

Predicted soil loss and the contribution of soil map units in a tropical protected forest: RUSLE assessment of Ir. H. Djuanda Forest Park, Indonesia

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ABSTRACT

Soil erosion degrades soil and water resources in tropical protected areas. We mapped RUSLE-predicted soil loss in Ir. H. Djuanda Forest Park, West Java, Indonesia, and quantified the contribution of soil map units (SMUs) to spatial variation in model inputs. Rainfall erosivity was derived from 2016–2025 CHIRPS precipitation using the modified Fournier index and Arnoldus relation, giving a period-mean R of $13,825.61 \text{ MJ mm} \cdot \text{ha}^{-1} \cdot \text{h}^{-1} \cdot \text{yr}^{-1}$. Soil erodibility was derived from a 1:50,000 soil map and SoilGrids organic carbon, the topographic factor from the DEMNAS grid using the Desmet–Govers formulation, and cover from SPOT-6 imagery (overall accuracy 82.5%, kappa 0.77). Cells with at least 300 contributing cells were treated as concentrated-flow cells and excluded from the hillslope calculation. The baseline $\text{RUSLE} \times \text{SMU}$ intersection contained 493.32 ha of valid estimates, with 93.36% below $385.14 \text{ t} \cdot \text{ha}^{-1} \cdot \text{yr}^{-1}$ and a maximum predicted soil loss of $8,184.15 \text{ t} \cdot \text{ha}^{-1} \cdot \text{yr}^{-1}$. SMU-4 contained 97.0% of the 32.74 ha above $385.14 \text{ t} \cdot \text{ha}^{-1} \cdot \text{yr}^{-1}$. The area-weighted variance of $\ln(K)$ was 0.16% of that of $\ln(C)$, indicating substantially greater spatial contrast from land cover than from SMU-based K classes. Sensitivity testing showed that concentrated-flow treatment strongly affected the upper tail, whereas median LS changed by less than 10% between the unmasked and 75-cell scenarios. Without independent erosion measurements, the results are interpreted as modelled soil-loss potential and spatial screening information rather than measured erosion rates.

Keywords: soil erosion; RUSLE; soil map units; modified Fournier index; sensitivity analysis; protected area; West Java

INTRODUCTION

Soil erosion reduces soil quality, redistributes nutrients and organic matter, and increases sediment delivery to downstream environments. It is a common form of land degradation in the tropics (Zou et al., 2024; Askari et al., 2023). In

tropical forest landscapes, erosion also affects vegetation condition and hydrological regulation, which can weaken the capacity of protected areas to maintain ecosystem functions (Borrelli et al., 2021). Biodiversity conservation, carbon storage, flood regulation and watershed protection can all suffer as a result (Liu et al., 2018;

Mandal et al., 2021; Katayama et al., 2023; Akpa et al., 2024; Fernández et al., 2025; Iskhar, 2025; Ghute et al., 2026).

Spatially explicit assessment is therefore important for environmental management. The Revised Universal Soil Loss Equation (RUSLE) remains widely used because its factor structure can be parameterized spatially and integrated with geographic information systems (GIS) (Alewell et al., 2019; Boakye et al., 2020). Recent applications in Ecological Engineering & Environmental Technology (EEET) demonstrate the continued use of RUSLE–GIS for spatial erosion assessment and environmental management (Eddefli et al., 2023; Mohsen et al., 2025). However, RUSLE estimates average annual sheet-and-rill soil loss and should not be interpreted as a direct measurement of total erosion or sediment yield (Benavidez et al., 2018).

Remote sensing and GIS improve how RUSLE represents land cover and topography. Assaoui et al. (2023) combined RUSLE, GIS and remote sensing to map water erosion, and Abrouri et al. (2026) compared satellite-derived RUSLE inputs with field measurements. Both studies stress transparent parameterization and matched scales among datasets. Most RUSLE studies stop at mapping the magnitude of soil loss, and few link the estimates to soil–landscape units for conservation planning in tropical protected forests.

Rainfall erosivity is a major source of uncertainty, because equations based on monthly or daily rainfall cannot capture event-scale intensity and kinetic energy. Erosivity estimates depend on the temporal resolution of the record and on how erosive events are defined (Brychta & Janeček, 2019). A similar source of uncertainty arises from the representation of topography. The topographic factor adds further uncertainty, since slope length and steepness depend on DEM resolution and on the flow-routing method (Brychta & Brychtová, 2020).

Soil representation matters as well. Regional studies often assign one erodibility value to broad soil classes, which hides differences among soil–landscape positions. Soil map units (SMUs) retain more of this information and relate soil properties to landscape position. In this study, rather than assuming that SMUs necessarily improve model accuracy, we quantify how much spatial contrast the SMU-based K layer contributes relative to the land-cover C layer. This framing avoids equating a soil-unit overlay

with improved predictive accuracy when no independent erosion observations are available.

Ir. H. Djuanda Forest Park (Tahura Ir. H. Djuanda) is a conservation area in West Java Province. It forms part of the upper Cikapundung catchment and provides habitat for many plant and animal species. The park lies on volcanic terrain with hilly to steep slopes and receives high rainfall through the year. Tourism and land-use enclaves add pressure, and vegetation change in parts of the park may raise erosion risk. Park managers need spatial information on erosion classes to plan soil and water conservation.

This study assesses predicted sheet-and-rill soil loss in Ir. H. Djuanda Forest Park with RUSLE and quantifies the contribution of SMUs to its spatial pattern. We aimed to (1) map predicted soil loss, (2) describe its distribution within SMUs, (3) quantify how much spatial variation the soil map carries compared with land cover, and (4) test how parameter choices, including the treatment of concentrated flow in the topographic factor, change the results. The third aim is deliberately framed as a variance comparison rather than an accuracy claim because no independent erosion observations were available for validation.

MATERIALS AND METHODS

Study area

The study area is Ir. H. Djuanda Forest Park, a conservation forest that extends across Bandung City, Bandung Regency and West Bandung Regency (Fig. 1). The landscape comprises dissected volcanic terrain, forest, river valleys and scattered human activity, with the Cikapundung River and its steep valley margins as the main landforms. We used the official boundary set by Decree of the Minister of Environment and Forestry No. SK.5998/MenLHK-PKTL/KUH/PLA.2/10/2016. The mapped area covers 528.393 ha, elevation ranges from about 700 to 1,500 m a.s.l., and slopes range from 0 to 65%. The park lies near 6°52' S and 107°30' E. The location and spatial boundaries of the research area are presented in Figure 1.

Data sources and spatial processing

Table 1 lists the datasets. All layers were projected to WGS 84 / UTM zone 48S

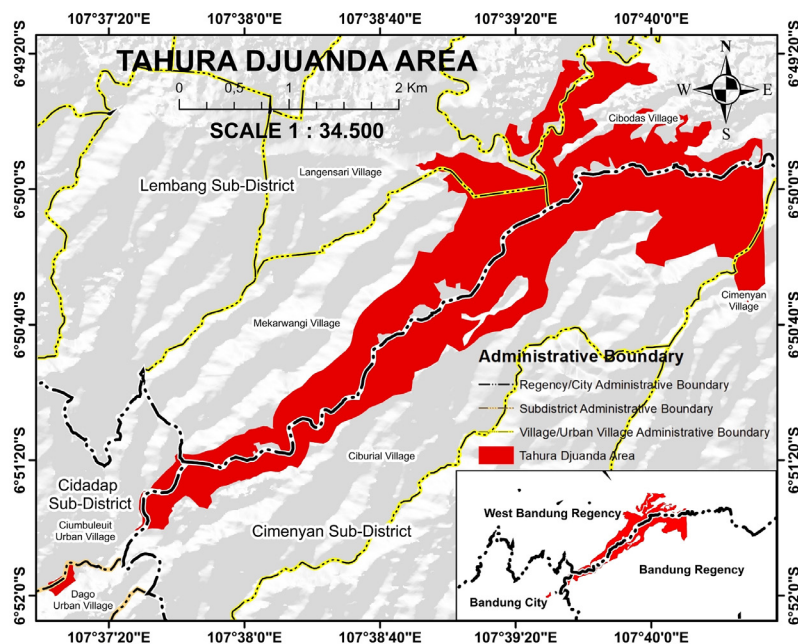


Figure 1. Location and boundary of Ir. H. Djuanda Forest Park

(EPSG:32748) and aligned to a common 8.3910665-m computational grid, with DEMNAS used as the snap raster. The cell size corresponds to the DEMNAS processing grid used in the analysis, with a cell area of 70.409997 m². Accordingly, the contributing-cell thresholds correspond to approximately 2.11 ha for 300 cells, 0.53 ha for 75 cells, 1.06 ha for 150 cells, and 14.08 ha for 2,000 cells. The common grid was used to perform cell-by-cell raster arithmetic and does not imply that the coarser CHIRPS and soil-map inputs contain information at 8.3910665-m spatial resolution. The

implications of this scale mismatch are considered in the Discussion (Gertner et al., 2002).

Field observations and interviews with managers of UPTD Tahura Ir. H. Djuanda were used to check land cover and to document the presence or absence of visible support practices. The field photographs shown in Figure 3 are qualitative documentation and are not treated as a statistical validation dataset.

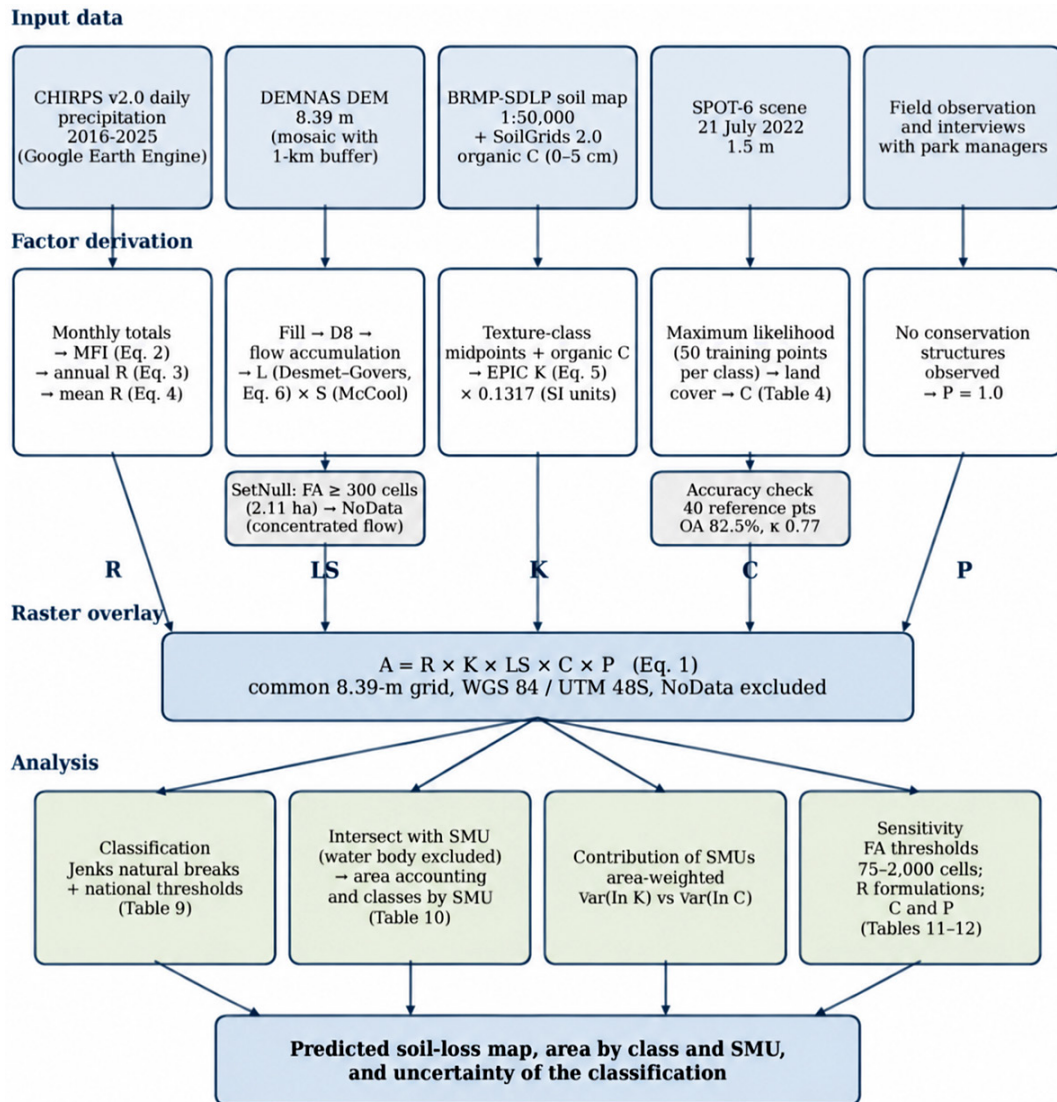
Figure 2 summarizes the workflow from input data to the soil-loss classification. The tool settings, raster-calculator expressions and overlay steps are documented in Supplementary Figs. S1–S9.

Table 1. Datasets used for the soil-loss assessment

Dataset	Source	Period / scale	Native resolution	Product identifier	Use
Precipitation	CHIRPS v2.0 daily, UCSB Climate Hazards Group, via Google Earth Engine	2016–2025, summed to monthly totals	0.05° (~5.5 km); spatial mean at 5,000 m	UCSB-CHG/CHIRPS/DAILY	Rainfall erosivity (R)
Digital elevation model	DEMNAS, https://tanahair.indonesia.go.id	2018	8.39 m (0.27 arc-second)	Tile 1209-31 (NLP)	Slope and LS factor
Soil map units	BRMP-SDLP	1:50,000	Minimum legible delineation ≈ 12.5 ha	Tanah_1209-31	Textural class, soil description, SMU boundaries
Soil organic carbon	SoilGrids 2.0, ISRIC	0–5 cm, mean	250 m	Soil organic carbon (soc) layer	Organic carbon term in Eq. 5
Satellite imagery	SPOT-6, BRIN	21 July 2022	1.5 m	SPOT6_PMS_202207210244311_ORT	Land cover and C factor
Park boundary	UPTD Tahura Ir. H. Djuanda	2017	Vector	SK.5998/MenLHK-PKTL/KUH/PLA.2/10/2016	Study-area delineation

Table 2. Spatial processing settings and software

Element	Setting
GIS software	ArcMap 10.8.2
Coordinate reference system	WGS 84 / UTM zone 48S (EPSG:32748)
Computational grid	8.39-m cells (native DEMNAS resolution, 8.391 m); DEMNAS as snap raster
Sink filling	Spatial Analyst Fill tool, applied before flow direction and flow accumulation
Flow direction and accumulation	D8, Spatial Analyst tools, on a DEMNAS mosaic extended 1 km beyond the park boundary
LS factor	Desmet–Govers (1996) slope length with McCool et al. (1987, 1989) steepness and exponent; concentrated-flow cells (≥ 300 contributing cells, 2.11 ha) excluded
Slope	Spatial Analyst Slope tool, in percent; continuous slope used for LS; six classes (0–3, 3–8, 8–15, 15–25, 25–40, >40%) used for display only
DEM edge handling	Flow accumulation computed on the 1-km buffer and extracted to the park boundary
Resampling	Nearest neighbour for categorical layers, bilinear for continuous layers
NoData handling	Extreme LS values and concentrated-flow cells set to NoData and excluded from all area totals; never converted to zero
Water bodies	SMU-7 excluded from the terrestrial calculation and kept for delineation
Area computation	Polygon areas of the RUSLE $\times$ SMU intersection, water body excluded (area accounting in Table 10)

**Figure 2.** Workflow of the RUSLE assessment, from input data and factor derivation to raster overlay, SMU analysis and sensitivity testing

RUSLE model

We estimated predicted annual sheet-and-rill soil loss as:

$$A = R \times K \times LS \times C \times P \quad (1)$$

where: A is predicted annual soil loss ($t \cdot ha^{-1} \cdot yr^{-1}$), R is rainfall erosivity ($MJ \cdot mm \cdot ha^{-1} \cdot h^{-1} \cdot yr^{-1}$), K is soil erodibility ($t \cdot ha^{-1} \cdot yr^{-1} \cdot MJ^{-1} \cdot mm^{-1}$), LS is the slope length and steepness factor, C is the cover-management factor and P is the support-practice factor.

With R and K in SI units, A comes out in $t \cdot ha^{-1} \cdot yr^{-1}$. We treat RUSLE as a screening model for sheet and rill erosion; gully and channel erosion, mass movement and sediment delivery lie outside its scope (Benavidez et al., 2018).

Rainfall erosivity factor

No sub-hourly rainfall records were available for the park, so rainfall erosivity was estimated from monthly precipitation with the modified Fournier index (MFI) and the Arnoldus relation in the form given by (Chen et al., 2023). We summed daily CHIRPS v2.0 precipitation (Funk et al., 2015) was aggregated to monthly totals for 2016–2025 in Google Earth Engine and averaged the totals over the park at a 5,000-m scale, which gave one monthly series. For each year,

$$MFI = \sum(i = 1 \text{ to } 12) P_i^2 / P \quad (2)$$

$$R = 17.02 \times 10^{[1.5 \log_{10}(MFI) - 0.8188]} \quad (3)$$

where: P_i is precipitation in month i (mm) and P is annual precipitation (mm).

The coefficient 17.02 was retained for the selected Arnoldus formulation. The period-mean

R was calculated as the arithmetic mean of the ten annual R values. Because the analysis uses a single spatially averaged precipitation series, R is uniform across the park and spatial variation in A is generated by K, LS and C.

$$\bar{R} = \left(\frac{1}{10} \right) \sum_{2016}^{2025} R_y \quad (4)$$

Because the series is a single spatial mean, R is uniform across the park, and spatial variation in A comes from K, LS and C.

Soil erodibility factor

We computed erodibility for each SMU with the EPIC equation of Sharpley and Williams (1990), following Abidare et al. (2026):

$$K = \left(0.2 + 0.3 \exp \left[-0.256 SAN \left[1 - \frac{SIL}{100} \right] \right] \right) \times \left(\frac{SIL}{CLY + SIL} \right)^{0.3} \times \left(1 - \frac{0.25C}{C + \exp[3.72 - 2.95C]} \right) \times \left(1 - \frac{0.7SN1}{SN1 + \exp[-5.51 - 2.95SN1]} \right) \quad (5)$$

where: SAN, SIL and CLY are sand, silt and clay contents (%), Corg is organic carbon (%) and $SN1 = 1 - SAN/100$.

The result was multiplied by 0.1317 to convert from US customary to SI units. The soil map did not provide measured particle-size data for the mapped units; therefore, sand, silt and clay percentages were represented by the midpoint of the textural class named in the BRMP-SDLP legend. Organic carbon was obtained from the SoilGrids 2.0 SOC mean layer for 0–5 cm (Poggio et al., 2021) and converted to percentage organic carbon according to the SoilGrids product metadata. The selected SOC layer did not require spatial imputation in the reported analysis. SMU-1, SMU-2 and SMU-3 have similar textural values; SMU-4,

Table 3. Soil attributes, intermediate terms of Eq. 5 and erodibility by SMU. The fourth term of Eq. 5 equals 1.000 for all units; K in $t \cdot ha^{-1} \cdot yr^{-1} \cdot MJ^{-1} \cdot mm^{-1}$

SMU	Sand (%)	Silt (%)	Clay (%)	Organic C (%)	f_{csand}	f_{cl-si}	f_{orgc}	K (SI)
SMU-1	32.7	31.0	36.3	4.5	0.3684	0.7925	0.7500	0.0288356
SMU-2	32.7	31.0	36.3	4.5	0.3684	0.7925	0.7500	0.0288356
SMU-3	32.7	31.0	36.3	4.2	0.3684	0.7925	0.7500	0.0288358
SMU-4	26.7	48.3	25.0	2.3	0.4107	0.8824	0.7550	0.0360316
SMU-5	26.7	48.3	25.0	2.3	0.4107	0.8824	0.7550	0.0360316
SMU-6	26.7	48.3	25.0	3.5	0.4107	0.8824	0.7501	0.0357990

SMU-5 and SMU-6 form a second textural group and differ mainly through organic carbon.

Topographic factor

LS was calculated with the unit-contributing-area formulation of Desmet, P.J.J Govers (1996). Sinks were filled on a DEMNAS mosaic extended 1 km beyond the park boundary, so that upslope flow entering the park was retained. D8 flow direction and flow accumulation were then derived, and the results were extracted to the park boundary. The slope-length factor of cell i,j is given by Eq. (6).

$$L_{i,j} = \frac{(A_{in} + D^2)^{m+1} - A_{in}^{m+1}}{D^{m+2} x^m 22.13^m} \quad (6)$$

where: A_{in} is the contributing area at the cell inlet, calculated from flow accumulation and the cell area of 70.41 m², D is the cell size dimension used in the LS calculation (8.39 m); x is 1 for cardinal and $\sqrt{2}$ for diagonal flow, and 22.13 m is the unit plot length (Wischmeier, W. H., & Smith, 1978).

The slope-length exponent m follows (McCool et al., 1989).

$$m = \frac{\beta}{1 + \beta}, \beta = \frac{\sin\theta/0.0896}{3 (\sin\theta)^{0.8} + 0.56} \quad (7)$$

where: θ is the slope angle. The slope factor follows (McCool et al., 1987), with $S = 10.8 \sin \theta + 0.03$ where $\tan \theta < 0.09$ and $S = 16.8 \sin \theta - 0.50$ elsewhere, and $LS = L \times S$.

RUSLE describes sheet and rill erosion, while flow accumulation grows without bound along valley floors. We therefore treated cells with at least 300 contributing cells (2.11 ha in the production raster) as concentrated flow and excluded them from the hillslope LS surface. This threshold lies within the range reported for channel initiation in steep terrain (Montgomery & Dietrich, 1988). Extreme LS values that remained after

routing were set to NoData. Because LS depends on DEM resolution and GIS implementation, alternative thresholds of 75, 150 and 2,000 cells and an unmasked case were tested (Gertner et al., 2002; Brychta & Brychtová, 2020).

Cover-management factor

The SPOT-6 scene acquired on 21 July 2022 was classified by supervised maximum likelihood into forest, shrubland, built-up and water using 50 training points per class. The C values were taken from the cited RUSLE literature in Table 4. Field observation indicated that mapped built-up areas consisted mainly of small facilities embedded in vegetated surroundings; consequently, the shrubland C value was used for the built-up class as an operational representation of the observed surface condition. This equivalence is a modelling assumption, not a claim that impervious surfaces have the same intrinsic cover factor as shrubland.

For accuracy assessment, 10 reference points were interpreted for each mapped class (40 points total) using high-resolution Google Earth imagery and field verification. The reference points were intended to be independent of the training points; the archived sampling record should be retained as evidence of this independence.

Support-practice factor

Field observation and interviews with park managers found no visible terraces, contour tillage, strip cropping or runoff barriers in the observed areas; P was therefore set to 1.0 throughout. This represents an absence-of-mapped-support-practice assumption and provides an upper-bound screening estimate for the support-practice component. The field photographs in Figure 3 are qualitative evidence of site condition; they are not an independent statistical verification of P.

Soil-loss classification and SMU analysis

Predicted soil loss on the baseline surface was grouped into five classes with the Jenks

Table 4. Cover-management factor values

Land-cover class	C factor	Basis
Forest land	0.001	Putra et al. (2018); Alemu et al. (2025); Ascencio-Sanchez et al. (2025)
Shrubland	0.05	Alemu et al., 2025; Tesfaye et al., 2026
Built-up	0.05	Alemu et al. (2025); shrubland value adopted after field verification
Water body	Excluded	Excluded from the terrestrial calculation

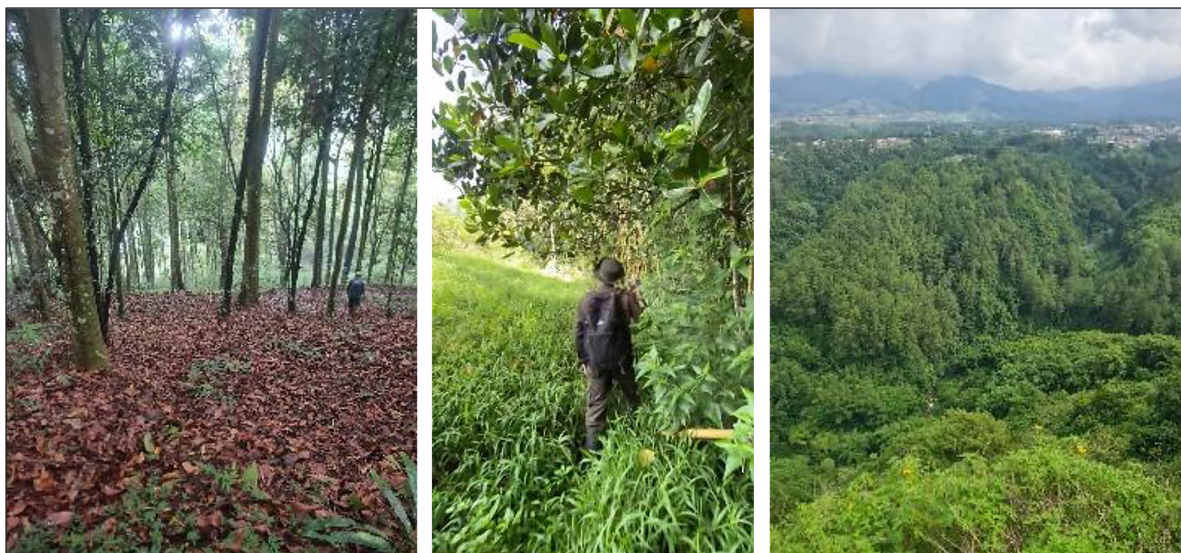


Figure 3. Illustrative field photographs used as qualitative documentation of observed site condition and absence of visible support-practice structures. The photographs are not treated as a statistical validation dataset

natural-breaks method (Jenks, 1967). To aid interpretation, each natural-break class was compared with the Indonesian erosion-severity thresholds of very low < 15, low 15–60, moderate 60–180, high 180–480 and very high > 480 $\text{t}\cdot\text{ha}^{-1}\cdot\text{yr}^{-1}$ (Petunjuk Teknis Penyusunan Data Spasial Lahan Kritis, 2013; Seika et al., 2021). The soil-loss raster was intersected with the SMU polygons, the water body was excluded, and the area of class c in unit s was calculated as defined in Eq. (8).

$$P_{(c,s)} = \left(\frac{A_{(c,s)}}{A_{(s)}} \right) \times 100 \quad (8)$$

where: $A_{c,s}$ is the area of soil-loss class c in SMU s and A_s is the modelled area of that SMU.

Because K is constant within each SMU and C takes two mapped values, area-weighted variances of $\ln(K)$ and $\ln(C)$ were calculated separately. Their ratio is interpreted only as a comparison of spatial variance represented by the mapped K and C classes, not as a decomposition of the variance of predicted soil loss.

Sensitivity analysis

The concentrated-flow treatment was tested by recomputing LS with no exclusion and with thresholds of 75, 150 and 2,000 contributing cells. Soil loss was recomputed for the unmasked case and for thresholds of 75 and 2,000 cells, while all other inputs and the

Desmet–Govers equations were held constant. Scenarios were compared using the LS distribution, raster-valid area and maximum predicted soil loss. Natural-break limits were recalculated separately for each scenario, therefore, class-area percentages are not used for direct cross-scenario comparison. A separate one-at-a-time proportional sensitivity test was applied to R , K , C and P by perturbing each factor by $\pm 10\%$ while holding the other factors constant. The standardized sensitivity coefficient was calculated as $S_x = (\Delta A/A)/(\Delta X/X)$. Because Eq. (1) is multiplicative, a uniform $\pm 10\%$ perturbation in one factor produces an approximately $\pm 10\%$ change in predicted soil loss ($S_x = 1.0$). These tests quantify algebraic parameter sensitivity and should not be interpreted as empirical uncertainty intervals.

RESULTS

Soil map units and modeling area

Seven SMUs occur in the park (Table 5). SMU-4 dominates with 398.153 ha (75.52% of the terrestrial area), followed by SMU-5 with 101.488 ha (19.25%). Excluding the water body (SMU-7, 1.208 ha) leaves a terrestrial area of 527.185 ha. The $\text{RUSLE} \times \text{SMU}$ intersection contains 493.32 ha with valid soil-loss estimates (93.58% of the terrestrial area); the difference between this value and raster-level valid area reported in the

Table 5. Area and soil–landscape context of the soil map units. Shares refer to the terrestrial area

SMU	Area (ha)	Share (%)	Landform / slope	Soil description
SMU-1	5.801	1.10	Lower volcanic slopes; 8–15%	Umbric Andosol, very deep, well drained, moderately fine texture, acid, high CEC, very low base saturation (Thaptic Hapludands)
SMU-2	17.188	3.26	Lower volcanic slopes; 15–25%	Umbric Andosol, very deep, well drained, moderately fine texture, acid, moderate CEC, very low base saturation (Typic Hapludands)
SMU-3	0.869	0.16	Lower volcanic slopes; 25–40%	Umbric Andosol, very deep, well drained, moderately fine texture, slightly acid, high CEC, medium base saturation (Typic Hapludands)
SMU-4	398.153	75.52	Lower volcanic slopes; 25–40% and >40% (escarpment)	Oxic Latosol, very deep, well drained, fine texture, very acid, moderate CEC, low base saturation (Oxic Dystrudepts); with Umbric Andosol, deep, somewhat excessively drained (Typic Hapludands)
SMU-5	101.488	19.25	Central volcanic slopes; 15–25%	Eutric Cambisol, deep, well drained, fine texture, slightly acid, moderate CEC, high base saturation (Typic Eutrudepts); with Eutric Andosol (Typic Hapludands)
SMU-6	3.685	0.70	Lower volcanic slopes; 8–15%	Latosol, very deep, well drained, fine texture, very acid, moderate CEC, low base saturation (Oxic Dystrudepts)
SMU-7	1.208	—	Water body	Excluded from the terrestrial analysis

sensitivity analysis is explained by the subsequent SMU intersection and sliver-cell accounting.

Rainfall and rainfall erosivity

Annual CHIRPS precipitation ranged from 1,800.72 mm in 2023 to 4,033.10 mm in 2017, with a mean of 2,895.96 mm. Annual erosivity ranged from 7,149.59 to 25,194.33 MJ·mm·ha⁻¹·h⁻¹·yr⁻¹, a 3.5-fold spread, and the ten-year mean was 13,825.61 MJ·mm·ha⁻¹·h⁻¹·yr⁻¹. The period mean was used as the baseline R, while the annual range was retained for sensitivity analysis.

Spatial characteristics of RUSLE factors

K varies by a factor of 1.25 among SMUs, LS is strongly right-skewed, and C differs fiftyfold between forest and the shrubland and built-up classes (Table 7). R and P are uniform. Consequently, the mapped spatial variation in predicted predicted soil loss is primarily associated with LS and C, while the differences in K among SMUs are comparatively small.

Land-cover classification and accuracy

The land-cover map reached an overall accuracy of 82.5% and a kappa of 0.77 (Table 8). Forest had a user's accuracy of 100% and a producer's accuracy of 71.4%: three forest reference points

were mapped as shrubland and one as built-up. Shrubland had the lowest user's accuracy (60%). Because shrubland carries the higher C value, this class-specific error can increase the mapped area of elevated predicted soil loss. The accuracy assessment should therefore be considered when interpreting the upper tail of the erosion map.

Distribution of predicted soil loss

Predicted soil loss on the baseline modelled area reached 8,184.15 t·ha⁻¹·yr⁻¹ (Table 9, Fig. 5). Class 1, below 385.14 t·ha⁻¹·yr⁻¹, covers 460.58 ha (93.36%). The four upper classes cover 32.74 ha (6.64%). Classes 3–5 (16.00 ha, 3.24%) exceed the national very-high threshold of 480 t·ha⁻¹·yr⁻¹. Because the first Jenks class spans several national severity categories, the natural-break classification should not be interpreted as a replacement for the national severity thresholds (Petunjuk Teknis Penyusunan Data Spasial Lahan Kritis, 2013; Seika et al., 2021).

Modelled area and predicted soil loss within soil map units

The 33.87 ha of terrestrial area without a valid RUSLE × SMU estimate comprise 22.75 ha where the unmasked LS raster held No-Data after extreme values were removed, 8.91 ha of concentrated-flow cells removed by the

Table 6. Annual precipitation from CHIRPS, Modified Fournier index and rainfall erosivity computed with Equations 2 and 3, 2016–2025

Year	Precipitation (mm yr ⁻¹)	Modified Fournier Index	R (MJ mm ha ⁻¹ h ⁻¹ yr ⁻¹)
2016	2,499.64	252.36	10,355.71
2017	4,033.10	456.49	25,194.33
2018	2,602.06	292.99	12,955.14
2019	2,494.63	342.42	16,367.80
2020	3,040.17	300.68	13,468.32
2021	3,227.01	302.48	13,589.47
2022	3,328.58	303.21	13,638.52
2023	1,800.72	197.13	7,149.59
2024	2,836.30	281.68	12,212.02
2025	3,097.38	298.55	13,325.22
Mean	2,895.96	302.80	13,825.61

Table 7. Range and spatial behaviour of the RUSLE factors

Factor	Values in the model	Units	Spatial behaviour
R	13,825.61 (annual 7,149.59–25,194.33)	MJ mm ha ⁻¹ h ⁻¹ yr ⁻¹	Uniform over the park
K	0.0288356–0.0360316	t ha h ha ⁻¹ MJ ⁻¹ mm ⁻¹	Two textural groups following SMU boundaries
LS	Continuous; median 18.48, 99th percentile 173.59, maximum 526.76 on hillslope cells (Table 11)	Dimensionless	Highest on steep, convergent valley margins
C	0.001 (forest); 0.05 (shrubland, built-up)	Dimensionless	Main source of spatial variation
P	1.0	Dimensionless	Uniform (assumed)

300-cell threshold, and 2.21 ha lost as sliver polygons during the RUSLE × SMU intersection (Table 10). SMU-4 accounts for 26.23 ha of the excluded area.

The upper classes are concentrated in one unit. Class 2 occurs in every SMU but exceeds 0.1 ha only in SMU-4 (15.97 ha) and SMU-5 (0.69 ha). Class 3 occurs in SMU-4, SMU-5 and SMU-6, while classes 4 and 5 occur only in SMU-4. SMU-4 contains 31.76 of the 32.74 ha above 385 t·ha⁻¹·yr⁻¹ (97.0%), compared with 75.4% of the modelled area. The upper classes occur mainly in the north-eastern sector and along the Cikapundung valley margins, where shrubland and mapped built-up areas overlap steep slopes.

Erodibility contributes relatively little to the mapped contrast. The area-weighted variance of ln(K) is 0.0021, whereas the corresponding variance of ln(C) is 1.30 for the mapped land-cover classes. Thus, Var[ln(K)] is 0.16% of Var[ln(C)]. This ratio indicates that the

differentiation of K among the mapped SMUs is much smaller than the contrast introduced by land cover; it should not be interpreted as the percentage of soil-loss variance explained by SMUs.

Sensitivity analysis

The concentrated-flow threshold changes the upper tail of the LS distribution much more than its centre (Table 11). From the unmasked raster to the 75-cell threshold, the median LS decreases by 7.9%, while the 99th percentile decreases by 81.6% and the maximum decreases from 74,926 to 220. In the unmasked raster, 565 of the 575 cells with LS >1,000 (98.3%) lie on flow paths with at least 2,000 contributing cells. The effect carries through to soil loss (Table 12): the maximum decreases from 124,166 t·ha⁻¹·yr⁻¹ without exclusion to 14,435, 8,184 and 4,862 t·ha⁻¹·yr⁻¹ at thresholds of 2,000, 300 and 75 cells, respectively.

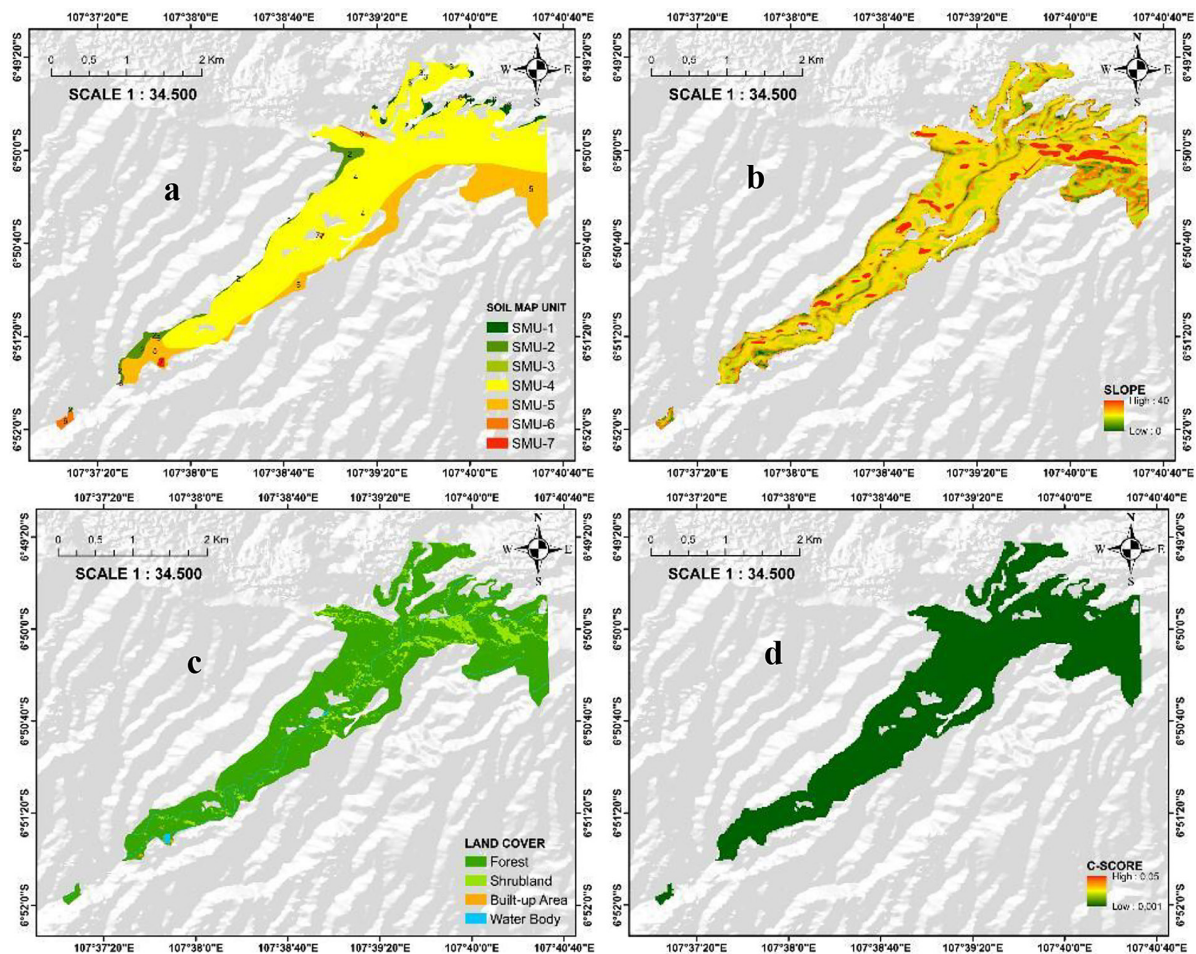


Figure 4. RUSLE inputs: (a) soil map units, (b) slope class, (c) land cover, (d) C factor. K follows the SMU boundaries in (a) with the values in Table 3, while R is uniform at $13,825.61 \text{ MJ} \cdot \text{mm} \cdot \text{ha}^{-1} \cdot \text{h}^{-1} \cdot \text{yr}^{-1}$

Table 8. Confusion matrix of the land-cover classification (rows: mapped class; columns: reference class). Overall accuracy 82.5%, kappa 0.77

Mapped class	Forest	Shrubland	Built-up	Water	Total	User's accuracy (%)
Forest	10	0	0	0	10	100.0
Shrubland	3	6	1	0	10	60.0
Built-up	1	0	8	1	10	80.0
Water	0	1	0	9	10	90.0
Total	14	7	9	10	40	
Producer's accuracy (%)	71.4	85.7	88.9	90.0		

Table 9. Predicted soil-loss classes on the baseline surface (Jenks natural breaks, 300-cell threshold) and the corresponding national severity classes. Areas from the $\text{RUSLE} \times \text{SMU}$ intersection, water body excluded

Class	Range ($\text{t ha}^{-1} \text{ yr}^{-1}$)	Area (ha)	Share (%)	National severity class
1	0–385.14	460.581	93.36	Very low to high
2	385.14–1,251.69	16.736	3.39	High to very high
3	1,251.69–2,375.01	11.375	2.31	Very high
4	2,375.01–4,332.78	3.450	0.70	Very high
5	4,332.78–8,184.15	1.175	0.24	Very high
Total	—	493.317	100.00	

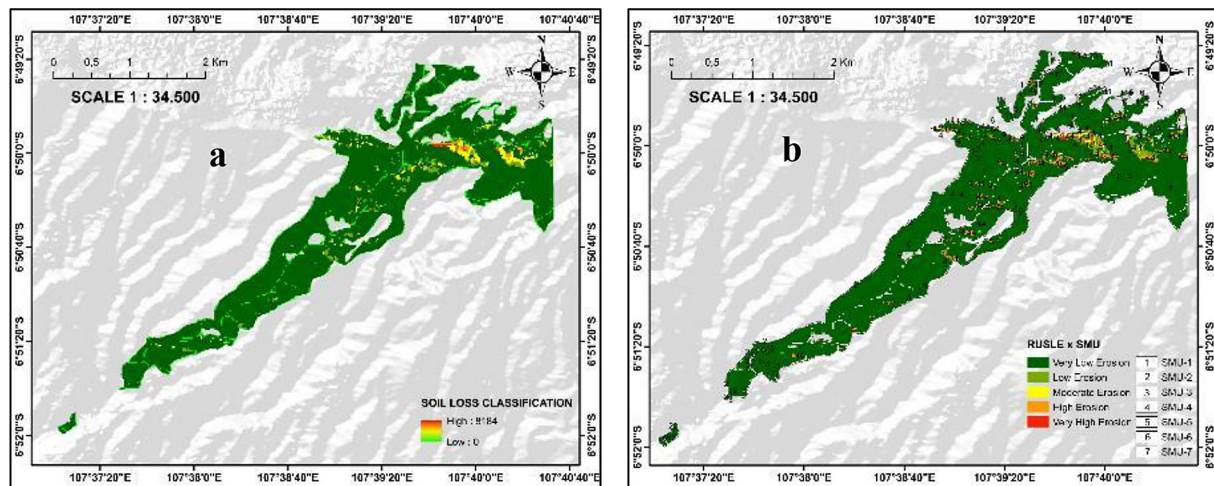


Figure 5. Predicted soil loss: (a) baseline surface using the 300-cell concentrated-flow threshold and the five Jenks classes in Table 9; (b) the same surface with SMU labels

Table 10. Area accounting and area of each soil-loss class (Table 9) by soil map unit, in hectares

SMU	Area (Table 5)	Modelled	Excluded	Class 1	Class 2	Class 3	Class 4	Class 5
SMU-1	5.801	5.407	0.394	5.399	0.008	—	—	—
SMU-2	17.188	15.900	1.288	15.880	0.020	—	—	—
SMU-3	0.869	0.822	0.047	0.797	0.025	—	—	—
SMU-4	398.153	371.926	26.227	340.166	15.972	11.164	3.450	1.175
SMU-5	101.488	95.766	5.722	94.918	0.689	0.159	—	—
SMU-6	3.685	3.496	0.189	3.421	0.023	0.053	—	—
Total	527.185	493.317	33.868	460.581	16.736	11.375	3.450	1.175

The factor-sensitivity analysis shows a transparent algebraic response. A uniform $\pm 10\%$ perturbation of R, K, C or P changes the baseline maximum by $\pm 10\%$, with $S_x \approx 1.0$ for each factor. This result is expected from the multiplicative structure of Eq. (1) and should not be confused with an empirical uncertainty interval. The concentrated-flow scenarios, in contrast, alter which cells are included in the hillslope RUSLE calculation and therefore have a much larger effect on the upper tail.

DISCUSSION

Predicted soil loss is spatially concentrated. The 6.64% of the modelled area above $385 \text{ t} \cdot \text{ha}^{-1} \cdot \text{yr}^{-1}$ occurs mainly on steep shrubland and mapped built-up land, and SMU-4 contains 97% of this area. The co-location of higher C values and steep LS conditions provides a spatial explanation for the concentration in the model. Because C is the factor most directly affected by short-term changes in ground cover within the present parameterization, the mapped high-prediction

Table 11. Distribution of LS under alternative concentrated-flow thresholds. The 300-cell threshold is the baseline; “excluded area” is the area removed by the stated threshold

Scenario	Area (ha)	Cells	P50	P90	P95	P99	Mean	SD	Max
Unmasked	—	76,227	19.14	71.47	107.72	600.06	114.00	1,511.86	74,926.10
2000 cells	14.08	75,215	18.78	67.56	94.96	267.35	32.52	55.38	1,261.90
300 cells (baseline)	2.11	74,344	18.48	64.68	86.84	173.59	28.94	36.13	526.76
150 cells	1.06	73,458	18.17	62.05	81.46	137.56	27.06	29.46	389.82
75 cells	0.53	71,864	17.63	58.46	75.13	110.66	25.16	24.88	220.05

Table 12. Predicted soil loss under alternative concentrated-flow thresholds. Valid area is the raster-level area retained before the $\text{RUSLE} \times \text{SMU}$ intersection and therefore includes water-body and raster-level sliver cells

Scenario	Valid area (ha)	Maximum ($\text{t ha}^{-1} \text{yr}^{-1}$)	Upper limit of class 1	Class 1 share (%)
Unmasked	505.55	124,166.44	1,460.78	96.99
2,000 cells	498.82	14,435.10	566.08	94.26
300 cells (baseline)	496.64	8,184.15	385.14	93.39
75 cells	479.37	4,862.30	305.09	93.46

Note: Raster-level valid area includes water-body cells and the raster-level intersection area; the 493.32-ha value in the main analysis is the terrestrial $\text{RUSLE} \times \text{SMU}$ intersection after sliver exclusion.

areas provide a logical focus for field verification of vegetation condition.

The absolute predictions require caution. The baseline maximum is $8,184.15 \text{ t ha}^{-1} \text{yr}^{-1}$, and 32.74 ha exceeds $385.14 \text{ t ha}^{-1} \text{yr}^{-1}$. Three parameter characteristics contribute to this magnitude: the period-mean erosivity of 13,825.61 derived from monthly rainfall, the Desmet–Govers LS distribution on steep terrain, and the literature-based C value of 0.05 assigned to shrubland and mapped built-up land. The sensitivity analysis shows that alternative concentrated-flow treatments change the maximum substantially, while the $\pm 10\%$ factor tests demonstrate the direct proportionality of the multiplicative model. The map should therefore be interpreted primarily as a spatial screening of relative sheet-and-rill erosion potential rather than as a field-measured erosion rate (Benavidez et al., 2018).

The mapped SMUs provide limited differentiation of K in this study because the units are dominated by two textural groups and the applied EPIC equation does not use the chemical properties that distinguish several of the Andosol units. The variance comparison indicates that the K contrast among SMUs is much smaller than the C contrast among land-cover classes. This does not demonstrate that SMUs improve predictive accuracy; rather, it quantitatively shows how much soil-unit differentiation is represented in the current RUSLE parameterization. SMUs remain useful for linking predicted erosion patterns to mapped soil–landscape context and for organizing subsequent field verification.

Four sources of uncertainty are particularly relevant. First, the treatment of concentrated flow strongly affects the upper tail of LS and predicted soil loss, although the median LS changes little across the tested thresholds. Second, the C factor is assigned from literature values and the shrubland class has a user’s accuracy of only 60%, so

misclassification can affect the extent of higher predicted values. Third, rainfall erosivity derived from monthly data is sensitive to temporal resolution because monthly data do not resolve event-scale rainfall intensity (Brychta & Brychtová, 2020). Fourth, the input datasets operate at different spatial scales: CHIRPS provides one spatially averaged rainfall series for the park, the soil map has a minimum legible delineation of about 12.5 ha, the common computational grid is 8.35 m, and SPOT-6 imagery is 1.5 m. Resampling to the common grid does not create spatial detail absent from the coarser inputs (Gertner et al., 2002). In addition, 6.4% of the terrestrial area has no valid $\text{RUSLE} \times \text{SMU}$ estimate.

The spatial concentration of higher predicted soil-loss classes suggests that field verification can be targeted rather than applied uniformly across the park. The 32.74 ha above $385 \text{ t ha}^{-1} \text{yr}^{-1}$, almost all in SMU-4, provide a defined area for checking vegetation condition, visible sheet and rill erosion, and the validity of the concentrated-flow threshold. Any site-specific conservation intervention should follow field verification because the values are modelled screening estimates (Abrouri et al., 2026).

We did not validate the RUSLE output against measured erosion or sediment yield, and no independent erosion dataset was available for the park. The predicted values therefore represent modelled soil-loss potential and should not be read as measured erosion rates. The C and P values are class-level constants from the literature and field observation, and the particle-size data come from textural classes, so K resolves textural groups only. The estimates exclude 33.87 ha of concentrated-flow, NoData and sliver cells. RUSLE does not represent gully erosion, mass movement or sediment delivery, which may be important on steep valley margins where the highest values occur.

Future validation should include a field survey stratified by SMU, slope class and land cover,

with additional sampling in the 32.74 ha occupied by the upper predicted classes. A fixed field protocol could record rills, pedestals, exposed roots and sheet-wash indicators and compare field scores with the predicted spatial pattern. Mapping channel heads during the same survey would also provide field evidence for refining the concentrated-flow threshold.

CONCLUSIONS

Predicted sheet-and-rill soil loss in Ir. H. Djuanda Forest Park was spatially concentrated. The baseline RUSLE $\times$ SMU analysis produced 493.32 ha of valid estimates, of which 93.6% was below $385.14 \text{ t}\cdot\text{ha}^{-1}\cdot\text{yr}^{-1}$ and 32.74 ha was above that value. SMU-4 contained 97% of the above $385 \text{ t}\cdot\text{ha}^{-1}\cdot\text{yr}^{-1}$.

The mapped SMUs produced relatively small differences in K compared with the contrast introduced by land cover: $\text{Var}[\ln(K)]$ was 0.16% of $\text{Var}[\ln(C)]$. The concentrated-flow threshold strongly affected the upper tail of LS and the maximum predicted soil loss but changed the median LS by less than 10% between the unmasked and 75-cell scenarios. The results therefore support use of the map for spatial screening, while the absolute magnitudes should be treated as modelled estimates rather than measured erosion rates.

The results are therefore most appropriately used for spatial screening and prioritization of field verification. The absolute magnitudes should be treated as modelled estimates, and field verification of the upper predicted classes should precede site-specific conservation works.

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Data Availability

The RUSLE factor layers (R, K, LS, C and P), the predicted soil-loss map, the RUSLE $\times$ SMU intersection, the park boundary and the land-cover map are available as shapefiles from the corresponding author on reasonable request, subject to the data-use conditions of the source datasets. The

annual precipitation and erosivity series are provided in Table. A reproducibility version of the Google Earth Engine workflow for the CHIRPS monthly series is provided in Supplementary Information S3; the archived production script should be used if any implementation parameter differs. The SMU source data are subject to the access conditions of BRMP-SDLP. The original SPOT-6 scene cannot be redistributed under its commercial licence; its identifier and acquisition date are given in Table 1.

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