (texture, organic matter, stones and saturated hydraulic conductivity).
- **C**: Land cover management factor (0-1 scale): Can be either generated using look-up tables of published coefficient values for different land cover types or can be estimated from NDVI using equations for temperate or tropical environments. Lower numbers indicate greater levels of prevented erosion.
- **P**: Support practices factor (0-1 scale): Often excluded from *RUSLE* applications as there is little spatially explicit information available on this. Can be estimated using available coefficients for slope categories, known agricultural practices (e.g. reduced tillage, contouring, terracing) and from information on barriers (e.g. hedges and field walls). For this report, this factor was set to 1 universally (no support practices present).
- **LS**: Slope length-steepness factor (dimensionless): Calculated from a digital elevation model using recommended formulae.
- **R**: Rainfall erosivity factor (MJ mm ha^{-1} h^{-1} yr^{-1}): Can be either an existing rainfall erosivity map generated from location points with long-term measurements or can be estimated from mean annual rainfall using a range of region-specific equations.

Table 2 summarises the data we used for *RUSLE* calculations in this pilot report. Observational soil erosion and sediment load data are limited in our study region, so comparisons are limited to *JULES* outputs against equivalent results from *InVEST*.

Table 2: Primary datasets used in the soil erosion modelling. Note that *JULES* uses additional datasets, however, these are not relevant to the calculation of soil erosion based on the *RUSLE* model.

Dataset	Variable(s)	Spatial resolution	Temporal resolution	Spatial coverage	Time range
HydroSHEDS v1	Topography [slope length & steepness; catchment area; altitude]	30 arc-seconds (WGS 84 CRS)	-	Global	-
SoilGrids 250m v1	Soil [SOC; clay; sand; silt; USDA texture; stones; soil erodibility]	250 m (global homolosine projection CRS)	-	Global	-
ISIMIP 3b	Climate [precipitation; rainfall erosivity]	0.5 degree (WGS 84 CRS)	Daily	Global	01/01/01-31/12/01
ESA Land Cover Climate Change Initiative	Land cover [PFTs; LULC management factor]	300 m?	Annual	Global	2010

2.2 Ancillary factors common to *InVEST* and *JULES*

The following sub-sections detail the required functions required to integrate *RUSLE*-based soil erosion into the *JULES* model.

Soil erodibility factor *K*

The K-factor formula incorporates several aspects of soil physical structure (Wischmeier & Smith, 1978):

$$K = 2.76 \times 10^{-7} \times M^{1.14} \times (12 - OM) + 0.0043(s - 2) + 0.0033(p - 3)$$

Where:

- M = soil textural factor which is the product of (silt + v. fine sand) * (100 - clay)
    - Units = %; Very fine sand can be assumed to equal 0.2 * sand content
- OM = soil organic matter (%), which will likely need to be estimated from soil organic carbon concentration
    - Recommend using the van Bemmelen conversion factor which assumes an upper limit of 58% organic carbon in SOM: SOC (g/kg) * 0.172 = SOM (%)
    - Also, set all SOM values >4 % to 4; soil erodibility is not designed for soils richer in organic matter than this threshold.
- s = soil structural class code (see Table 3)
- p = soil permeability class code (see Table 4)

Table 3: Soil structure class codes, descriptions & typical USDA texture classes.

Structure code	Description	Typically associated texture groups
1	Very fine granular	Sand, loamy sand, and sandy loam
2	Finer granular	Sandy clay, sandy clay loam, silt loam and silt
3	Medium or coarse granular	Clay loam and silty clay loam
4	Blocky, platy or massive	Clay and silty clay

Table 4: Soil permeability class codes, saturated hydraulic conductivity (ksat) ranges & typical USDA texture classes.

Permeability	K_{sat} (cm day^{-1}) range	Typically associated texture groups
1	≥146.4	Sand
2	48.72–146.4	Loamy sand and sandy loam
3	12.24–48.72	Loam and silty loam

4	4.8–12.24	Sandy clay loam and clay loam
5	2.4–4.8	Silty clay loam and sandy clay
6	<2.4	Silty clay and clay

JULES includes multiple pedotransfer options to estimate k_{sat}. These could be used instead of USDA soil texture class to determine permeability codes and might prove to be more accurate (Gupta, Borrelli, Panagos, & Alewell, 2024). However, for this pilot study, *JULES* was run only with the standard pedotransfer functions already available in the model (Cosby, Homberger, Clapp, & Ginn, 1984).

The presence of stone fragments in the topsoil can reduce the amount of erosion that occurs via sheet, rill or inter-rill erosion at a range of spatial scales. At the macroplot scale ($>10^1$ m^2), the effect of stones on topsoil erosion can be modelled (Poesen, Torri, & Bunte, 1994) as follows:

$$St = e^{-0.04(R_c-10)}$$

Where:

- St = the stoniness correction factor
- R_c = the percentage of stones ($10\% < R_c < 100\%$) in the topsoil

If the St formula above returns a value > 1, set to 1; then you can calculate a modified K-factor value by multiplying the stoniness correction factor by the previously calculated K-factor value.

Land cover & crop management factor *C*

The C-factor incorporates the combined effect of all interrelated vegetation cover and management variables on soil erosion by water. One approach, which relies on extensive literature & data reviews, is to set up a “biophysical table” that links distinct land cover classes to a specific C-factor value. For this method, it is sensible to split the assignment of C-factor into 2 parts: one for semi-natural environments, and one for croplands.

Within *JULES*, land cover is represented by proportions of different plant functional types (PFTs). Each of these PFT categories can be assigned a C-factor based on recommended values from the wider literature, and each cell can be assigned an overall C-factor by using proportions of each PFT category to calculate a weighted average. Recommended values for C-factor are displayed in Table 5.

For agricultural land, information on crop types for a region of interest is required to determine the most suitable C-factor for croplands. The FAO holds data on crop statistics at national level (see FAOSTAT) from which statistics on harvested areas of different crop types can be combined with recommended C-factor values (Table 6) to derive an overall C-factor for croplands. It is recommended that a 5-year average (with the final year being the equivalent of the land cover map) be taken to account for recent crop rotations (Borrelli, et al., 2017); in this instance, data from 2006-2010 for South Africa were used to align with the 2010 land cover map.

Table 5: PFT categories and typical C-factor values, based on recommended values compiled for International Geosphere-Biosphere Programme (IGBP) land cover types.

PFT name	PFT code	IGBP land cover type	C-factor
BDT (broadleaf deciduous forest)	1	Forest	0.00155
BET-Tr (broadleaf evergreen tropical forest)	2		0.00155
BET-Te (broadleaf evergreen temperate forest)	3		0.00155
NDT (needleleaf deciduous forest)	4		0.00155
NET (needleleaf evergreen forest)	5		0.00155
C3GN (C3 grassland natural)	6	Rangeland	0.08
C3GC (C3 grassland crop)	7	Cropland	Custom
C3GP (C3 grassland pasture)	8	Rangeland	0.08
C4GN (C4 grassland natural)	9	Rangeland	0.08

C4GC (C4 grassland crop)	10	Cropland	Custom
C4GP (C4 grassland pasture)	11	Rangeland	0.08
DSh (deciduous shrub)	12		0.08
Esh (evergreen shrub)	13		0.08
Oil Palm (Commercial)	14	Cropland (fruit trees)	0.15
Oil Palm (Smallholder)	15		0.15
Urban	16	Urban & built-up	0
Inland water (permanent lakes & reservoirs)	17	Water	0
Bare soil	18	Barren or sparsely vegetated	1
Land ice (glaciers & ice sheets)	19	Snow & ice	0

Table 6: C-factor values for specific crop groups.

Crop group	Crop sub-group	C-factor
1) Cereal grains	Various	0.2
	Maize	0.38
	Rice	0.15
2) Legume vegetables	Various	0.32
3) Root & tuber vegetables	Various	0.34
4) Fruiting vegetables	Various	0.25

5) Cucurbit vegetables	Various	0.25
6) Bulb vegetables	Various	0.3
7) Leafy vegetables	Various	0.25
	Tobacco	0.5
8) Forage, fodder & straw of cereal grains	Mixed legumes	0.15
	Mixed grasses	0.1
9) Grapes & hops	Grapes	0.35
	Hops	0.42
10) Oilseeds	Various	0.25
	Cotton	0.4
11) Fibre crops	Fibre crops	0.28
12) Berries	Various	0.15
	Strawberries	0.2
13) Shrubs, herbs & spices	Various	0.15
	Coffee	0.2
14) Trees / fruit trees, including oil palm	Various	0.15

Combined slope length-steepness factor *LS*

The LS-factor can be calculated from several different equations. The Desmet & Govers (1996) formulation is the typical one used in *RUSLE* applications, including within *InVEST*'s Sediment Delivery Ratio model. LS is calculated for each grid cell as follows (Desmet & Govers, 1996):

$$LS_i = S_i \frac{(A_{i-m} + D^2)^{m+1} - A_{i-in}^{m+1}}{D^{m+2} \times x_i^m \times (22.13)^m}$$

Where:

- S_i is the slope factor for grid cell, i, calculated as a function of slope. s is the percentage slope and θ is the slope in degrees:

$$S = \begin{Bmatrix} 10.8\sin(\theta) + 0.03, where\ s < 9\% \\ 16.8\sin(\theta) - 0.50, where\ s \ \geq 9\% \end{Bmatrix}$$

- $A_{i\text{-}m}$ is an estimate of the specific catchment area, calculated as:

$$\sqrt{n\ upstream\ pixels\ \times pixel\ area}$$

- D is the grid cell linear dimension (m)
- x_i is the aspect length of grid cell, i, calculated by:

$$x_i = |\sin\alpha_i| + |\cos\alpha_i|$$

m is the *RUSLE* length exponent factor (typically, this is capped at 122m – the maximum length used in the original USLE experimental plots – to avoid overestimation of LS factor values in heterogeneous landscapes but this could be set as an adjustable parameter).

Rainfall erosivity factor *R*

Two regression-based approaches are available for Africa. The first is applicable for West Africa primarily (Roose, 1975):

$$R_{annual} = MAR * 0.5 * 1.73$$

Where:

- R_{annual} is the annual rainfall erosivity index
- MAR is the mean annual rainfall (mm yr^{-1})

The second approach applies primarily to East Africa (Moore, 1979) and involves first estimating rainfall kinetic energy (KE) before using this to estimate rainfall erosivity:

$$KE = 3.96 * MAR + 3122$$

$$R_{annual} = 17.02 * (0.029 * KE - 26)$$

The proposed formulas by Roose and Moore may work well for West and East Africa, respectively, where the regression functions between mean annual rainfall and rainfall erosivity were originally developed. However, in South Africa, this might not hold true. We could look at other rainfall erosivity estimations carried out in

South Africa which apply calibrated sinusoidal functions to daily data (Johnson, 2018), but this might be very time consuming and therefore better for follow-up work after 2024. For this pilot, we have focussed on the simpler Roose (1975) formula.

2.3 *InVEST* Sediment Delivery Ratio (SDR) model

The *InVEST* (Integrated Valuation of Ecosystem Services and Tradeoffs) platform includes 20 free, open-source software models to simulate the delivery of several supporting and final ecosystem services over space and time (Natural Capital Project, 2024). The *InVEST* Sediment Delivery Ratio (SDR) model is used to quantify and map the overland sediment generation and delivery to the stream, as well as quantify the role played by land cover and management practices (e.g. tree planting and incorporating cover crops to arable systems) in preventing soil loss or trapping eroded sediments before they reach waterbodies. The information that the SDR model produces can help to inform strategies for a wide range of stakeholders to conserve soil and reduce sediment loads through changes in land use and management practices, including NbS (Hamel, Chaplin-Kramer, Sim, & Mueller, 2015). Thus, the SDR model is not only a useful tool in itself for assessing the impacts of soil erosion and quantifying the mitigation from NbS-oriented land management practices but should also provide a useful comparison with *JULES*-simulated erosion outputs.

Erosion and retention of soils are natural processes that ultimately govern the flux of sediments into water. The key sources of sediment and processes of transmission from land to water include overland erosion through sheetwash and rills (detachment and transport of soil particles by rainfall and surface runoff), gullying (deeper channels that concentrate flow), sediment exchange between river channels and floodplains (bed and bank erosion as well as overbank deposition), and mass movements (landslides, mudflows and rockfalls) (Merritt, Letcher, & Jakeman, 2003). Of the aforementioned processes, the SDR model focuses only on overland erosion as represented by *RUSLE*. The outputs generated by the model include gross soil erosion rates (excluding gully erosion, q.v. Table 1), prevented soil erosion by vegetation and land management practices, sediment load delivered to the stream annually, and the amount of sediment retained on land by vegetation and topographic features.

The SDR model is spatially explicit and works by first computing the gross soil erosion from each pixel, then secondly, the sediment delivery ratio (the proportion of eroded soil that reaches the river network). Once eroded sediment reaches the river network, it is assumed that all sediment will be delivered to the catchment outlet, ignoring all in-stream processes or possible transfers to the floodplain. Whilst these processes may prove significant in some catchments, particularly larger basins with more complex patterns of sediment (dis)connectivity (Fryirs, 2013), this simplification greatly increases the tractability of the model, keeping simulation run-times and the total number of parameters requiring calibration to a minimum (Hamel, Chaplin-Kramer, Sim, & Mueller, 2015).

For the calculation of gross erosion rates and the prevented soil loss from land cover management, the SDR model takes as inputs: a rainfall erosivity layer, a soil erodibility layer, a DEM from which the *RUSLE* slope length-steepness factor is calculated, a layer representing discrete land cover classes, and a biophysical table which, together with the land cover map, is used to represent the land cover management and support practices factors. For the SDR model, we used the spatial datasets listed in Table 2 as inputs. Further details on the calculation of each of these *RUSLE* factors is the same as described in Section 2.2 for input into the *JULES* model.

To calculate the sediment delivery ratio, the SDR model relies on a connectivity index-based approach (Borselli, Cassi, & Torri, 2008). The connectivity index (IC) describes the strength of the hydro-sedimentary linkages between sources of sediment and the river network. Higher values of IC thus imply a greater fraction of eroded sediment from an upslope pixel is delivered to a downslope sink. Higher IC values typically arise when the flow paths between sediment sources and sinks is short, steep and/or sparsely vegetated, meanwhile lower IC values are generally associated with gentler slopes and denser vegetation cover (Borselli, Cassi, & Torri, 2008).

IC is a function of the area upslope of each grid cell, D_{up}, and the flow path between the grid cell and the nearest stream, D_{dn}. If the upslope area is large, has lower slope, and dense vegetation cover, D_{up} will be relatively low which will indicate a low potential for eroded sediment to transfer to water courses; this will also be the case if the D_{dn} is low. IC is calculated as a logarithmic function of the ratio between D_{up} and D_{dn} as follows:

$$IC = log_{10}\left(\frac{D_{up}}{D_{dn}}\right)$$

Threshold slopes, S_{th}, and cover management factors, C_{th}, are used in calculating D_{up} and D_{dn}. A lower bound is set for both threshold S and C values to avoid infinite values for IC, while an upper bound is also set to the threshold S to mitigate bias associated with high IC on steep slopes (Cavalli, Trevisani, Comiti, & Marchi, 2013):

$$S_{th} = \begin{Bmatrix} 0.005, for\ S < 0.005 \\ S, for\ 0.005 \leq S \leq 1 \\ 1, for\ S > 1 \end{Bmatrix}$$

$$C_{th} = \begin{Bmatrix} 0.001, for\ C < 0.001 \\ C, for\ 0.001 \leq C \leq 1 \end{Bmatrix}$$

D_{up} is the upslope component defined as:

$$D_{up} = \overline{C_{th}S_{th}}\sqrt{A}$$

Where for the upslope contributing area (m^2), C_{th} and S_{th} in the specific equation above are the averaged threshold C factor and the averaged threshold slope gradient, respectively.

D_{dn} is given by:

$$D_{dn} = \sum_i \frac{d_i}{C_{th,i} \times S_{th,i}}$$

Where d_i is the length of the flow path along the ith cell according to the steepest downslope direction (m), $C_{th,i}$ and $S_{th,i}$ are the threshold cover and slope gradient of the ith cell, respectively. In the SDR model, both the upslope and downslope contributing areas are delineated from a Multiple Flow Direction algorithm.

The SDR for a grid cell, i, is derived from the IC (Vigiak, Borselli, Newham, McInnes, & Roberts, 2012):

$$SDR_i = \frac{SDR_{max}}{1 + \exp\left(\frac{IC_0 - IC_i}{k}\right)}$$

Where SDR_{max} is the maximum theoretical SDR, typically set to 0.8 (though it has been suggested setting this equal to the proportion of sediment finer than coarse sand, <1mm (Vigiak, Borselli, Newham, McInnes, & Roberts, 2012)); IC_0 and k are calibration parameters that define the shape of the SDR-IC relationship. The effect of these latter 2 parameters on the SDR is illustrated in Figure 3.

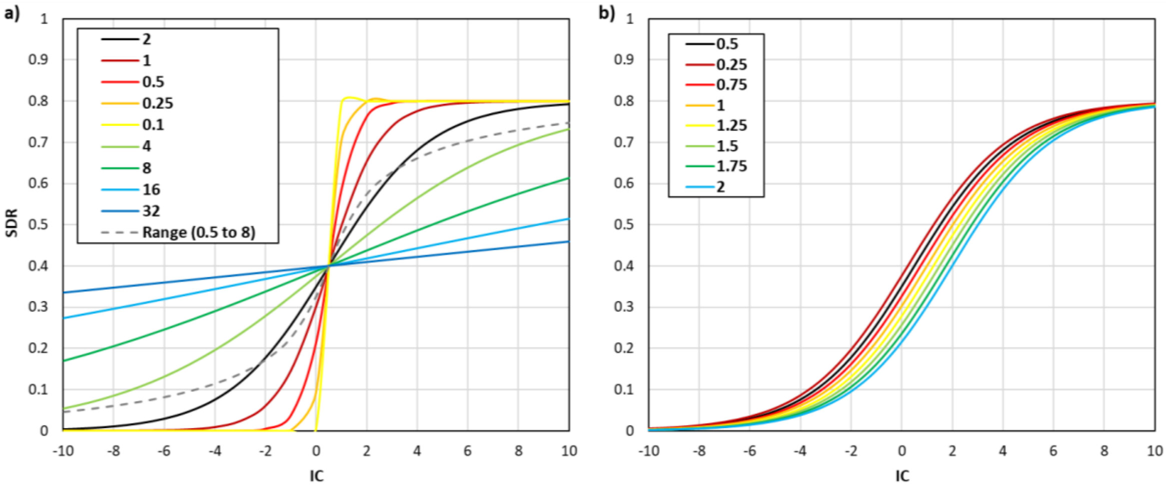


Figure 3: Relationship between IC and SDR, with an upper SDR limit (SDRmax) set to 0.8: a) Effects of selecting different k values (default is 2, but should be calibrated); b) Effects of selecting different IC0 values (default is 0.5).

Sediment export from a given grid cell, E$_i$ (t pixel^{-1} yr^{-1}) is given by:

$$E_i = RUSLE_i \times SDR_i$$

By aggregating all E$_i$ values for a defined catchment area, predicted sediment loads can be compared with observed values collected from stream gauges for calibration and/or evaluation purposes.

The SDR model also outputs projections of the total sediment that is deposited (D$_i$) along the flow path downslope from the source. Knowledge of deposition rates is useful for calculating net sediment change for a given pixel (i.e. gross erosion minus deposition) and is calculated as follows:

$$D_i = USLE_i(1 - SDR_i)$$

The amount of eroded sediment that is retained on a pixel is a function of both the absolute difference in SDR values from pixel, i, to the downslope pixel(s) it drains to, and how numerically close the downslope SDR value is to 1 (a stream pixel). These mechanics can be captured as follows:

$$\Delta T_i = \frac{\left(\sum_{k\epsilon\{directly\ downslope\ from\ i\}} SDR_k \times p(i,k)\right) - SDR_i}{1 - SDR_i}$$

Where T is the trapping of sediment and p(i, k) is the proportion of flow from pixel, i, to pixel, k. Then, the amount of sediment flux that is retained on any pixel in the flow path is defined as a weighted flow of upslope flux:

$$T_i = \Delta T_i \times \left(\sum_{j \in \{pixels\ that\ drain\ to\ i\}} F_j \times p(j,i) \right)$$

Where Fi is the total sediment export that does not reach the stream, defined as follows:

$$F_i = (1 - \Delta T_i) \times \left(\sum_{j \in \{pixels\ that\ drain\ to\ i\}} F_j \times p(j,i) + D_i \right)$$

As mentioned before, the SDR model is also capable of quantifying the role of land cover and management in preventing soil erosion and export to river networks. In the case of avoided erosion, this ecosystem service is calculated as follows:

$$AER_i = RKLS_i - USLE_i$$

Where AER$_i$ is the amount of erosion avoided on pixel, i, and the difference between RKLS$_i$ and USLE$_i$ reflects the total benefit conferred from local land cover and supporting management practices, since RKLS is equivalent to the full RUSLE equation without the multiplication of the cover management and support practices factors.

Avoided sediment export reflects both the avoided erosion as well as the trapping of eroded sediment delivered from upslope of the pixel. This may be conceptualised as the total soil that is retained on the pixel which is calculated as follows:

$$AEX_i = (RKLS_i - USLE_i) \times SDR_i + T_i$$

Where AEX_i is the total sediment retention occurring in pixel, i, from both local and upslope erosion sources. Similar to avoided erosion, the difference between $RKLS_i$ and $USLE_i$ reflects the total benefit conferred from local land cover and supporting management practices, and multiplying this by the local sediment delivery ratio (SDR_i) provides the amount of erosion originating on pixel, i, which does not enter a stream. Lastly, T_i is the total upslope sediment trapped on pixel, i, also preventing transmission to the river network.

2.4 *JULES* land surface model

JULES (the Joint UK Land Environment Simulator; https://jules.jchmr.org) is a community land surface model that is used both as a standalone model and as the land surface component in the Met Office Unified Model. *JULES* is a core component of both the Met Office's modelling infrastructure and NERC's Earth System Modelling Strategy. *JULES* simulates many land surface variables (e.g. vegetation productivity, fluxes between the land surface and the atmosphere) including a full water balance and hydrological cycle.

JULES version 7.7 (released 2024) was used for the simulations in this pilot study. Meteorological data for driving *JULES* was acquired from the ISIMIP project. Every grid cell across the region consisted of vegetation-based surface types (Plant Functional Types, PFTs, see Table 5) as well as fractional coverages of four non-vegetation types (urban area, open water (lakes and reservoirs), bare soil (desert or rocky outcrops) and land-ice (which did not occur in our study region)), all derived from publicly-available data sources (Table 2).

JULES can simulate several hydrological processes involved in the movement, storage and exchange of water within the land surface and the atmosphere. These processes encompass the temporal changes of soil moisture content across different soil layers, the infiltration of precipitation into the soil, and the redistribution of water within the soil profile. The model takes into account factors such as soil texture, land cover, and soil moisture to determine the rate of infiltration. Soil hydraulic properties, including the related hydraulic conductivity and water characteristic curves, are used internally to influence the movement and storage of water in the soil.

Surface runoff occurs when the soil is saturated and cannot absorb additional water, resulting in water moving across the land surface as runoff (Marthews, et al., 2022). *JULES* takes a water balance approach to simulating runoff, where runoff is the residual of a balance calculation involving precipitation, evapotranspiration and drainage (Figure 4). This involves the application of an internal soil hydraulics model to simulate drainage (Figure 5).

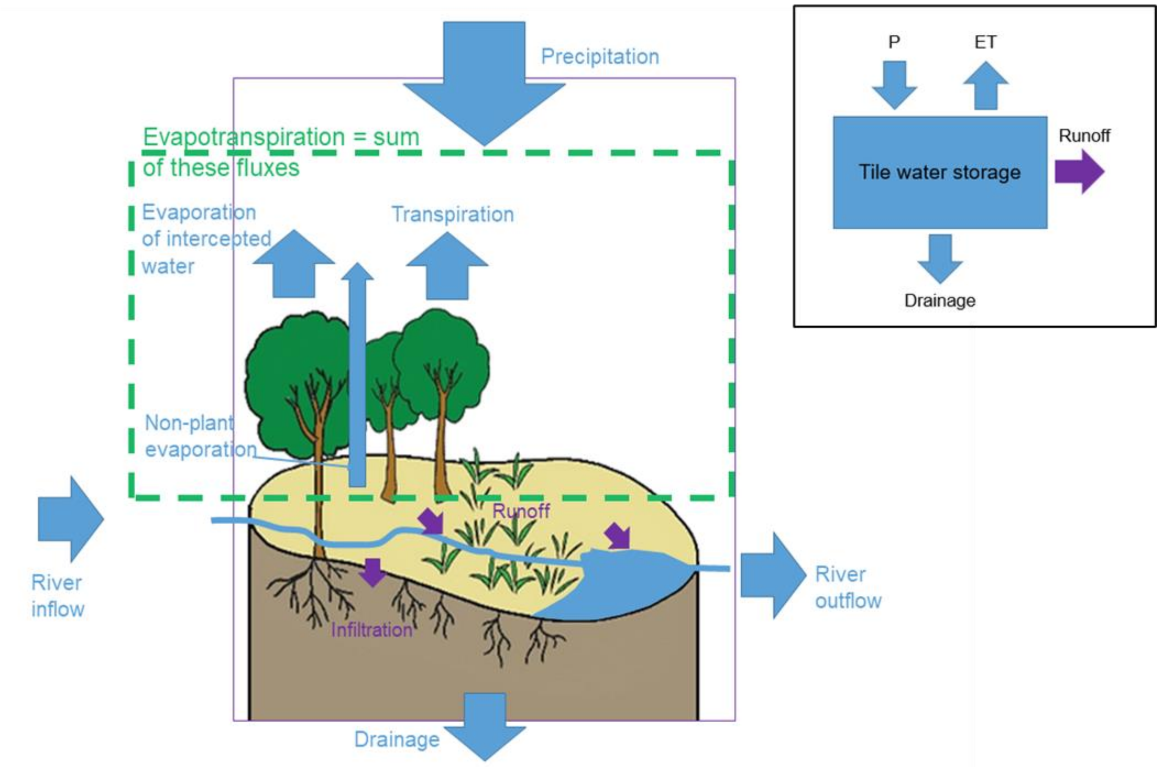


Figure 4: The water balance of a grid cell as simulated by the land surface model, *JULES*.

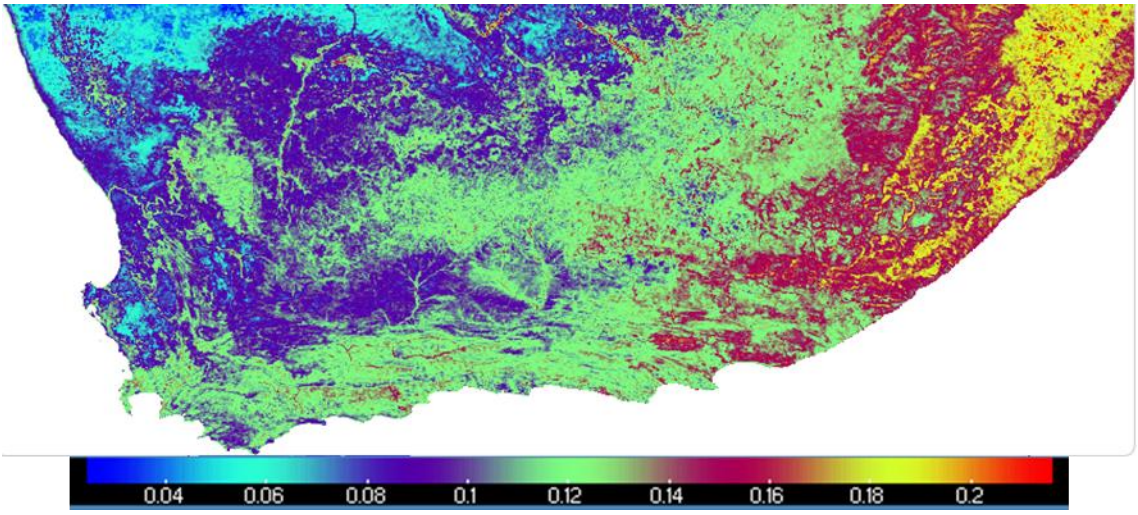


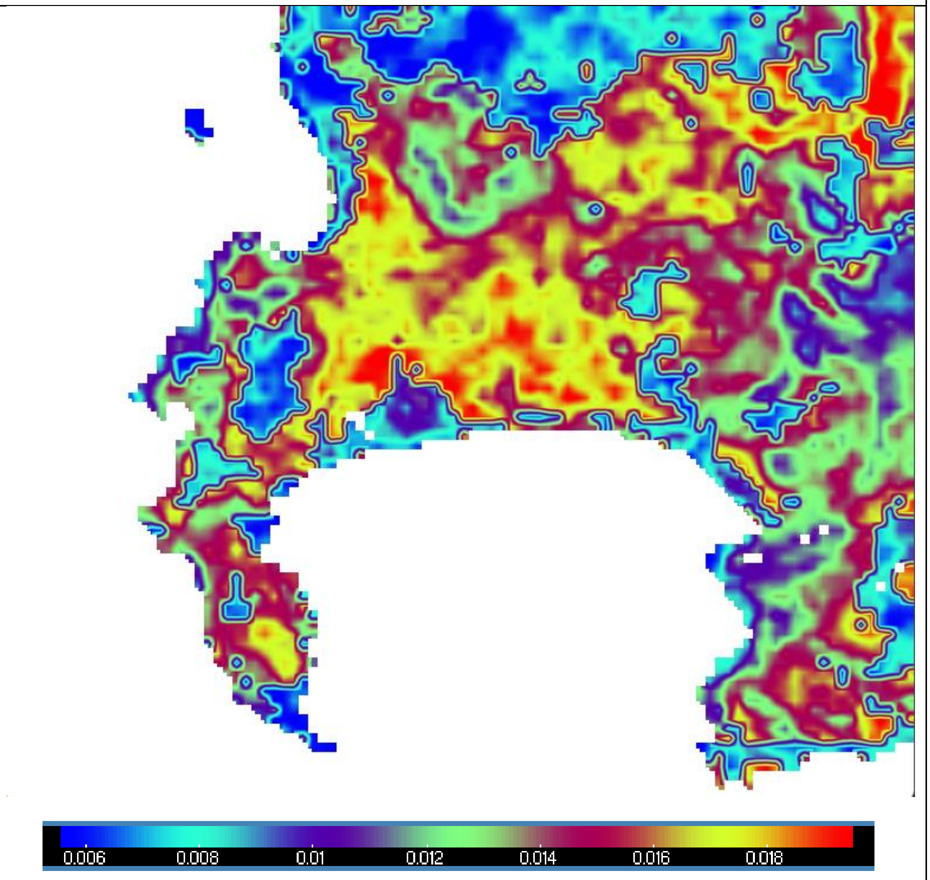
Figure 5: JULES uses high-resolution soil information based on pedotransfer functions applied to SoilGrids 250m data; for example, soil moisture content at permanent wilting point (SM_WILT) illustrated here (in m^3/m^3).

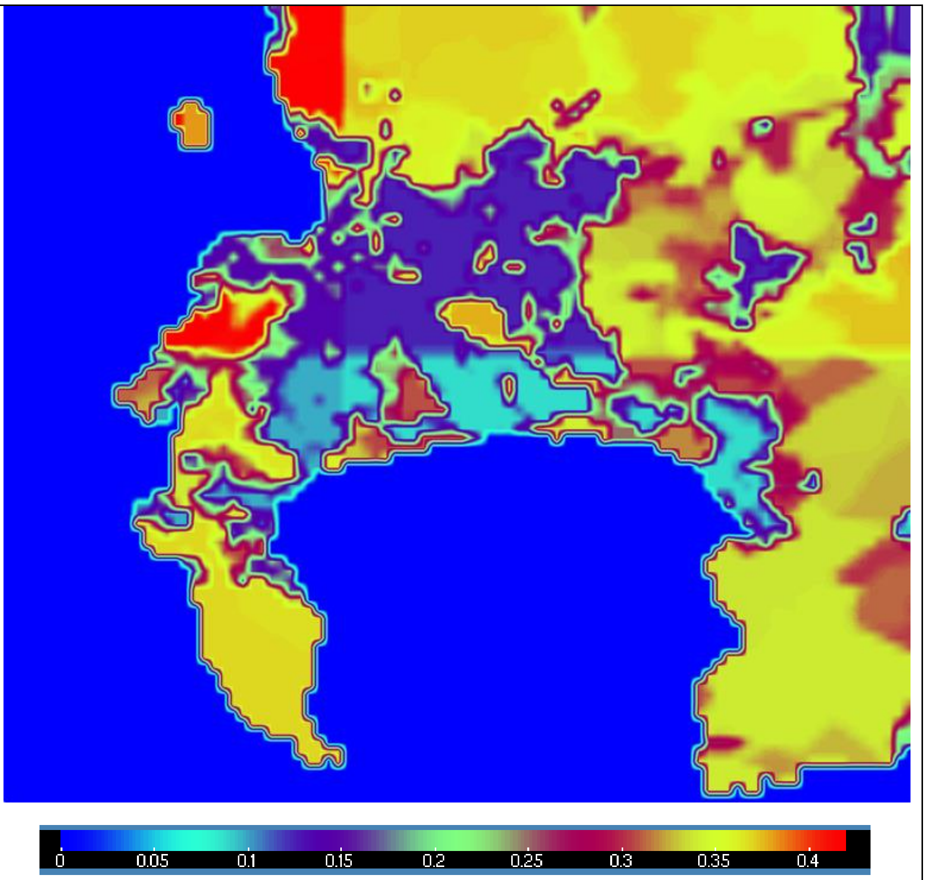
After having simulated the study regions with *JULES*, a bespoke soil erosion post-processing workflow called *SEPP_Workflow* was created in order to assemble the data required for estimating runoff-based soil erosion rates (see Appendix).

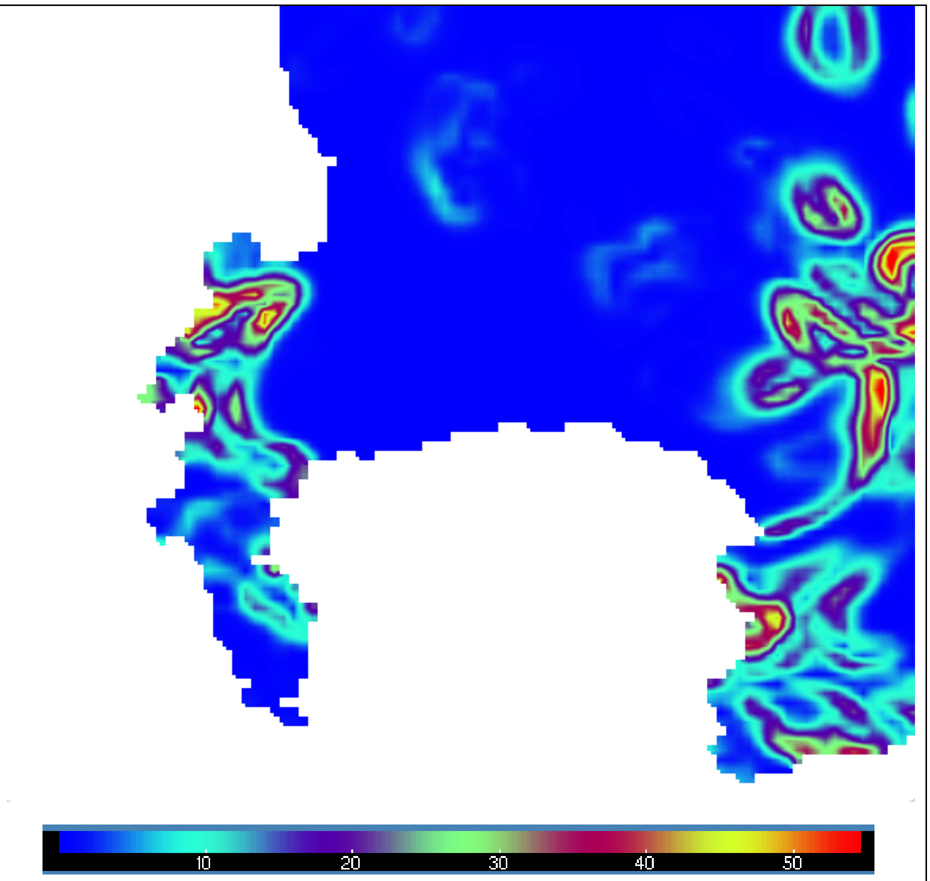
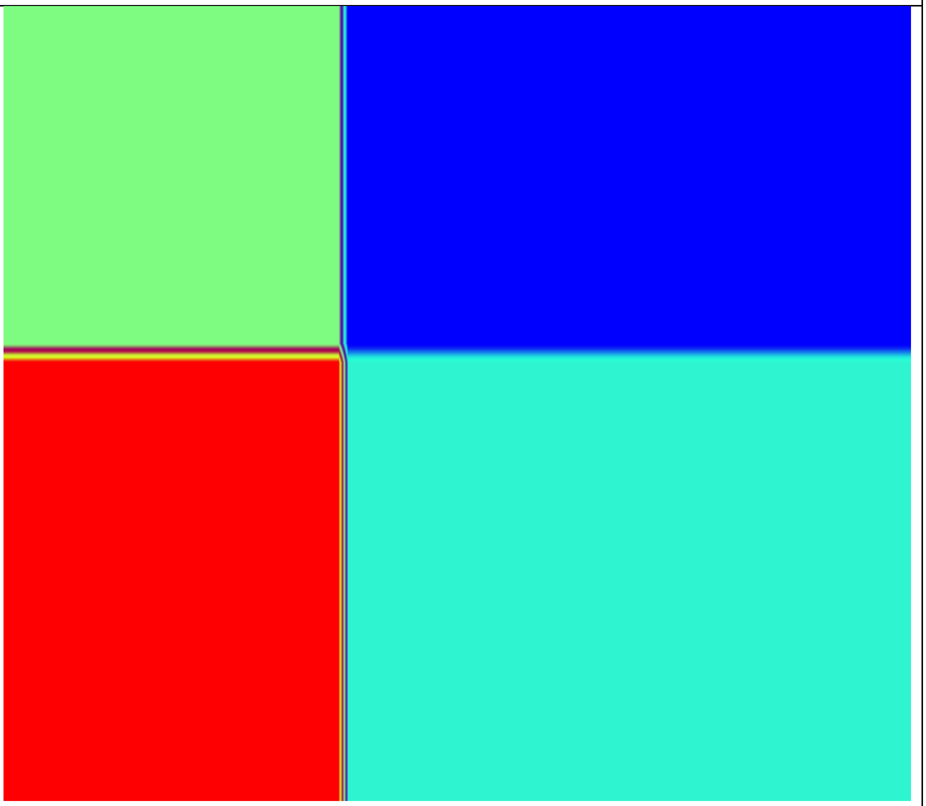
3. Results & Discussion

3.1 Factor maps produced in *JULES*

Results of calculating the ancillary factors that are common to both the *InVEST* and the *JULES* modelling approaches are presented in Figure 6 (W region) and Figure 7 (E region).

Factor	West Region
K factor: Soil erodibility factor in t ha h ha^{-1} MJ^{-1} mm^{-1}	

C factor: Land cover & crop management factor (dimensionless 0-1)	
P factor: Agricultural support practices (erosion control) factor (for now, we are simply assuming that this =1.0).	=1.0 everywhere

LS factor: Combined slope and length steepness factor (dimensionless)	
R factor: Rainfall erosivity factor in MJ mm ha^{-1} h^{-1} yr^{-1} (annual)	

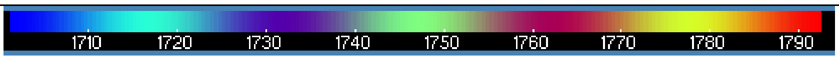
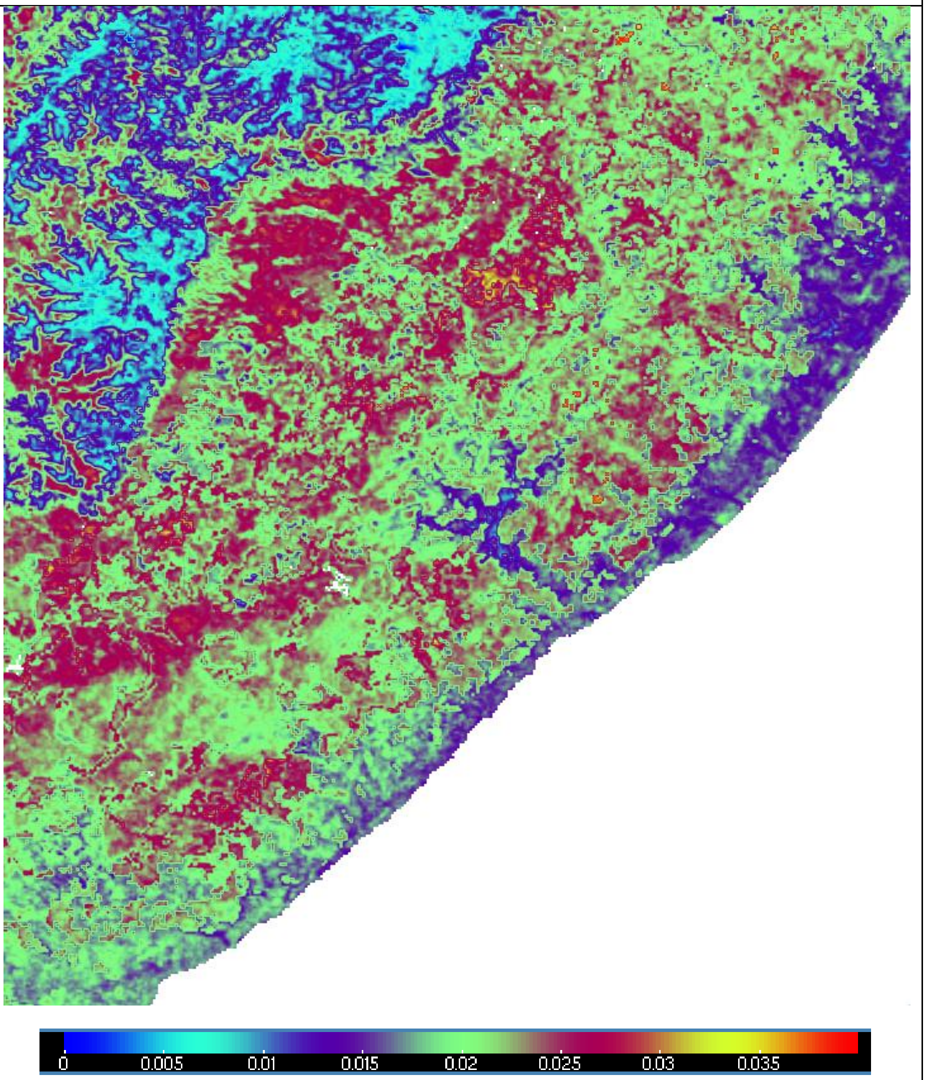
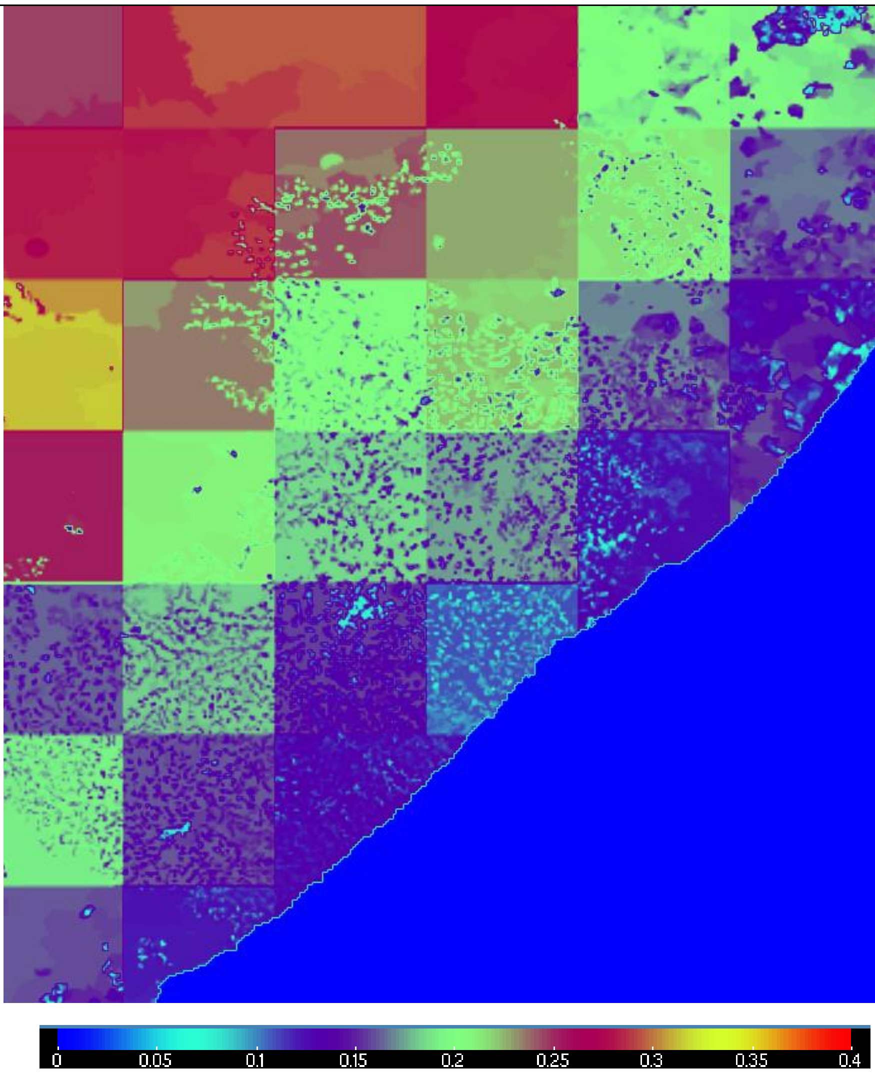
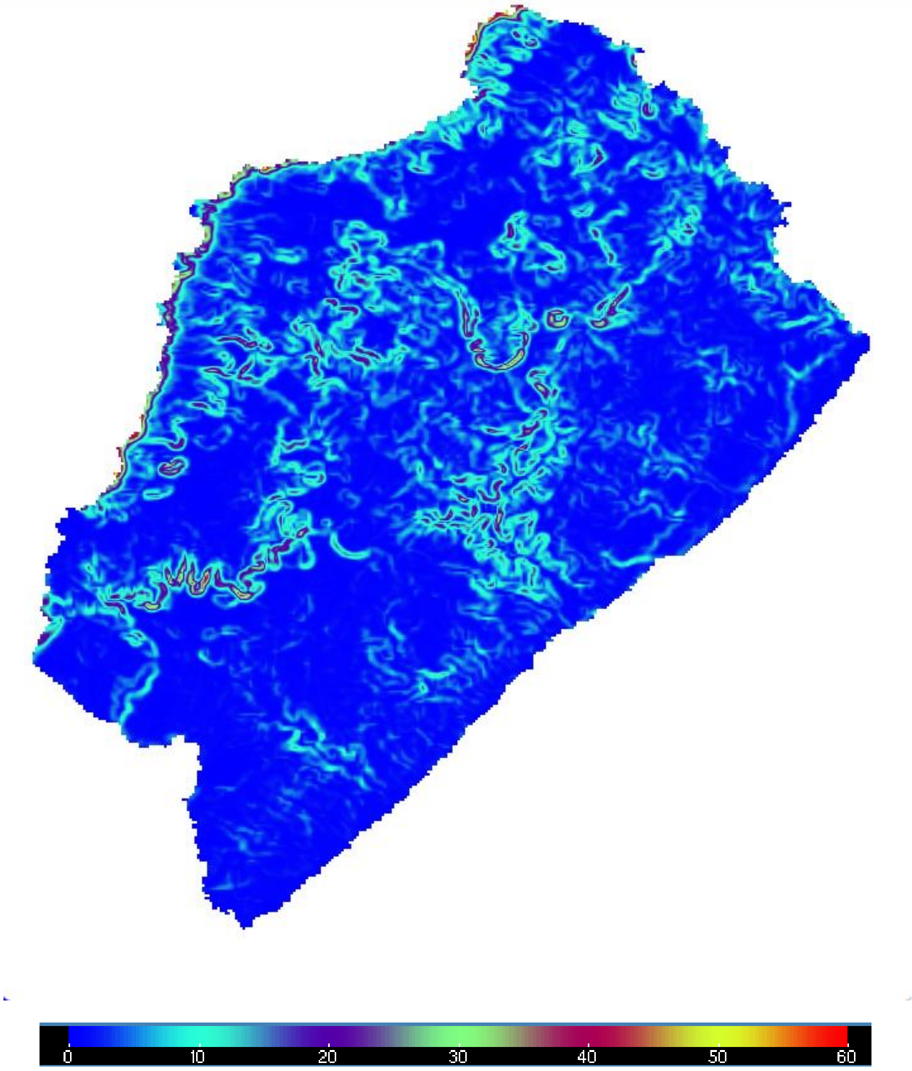
	

Figure 6: Data layers for calculation of RUSLE (eqn1) for the West Region. For the rainfall erosivity factor, R, although these rainfall numbers are coming from coarse-resolution ISIMIP data, the numbers are well-calibrated and bias corrected.

Factor	East Region
K factor: Soil erodibility factor in t ha h ha^{-1} MJ^{-1} mm^{-1}	

C factor: Land cover & crop management factor (dimensionless 0-1)	
P factor: Agricultural support practices (erosion control) factor (for now, we are simply assuming that this =1.0).	=1.0 everywhere

LS factor: Combined slope and length steepness factor (dimensionless)	

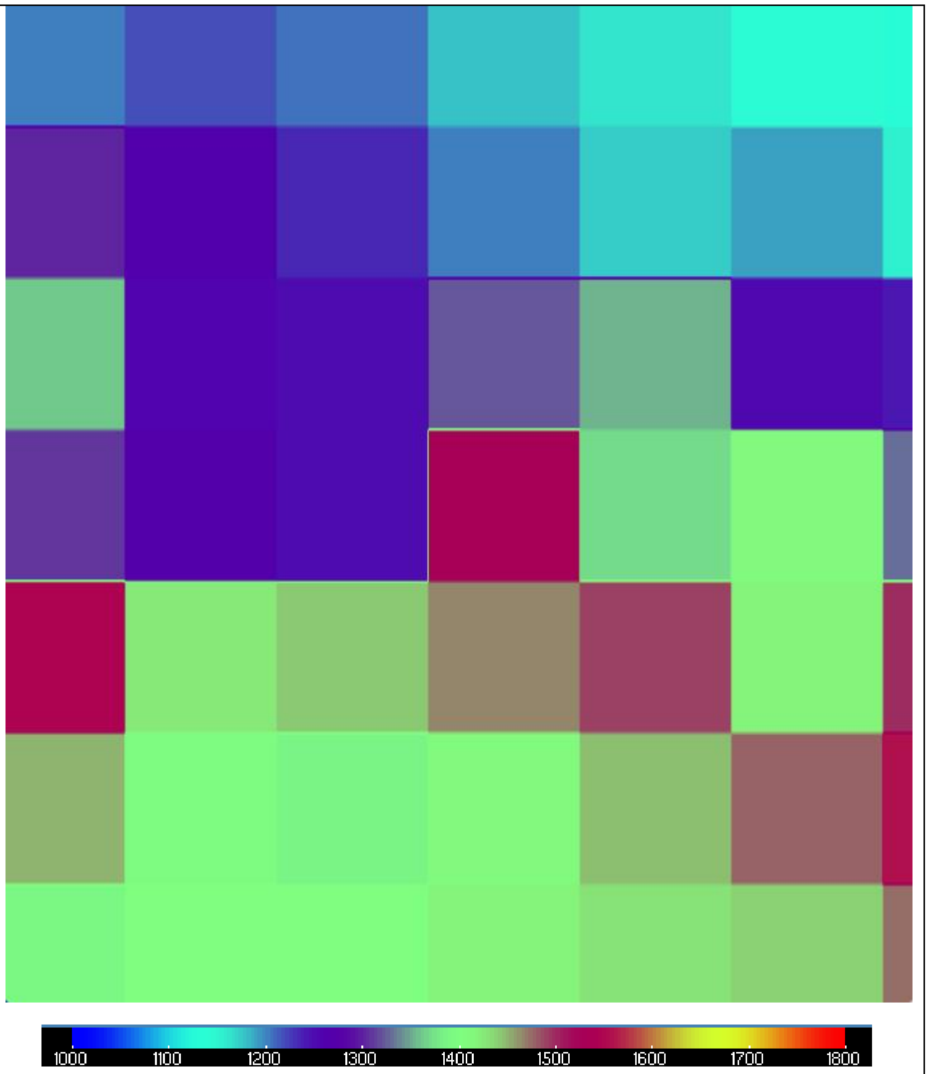
R factor: Rainfall erosivity factor in MJ mm ha^{-1} h^{-1} yr^{-1} (annual)	

Figure 7: Data layers for calculation of RUSLE (eqn1) for the East Region. For the rainfall erosivity factor, R, although these rainfall numbers are coming from coarse-resolution ISIMIP data, the numbers are well calibrated and bias-corrected.

3.2 Erosion, sediment export & avoided soil loss by *InVEST*

Simulated soil erosion and sediment exports by the SDR model were shown to be highest in the majority of the Eastern Cape catchment areas and in the central third of the Western Cape catchment systems (Figure 8). In the Eastern Cape, these patterns are likely driven by a combination of relatively high rainfall erosivity and steep, long slopes with few breaks to interrupt sediment transport pathways to water courses. In the Western Cape, these patterns likely reflect the intersection of arable cropland systems with steep, long slopes. Soil erodibility does not differ much between the 2 pilot catchment areas and rainfall erosivity appears to be higher in the east than in the west. The Western Cape catchments are generally situated on gentler slopes, hence the relatively low erosion rates in much of the Western Cape compared to the Eastern Cape. Unsurprisingly, in both systems, deposition rates are highest in river valley bottom areas and other topographic lows (e.g. along foot-slopes of hills), and we can map areas that may be long-term sites of net erosion and net deposition (Figure 8).

As well as soil erosion and export of sediments to water courses, the SDR model produces maps of soil losses that are prevented, either in situ by local land cover and management, or trapped by vegetation between the erosion source and water course downslope. These maps give a useful indication of the role vegetation and land management play in stopping further land degradation compared to how the landscape would be represented in the absence of vegetation or land management interventions. Our simulations suggest that an even larger extent of erosion and sediment export is being prevented in the Eastern Cape than in the Western Cape (Figure 9). These patterns likely arise because both rainfall erosivity and slope length-steepness values tend to be much greater in the Eastern Cape catchments.

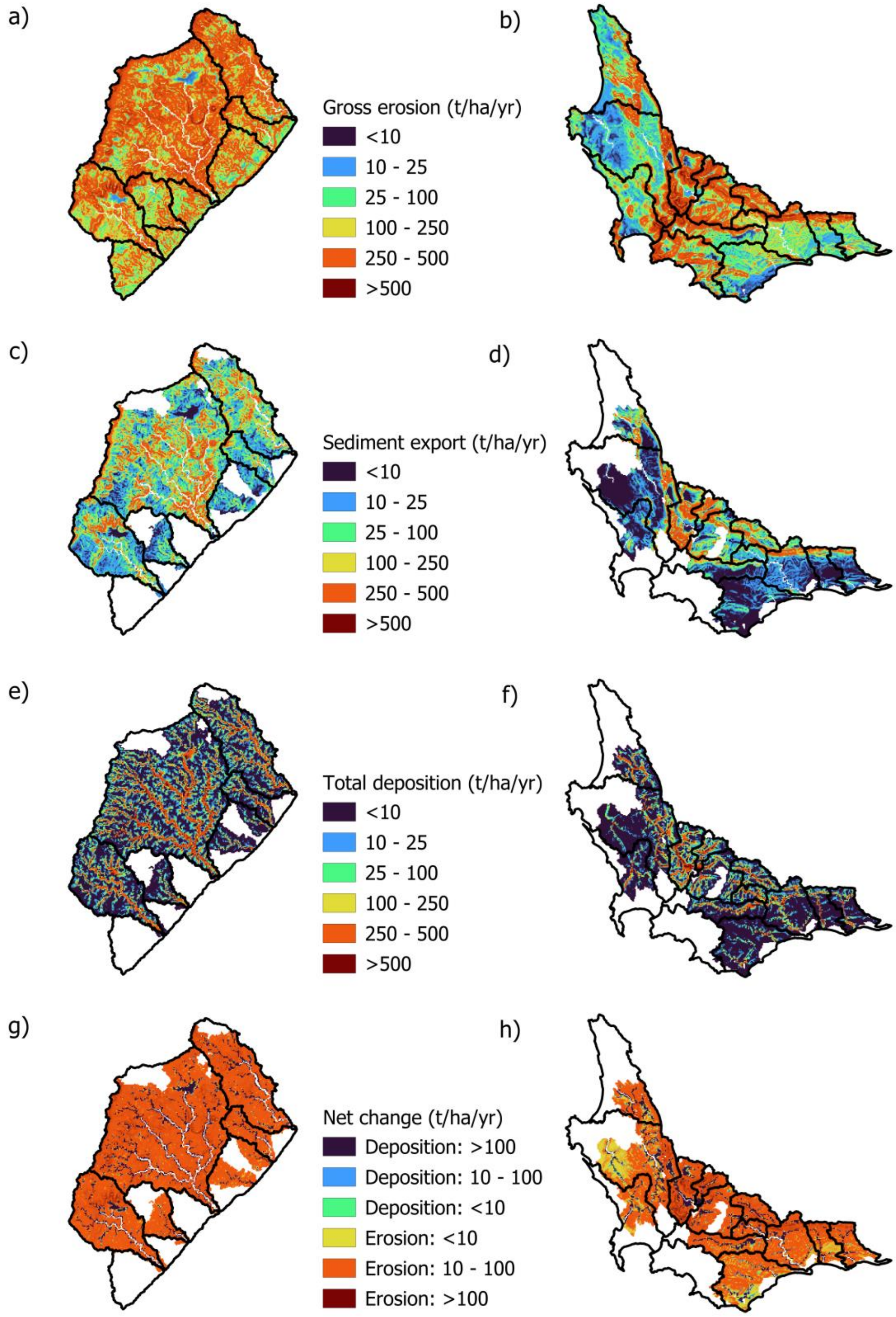


Figure 8: Gross soil erosion rates for the Eastern Cape (a) and Western Cape (b); sediment export to rivers (c) and (d); deposited soil eroded from upslope (e) and (f); net soil loss or gain (g) and (h).

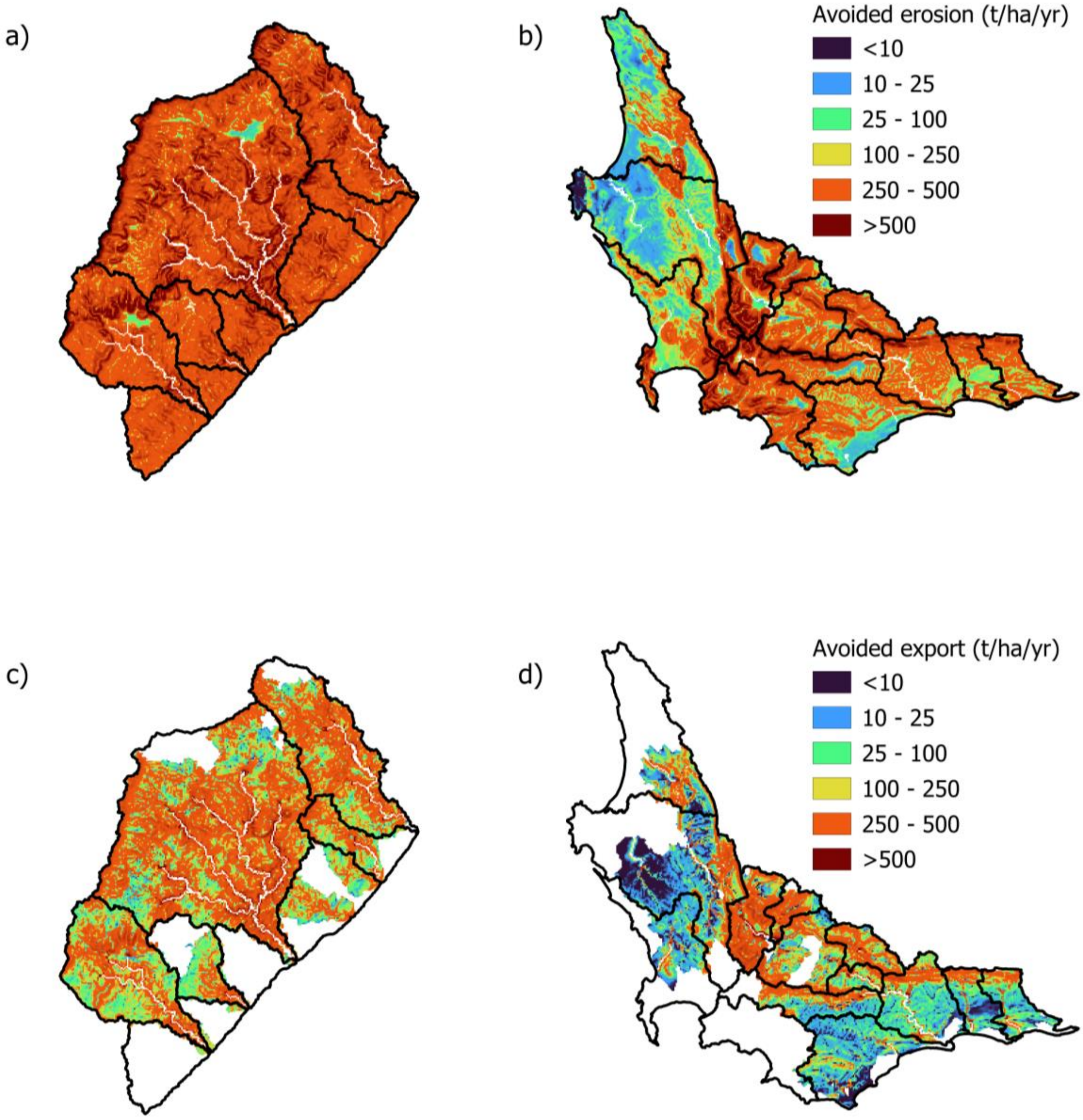


Figure 9: Soil erosion prevented by land cover and management in the Eastern Cape (a) and Western Cape (b), as well as eroded sediments trapped by standing vegetation in these catchments (c) and (d), respectively.

3.3 Patterns of surface runoff & soil loss modelled by *JULES*

The JULES land surface model was run in 2 subregions of South Africa covering the western and eastern cape regions. This was followed by application of SEPP_Workflow producing the outputs in Figure 10 and Figure 11.

Factor	West Region

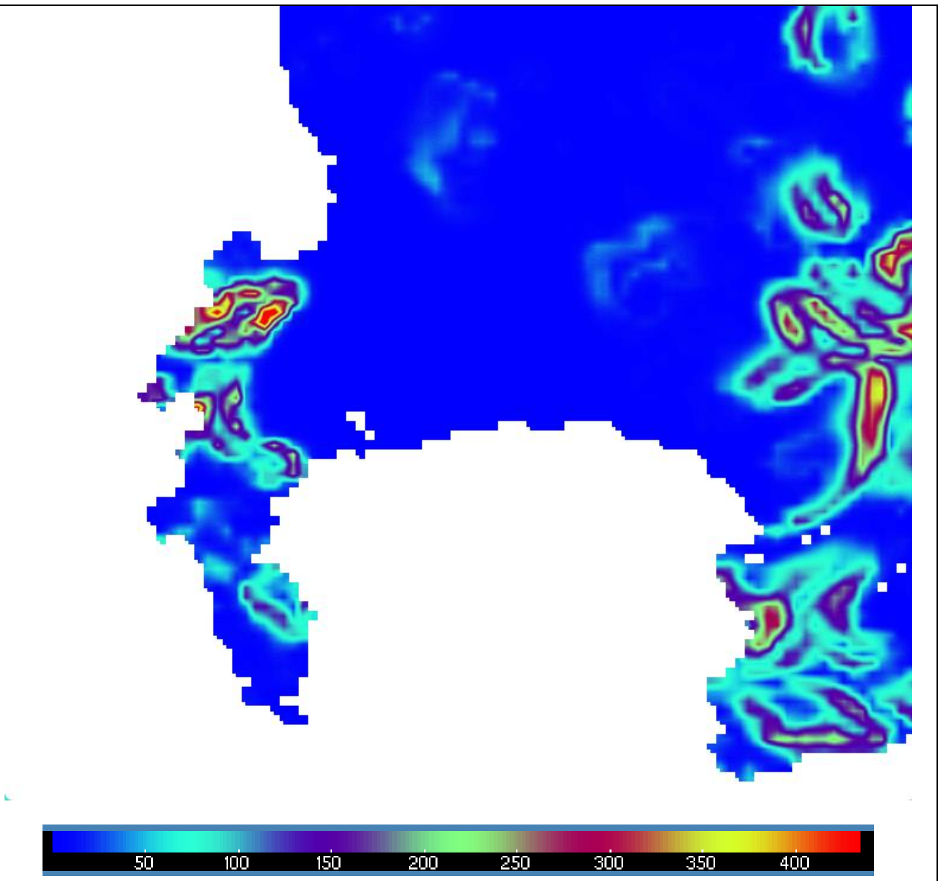
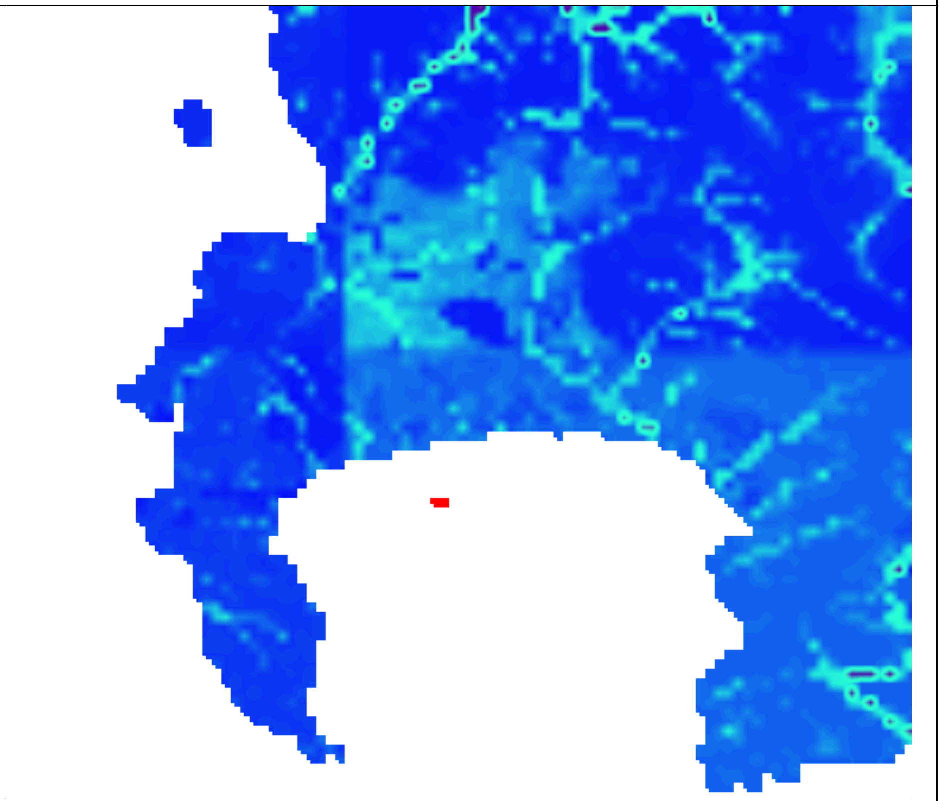
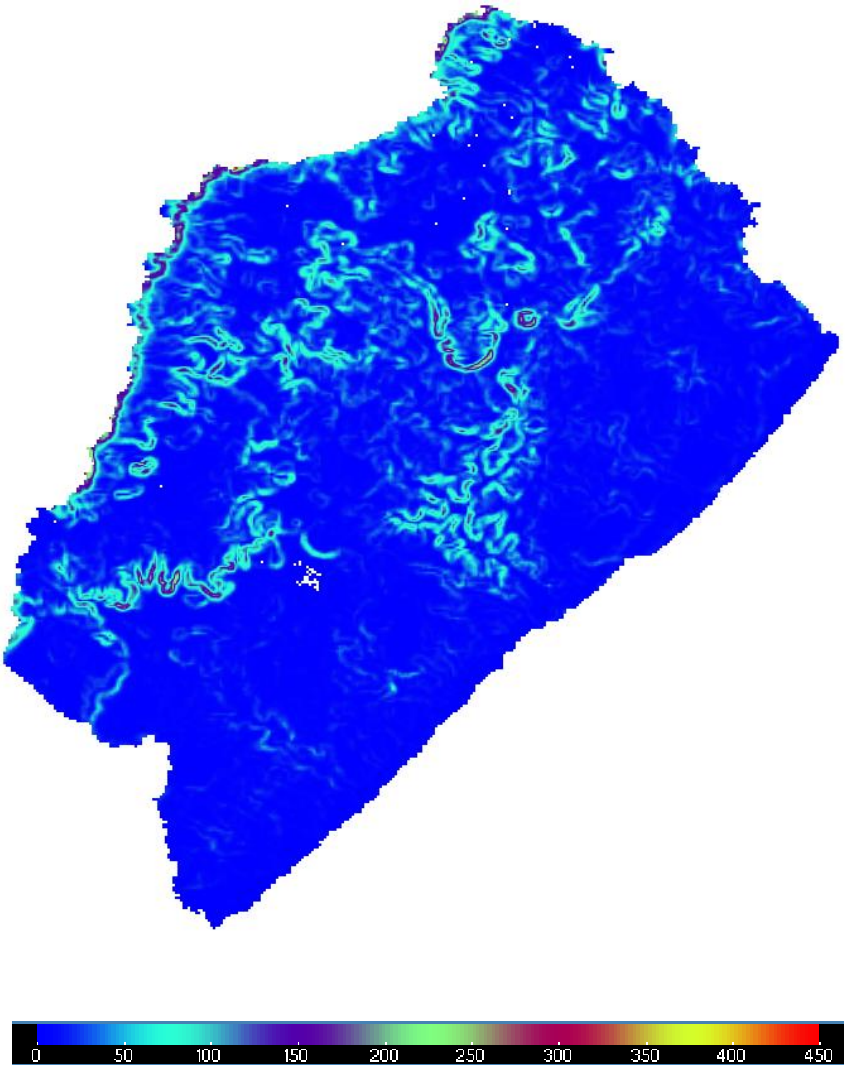
With the factors shown in Fig. X1X, we can calculate *RUSLE* using eqn1, i.e. the erosion rate in t ha^{-1} yr^{-1} (q.v. eqn1)	
Surface runoff in kg m^{-2} per year from *JULES*	

Figure 10: Outputs of *JULES* and SEPP_Workflow for the West region.

Factor	East Region
With the factors shown in Fig. X1X, we can calculate *RUSLE* using eqn1, i.e. the erosion rate in t ha^{-1} yr^{-1} (q.v. eqn1)	

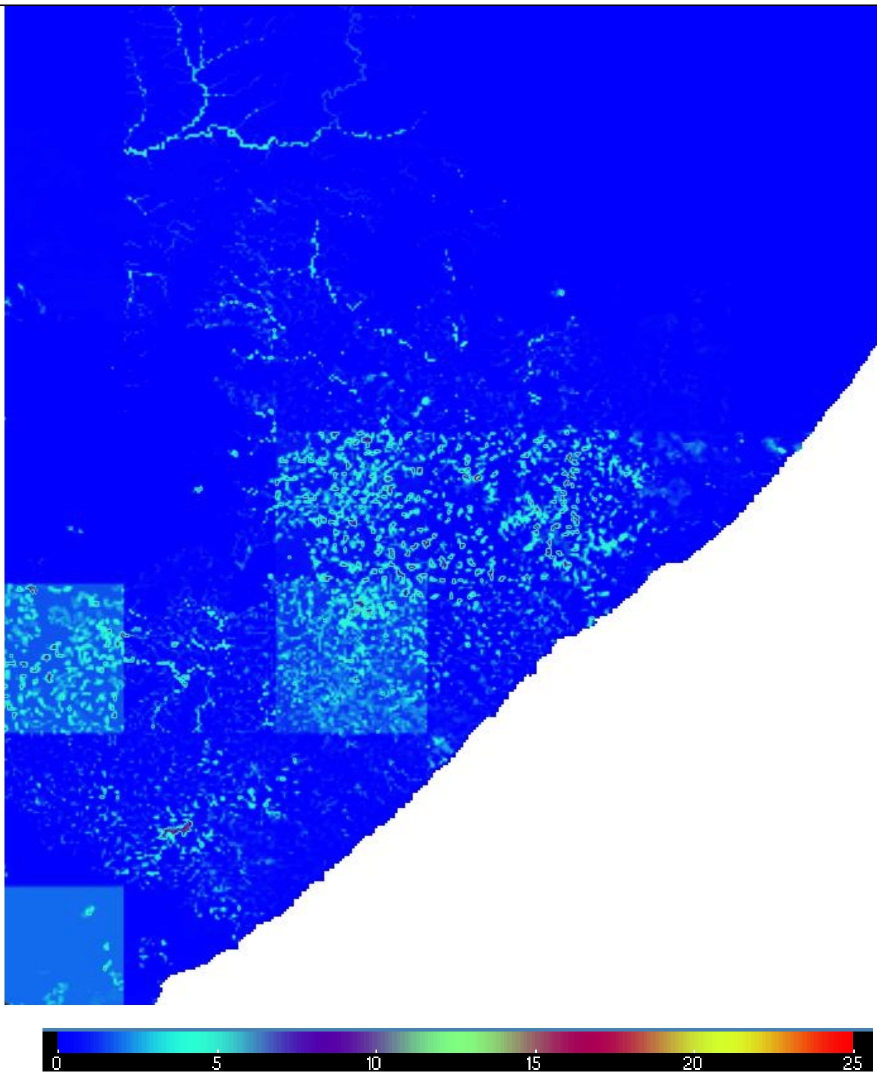
Surface runoff in kg m^{-2} per year from *JULES*	

Figure 11: Outputs of JULES and SEPP_Workflow for the East region.

Firstly, the calculation of *RUSLE* can be shown to be very similar to that from *InVEST* (1st row in both Figure 10 and Figure 11), although the rainfall factor for *JULES* is taken from ISIMIP meteorological data, which is slightly different from the rainfall factor estimated by *InVEST*. By comparing the *RUSLE* maps to the runoff maps in Figure 10 and Figure 11, it is immediately clear that runoff-based erosion is expected to occur at locations spatially distinct from the fine-scale erosion predicted by *RUSLE*.

Because the spatial distribution of surface and total runoff (and therefore any highs of runoff-based surface erosion) is spatially disconnected from the distribution of soil erosion predicted by the *RUSLE* approach, any estimate of total erosion from both sources must be understood as coming from an additive process: simply appending an extra multiplicative factor to the *RUSLE* will not be able to produce a good estimate of both fine- and large-scale erosion in these landscapes.

The next step for the *JULES* modelling part of this project would be to compare these runoff maps for estimates of runoff-based erosion across these regions for the time periods concerned. Although this was beyond the scope of this pilot project, we hope that we will be able to carry out that step in a follow-up project.

3.4 Existing Sub-Saharan African erosion assessments

Our simulations indicate that soil erosion and sediment exports into streams are much greater in the Eastern Cape river catchments than they are in the Western Cape systems. Previous soil erosion estimates based on RUSLE for South Africa (Le Roux, Morgenthal, Malherbe, Pretorius, & Sumner, 2008) appear to reflect this as well; however, the magnitudes of estimated soil losses are considerably lower than our estimates Figure 12. For this pilot project, we have ignored the role of the RUSLE support practices factor entirely due to a lack of spatially explicit data to inform this in our modelling, and there are likely large differences in how we have estimated rainfall erosivity, slope length-steepness and land cover and management factors compared to the method employed by Le Roux et al (soil erodibility should be calculated the same way, and the main difference here will relate to our use of global data from SoilGrids rather than local South African soil information). With regard to sediment exports, observed sediment export rates appear to increase from west to east (Figure 12), though these reflect a wide range of timescales over the 20th and early 21st Century, and in some cases, the timespan was unspecified in the compiled dataset (Vanmaercke, Poesen, Broeckx, & Nyssen, 2014).

SSA is susceptible to a wide variety of soil erosion processes that are not reflected by RUSLE-based models. Two major examples include gullying and wind erosion (Figure 13). Risk maps have been generated for both gullying (De Geeter, Verstraeten, Poesen, Campforts, & Vanmaercke, 2023) and wind erosion (Fenta, et al., 2020) at regional to continental scales for SSA. Areas that show a high risk of gullying and/or wind erosion will be challenging to apply the NbS-TISE framework to until these processes can be incorporated into the assessment accurately. Similarly, NbS-TISE is not currently designed to capture mass movements (e.g. landslides) or sediment exchanges associated with channel-floodplain evolution; these will require more sophisticated erosion and landscape evolution models such as CAESAR-Lisflood (Feeney, Chiverrell, Smith, Hooke, & Cooper, 2020).

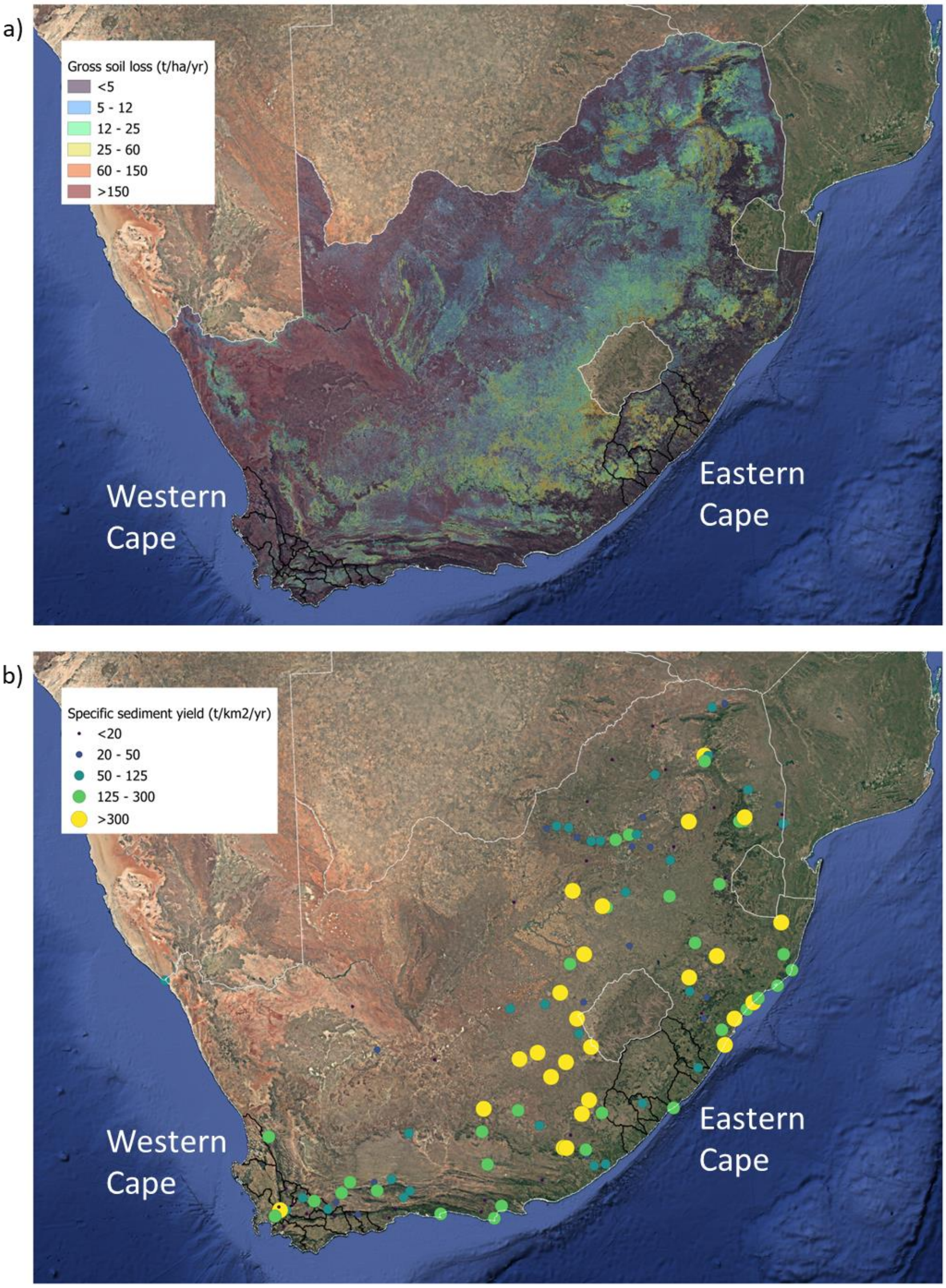


Figure 12: Gross soil erosion rates estimated from RUSLE by Le Roux et al. (2008) (a); Specific sediment yields estimated from long-term observations of South African rivers compiled by Vanmaercke et al. (2014) (b).

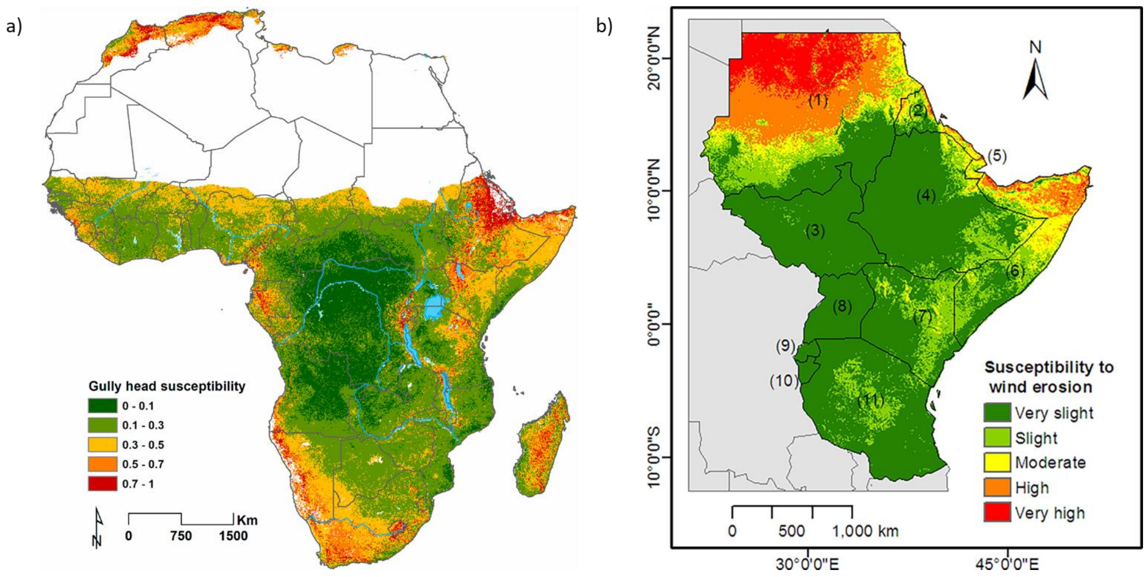


Figure 13: Major forms of soil erosion in SSA not covered by RUSLE-based soil erosion, including gullying (a) and wind erosion (b). The maps come from De Geeter et al. (2023) and Fenta et al. (2020), respectively.

3.5 Implications of the pilot project

This pilot project has delivered a new decision support tool, NbS-TISE, which has been successfully demonstrated as a proof of concept in 2 contrasting South African catchment systems (the Western Cape including the Berg-Breede rivers and the Eastern Cape centred around the Umzumvibu system). The 2 primary products of this work include:

(1) Successful integration of soil erosion modelling capabilities (based on the RUSLE model) into a process-based land surface model (JULES).

(2) Generated new information products relevant to soil erosion in Sub-Saharan Africa, including model estimates of sediment flux into waterways, surface runoff paths, and prevented degradation as a result of land cover and management.

Through further development and application (see Section 4), this new NbS-TISE tool should provide valuable decision-support information to directly inform on 2 aspects of net-zero-plus (maintaining a healthy and productive environment; adapting and building resilience to a changing climate).

The TES-NbS project team at ACDI (University of Cape Town) have a strong desire to expand beyond looking at water and carbon balances (Holden, et al., 2024). We wish to work with this team long-term in exploring wider impacts of NbS in Southern Africa, including the trade-offs relating to biodiversity, food and water. This is precisely in line with NC-International aims. We will also invite and encourage ACDI scientists to apply for the new NC-International Visiting Scientists programme to visit UKCEH in 2025.

This project also ties in directly with current long-term international initiatives (Figure 1):

- The **UN Environment Programme (UNEP)**, who are working “through agroforestry, reforestation and afforestation programmes, particularly in tropical regions, to reduce land degradation while soaking up carbon” (https://www.unep.org/unga/our-position/unep-and-nature-based-solutions).
- The **International Union for the Conservation of Nature (IUCN)**, which is looking specifically at mitigation of the effects of climate change through NbS (UNEP 2021).
- The **Global Centre on Biodiversity for Climate (GCBC)** has a strong focus on the conservation and sustainable use of biodiversity in ODA-eligible countries and would be very interested in a new tool to estimate the impacts of NbS on soil degradation.

This project can strengthen the position of UK science in international NZ+ research by leading on projects with these partners in the future. These collaborations either already exist (the ACDI) or may be built on the basis of the use of a tool such as *NbS-TISE*. This would put UKCEH in pole position for future projects with these partners not just in Sub-Saharan Africa, but anywhere in the world.

4. Potential future directions

4.1 Application beyond the 2 pilot study catchments

The *NbS-TISE* tool is innovative, and it is based on elements that already exist, allowing it to be assembled relatively quickly. Now the tool has been tested in the pilot study catchments, the next step will be to work with other WPs in NC-International and international partners to apply this tool elsewhere.

Firstly, we would validate the use of this tool across a wider set of catchments in Sub-Saharan Africa, linking with ongoing work in East Africa (WP2C) as well as West Africa (WP3C). We would intend this to lead quickly to a future paper summarising the application of RUSLE combined with JULES across the SSA domain. This will also open an opportunity to collaborate with the UK Met Office and formalise any code modifications to JULES that have been suggested through our work.

Secondly, we envisage applying this tool also in SE Asia (WP2B), working with the partnership networks in Malaysia and Indonesia currently being formed through the NC-International project. The greater extent of rainforest biomes, and the steep slopes of many areas in SE Asia will present further challenges (e.g. Borneo, where flash flooding on the steep terrain is a much greater problem). Additionally, it would be useful to investigate the vulnerability of oil palm plantations to soil erosion and flash flooding, which is a known issue across SE Asia that the NbS-TISE tool would be ideal to address.

Finally, we would like to use existing links with colleagues at CGIAR to investigate the application of this tool even more widely.

4.2 Integrating more sophisticated erosion routines

RUSLE is arguably the simplest and commonest form of soil erosion estimation available. While the incorporation of *RUSLE* into *JULES* should open several opportunities for large-scale and scenario-based soil erosion modelling, there are many other research questions that will remain out of reach without significant further modification beyond what has been achieved in this pilot project. *RUSLE* is designed to only designed to simulate soil erosion rates via rills and sheetwash; gullying, landslides and sediment exchange between river channels and floodplains are not considered. Additionally, annual soil erosion estimates can obscure significant detail, particularly high magnitude, but short-lived (on the order of hours to days) soil erosion events. For example, if annual rainfall declines over time, but more events with more extreme rainfall increase in magnitude, *RUSLE*-based models will likely indicate a decline in soil loss rate over time, whereas daily time-stepped models based on *MUSLE* (the Modified USLE) or *MMF* (Morgan-Morgan-Finney model) may indicate the opposite (Eekhout & De Vente, 2019).

Daily time-stepped model routines would allow soil erosion in response to extreme weather events to be captured much more easily and these routines underpin common catchment model such as the *SWAT* (Soil and Water Assessment Tool) model, which is based on *MUSLE*. A natural next step for further erosion model integration into *JULES* would be to incorporate *MUSLE* (Williams & Berndt, 1977), which is structured like *RUSLE* as follows:

$$S_y = a(Qq_p)^b KLSCP$$

Where, in place of rainfall erosivity (R), Q is the volume of runoff (m^3), q_p is the peak flow rate ($m^3\ s^{-1}$), K, LS, C and P are the USLE soil erodibility, slope length-steepness, land cover management and support practices factors (described earlier in Section 2), with a and b being location coefficients that are usually calibrated for the region of interest. S_y is the sediment yield (tons). Application of *MUSLE*, particularly within *SWAT*, has been very broad hitherto (Gassman, Sadeghi, & Srinivasan, 2014). *MUSLE*’s application also includes simulation of sediment loads following wildfire as part of a post-fire management decision support tool (De Girolamo, et al., 2022), which could be of particular interest for future NC-International work in both SSA and SE Asia (as well as other regions worldwide).

In this pilot study, we were not able to compare the *JULES*-generated runoff maps against independent estimates of runoff-based soil erosion across Sub-Saharan Africa. However, in a follow-up project it would be relatively straight-forward to do so and this would be a way of calibrating the extra parameters in the *MUSLE* equation and using them to modify the *RUSLE* approach of the *NbS-TISE* tool. It is very reasonable to assume that this would lead to a more generally applicable method for estimating soil erosion rates in real time across the whole Sub-Saharan African region.

There are several other daily time-stepped erosion models available including the *MMF*, *DHSVM*, *HSPF*, *INCA*, *WEPP* and *SHETRAN* models. In the last few years, the *SPHY* (Spatial Processes in Hydrology) model was updated to incorporate soil erosion processes represented by the *MMF* model to form *SPHY-MMF* (Eekhout, Terink, & De Vente, 2018). *MMF* possesses key advantages over USLE-based models in that it represents both soil detachment via rainfall impact as well as erosion via surface runoff, deposition along flow paths, sediment yield by routing detached sediment, and hydraulic roughness (Gauckler-Manning’s n) from dynamic vegetation development. Whilst it would likely be significantly more complex to incorporate *MMF* into *JULES*, the current source code (written in Python) for *SPHY-MMF* (which is openly available on GitHub) includes code for several other daily soil erosion models (Eekhout, et al., 2021) as well as a recently introduced channel erosion model which may be useful for gully erosion (Eekhout, Jodar-Abellan, Carrillo-Lopez, Boix-Fayos, & De Vente, 2024).

Ultimately, there will be a limit to the full detail of soil erosion and sediment redistribution across the landscape that can be captured in further updates to the JULES model code. For instance, the CAESAR-Lisflood model perhaps represents the most complex model of sediment redistribution available. CAESAR-Lisflood combines a landscape evolution model (Cellular Automata Evolutionary Slope And River) with a hydrodynamic model (Lisflood) to simulate rainfall-runoff, erosion and topographic changes over space and time (Coulthard, et al., 2013), and is applicable across virtually all forms of erosion process at river catchment and valley-reach scales. Critically, the model is “morphodynamic”; that is, it updates topography across the region of interest at the start of each time step, which captures the fact that landscape morphology has a direct influence on subsequent patterns of erosion, sediment flux and deposition. Whilst this yields the most accurate model of sediment redistribution processes available, there comes a trade-off in the form of lengthy simulation times, limiting the space and timescales that one could apply the model to. Given that JULES is commonly applied at large regional to global scales, it is highly unlikely that one would look to incorporate a fully morphodynamic erosion and landscape evolution model into JULES.

5. Appendix: The SEPP_Workflow for *JULES*

A bespoke workflow was created for assembling the data layers required for estimating soil erosion from JULES outputs as a post-processing step. This consists of the following:

```
#Calculate a spatially-explicit estimate of soil erosion using the (inputs and) outputs of a JULES run:

#On JASMIN:
module load jasmin-sci
cd ~/ancils/RUSLE

#Cape Town small example:
export text1=Test
export LONMIN=18.2
export LONMAX=19.0
export LATMIN=-34.4
export LATMAX=-33.7

#SoDurbanW
export text1=W
#x_bounds=17.8,22.1
#y_bounds=-34.8,-31.6
export LONMIN=17.8
export LONMAX=22.1
export LATMIN=-34.8
export LATMAX=-31.6

#SoDurbanE
export text1=E
#x_bounds=27.6,30.6
#y_bounds=-32.9,-29.6
export LONMIN=27.6
export LONMAX=30.6
export LATMIN=-32.9
export LATMAX=-29.6


export outfile="SoDurban${text1}_1km_RUSLE.nc"


#Rainfall erosivity (taken from 2002 data):
ncea -Oh -F -d lat,$LATMIN,$LATMAX -d lon,$LONMIN,$LONMAX
/gws/nopw/j04/tesnbsclim/SoDurban/isimip3b_SoDurban_1km_rainAdjust_2002.nc $outfile
```

```
ncap2 -Oh -s "rain=rainAdjust*86400" $outfile $outfile
ncatted -Oh -a units,rain,o,c,"mm per day" $outfile
ncatted -Oh -a long_name,rain,d,c, $outfile
ncwa -Oh -a time $outfile $outfile
ncap2 -Oh -s "rain=rain*365.25" $outfile $outfile
ncatted -Oh -a units,rain,o,c,"mm per year" $outfile
ncks -Oh -x -v rainAdjust $outfile $outfile
ncks -Oh -x -v time $outfile $outfile
#At this point I have rain in MAR mm/yr as "rain" in $outfile

#Moore (1979) equation for rainfall erosivity factor is R_annual=17.02*(0.029*(3.96*MAR+3122)-26)
ncap2 -Oh -s "Rfactor=17.02*(0.029*(3.96*rain+3122)-26)" $outfile $outfile
ncatted -Oh -a units,Rfactor,o,c,"MJ mm ha-1 h-1 yr-1" $outfile
ncatted -Oh -a long_name,Rfactor,o,c,"Rainfall erosivity factor (annual)" $outfile
ncatted -Oh -a cell_methods,Rfactor,d,c, $outfile

#If I want to pull in any data from HSAncil, I can (here's an example pulling in some ksat numbers):
ncea -Oh -F -d lat,$LATMIN,$LATMAX -d lon,$LONMIN,$LONMAX ~/ancils/HSAncil_SoDurban_1km_OPP.nc HSAncil_data.nc
ncks -Ah -v ksat_Cosby HSAncil_data.nc $outfile
rm HSAncil_data.nc

#K factor requires soil texture numbers that aren't present in HSAncils (although the ksat is there so I could use that).
module load jasr
gdal_translate -of netCDF RUSLE_K_SoDurban.tif RUSLE_K_SoDurban.nc
ncrename -Oh -v Band1,Kfactor RUSLE_K_SoDurban.nc RUSLE_K_SoDurban.nc
ncatted -Oh -a units,Kfactor,o,c,"t ha h ha-1 MJ-1 mm-1" RUSLE_K_SoDurban.nc
ncatted -Oh -a long_name,Kfactor,o,c,"Soil erodibility factor (Wischmeier & Smith 1978)" RUSLE_K_SoDurban.nc
ncea -Oh -F -d lat,$LATMIN,$LATMAX -d lon,$LONMIN,$LONMAX RUSLE_K_SoDurban.nc tmp.nc
ncks -Ah -v Kfactor tmp.nc $outfile
rm RUSLE_K_SoDurban.nc tmp.nc

#LS factor requires slope and some other topographical numbers that I could get/estimate from HSAncil.
gdal_translate -of netCDF RUSLE_LS_SoDurban.tif RUSLE_LS_SoDurban.nc
ncrename -Oh -v Band1,LSfactor RUSLE_LS_SoDurban.nc RUSLE_LS_SoDurban.nc
ncatted -Oh -a units,LSfactor,o,c,"(dimensionless)" RUSLE_LS_SoDurban.nc
ncatted -Oh -a long_name,LSfactor,o,c,"Combined slope and length steepness factor (Desmet & Govers 1996)"
RUSLE_LS_SoDurban.nc
ncea -Oh -F -d lat,$LATMIN,$LATMAX -d lon,$LONMIN,$LONMAX RUSLE_LS_SoDurban.nc tmp.nc
ncks -Ah -v LSfactor tmp.nc $outfile
rm RUSLE_LS_SoDurban.nc tmp.nc

#C factor requires crop (or NDVI) information, so I could get/estimate from HSAncil.
gdal_translate -of netCDF RUSLE_C_SoDurban.tif RUSLE_C_SoDurban.nc
ncrename -Oh -v Band1,Cfactor RUSLE_C_SoDurban.nc RUSLE_C_SoDurban.nc
ncatted -Oh -a units,Cfactor,o,c,"(dimensionless; 0-1)" RUSLE_C_SoDurban.nc
ncatted -Oh -a long_name,Cfactor,o,c,"Land cover and management factor (Borrelli et al. 2017)" RUSLE_C_SoDurban.nc
ncea -Oh -F -d lat,$LATMIN,$LATMAX -d lon,$LONMIN,$LONMAX RUSLE_C_SoDurban.nc tmp.nc
ncks -Ah -v Cfactor tmp.nc $outfile
rm RUSLE_C_SoDurban.nc tmp.nc
```

```
#P factor we are currently assuming to be =1
ncap2 -Oh -s "Pfactor=Kfactor^0.0" $outfile $outfile
ncatted -Oh -a units,Pfactor,o,c,"(dimensionless; 0-1)" $outfile
ncatted -Oh -a long_name,Pfactor,o,c,"Agricultural support practices factor" $outfile

#Now combine all together:
ncap2 -Oh -s "RUSLE=Rfactor*Kfactor*LSfactor*Cfactor*Pfactor" $outfile $outfile
ncatted -Oh -a units,RUSLE,o,c,"t ha-1 yr-1" $outfile
ncatted -Oh -a long_name,RUSLE,o,c,"RUSLE-based Erosion rate (estimated)" $outfile

#None of this, of course, includes any estimate of runoff erosion (not covered by RUSLE), which I would be able to estimate
from the runoff output from JULES.
export zap="$SCR/TEST7.7/SoDurban${text1}_RFMh.Daily.nc"
ncks -Ah -v runoff $zap $outfile
ncwa -Oh -a time $outfile $outfile
ncap2 -Oh -s "runoff=runoff*86400*365.25" $outfile $outfile
ncatted -Oh -a units,runoff,o,c,"kg/m2 per year" $outfile
ncks -Oh -x -v time $outfile $outfile
ncatted -Oh -a coordinates,runoff,d,c, $outfile
ncatted -Oh -a cell_methods,runoff,d,c, $outfile

#For the next command you may need to remove time_bounds first using ncks -x -v time_bounds $outfile $outfile
ncks -Oh -x -v time_bounds $outfile $outfile

ncks -Ah -v surf_roff $zap $outfile
ncwa -Oh -a time $outfile $outfile
ncap2 -Oh -s "surf_roff=surf_roff*86400*365.25" $outfile $outfile
ncatted -Oh -a units,surf_roff,o,c,"kg/m2 per year" $outfile
ncks -Oh -x -v time $outfile $outfile
ncatted -Oh -a coordinates,surf_roff,d,c, $outfile
ncatted -Oh -a cell_methods,surf_roff,d,c, $outfile
ncks -Oh -x -v time_bounds $outfile $outfile

ncks -Oh -3 $outfile $outfile
ncks -Oh -4 $outfile $outfile

ncview -minmax all $outfile &
```

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