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High forest cover does not preclude localized modeled erosion pressure: A screening and management-prioritization assessment of the Warjori Watershed, West Papua, Indonesia

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Abstract

Aggregate watershed indicators can obscure concentrated environmental pressure in mountainous tropical landscapes. This study integrated forest cover, regulatory permanent-vegetation cover, statutory critical-land classes, and a land-unit Universal Soil Loss Equation (USLE) scenario to screen land condition and identify management priorities in the 152,782.33-ha Warjori Watershed, West Papua, Indonesia. The assessment used land cover, critical-land status, 2025 monthly rainfall, soil units, slope classes, soil depth, and supporting spatial data. Primary and secondary forest covered 84.14% of the watershed, while regulatory permanent vegetation covered 91.92%. Critical and Very Critical land accounted for 6.26%; however, Moderately Critical to Very Critical classes together accounted for 88.06%. The erosion-index dataset contained 4,270 land units covering 152,733.91 ha. The 2025 scenario yielded area-weighted modeled soil loss of 19.54 t ha^{-1} yr^{-1}, area-weighted tolerable soil loss of 5.02 t ha^{-1} yr^{-1}, and a weighted mean unit-level erosion index of 8.72. High and Very High erosion-index classes covered 51.35% of the modeled area. These results reveal a scale mismatch between favorable aggregate vegetation indicators and locally elevated modeled pressure. Management screening supports four complementary actions: forest protection, preventive management of Moderately Critical land, rehabilitation of degraded non-forest sites, and field verification of high-index units. Because rainfall covered one year, LS was class-based, several coefficients were transferred, P was fixed at 1.0, the tolerable-loss lookup was incomplete, and field validation was unavailable; the estimates should be interpreted as management-screening evidence rather than measured erosion or sediment delivery.

Keywords: Critical Land; Erosion Index; Permanent Vegetation; Screening Assessment; Soil Loss; Watershed Prioritization

1. Introduction

Watersheds integrate hillslope, channel, vegetation, soil, and land-use processes across hydrologically connected upstream and downstream zones. Changes in land cover and surface condition influence infiltration, runoff generation, soil detachment, sediment transfer, water quality, and ecosystem services. Effective watershed management therefore requires indicators that distinguish broad landscape condition from localized degradation and that are matched to the spatial scale at which protection, prevention, and rehabilitation decisions are made [1,2]. Tropical-forest hydrology

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further shows that forest-water relationships are process- and scale-dependent rather than reducible to a single percentage of tree cover [3,4].

In humid tropical and mountainous environments, forest canopy, litter, roots, and understory commonly reduce raindrop impact, promote infiltration, and stabilize soil; however, this protection is spatially heterogeneous. Deforestation and landscape fragmentation can intensify runoff and flood response [5,7], while steep terrain, roads, trails, canopy openings, shallow soils, and altered soil hydraulic properties can produce localized erosion even within predominantly forested landscapes [6-8]. Hydrological benefits may also vary nonlinearly with tree-cover density and site water balance [9]. Thus, high aggregate forest cover should be interpreted as a broad protective condition, not as proof that every land unit has low erosion pressure.

Indonesia's watershed-monitoring framework combines land condition, water regime, socioeconomic conditions, investment in water infrastructure, and spatial utilization. Within the land-condition component, permanent-vegetation cover, critical-land percentage, and erosion index are used as operational indicators [10,11]. These indicators are useful for screening, but they are not necessarily independent. Statutory critical-land mapping may already incorporate land cover, slope, erosion hazard, productivity, or land function; integrated remote-sensing and terrain-based critical-land assessments likewise demonstrate that such classes are composites of several environmental attributes rather than independent observations [12]. Consequently, agreement among indicators should not automatically be treated as independent validation.

The Universal Soil Loss Equation (USLE) and related models are widely used when direct erosion measurements are unavailable. USLE estimates average sheet and rill erosion from rainfall erosivity, soil erodibility, slope length and steepness, cover management, and support practice factors [13,14]. Its operational simplicity is valuable for screening, but uncertainty can arise from parameter transfer, spatial resolution, topographic algorithms, unit consistency, temporal representativeness, and missing validation [15-17]. Reviews of erosion and sediment models further emphasize that empirical soil-loss estimates are sensitive to model purpose, process representation, spatial scale, parameterization, and the distinction between hillslope erosion and sediment yield [18-20]. USLE does not directly simulate gully erosion, riverbank erosion, landslides, deposition, or sediment delivery to channels.

Soil erosion is a globally important land-degradation process whose magnitude is being reshaped by land-use change and climate forcing [21,22]. Comparisons of natural and human-accelerated erosion rates show that management can move landscapes far beyond background geomorphic rates [23], with consequences for long-term agricultural sustainability, soil productivity, and ecosystem functioning [24,25]. These findings support the use of erosion models for risk screening, but they also reinforce the need to separate relative management priority from claims of directly measured soil loss.

GIS and remote sensing have expanded watershed-scale erosion assessment by integrating land cover, terrain, soils, and rainfall, including applications in Indonesia and other tropical or mountainous catchments [26-31]. The resulting maps are useful for identifying relative contrasts, but their reliability depends on data quality, parameter provenance, and topographic representation. The Warjori Watershed, a forest-dominated mountainous watershed in West Papua, provides a relevant setting for examining whether favorable aggregate vegetation indicators can coexist with elevated modeled pressure in particular terrain-soil-cover combinations. Relatively few studies explicitly reconcile Indonesian regulatory indicators with unit-level erosion screening while translating uncertainty into transparent management-priority rules.

This study therefore aimed to: (1) quantify forest cover and regulatory permanent-vegetation cover as distinct indicators; (2) quantify Critical and Very Critical land while retaining the complete distribution of statutory critical-land classes; (3) summarize scenario-based USLE soil loss and erosion-index estimates at the land-unit level; (4) interpret the partial regulatory land-condition score without assigning an unsupported overall watershed class; and (5) convert the available evidence into a cautious screening and management-prioritization framework.

2. Materials and Methods

2.1. Study area and assessment design

The assessment was conducted for the Warjori Watershed in West Papua, Indonesia. The source boundary extends approximately from 133°30′ to 134°00′ E and from 0°40′ to 1°30′ S and has a reported area of 152,782.33 ha. The administrative context intersects Manokwari, South Manokwari, and Arfak Mountains regencies. The landscape is predominantly hilly to mountainous, draining toward the northern coastal zone (Figure 1).

The study was designed as a screening-level spatial assessment rather than a validated measurement of actual erosion. It evaluated only the land-condition subset of the Indonesian watershed-monitoring framework. Water regime, socioeconomic conditions, water-infrastructure investment, and spatial-utilization criteria were outside the analytical scope; therefore, no official overall watershed-performance category was assigned. The assessment design followed the principle that environmental models should have an explicit decision purpose, transparent assumptions, and evaluation criteria proportionate to the available data [32-35]. Accordingly, the analysis was used to compare relative management concern and define verification needs, not to claim predictive certainty.

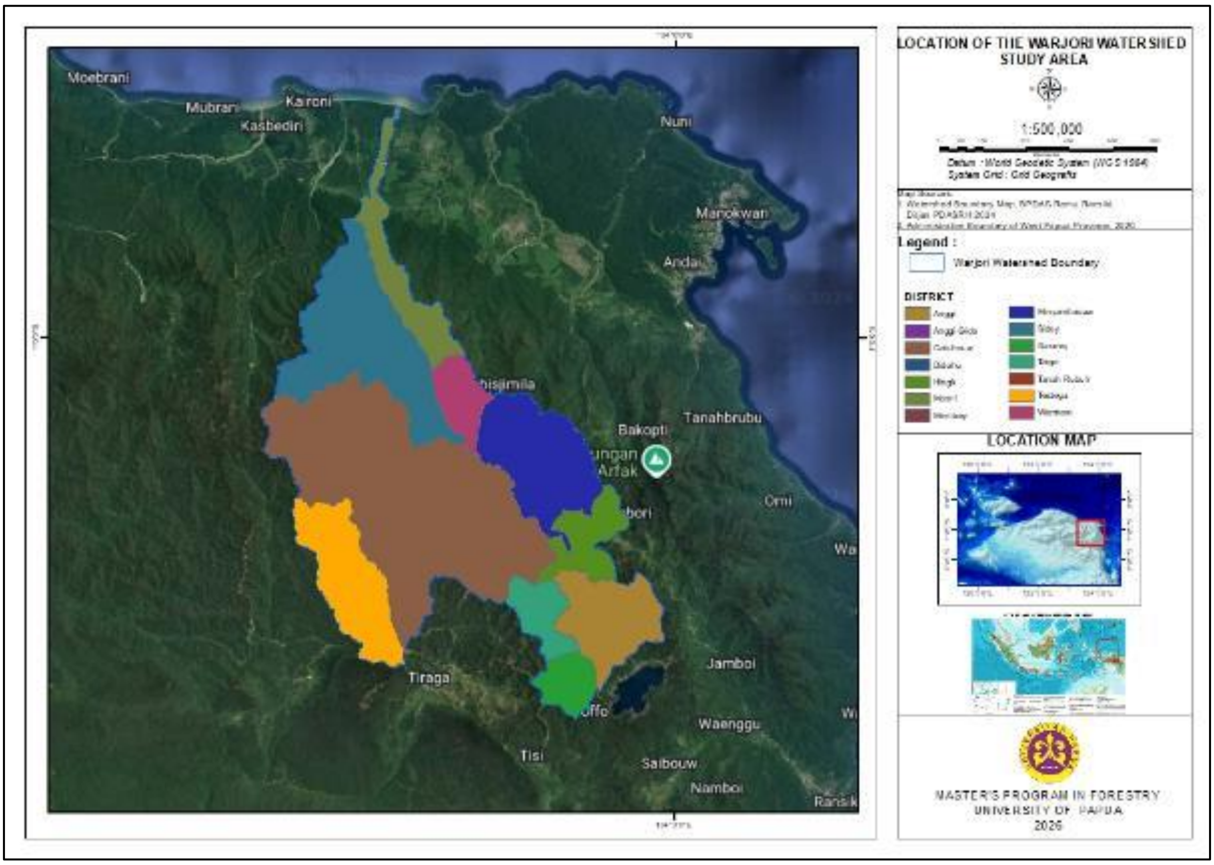

Figure 1 Location and administrative context of the Warjori Watershed in West Papua, Indonesia. Administrative colors in the source map represent Manokwari, South Manokwari, and Arfak Mountains regencies.

2.2. Data sources, spatial units, and quality control

The assessment used institutional watershed-boundary, land-cover, critical-land, soil, and topographic data; monthly rainfall for 2025; soil-depth attributes; and supporting field documentation. Source layers were stored in the WGS 84 geographic coordinate system. Data provenance, spatial harmonization, and classification quality were treated as integral components of model reliability because remote-sensing and GIS-derived erosion assessments can propagate uncertainty from input layers into final maps [31,33,34]. Because the archived workflow did not preserve a complete projected-coordinate processing chain, reported areas were treated as source-derived attributes rather than newly calculated planimetric areas. Formal sensitivity and uncertainty analyses were not attempted because the raw parameter distributions and reproducible processing archive were unavailable; performing such analyses without defensible input ranges can create false confidence [36,37].

Table 1 Data sources, analytical use, and principal quality constraints

Dataset	Source/year	Analytical use	Quality constraint
Watershed boundary	BPDAS Remu Ransiki; 2024/2025	Clipping and reported watershed area	Custodian metadata and projected-area recalculation were not preserved.
Land cover	BPKHTL Region XVII Manokwari; 2024/2025	Forest cover and permanent-vegetation indicator	No independent classification-accuracy matrix was available.
Critical land	BPDAS Remu Ransiki/national layer; 2024/2025	Critical-land percentage and preventive screening	Potential dependence on cover, slope, erosion, productivity, or land function.
Soil units	Institutional land-unit attributes; 2025	Assignment of K values	Laboratory or pedotransfer documentation was incomplete.
Slope/topography	DEM-derived classes; 2025	Class-based LS assignment	DEM resolution, slope units, and anomalous class frequencies require audit.
Rainfall	BMKG/supporting rainfall data; 2025	Monthly Lenvain erosivity scenario	One-year scenario; not long-term climatology.
Soil depth	Land-unit attribute table; 2025	Tolerable soil loss	The original depth-to-T conversion lookup was not preserved.

Land units were generated by overlaying the watershed boundary, land cover, critical-land class, soil unit, slope class, and soil depth. Overlay-based units are useful for maintaining categorical traceability, but boundary mismatch, raster resolution, resampling, and classification error can compound across layers [31,34,35]. The erosion-index dataset contained 4,270 units covering 152,733.91 ha, equivalent to 99.968% of the reported watershed area. The remaining 48.42 ha were retained as an explicit coverage gap and were not redistributed proportionally among classes.

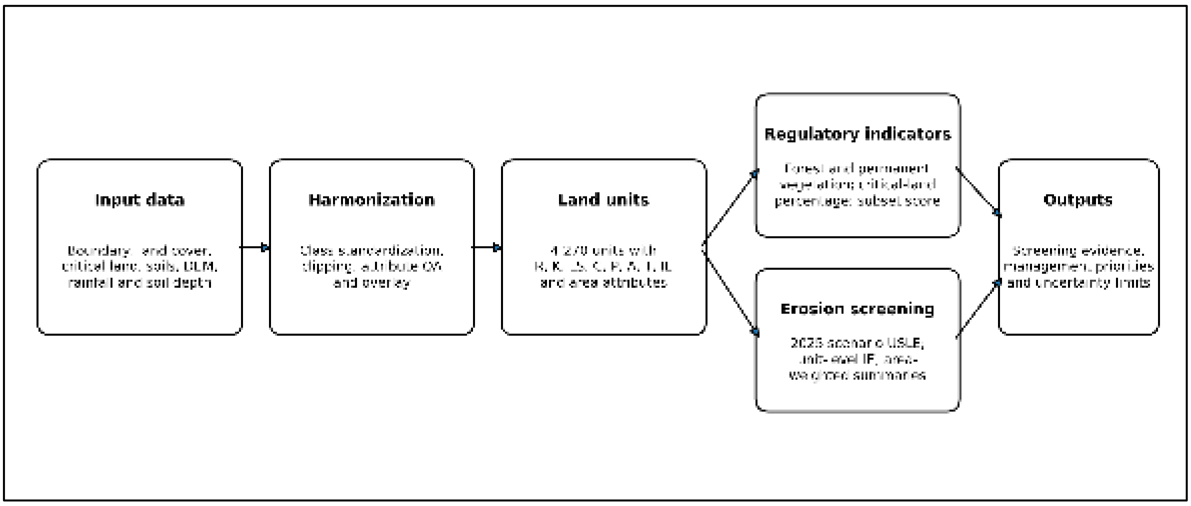

Figure 2 Analytical workflow separating regulatory land-condition indicators, scenario-based erosion screening, management prioritization, and uncertainty limits.

2.3. Forest cover, permanent vegetation, and critical land

Forest cover was calculated as the combined area of primary and secondary dryland forest. Regulatory permanent vegetation followed the classes represented in the source data and the national monitoring framework: primary forest, secondary forest, shrub, swamp shrub, and plantation [10,11]. Savanna/grassland was excluded because its permanence and protective condition could not be established from the class label. The distinction between ecological forest cover and the broader regulatory indicator is necessary because hydrological and erosion-control functions depend on canopy structure, ground cover, soil properties, and disturbance, not simply on a nominal vegetation class [3,4,6,8]. The indicators were calculated as:

Forest cover or PPV (%) = (included class area / watershed area) × 100

The formal critical-land percentage (PLK) was calculated as the sum of Critical and Very Critical land divided by the total watershed area. Moderately Critical land was excluded from the formal numerator but retained as a preventive-management statistic [10,11]. Because the critical-land layer may contain variables also used in erosion modeling, and because integrated critical-land mapping commonly combines spectral and terrain information [12], it was interpreted as complementary screening information rather than an independent model-validation dataset.

2.4. Scenario-based USLE screening

Potential sheet and rill erosion for land unit i was represented as $A_i = R_i \times K_i \times LS_i \times C_i \times P_i$, where A is modeled soil loss, R is rainfall erosivity, K is soil erodibility, LS is the combined slope-length and slope-steepness factor, C is the cover-management factor, and P is the support-practice factor [13-20]. Monthly rainfall erosivity for the 2025 scenario was estimated using the Lenvain relationship $R_m = 2.21(P_m)^{1.36}$, with monthly rainfall P expressed in centimeters, as summarized for Indonesian applications by Arsyad [38]. The annual scenario factor was the sum of monthly values. Parameterization was interpreted conservatively: land-cover-dependent C assignments were treated as generalized coefficients [39], rainfall-dependent results were labeled as a one-year scenario because robust erosivity characterization generally requires high-temporal-resolution and multi-year records [40], and the analysis acknowledged the event-scale and climate-response limitations of USLE-family models [41,42].

K values were inherited from the soil-unit parameter table. LS values were assigned by slope class rather than calculated continuously from the upslope contributing area. This class-based representation differs from GIS methods that derive slope length and convergence from contributing area, unit stream power, and continuous terrain geometry [43-45]. C values were assigned by land-cover class, and P was set to 1.0 because no spatially explicit inventory of conservation practices was available. These choices reproduce the archived screening parameterization; they should be interpreted as comparative assumptions rather than locally calibrated measurements [39,41,42]. The complete K and C/P tables are provided as Supplementary Tables S1 and S2.

2.5. Tolerable soil loss, erosion index, and regulatory subscore

The erosion index for unit i was calculated as $IE_i = A_i/T_i$, where T is the tolerable soil loss. T values were inherited from soil-depth-linked land-unit attributes. Because the original soil-depth-to-T lookup was unavailable, T-based inference was treated as provisional. The weighted mean unit-level IE was calculated as $\Sigma(IE_i \times L_i)/\Sigma L_i$, where L is unit area. The weighted mean of unit-level ratios was reported separately from the ratio of weighted mean A to weighted mean T because the two quantities are not mathematically equivalent. This separation reduces the risk that aggregation choices or poorly constrained parameters are hidden behind a single summary statistic [35,37].

In the regulatory context, the PLK, permanent vegetation, and IE scores were combined using the weights specified in Regulation P.61/Menhut-II/2014 [10]. The resulting value was reported only as a partial land-condition subscore and was not interpreted as an official overall watershed-performance class.

2.6. Management-prioritization logic

The screening evidence was translated into four action-oriented priority categories: protection, prevention, rehabilitation candidates, and field verification. This rule-based structure was designed as management triage, consistent with good environmental-model practice, in which model outputs are explicitly linked to a decision context and evidential confidence [32-34]. The framework did not assign engineering prescriptions or final site boundaries. Because the archived material lacked the geometry needed to cross-tabulate all 4,270 units, the priority categories were interpreted as decision rules that guide subsequent spatial analysis and field confirmation rather than as a completed intervention map.

2.7. Uncertainty characterization and inference limits

Uncertainty was characterized qualitatively by identifying the data source, likely direction or magnitude of influence, and the interpretive control adopted in the manuscript. Three evidence levels were distinguished: (i) source-table indicators, which support watershed-scale descriptive statements; (ii) scenario-model outputs, which support relative screening but not validated rates; and (iii) site-specific intervention hypotheses, which require geometry, cross-tabulation, and field verification. This tiered interpretation follows established guidance on model purpose, equifinality, uncertainty communication, performance evaluation, and sensitivity analysis [33-37]. No confidence intervals or formal Monte Carlo analysis were calculated because raw parameter distributions and the complete processing archive were unavailable; one-year rainfall and generalized USLE factors also precluded robust probabilistic inference [41,42].

3. Results and Discussion

3.1. Landscape condition: forest cover, permanent vegetation, and critical land

Primary dryland forest occupied 106,805.56 ha (69.91%) and secondary dryland forest occupied 21,742.46 ha (14.23%). Forest cover was therefore 128,548.02 ha, or 84.14% of the watershed. Adding shrub, swamp shrub, and plantation increased the total area of regulatory permanent vegetation to 140,442.08 ha, or 91.92%. Reporting both indicators is important because the regulatory definition is broader than ecological forest cover and should not be interpreted as equivalent to intact tree cover. Extensive forests generally support infiltration, soil protection, and hydrological regulation [3,4], but research in steep tropical terrain shows that local disturbance, terrain connectivity, and soil hydraulic changes can weaken protection within otherwise forest-dominated landscapes [6-9].

Table 2 Land-cover distribution and calculation of forest and regulatory permanent-vegetation indicators

No.	Land-cover class/metric	Area (ha)	Area (%)	PPV status or interpretation
1	Primary dryland forest	106,805.56	69.91	Included
2	Secondary dryland forest	21,742.46	14.23	Included
3	Shrub	11,382.00	7.45	Included
4	Savanna/grassland	10,200.25	6.68	Excluded
5	Mixed dryland agriculture	1,587.67	1.04	Excluded
6	Plantation	386.74	0.25	Included
7	Open land	230.76	0.15	Excluded
8	Settlement	159.21	0.10	Excluded
9	Swamp shrub	125.32	0.08	Included
10	Transmigration area	85.05	0.06	Excluded
11	Dryland agriculture	77.30	0.05	Excluded
	Forest cover: primary + secondary forest	128,548.02	84.14	Ecological cover metric
	Regulatory permanent vegetation	140,442.08	91.92	Forest + shrub + swamp shrub + plantation

Moderately Critical land dominated the statutory map, covering 124,985.46 ha (81.81%). Critical and Very Critical land together covered 9,558.06 ha, corresponding to a formal PLK of 6.26%. The broader Moderately Critical to Very Critical classes occupied 134,543.52 ha (88.06%). Thus, a relatively small formal critical-land area coexisted with a large area requiring preventive management under the regulatory framework [10,11]. The critical-land distribution should not be used as independent confirmation of the USLE because the mapping logic may share land-cover, slope, and erosion-related inputs; similar integrated mapping approaches combine spectral and terrain variables [12].

Table 3 Statutory critical-land distribution

Critical-land class	Area (ha)	Area (%)
Non-critical	13,800.15	9.03
Potentially critical	4,438.66	2.91
Moderately critical	124,985.46	81.81
Critical	9,481.77	6.21
Very critical	76.29	0.05
Total	152,782.33	100.00

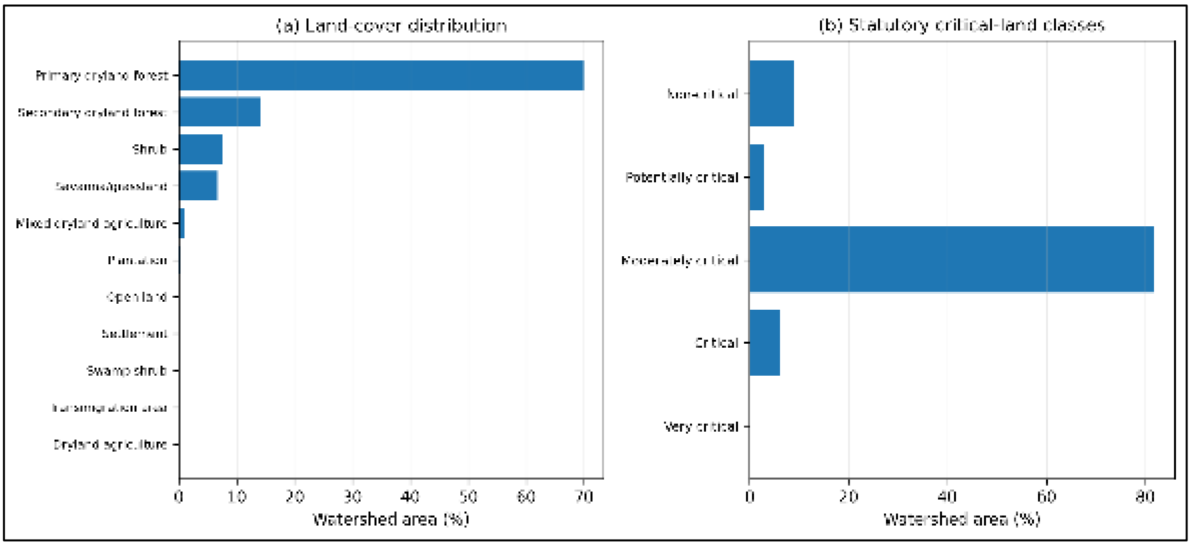

Figure 3 Distribution of (a) land-cover classes and (b) statutory critical-land classes in the Warjori Watershed.

The combination of 84.14% forest cover, 91.92% regulatory permanent vegetation, and 81.81% Moderately Critical land illustrates why aggregate indicators must be interpreted according to their purpose. Forest and permanent vegetation describe broad cover retention and potential hydrological protection [3,4], whereas critical land classes identify condition and management concerns through a composite regulatory framework [10-12]. They are complementary but not interchangeable, and their coexistence does not constitute independent cross-validation.

3.2. Rainfall scenario and model factors

Total rainfall in 2025 was 2,322.90 mm, and the monthly Lenvain erosivity values summed to 1,547.48. November had the highest rainfall and erosivity values (Figure 4). These results characterize the 2025 scenario only and should not be interpreted as long-term climatic erosivity. Global erosivity assessments rely on high-temporal-resolution, multi-year records to capture climatic variability [40], while erosion response can change nonlinearly with precipitation amount, intensity, and surface cover [42].

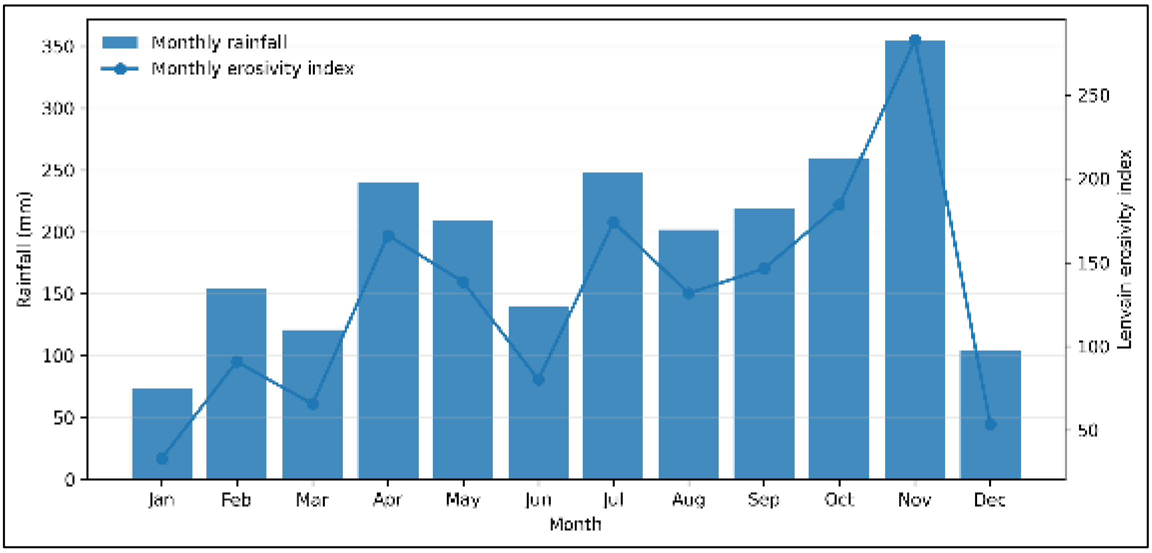

Figure 4 Monthly rainfall and Lenvain erosivity index for the 2025 screening scenario.

The area-weighted K value was 0.191, with assigned unit values ranging from 0.075 to 0.323. Typic Eutrudepts and Lithic Eutrudepts represented 78.94% of the watershed. The area-weighted CP value was 0.0124. Primary and secondary forests had low C values, whereas open land and transmigration areas had higher values. Because K and C were inherited coefficients rather than locally calibrated measurements, their role is comparative and screening-oriented. Reviews of USLE applications identify transferred K and C values, generalized management assumptions, and event-to-annual scaling as influential sources of uncertainty [15-17,39,41,42].

The slope-class distribution warrants particular caution. The >40% class accounted for 82.39% of the watershed, the 8-15% class was absent, and the 25-40% class accounted for only 0.06% (Table 4). This pattern may reflect a strongly dissected mountain landscape, but it may also indicate DEM-resolution effects, slope-unit confusion, or class-boundary problems. Raster LS methods based on contributing area and continuous slope geometry are specifically designed to capture convergence and slope-length effects that broad classes cannot represent [43-45]. The weighted class-based LS value of 8.22 should therefore be considered a high-influence uncertainty.

Table 4 Slope classes and assigned LS factors

Slope (%)	Class	LS	Area (ha)	Area (%)
0-8	Flat	0.4	8,723.03	5.71
>8-15	Gentle	1.4	0.00	0.00
>15-25	Moderately steep	3.1	18,098.38	11.85
>25-40	Steep	6.8	88.06	0.06
>40	Very steep	9.5	125,872.86	82.39
Total/weighted LS		8.22	152,782.33	100.00

3.3. Modeled soil loss, tolerable loss, and erosion index

Across the 4,270 land units, area-weighted modeled soil loss was 19.54 t ha^{-1} yr^{-1} and area-weighted tolerable soil loss was 5.02 t ha^{-1} yr^{-1}. The weighted mean unit-level IE was 8.72, while the ratio of weighted mean A to weighted mean T was 3.89. The difference is not an arithmetic error. Averaging unit-level ratios gives greater influence to units with small T and therefore reflects a different aggregation operation from dividing two area-weighted means.

Table 5 Summary of screening metrics and erosion-index classes

Metric/class	**Result**	**Interpretation**
Rainfall erosivity, R	1,547.48	2025 Lenvain scenario
Area-weighted K	0.191	Transferred soil-unit coefficients
Area-weighted class-based LS	8.22	Slope-class assignment
Area-weighted CP	0.0124	P = 1.0 throughout
Area-weighted modeled A	19.54 t ha^{-1} yr^{-1}	Mean of unit-level products
Area-weighted T	5.02 t ha^{-1} yr^{-1}	Inherited soil-depth-linked values
Weighted mean unit-level IE	8.72	$\Sigma(IE_iL_i)/\Sigma L_i$
Ratio of weighted mean A to T	3.89	19.54/5.02; not equivalent to mean IE
Very low IE (<=0.5)	70,169.14 ha (45.94%)	1,268 units
Low IE (>0.5-1.0)	2,498.38 ha (1.64%)	247 units
Moderate IE (>1.0-1.5)	1,636.91 ha (1.07%)	223 units
High IE (>1.5-2.0)	14,952.66 ha (9.79%)	391 units
Very high IE (>2.0)	63,476.82 ha (41.56%)	2,141 units
High + Very high IE	78,429.48 ha (51.35%)	Share of modeled area
Modeled-area coverage	152,733.91 ha (99.968%)	48.42-ha explicit gap

High and Very High IE classes covered 51.35% of the modeled area. This does not mean that half of the watershed was observed to undergo severe erosion. Rather, the model identified units where the combination of assigned R, K, LS, C, P, and T produced a high screening ratio. The distinction is central because USLE estimates gross sheet and rill erosion potential, not sediment yield, mass wasting, or field-validated degradation [15-20]. In addition, alternative parameter combinations can generate similar outputs, so the mapped class should be treated as a hypothesis for verification rather than a deterministic statement of site condition [35].

3.4. Scale mismatch and regulatory interpretation

The central finding is a scale-dependent contrast: extensive forest and permanent vegetation coexisted with a large modeled share of High and Very High IE. This apparent contradiction is plausible because forest cover is aggregated over the watershed, whereas IE responds to local combinations of steep terrain, shallow soil, cover class, and tolerable loss. Forest canopy, litter, roots, and understory generally reduce soil detachment and regulate water pathways [3,4], but protection can be weakened locally by roads, trails, fragmentation, canopy openings, sparse understory, concentrated drainage, or altered soil hydraulic properties [5-9]. Conversely, class-based LS and small inherited T values may elevate model ratios even where field erosion is limited, a recognized challenge in regional erosion and sediment modeling [18-20].

Applying the national indicator scores produced a raw land-condition subset score of 35.0 and an exploratory normalized mean indicator score of 0.875. These values represent only PLK, permanent vegetation, and IE. They were not labeled “good,” “poor,” or any other official overall class because the remaining regulatory criteria were not evaluated. This avoids overextending a partial score into a complete watershed-performance assessment.

The results are consistent with broader GIS-based erosion research, which shows that topographic representation, cover coefficients, and model implementation can substantially affect the magnitude and spatial pattern of USLE-type estimates [15-20,26-31]. The anomalous slope-class distribution is particularly important because terrain algorithms based on contributing area, slope geometry, and flow convergence can yield LS patterns that differ from those produced by categorical assignments [43-45]. The contribution of the present assessment is therefore not a claim of precise erosion measurement, but the explicit reconciliation of regulatory cover indicators, statutory land condition, unit-level modeled pressure, and inference boundaries.

3.5. Screening-based management priorities

The available evidence supports differentiated management rather than a single watershed-wide intervention. Forest protection remains essential because primary and secondary forests form the dominant protective cover and sustain multiple hydrological functions [3,4,6]. The large Moderately Critical area indicates a broad need for preventive management under the regulatory framework [10-12], while Critical and Very Critical non-forest land should be considered for rehabilitation. This prioritization is also consistent with global evidence that land-use change can accelerate erosion beyond natural rates and threaten long-term soil and ecosystem sustainability [21-25]. High-index units should nevertheless be verified before site-specific structural measures are designed, particularly where they occur in apparently well-forested settings.

Table 6 Management-prioritization framework derived from the screening evidence

Priority category	Screening criterion	Management direction	Confidence and limitation
Protection priority	Primary/secondary forest, especially on steep terrain	Avoid conversion; maintain canopy, understory and litter; control road, trail and drainage impacts	High for broad action; location-specific threats require field confirmation
Prevention priority	Moderately Critical land, particularly on steep terrain or near drainage pathways	Maintain ground cover; control clearing; promote agroforestry, riparian buffers, and road/trail drainage	Moderate; statutory class is available but may not be independent of other inputs
Rehabilitation candidates	Critical/Very Critical land combined with non-forest, annual-use, open, or exposed surfaces	Vegetative rehabilitation, ground cover, contour-aligned practices, bioengineering or structural measures after site assessment	Moderate at class level; exact intersection areas were not available
Verification priority	High/Very High IE units, especially unexpected high values under forest cover	Field checks of soil depth, cover condition, erosion features, drainage concentration, turbidity or sediment indicators	Low for direct intervention until geometry and field evidence are available

The framework functions as management triage. It distinguishes areas that should remain protected, areas where degradation should be prevented, candidate classes for rehabilitation, and model outputs requiring verification. This is an appropriate use of a screening model when decision rules, assumptions, and evidential confidence are stated explicitly [32-37]. It is not a replacement for detailed site design, land-tenure consultation, engineering assessment, participatory planning, or field validation of erosion processes.

3.6. Uncertainty, robustness, and appropriate use

Table 7 Principal sources of uncertainty and interpretive controls

Component	Current treatment	Likely influence	Interpretive control
Coordinate system and area	Source layers were stored in WGS 84; a complete projected workflow was not archived	Moderate for precise area/topographic derivatives	Treat areas as source-derived; avoid false spatial precision.
Rainfall erosivity	Only 2025 monthly rainfall was available	High for climatic representativeness	Label all R-dependent outputs as a 2025 scenario.
K coefficients	Transferred soil-unit values without full local calibration	Moderate to high; direction unknown	Interpret comparatively; disclose the complete parameter table.
LS factor	Assigned by slope class; no continuous flow accumulation	High in steep terrain	Treat magnitude and local pattern as screening evidence; audit DEM before hotspot claims.

C and P factors	Categorical C values; P fixed at 1.0	Moderate; P may be conservative where practices exist	Do not interpret values as observed management performance.
T and IE	Depth-linked T lookup was not preserved	High for IE magnitude and class	Report A and T separately; report both mean IE and ratio of means; label IE provisional.
Critical-land dependence	May share cover, slope or erosion inputs	Moderate for apparent agreement among indicators	Do not use critical land as independent validation of USLE.
Coverage gap	48.42 ha outside the IE dataset	Low for watershed totals	Retain explicitly; do not redistribute among classes.
Validation	No plot erosion, sediment yield, turbidity or field-validation dataset	High for predictive accuracy	Do not claim measured erosion, sediment delivery, or verified hotspots.

The watershed-scale land-cover and critical-land totals are arithmetically consistent and suitable for descriptive screening, although classification accuracy was unavailable. The modeled A and IE outputs are less robust because several influential factors were transferred, simplified, or incompletely documented. Environmental-model literature emphasizes that uncertainty should be traced to data, parameters, model structure, aggregation, and evaluation criteria rather than represented by a single generic caveat [33-37]. In the present study, one-year rainfall, generalized factor values, class-based LS, and an incomplete T lookup are especially influential [41,42]. Site-specific recommendations therefore have the lowest evidential confidence until the 4,270 unit geometries are recovered, cross-tabulated, and verified in the field.

A future analytical upgrade should reproject all layers to WGS 84/UTM Zone 53S (EPSG:32753), use multi-year rainfall erosivity, calculate raster LS from a hydrologically conditioned DEM, recover or reconstruct K/C/P/T provenance, summarize unit-level distributions and outliers, map the priority intersections, and compare modeled outputs with erosion features, sediment, or turbidity indicators. These steps follow established recommendations for model performance evaluation, sensitivity analysis, and transparent uncertainty treatment [34,36,37]. Multi-year high-resolution rainfall data [40] and terrain algorithms based on contributing area and continuous slope geometry [43-45] would be particularly important for converting the present screening study into a stronger predictive and spatially prescriptive assessment.

4. Conclusion

The Warjori Watershed retained extensive forest cover (84.14%) and regulatory permanent vegetation (91.92%). Critical and Very Critical land represented 6.26%, while Moderately Critical to Very Critical classes occupied 88.06%. The 2025 USLE scenario produced area-weighted modeled soil loss of 19.54 t ha^{-1} yr^{-1} and a weighted mean unit-level IE of 8.72; High and Very High IE classes covered 51.35% of the modeled area.

These findings demonstrate that favorable aggregate vegetation indicators do not preclude locally elevated modeled erosion pressure in a mountainous tropical watershed. The available evidence is most defensibly used for screening and management triage: protect primary and secondary forest, prevent deterioration across Moderately Critical land, identify degraded non-forest sites as rehabilitation candidates, and verify high-index units before prescribing interventions. The numerical outputs should not be interpreted as measured erosion, sediment delivery, or validated hotspot locations. Transparent uncertainty limits are therefore part of the principal result, not merely an analytical weakness.

Compliance with ethical standards

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Disclosure of conflict of interest

The authors declare that they have no conflict of interest.

Statement of ethical approval

Ethical approval was not required because the study used primary and secondary environmental, spatial, and climatic data and did not involve human participants or animals.

Statement of informed consent

Informed consent was not applicable because the study did not involve human participants.

Data availability

Institutional spatial data are subject to the access conditions of their custodians. Derived summary tables are reported in the manuscript and supplementary material. The unit-level data, metadata, and processing workflow should be shared in a permanent repository, subject to any applicable licensing.

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