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Assessing soil erosion on post-mining and analogous natural landscapes with SIBERIA and SSSPAM models

I.P. Senanayake [a] and **G.R. Hancock** [a]

[a] *School of Engineering, The University of Newcastle, Callaghan, NSW 2308, Australia*
Email: indishe.senanayake@newcastle.edu.au, greg.hancock@newcastle.edu.au

Abstract: Long-term erosional stability is a key concern for post-mining landforms in Australia, which are typically constructed using waste and overburden materials. Assessing erosion and gully development on these landforms, ranging from short time scales to millennia, is critical for sustainable rehabilitation. A practical and scalable approach is to use landform evolution models (LEMs), which simulate terrain change over time and are increasingly applied at both the design and operational stages of mine closure planning.

With recent advancements in remote sensing technologies such as LiDAR and photogrammetry, high-resolution digital elevation models (DEMs) with sub-metre accuracy are now available and serve as key inputs to LEMs. As the goal is for constructed post-mining landforms to blend seamlessly with surrounding natural landscapes over time, it becomes essential to compare their erosional performance. Such comparisons, particularly between constructed and nearby natural analogue catchments, are limited in southeastern Australia, where several large-scale coal mines are in operation.

This study presents a comparison of long-term erosional behaviour between a constructed mine rehabilitation plot and a nearby natural grazing catchment with similar topography. Two LEMs were used: (i) SIBERIA, a widely applied first-generation landform model, and (ii) SSSPAM (State-Space Soil Production and Assessment Model), a recently developed LEM capable of simulating coupled soilscape and landform processes. The models were parameterised using site-specific inputs, including rainfall, particle size distribution, and vegetation characteristics (representing dense grass cover). A high-resolution LiDAR-derived DEM (resampled to 1 m) was used as the primary terrain input. Simulations were run for 100 years with annual time steps. Erosion rates were estimated by comparing the simulated DEMs after 100 years to the initial terrain surface.

The SIBERIA and SSSPAM simulations produced average annual erosion rates of 1.07 t ha^{-1} yr^{-1} and 0.35 t ha^{-1} yr^{-1} for the analogue site, and 2.69 t ha^{-1} yr^{-1} and 1.29 t ha^{-1} yr^{-1} for the mine rehabilitation plot. Results showed that both landscapes experienced low erosion rates, suggesting that both landforms are erosionally stable. Field observations and analysis of multitemporal LiDAR datasets from the past five years support these findings, showing no significant gully expansion over time.

The findings highlight that well-designed post-mining landforms can achieve long-term erosional stability comparable to natural landscapes. With the increasing availability of high-resolution terrain and vegetation data from remote sensing technologies and the integration of GIS and advanced LEMs, it is now possible to assess and predict landscape change with greater accuracy. LEMs such as SIBERIA and SSSPAM are powerful tools not only for mine rehabilitation but also for broader applications in sustainable land management, agriculture, restoration planning, and erosion risk assessment under changing environmental conditions.

Keywords: *Landform evolution modelling, post-mining landforms, SIBERIA, soil erosion, SSSPAM*

1. INTRODUCTION

In the Australian mining industry, once valuable minerals are extracted, the remaining waste and overburden material is typically stockpiled at designated sites and capped with topsoil to support vegetation growth. These post-mining landforms are then rehabilitated by establishing native or introduced pasture and vegetation species. Over time, the aim is for these engineered landforms to integrate with the surrounding natural landscape. However, due to the physical and chemical properties of the waste materials, these landforms are often highly susceptible to erosion. As a result, they can experience significant soil loss, with the formation of rills and gullies, leading to environmental issues such as sedimentation and reduced landform stability (Lowry et al. 2019; Tibbett 2024). Therefore, assessing erosion rates and gully formation is a critical concern for ensuring the long-term sustainability of post-mining landscapes. It is essential to evaluate their long-term erosional stability during both the design and operational phases.

While field measurements and observations offer valuable insights into erosion processes, they are limited in their ability to capture long-term trends and broader landscape evolution. First-generation erosion models such as USLE, RUSLE, and WEPP, originally developed for agricultural catchments, can estimate hillslope erosion but have key limitations (Willgoose 2018; Tiwari et al. 2000). These models typically predict erosion only (not deposition), and they are not designed to represent dynamically evolving landscapes.

In contrast, process-based Landform Evolution Models (LEMs), which operate on gridded or triangulated regular network (TIN)-based representations of topography using Digital Elevation Models (DEMs), can simulate both erosion and deposition over time (Hancock et al. 2025). LEMs such as SIBERIA (Willgoose et al. 1991a, 1991b, 1991c), CAESAR-Lisflood (Coulthard et al. 2013), and SSSPAM (Welivitiya et al. 2019) have been applied in the mining industry to model landscape change and provide useful insights into long-term erosion and landform evolution.

However, erosion on hillslopes can result from both fluvial and diffusive processes, and it is important to assess whether engineered post-mining landforms behave similarly to nearby natural landscapes. Comparing erosion patterns between rehabilitated and natural catchments can help assess the sustainability of the former. In this context, the present study compares the erosion rates and behaviour of a natural landscape, selected as an analogue to a post-mining landform, with those of a nearby rehabilitated mining site.

2. STUDY AREA

The study area comprises two sites: a rehabilitated post-mining landform and a natural landscape that serves as an analogue to it. Both sites are located in southeastern Australia, approximately 5 km apart, and share similar meteorological characteristics. The region receives an average annual rainfall of around 611 mm, and the mean annual temperature is approximately 24 °C, with monthly temperatures ranging from 16.8 °C in July to 31.8 °C in January, based on data from the nearest Bureau of Meteorology stations (www.bom.gov.au).

The rehabilitated post-mining landform (Figure 1a) lies adjacent to a coal mine. The mine waste piles are capped with stripped topsoil, and vegetation has been established as part of the rehabilitation process, primarily consisting of a mixture of native and imported pasture species. A 60 m × 30 m hillslope within this post-mining landform has been designated as an observation plot (demarcated in yellow in Figure 1a). An area of 84 m × 103 m, which includes this observation plot, was used as the first area of interest (AOI) and will hereafter be referred to as the rehab area.

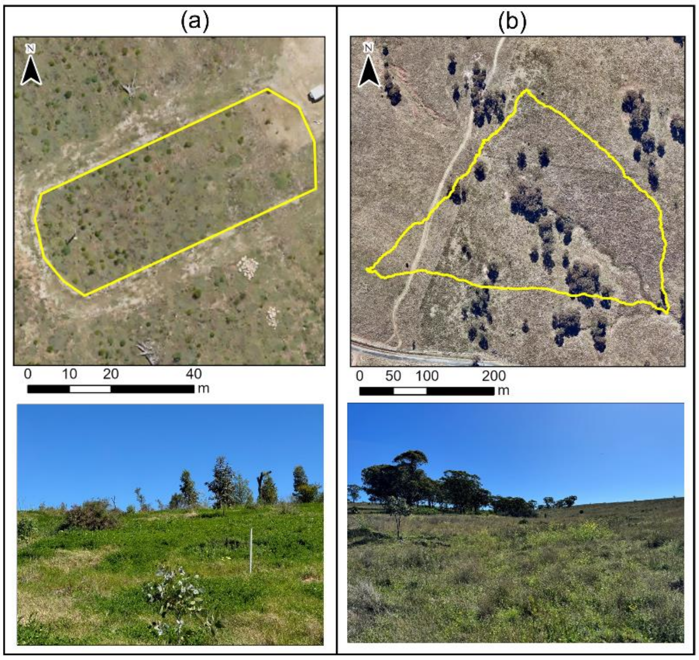

Figure 1 The study areas used for this study (a) mine-rehabilitation plot, and (b) the analogue catchment. The boundaries of the observation plot and the catchment are marked in yellow.

The analogue site, selected as the second AOI in this study (Figure 1b) to enable comparison of erosion rates, features gently rolling hills and undulating slopes. Although it has been used for cattle grazing, it has remained undisturbed for at least the past 30 years. The catchment covers an area of 77,766 m² and contains a large gully along the main drainage line. The slope from the highest point to the outlet is approximately 9°, closely matching the rehab area's slope of 9.8°. Over the central part of the catchment, the slope from the catchment boundary to the main channel at the centre is approximately 8°. A farm dam located at the catchment outlet functions both as a water source for cattle and as a sediment retention basin. The rehab area demonstrates denser grass cover compared to the analogue catchment. However, both study sites are predominantly covered with grass, according to historic satellite images.

3. DATA AND METHODS

3.1. LEM description

A brief description of the SIBERIA and SSSPAM models, including their governing equations and underlying processes, is provided in this section.

3.1.1. SIBERIA

SIBERIA is a first-generation LEM, which simulates both fluvial and diffusive soil transport using the combined sediment transport rate:

$$q_s = q_{sf} + Q_{sd} \tag{1}$$

where q_s denotes the total sediment transport rate per unit width (m³ s⁻¹ m⁻¹), with q_{sf} and q_{sd} representing the contributions from fluvial and diffusive processes, respectively. The fluvial transport component is expressed as:

$$q_{sf} = \beta_1 Q^{m_1} S^{n_1} \tag{2}$$

and the diffusive component is represented as:

$$q_{sd} = DS \tag{3}$$

In these equations, Q is the unit discharge ($m^3\ s^{-1}\ m^{-1}$), S is the local slope ($m\ m^{-1}$), and D is the soil diffusivity ($m^3\ s^{-1}\ m^{-1}$). The coefficients β_1, m_1, and n_1 are site-specific calibration parameters.

To estimate runoff, the model uses a sub-grid scaling approach, relating discharge to the upslope contributing area AAA through the relationship:

$$Q = \beta_3 A^{m_3} \tag{4}$$

Here, β_3 is a runoff coefficient and m_3 is an area exponent, both of which require calibration for specific terrain conditions. Flow directions are computed using the D8 algorithm. Further methodological and theoretical details can be found in Willgoose et al. (1991a), Willgoose et al. (1991b), Willgoose et al. (1991c) and Willgoose (2005).

3.1.2. SSSPAM

SSSPAM (Welivitiya et al. 2019; Welivitiya et al. 2021; Welivitiya et al. 2025a; Welivitiya et al. 2025b) is a landform evolution model coupled with a pedogenesis component. It simulates processes such as fluvial and diffusive erosion, sediment deposition, soil weathering, and surface armouring. The model tracks the evolution of particle size distribution (PSD) across layered soil profiles at each pixel and can also estimate the PSD of transported sediments. Unlike SIBERIA (years) and CAESAR-Lisflood (hours), which run on fixed time steps, SSSPAM operates flexibly from days to years. This enables simulation of both long-term evolution (e.g., with annual rainfall) and short-term storm-driven erosion. Key inputs include DEMs, rainfall, and surface PSD data (Welivitiya and Hancock 2023).

Fluvial erosion is calculated using:

$$E_f = Keq^{\alpha_1}S^{\alpha_2}T \tag{5}$$

where e is erodibility, q is unit discharge (m³/s/m), S is slope, T is the time step, and α_1, α_2 are empirical exponents. The potential volume of erosion is limited by the surface grading and the Threshold Entrainment Diameter (TED), calculated as:

$$TED = C_{th}(nq)^{0.6}S^{0.7} \tag{6}$$

with C_{th} as a calibrated parameter and n the Manning roughness coefficient.

Discharge per unit width is estimated as:

$$q = \frac{rA}{w_f} \tag{7}$$

where r is runoff rate (m/s), A is contributing area (m²), and w_f is flow width (typically the DEM resolution).

Selective erosion is governed by an erosion transition matrix:

$$A_{kk} = \begin{cases} \frac{a}{d_k^m} gk^v & for\ k < M \\ 0 & for\ k \geq M \end{cases} \tag{8}$$

where d_k is the mean particle diameter for class k, gk is the grading fraction, m and v are exponents, and a is a scaling parameter. M denotes the class corresponding to TED.

Diffusive erosion is given by:

$$E_d = \begin{matrix} DS & for\ S - \frac{DS}{X^3} < S_{th} \\ (S - S_{th})X^2 & for\ S - \frac{DS}{X^3} \geq S_{th} \end{matrix} \ . \tag{9}$$

with D as diffusivity (m³/s/m), S the slope, and S_{th} the threshold slope. Diffusion is not size-selective, so particle size distribution of eroded and remaining material remains the same.

SSSPAM models deposition using sediment flux and a transition matrix based on critical immersion depth, which determines whether particles of a certain size settle out. This accounts for selective deposition: larger particles settle more readily, while smaller ones remain suspended longer. The deposition formulation is detailed in Welivitiya et al. (2019).

3.2. LEM parameterisation

The accuracy of LEM simulations is highly dependent on site-specific parameterisation, including vegetation, hydrology, meteorological factors, and soil characteristics (Batista et al. 2019). A brief overview of the parameterisation methods used for SIBERIA and SSSPAM is provided in this section.

3.2.1. SIBERIA parameterisation

SIBERIA requires parameters for both sediment transport and runoff equations. Ideally, this is done using field data on hydrology and sediment yield (e.g., Evans et al. 1999; Hancock et al. 2000), but such data are often unavailable. In data-limited cases, parameters can be estimated using terrain characteristics, such as slope–area relationships derived from DEMs.

In this study, calibration used the relationship between upslope contributing area and slope from a 1 m DEM, following approaches by Willgoose et al. (1991c) and Stahler (1952). For catchments near geomorphic equilibrium, this relationship forms a power-law where the slope of the linear log-log fit (α) is:

$$\alpha = (m_3 m_1 - 1)/n_1 \tag{10}$$

Using α = 0.39, n_1 = 2, and m_3 = 1, the fluvial exponent m_1 was calculated as 1.6, consistent with erosion dominated by sheet wash and gullying (Kirkby 1971).

The sediment transport coefficient β_1 (from Eq. 2) is analogous to the RUSLE K factor. Based on core soil texture (30% sand, 25% silt, 45% clay), the K value of the analogue catchment was 0.022 (Hazelton & Murphy, 2007). A cover factor (C) of 0.02 was applied to parameterise the model for dense grass cover, i.e., $\beta_1 = K \times C$ (see Table 1). The rehab area was parameterised using a similar approach.

3.2.2. SSSPAM parameterisation

SSSPAM was parameterised using flume experiments, as described in Welivitiya and Hancock (2022). The setup involved a 3 m × 0.3 m × 0.4 m flume with an adjustable slope (0–35%). Water was supplied via a constant-head tank (0–20 L/min) and uniformly applied across the flume. Loosely placed soil was levelled and compacted over seven days through daily light wetting. Erosion trials began at the lowest slope and flow rate, gradually increasing to simulate different runoff scenarios. Runoff and sediment were collected at each stage, with measurements taken at 5%, 20%, and 35% slopes. These data informed parameter calibration using a Monte Carlo approach. Detailed description on SSSPAM parameterisation is presented in Welivitiya and Hancock (2022). Parameter values used in this study for the analogue catchment and the rehab area, for both SIBERIA and SSSPAM, are listed in Table 1. Only the dense cover scenario was considered.

Table 1 SIBERIA and SSSPAM parameters used in this study.

LEM	AOI	Parameter		
		m_1	n_1	$\beta 1$
SIBERIA	Rehab area	1.5	2.0	0.00002 (dense grass cover)
	Analogue catchment	1.6	2.0	0.0004 (dense grass cover)
		α_1	α_2	e
SSSPAM	Rehab area	1.149	2.5	0.01135/y (dense grass cover)
	Analogue catchment	1.334	2.883	0.3902/y (dense grass cover)

3.3. Model setup and simulations

Both LEMs were run for 100 years at annual time steps using the parameters listed in Table 1. High-resolution airborne LiDAR-derived DEMs, resampled to a 1 m grid, were used as the primary input. Average annual rainfall and soil grading data were also provided as inputs to SSSPAM. The simulated DEM at year 100 was compared to the initial DEM to calculate elevation changes and estimate soil erosion rates. SSSPAM's weathering functions were not used in this study.

4. RESULTS AND DISCUSSION

The SIBERIA and SSSPAM models showed average erosion rates of 1.07 t ha^{-1} yr^{-1} and 0.35 t ha^{-1} yr^{-1} for the analogue site, and 2.69 t ha^{-1} yr^{-1} and 1.29 t ha^{-1} yr^{-1} for the mine rehabilitation plot, respectively, when parameterised for dense cover. When erosion rates were calculated at each step from the initial time step, $t = 0$, SIBERIA and SSSPAM produced mean values of 1.0 t ha^{-1} yr^{-1} (standard deviation, σ = 0.1 t ha^{-1} yr^{-1}) and 0.29 t ha^{-1} yr^{-1} (σ = 0.02 t ha^{-1} yr^{-1}), respectively, for the analogue catchment. For the rehab area, SIBERIA produced a mean value of 2.29 t ha^{-1} yr^{-1} (σ = 0.46 t ha^{-1} yr^{-1}), while SSSPAM produced 1.03 t ha^{-1} yr^{-1} (σ = 0.03 t ha^{-1} yr^{-1}). No deep gullies were observed in either AOI after 100 years. The ability of SSSPAM to model surface armouring may result in comparatively lower erosion rates than SIBERIA. However, some rilling developed in the analogue catchment, extending from the catchment boundaries towards the main channel, and along the downslope direction of the rehab area hillslope. Deposition was also evident in the main channel of the analogue catchment over time. Notably, most soil erosion models are unable to capture such depositional processes as effectively as LEMs.

The average hillslope erosion rate in the Hunter region, where the study sites are located, from 2000 to 2017, is calculated to be 3.74 t ha^{-1} yr^{-1} (Yang 2020). The erosion rates of the two AOIs are lower than this value, indicating comparatively low erosion rates and erosional stability. For the analogue catchment, the RUSLE-based hillslope erosion rate with vegetation cover in 2020, calculated by (Yang 2018), ranged from ~1.24 to 3.22 t ha^{-1} yr^{-1}, which is slightly higher but generally comparable to the results obtained in this study using SIBERIA and SSSPAM. Figure 2 displays the DEM after 100 years for both the analogue site and the mine rehabilitation plot, as simulated by SIBERIA and SSSPAM, compared with the initial DEM. Both SIBERIA and SSSPAM simulations captured the formation of shallow rills developing downslope on the post-mining landform and towards the central gully in the analogue catchment at 100 years.

4.1. Limitations and future work

LEMs are constrained by the simplifications they make when representing complex environmental processes. They cannot fully represent the dynamic and evolving interactions between climate, soil, vegetation, and land use. As a result, their outputs are indicative scenarios based on initial assumptions, which may change over time. Therefore, while LEMs are valuable for informing landform design, they are not intended to deliver exact forecasts of erosion rates or specific landscape features. The long-term stability of landforms relies not only on initial design but also on continued surface management practices.

The results only represent erosion rates under current conditions with dense grass cover. However, during extreme drought conditions, erosional behaviour may change, particularly when the soil surface is exposed (Senanayake 2025). Such alternative land cover scenarios were not investigated in this study, but a more detailed analysis in future work could provide valuable insights.

Additionally, erosion rates are influenced by multiple, complex, and interdependent factors. Variations in landscape or model parameters, such as vegetation cover or topography, can substantially affect the predicted outcomes. While these scenarios were beyond the scope of the current study, they represent important directions for future research.

First-generation LEMs such as SIBERIA operate through a command-line interface and require input files in specific formats, which can limit user-friendliness, particularly for industry applications. Developing a more accessible version with a graphical user interface (GUI), support for common data formats, and built-in tools for data preparation, visualisation, and analysis would significantly enhance its usability in industrial settings. Additionally, incorporating AI-driven workflows for rapid erosion detection and automated parameterisation holds great promise for future advancements.

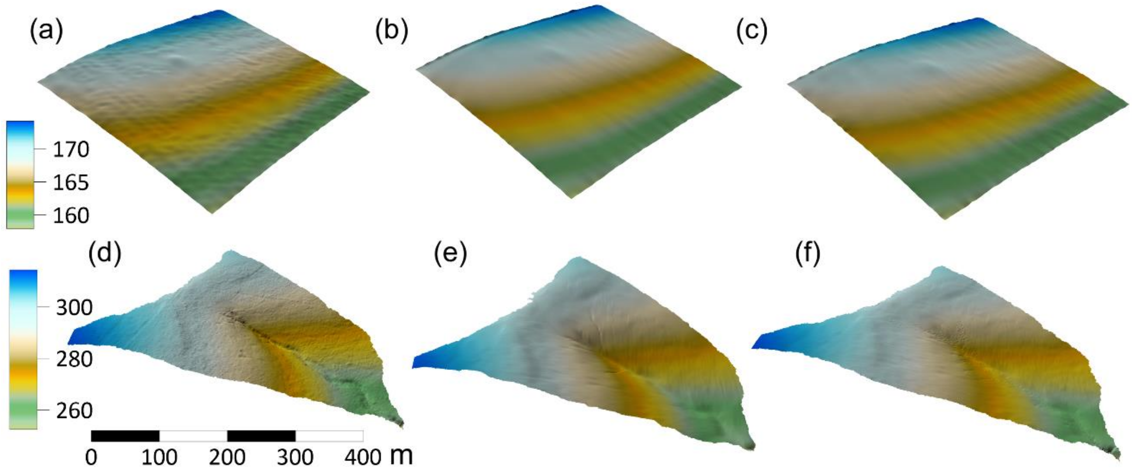

Figure 2 The DEM of the mine rehab area at (a) before simulations, (b) after 100 years of simulation using SIBERIA, and (c) after 100 years of simulation using SSSPAM; and the DEM of the analogue catchment at (d) before simulations, (e) after 100 years of simulation using SIBERIA, and (f) after 100 years of simulation using SSSPAM.

5. CONCLUSION

This study compared the 100-year erosional behaviour of a post-mining rehabilitation plot and a nearby natural site with similar climate and vegetation, using the first-generation LEM SIBERIA and the recently developed SSSPAM model with LiDAR-derived high-resolution DEMs. Results showed that both landforms are erosionally stable, with both models producing comparable outcomes that align well with field observations. The study highlights the value of using high-resolution DEMs in post-mining landform rehabilitation as a decision-support tool, helping to understand the erosional dynamics of constructed landscapes relative to adjacent natural terrain. These insights are important for assessing the long-term erosional sustainability and successful integration of rehabilitated landforms within their natural environment.

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