

Integrating soil erosion modelling and field verification for spatial assessment of critical land

Wahyu Hidayat^{1*}, Muhammad Anggri Setiawan^{2,3},
Dyah Rahmawati Hizbaron²

¹ Master Program on Planning and Management of Coastal Area and Watershed, Faculty of Geography, Universitas Gadjah Mada, Jl. Kaliurang, Yogyakarta, 55281, Indonesia

² Department of Environmental Geography, Faculty of Geography, Universitas Gadjah Mada, Jl. Kaliurang, Yogyakarta, 55281, Indonesia

³ Center for Disaster Studies, Universitas Gadjah Mada, Jl. Mahoni C-16, Bulaksumur, Yogyakarta, 55284, Indonesia

* Corresponding author's email: wahyuhidayat1991@mail.ugm.ac.id

ABSTRACT

Land degradation is a global environmental issue that affects the ecological functions and sustainability of land resources. In Indonesia, degraded land conditions are commonly addressed through the concept of critical land, particularly in watershed assessment, management, and rehabilitation. Spatial approaches have been widely applied to identify critical land over large areas; however, their representativeness is strongly influenced by input data quality and may not fully reflect site-level degradation conditions. This study assessed critical land using a spatial approach that integrated key biophysical parameters with field-based verification in part of the Serang Watershed. Critical land was identified using a multicriteria spatial approach based on P.3/PDASHL/SET/KUM.1/7/2018. Land cover was derived from Sentinel-2A imagery using Random Forest and quantitatively assessed using 45 field reference points. Soil erosion was estimated using USLE, with soil erodibility determined through laboratory analysis of 18 soil samples representing different land units. Five criticality classes were identified, with Slightly Critical land dominating 58.45% of the study area, while Critical and Highly Critical land accounted for 6.27%. Field-based verification of areas classified as Critical and Highly Critical revealed diverse degradation characteristics, including rill and gully erosion, topsoil loss, shallow soil, slope failure, and anthropogenic disturbances. These findings indicate that integrating spatial modelling with field-based verification can provide site-level information to support the interpretation of critical-land conditions and the development of site-specific soil conservation and land rehabilitation measures.

Keywords: critical land; field-based verification; land degradation; soil erosion; spatial analysis.

INTRODUCTION

Land degradation is a global issue that affects various social, economic, and environmental aspects (Kumar et al., 2024). In Indonesian, land degradation is represented through the concept of critical land, which is primarily used for watershed assessment, management, and rehabilitation. Critical land generally refers to land that has experienced degradation of its physical,

chemical, and biological properties (Naharudin, 2021; Zachrani et al., 2024), thereby reducing its capacity to provide ecosystem services (D'Odorico, Paolo; Ravi, 2016). This condition is characterized by declining land functions and productivity, particularly in supporting agricultural activities, and may develop gradually from mild to severe levels depending on the physical characteristics of the land and its management practices (AbdelRahman, 2023; Juwono &

Subagiyo, 2019; Kironoto et al., 2021). Critical land can occur naturally; however, its occurrence is increasingly dominated by anthropogenic activities (Kironoto et al., 2021). Increasing human activities may drive land cover changes and land use practices that are incompatible with the biophysical characteristics and land capability (Khan & Chen, 2025; Taufan & Pratomo, 2022; Wahyunto & Dariah, 2014; Windarto et al., 2020). Inappropriate land management may also accelerate soil erosion, representing one of the major degradation processes contributing to the development of critical land (Ekawati et al., 2026; Wairiu, 2017).

The Ministry of Environment and Forestry of the Republic of Indonesia (KLHK) uses critical land identification as one of the approaches for determining priorities for land management and rehabilitation (Ministry of Environment and Forestry, 2022). The identification refers to Technical Guidelines No. P.3/PDASHL/SET/KUM.1/7/2018 issued by the KLHK, which integrates biophysical characteristics and land-use conditions to determine the level and spatial distribution of critical land (Directorate General of Watershed and Protected Forest Management, 2018). Its implementation utilizes Geographic Information Systems (GIS) to spatially integrate multiple thematic datasets. Consequently, the reliability of critical land identification depends on the quality and representativeness of the spatial data used to describe actual land conditions.

Critical land identification based on spatial data does not always fully represent actual field conditions. Actual biophysical conditions in the field are highly dynamic, potentially resulting in discrepancies between the information represented in spatial datasets and observed site conditions. Field-based verification is therefore essential for evaluating the representativeness of spatial information and ensuring that spatial modelling results adequately describe actual conditions to support decision-making (Racca, P.; Zeuner, T.; Jung, J.; Kleinhenz, 2010).

Spatial modelling provides an efficient approach for assessing land degradation across extensive areas with heterogeneous environmental conditions (Enar et al., 2025). However, the reliability of spatial modelling depends on the quality, spatial resolution, and thematic accuracy of the input data (Foody et al., 2016; García-álvarez et al., 2019; Radoux & Bogaert, 2017). In critical-land assessment, the interpretation of degradation

conditions involves multiple biophysical characteristics, including land-cover conditions and soil erosion, which may not be fully captured by spatial datasets alone. Field-based verification can therefore complement spatial modelling by providing direct observations of degradation characteristics at selected sites, particularly in areas identified as having high levels of criticality. In addition, field verification results are essential for evaluating the representativeness of spatial information and ensuring that spatial modelling results adequately describe actual conditions to support decision-making (Racca, P.; Zeuner, T.; Jung, J.; Kleinhenz, 2010).

Several studies have identified critical land in accordance with existing technical guidelines. In general, these studies have focused on producing spatial representations of critical land, whereas the representativeness of the identification results in relation to actual field conditions has received relatively limited attention, as reflected in studies by Narendra (2019), Widyatmanti et al., (2018), and Zachrani et al., (2024). Moreover, efforts to strengthen the representativeness of key input parameters and subsequently examine modelling outputs using direct field evidence remain limited. Therefore, an approach is needed that not only produces spatial information on critical land but also improves the representativeness of the input data and provides field-based evidence for interpreting the resulting critical-land conditions.

This study addresses this gap by integrating soil erosion modelling with field-based verification to assess critical land conditions in a portion of the Serang Watershed. The spatial assessment integrates land-cover and soil-erosion information to delineate critical-land conditions within the study area, while field observations are used to examine the observable characteristics of areas classified as Critical and Highly Critical. Unlike conventional map-accuracy assessment, the field observations are intended to provide qualitative evidence on the correspondence between modelled critical-land conditions and observable degradation characteristics at selected sites. Therefore, this study aims to assess the spatial distribution of critical land within part of the Serang Watershed by integrating soil erosion modelling and field-based verification, with particular attention to the representativeness of the input data and the observed degradation characteristics in the field.

METHODS

Study area

The study area covers part of the Serang Watershed, particularly its upstream to middle sections. The selection of the study area was based on its biophysical characteristics, particularly soil erosion, which constitutes one of the main parameters used in critical land identification. Relatively intensive erosion processes are concentrated in the upstream and middle parts of the watershed due to the topographic conditions and relatively steep slopes (Allafta, 2022). Administratively, the study area is located in Kulon Progo Regency, Special Region of Yogyakarta, and Purworejo Regency, Central Java, Indonesia, covering an area of 10,405.36 ha. The location of the study area is presented in Figure 1.

Research design and flow

This study was conducted through a series of analytical stages, including spatial data preparation, land cover mapping and accuracy assessment, soil sampling and laboratory analysis, critical land identification and classification, field-based verification of critical land conditions, and descriptive analysis. Critical land identification was conducted using a spatial multi-criteria analysis approach based on scoring and weighted overlay, referring to Technical Guidelines No. P.3/PDASHL/SET/KUM.1/7/2018. The overall research workflow is presented in Figure 2.

Based on Figure 2, the study generally consists of three main stages: land cover mapping, modelling of soil erosion hazard, and field-based verification of the resulting critical-land conditions. Phases 1 and 2 involve the development of spatial information for critical land identification using a quantitative approach through GIS-based spatial multi-criteria analysis. Land cover mapping is accompanied by quantitative accuracy assessment, while soil erosion hazard is estimated through spatial modelling based on biophysical parameters. Subsequently, Phase 3 involves field observations and descriptive evaluation of actual biophysical conditions in selected areas classified as Critical and Highly Critical. These observations are intended to provide field-based evidence for interpreting the modelled critical-land conditions rather than to constitute an independent statistical accuracy assessment of the critical-land map. Therefore, this study integrates quantitative spatial modelling with field-based observational and descriptive approaches to assess critical-land conditions.

Data collection

The data used in this study consisted of primary and secondary data to support the identification and evaluation of critical land conditions. Secondary spatial data included Sentinel-2A imagery, DEMNAS, rainfall data, land system maps, and forest area maps. Sentinel-2A imagery acquired in 2025 was used to derive land cover information using a Random Forest classification approach,

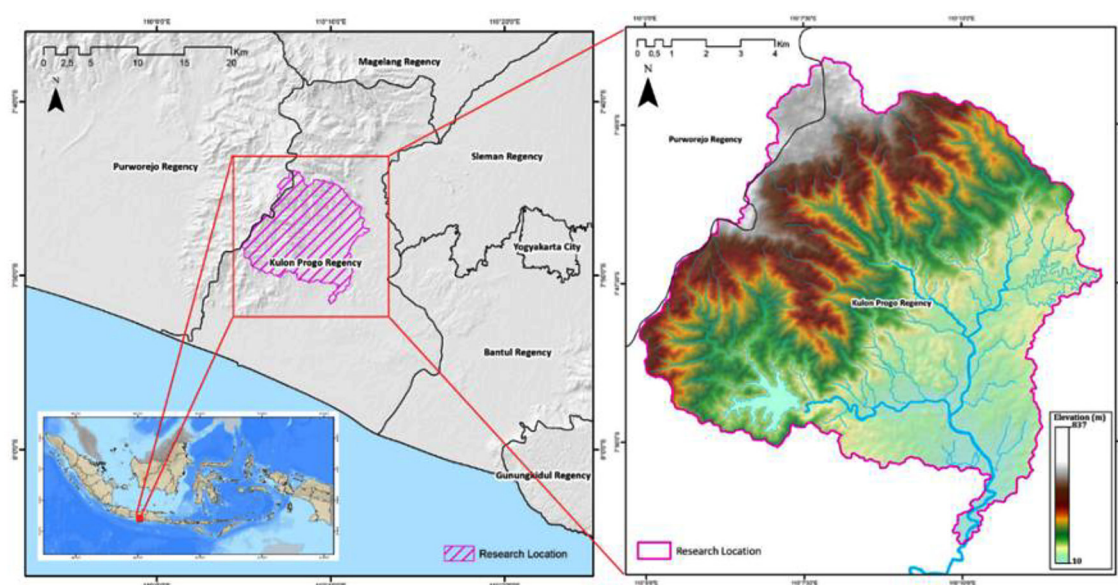


Figure 1. Map of the study area

which was subsequently used as the land cover parameter in critical land identification and as a basis for assigning the C and P factors in the erosion assessment. DEMNAS, a digital elevation model dataset, was used to derive slope information and topographic parameters for calculating the LS factor. Rainfall data were used to estimate the rainfall erosivity factor (R) through spatial interpolation of rainfall station data within and surrounding the study area. Land system data were used to delineate land units, whereas forest area data were used as one of the criteria for determining critical land classes. Primary data consisted of soil types and soil characteristics obtained through soil sampling within the predefined land units. Laboratory analyses were subsequently conducted to determine the soil erodibility factor (K). Additional field activities included land cover map accuracy assessment

and field-based verification of critical-land conditions. The land cover map was quantitatively assessed using field reference observations, whereas field-based verification of critical-land conditions was conducted to document observable degradation characteristics at selected sites. A detailed description of the data used in this study, including their sources and purposes, is presented in Table 1.

Data analysis

Land cover mapping

Land cover maps were derived through the extraction of information from Sentinel-2A imagery. This multispectral imagery provides adequate spatial resolution to support land cover identification and classification (Gound, 2022; Thuraipalam,

Table 1. Research data

No.	Data	Year	Spatial resolution/scale	Function	Data source
1	Sentinel-2A Imagery	2025	10 m	Land Cover Classes, CP factor, Land Unit Delineation	Copernicus Data Space Ecosystem (CDSE)
2	DEMNAS	2018	8 m	Slope, Land Unit Delineation, LS factor	Geospatial Information Agency (BIG)
3	Rainfall data	2025	10 m (interpolated)	R factor	Serayu Opak River Basin Authority
4	Soil characteristics	2026	1 : 50.000	K factor	Primary Data
5	Land system	2022	1 : 50.000	Land Unit Delineation	Geospatial Information Agency (BIG)
6	Forest Area	2026	1 : 250.000	Critical Land Classes	Ministry of Forestry

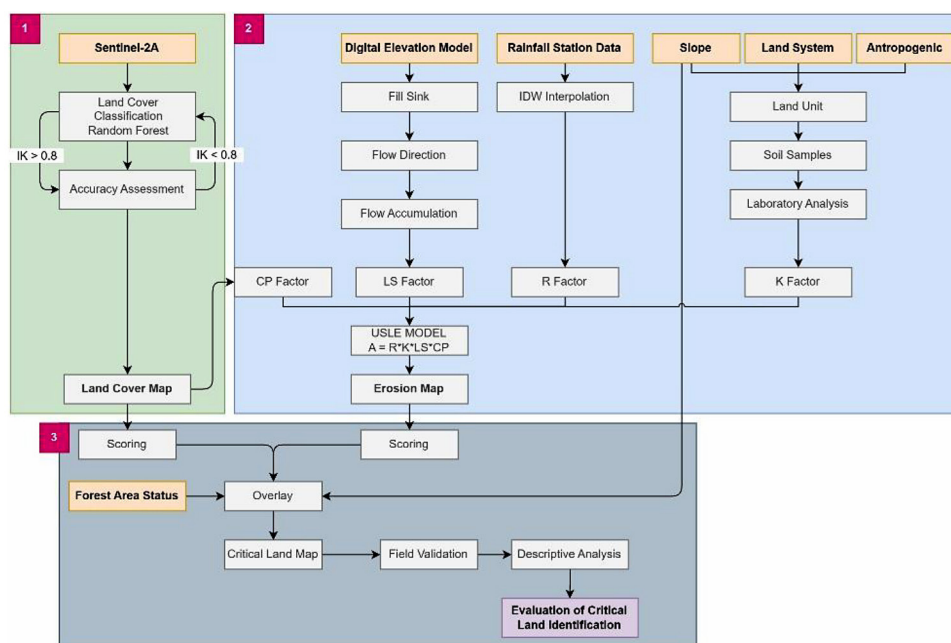


Figure 2. Research workflow

Gladima; Selvaraj, 2023). Land cover information was used as one of the main parameters for critical-land identification, as well as for land unit delineation and as a basis for assigning the C and P factors in the soil erosion assessment. Land cover information was extracted using a supervised classification approach based on the Random Forest algorithm. This algorithm has been widely applied in land cover classification and has demonstrated good performance in deriving land cover information from remote sensing data (Putri & Handayani, 2024).

The resulting land cover map was subsequently subjected to a quantitative accuracy assessment using 45 field reference points. The distribution of sample points was determined using a stratified random sampling approach to ensure that all land cover classes were adequately represented. Accuracy assessment was performed using a confusion matrix by comparing the classified land cover with field reference observations. The level of agreement was evaluated using the Kappa index, where a Kappa value greater than 0.80 indicates strong to almost perfect agreement (Landis & Koch, 1977). The calculation of the Kappa index is presented in Equation (1).

$$\text{Indeks Kappa} : \frac{N \sum_{i=1}^k x_{ii} - \sum_{i=1}^k (x_i + x_{+i})}{N^2 - \sum_{i=1}^k (x_i + x_{+i})} \quad (1)$$

where: N is the total number of samples, x_{ii} is the number of correctly classified samples in class I , x_i is the total number of samples in row I , x_{+i} is the total number of samples in column I , and k is the total number of land cover classes.

Land unit delineation and soil sampling

Land units were used as the spatial basis for soil sampling and as a spatial reference for field-based verification of critical-land conditions. The delineation of land units was based on the grouping of relatively homogeneous landscape characteristics, allowing each unit to serve as a sampling basis representing conditions over a broader spatial extent (Vacca et al., 2014; West, 2016). In this study, land unit delineation considered not only biophysical characteristics but also anthropogenic aspects representing human activities that contribute to changes in regional landscape characteristics (Lathifah et al., 2024).

Biophysical aspects in land unit delineation were represented by land system and slope maps. The slope map was derived from DEMNAS data

and subsequently classified into several slope classes using a Geographic Information System (GIS). Meanwhile, anthropogenic aspects were derived from the land cover map, which was reclassified according to the characteristics of human activities into urbanogenic, agrogenic, and natural classes. The biophysical and anthropogenic aspects were synthesized using an overlay approach in a GIS environment to generate land units. The resulting land units were subsequently used as the basis for determining soil sampling locations. Soil sampling was conducted using a purposive sampling approach by considering the representativeness of each land unit.

Soil samples were collected to represent each land unit within the 18 delineated land-unit polygons. Technically, soil sampling involved two types of samples: disturbed and undisturbed soil samples. Disturbed soil samples were used to analyse soil characteristics, including soil texture, organic matter content, and soil structure. Meanwhile, undisturbed soil samples were collected to determine soil permeability. Undisturbed samples were used to preserve the natural soil structure, allowing the physical characteristics and engineering properties of the soil to be assessed more representatively (Rajkumar, L.; Arti Sudam, P.; Madhira, 2023).

Soil erosion mapping

The soil erosion map was developed using the Universal Soil Loss Equation (USLE) model proposed by Wischmeier & Smith (1978) to estimate annual soil loss across the study area. The USLE model estimates soil loss through the integration of rainfall erosivity, soil erodibility, topographic conditions, cover and crop management, and support practices. The USLE equation used to estimate annual soil loss is presented in Equation (2).

$$A = R \times K \times L \times S \times C \times P \quad (2)$$

where: A is the estimated annual soil loss ($\text{ton ha}^{-1} \text{ year}^{-1}$), R is the rainfall erosivity factor, K is the soil erodibility factor, LS is the slope length and slope steepness factor, C is the cover-management factor; and P is the support practice factor.

The rainfall erosivity factor (R) was calculated using rainfall data obtained from rainfall stations located within and surrounding the watershed. Rainfall erosivity was estimated using the empirical equation developed by Bols (1978). The formula is presented in equation (3)

$$R_m = 6,119 \times (\text{Rain})_m^{1.21} \times (\text{Days})_m^{-0.47} \times (\text{Max } P)_m^{0.53} \quad (3)$$

where: R_m is the average monthly rainfall erosivity, $(\text{Rain})_m$ is the average monthly rainfall amount (cm), $(\text{Days})_m$ is the average number of rainy days in month m and $(\text{Max } P)_m$ is the average maximum daily rainfall in month m (cm).

Annual rainfall erosivity was calculated by summing the monthly rainfall erosivity values over a 12-month period, as expressed in equation (4).

$$R = \sum_{m=1}^{12} R_m \quad (4)$$

where: R is the annual rainfall erosivity factor and R_m is the monthly rainfall erosivity.

The soil erodibility factor (K) was determined based on soil physical and chemical characteristics obtained through laboratory analysis. The parameters included soil texture, organic matter content, soil structure class, and soil permeability class. The K factor was calculated using the equation developed by Wischmeier & Smith (1978), as presented in Equation (5).

$$K = \frac{(2,71 \times 10^{-4}(12 - OM)M^{1.14} + 4,20(S - 2) + 3,23(P - 3))}{100} \quad (5)$$

where: K is the soil erodibility factor expressed in SI units ($\text{ton ha h ha}^{-1} \text{ MJ}^{-1} \text{ mm}^{-1}$), OM is the percentage of organic matter, s is the soil structure class, p is the soil permeability class, and M is calculated as $(\% \text{ silt} + \% \text{ very fine sand}) \times (100 - \% \text{ clay})$.

The slope length factor (L) represents the influence of overland flow length on soil erosion, whereas the slope steepness factor (S) represents the influence of slope gradient on soil loss. Both factors can be spatially modelled using flow accumulation and slope information derived from a Digital Elevation Model (DEM) (Ekawati et al., 2026). In this study, the LS factor was calculated using the Moore and Burch equation, as presented in Equation (6) (Kebede et al., 2021).

$$LS : \left(\text{FlowAccumulation} \times \frac{\text{cell size}}{22,13} \right)^{0,4} \times \left(\frac{\sin(\text{slope})}{0,0896} \right)^{1,3} \quad (6)$$

The combined cover-management and support-practice factor (CP) represents the effects of vegetation cover, crop management, and soil conservation practices on soil loss. In this study, CP values were assigned according to the land-cover and management conditions present in the study area, based on values adopted from relevant previous studies (Ekawati et al., 2026; Kironoto et al., 2021). Only CP values corresponding to the land-cover classes identified in the study area were applied in the analysis (Table 2). Field observations were used to identify crop types, crop-management conditions, and soil-conservation practices relevant to the assignment of CP values. Dryland agricultural areas were predominantly characterized by tuber and grain crops, for which a CP value of 0.51 was assigned based on the corresponding crop-management category in the reference values. Paddy fields were differentiated according to slope condition and the presence of bench terraces. Paddy fields located on slopes of 0–8% were assigned a CP value of 0.02, whereas paddy fields on slopes greater than 8% were assigned a CP value of 0.04 where bench terraces were observed in the field. The assigned CP values were subsequently spatialized using the corresponding land-cover and slope information in a GIS environment.

USLE factors were subsequently integrated to estimate annual soil loss using the raster calculator function in a Geographic Information System (GIS) environment. The resulting soil loss values were then classified into soil erosion hazard classes. The classification of soil erosion hazard considered both the estimated soil loss and soil solum depth, as the severity of erosion is influenced by the effective thickness of the remaining soil.

Critical land mapping

Critical land mapping was conducted using a spatial multi-criteria analysis by integrating land cover and soil erosion hazard as the main parameters. Both parameters were used to determine critical-land conditions following Technical Guidelines No. P.3/PDASHL/SET/KUM.1/7/2018. The parameters were integrated using a scoring scheme representing a 60% contribution from land cover and a 40% contribution from soil erosion hazard. Land-cover scores range from 12 to 60, whereas soil erosion hazard scores range from 8 to 40. The classification and scoring schemes for land cover and soil erosion hazard are presented in table 3.

Table 2. CP values used in the soil erosion assessment

Land cover class	CP value
Forest	0.05
Mixed garden	0.20
Built-up land	0.00
Bare land	1.00
Paddy field (slope 0-8%)	0.02
Paddy field (slope >8%), bench terrace	0.04
Shrubland	0.10
Dryland agriculture	0.51
Water Body	0.00

The critical land score (CLS) was calculated by summing the land-cover score and soil erosion hazard score, as expressed in Equation (7). Because the scoring scheme represents maximum contributions of 60 and 40 for land cover and soil erosion hazard, respectively, the resulting critical land score ranges from 20 to 100. The resulting score was then classified into five criticality intervals, namely 0–36, >36–52, >52–68, >68–84, and >84–100, following the classification scheme specified in the technical guidelines.

$$CLS = LCscore + ECscore \quad (7)$$

where: *CLS* is the critical land score, *LCscore* is the land-cover score (12–60), and *ECscore* is the soil erosion hazard score (8–40)

The resulting critical land score was subsequently integrated with forest area status and slope classes to determine the final critical land class based on site conditions. The final classification followed a classification matrix that considers the combination of forest area status and slope conditions. The matrix used to determine the final critical land classes is presented in Table 4.

Field-based verification of critical-land conditions was conducted using a purposive sampling approach, with observation locations selected to represent areas classified as Critical and Highly Critical in the spatial modelling results. Field

observations focused on examining land-cover conditions, visible erosion indicators, and other physical land characteristics relevant to the interpretation of critical-land conditions. The observed erosion indicators included the severity and forms of erosion that could be directly identified in the field, according to the erosion classification and erosion types adopted in this study (Kironoto et al., 2021; Morgan, 2005). In addition, physical land conditions and disturbances associated with land-use activities were documented to support the interpretation of critical-land conditions. The field observations were subsequently compared descriptively with the spatial modelling results to examine the correspondence between modelled critical-land conditions and observable degradation characteristics at the selected sites. Because the observations were intentionally concentrated on areas classified as Critical and Highly Critical, they were not designed to provide an independent statistical accuracy assessment of the complete five-class critical-land classification. Therefore, the observations were used as qualitative field-based evidence to support the interpretation of critical-land conditions rather than for calculating a confusion matrix or class-specific accuracy statistics.

RESULT AND DISCUSSION

Land cover mapping and validation

Based on the Random Forest classification, eight land cover classes were identified in the study area. Forest was the dominant class, covering 5,716.04 ha, followed by mixed plantations (1,993.33 ha; 19.1%) and paddy fields (1,722.50 ha; 16.5%). Built-up land covered 386.76 ha (3.7%), while bare land represented the smallest class, covering only 23.61 ha (0.2%). The spatial distribution and proportion of each land cover class are presented in Figure 3.

The land cover map presented in Figure 3 was subsequently subjected to quantitative accuracy

Table 3. Scoring scheme for land cover and soil erosion hazard.

Land cover (LC)	LC score	Erosion class (EC)	EC score
Built-up land, paddy field, water body	12	≤ 15	8
Forest	24	>15 – 60	16
Mixed plantation	36	>60 – 180	24
Shrub, dryland agriculture	48	>180 – 480	32
Bare land	60	>480	40

Table 4. Classification of critical land based on forest area status and slope gradient.

Within forest area status					
Slope (%)	Critical land score				
	0 – 36	>36 - 52	>52 – 68	>68 – 84	>84 - 100
0 – 8	Non-critical	Non-critical	Potentially critical	Critical	Highly critical
8 – 15	Non-critical	Potentially critical	Slightly critical	Critical	Highly critical
15 – 25	Potentially critical	Slightly critical	Slightly critical	Critical	Highly critical
25 – 40	Slightly critical	Slightly critical	Slightly critical	Critical	Highly critical
>40	Slightly critical	Slightly critical	Slightly critical	Critical	Highly critical
Outside forest area status					
Slope (%)	Critical land score				
	0 – 36	>36 - 52	>52 – 68	>68 – 84	>84 - 100
0 – 8	Non-critical	Non-critical	Potentially critical	Slightly critical	Slightly critical
8 – 15	Non-critical	Potentially critical	Slightly critical	Slightly critical	Slightly critical
15 – 25	Potentially critical	Slightly critical	Slightly critical	Critical	Highly critical
25 – 40	Slightly critical	Slightly critical	Slightly critical	Critical	Highly critical
>40	Slightly critical	Slightly critical	Slightly critical	Critical	Highly critical

assessment using 45 field reference locations. Based on the 45 reference locations, the confusion matrix presented in Table 5 showed an overall accuracy of 86.67% and a Kappa index of 0.84. Producer's Accuracy values of 100% were obtained for forest, built-up land, bare land, shrubland, and water body classes. Meanwhile, User's Accuracy values of 100% were achieved for mixed plantations, built-up land, paddy fields, and water bodies. Classification discrepancies were primarily observed between forest and mixed plantation classes. Three locations classified as forest on the map were identified as mixed plantations during field verification. In addition, one sample classified as bare land was identified as a mixed plantation in the field. Similar discrepancies were observed for one dryland agriculture sample that was identified as shrubland and one paddy field sample that was identified as dryland agriculture during field verification. The dryland agriculture class showed the lowest Producer's and User's Accuracy values, with both reaching only 50%.

Pixel-based classification presents considerable challenges, particularly when vegetation characteristics are spectrally similar, spatially interspersed, and distributed across areas with complex topography, such as the study area (Danoedoro et al., 2023). As shown in Figure 3, relatively distinct spatial patterns were observed for forest and mixed plantation cover. The incorporation of Digital Elevation Model (DEM) data as an additional predictor in the Random Forest classification may have contributed

to distinguishing land-cover classes with similar spectral characteristics by providing complementary topographic information (LEES et al., 2008). Nevertheless, the overall classification result demonstrated very good agreement, with a Kappa index of 0.84, which falls within the almost perfect agreement category according to Landis & Koch (1977).

Land units and characteristic of soil sample

The resulting land unit map identified 18 land units (Figure 4), derived from the combination of land systems, slope gradients, and anthropogenic characteristics. The land systems within the study area consist of alluvial plains, hillocky plains, karstic plains, slopes, crests, and undulating plains, with slope classes ranging from 0–8% to more than 45%. The identified anthropogenic characteristics include urbanogenic, agrogenic, and natural conditions.

The largest land unit was Land Unit 16 (slope–25–45%–natural), covering 4,573.49 ha, followed by the hillocky plain–8–15%–agrogenic unit, covering 1,124.68 ha. In contrast, the smallest land units were Land Unit 04 (alluvial plain–25–45%–agrogenic), covering 19.43 ha, and Land Unit 18 (undulating plain–25–45%–natural), covering 22.26 ha. The total area of the land units differs from the total study area because water bodies were excluded from the land-unit classification, as these areas were not considered relevant for soil sampling or critical-land assessment.

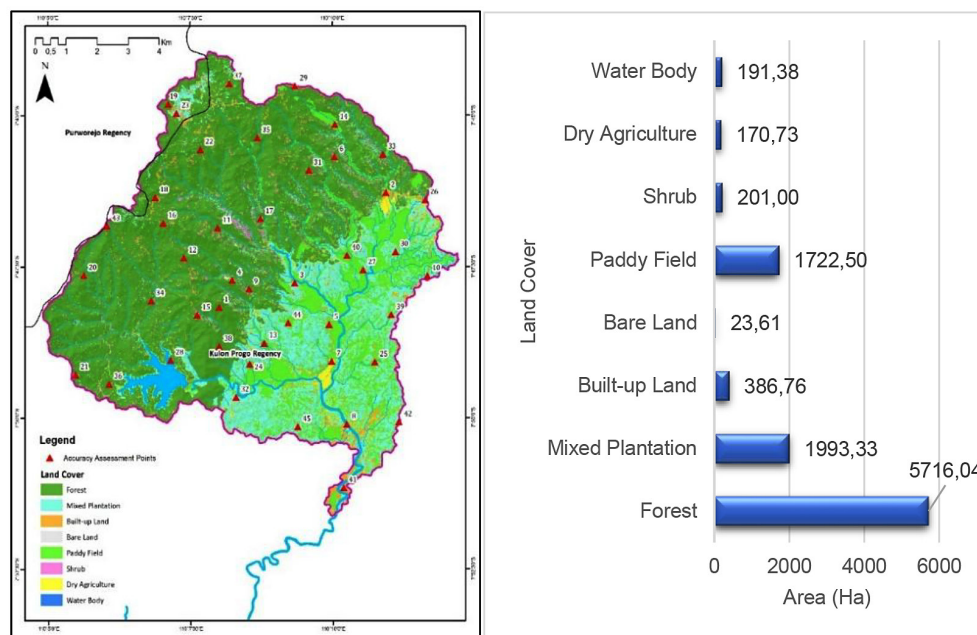


Figure 3. Land cover map and area distribution of each land cover class in 2025

Table 5. Accuracy assessment of the 2025 land-cover classification

Land cover	Field reference unit								Number of samples	Producer's accuracy	User's accuracy
	Forest	Mixed plantation	Built-up land	Bare land	Paddy field	Shrubland	Dryland agriculture	Water body			
Forest	10	3	0	0	0	0	0	0	13	100.00	76.92
Mixed plantation	0	9	0	0	0	0	0	0	9	69.23	100.00
Built-up land	0	0	5	0	0	0	0	0	5	100.00	100.00
Bare land	0	1	0	2	0	0	0	0	3	100.00	66.67
Paddy field	0	0	0	0	6	0	0	0	6	85.71	100.00
Shrubland	0	0	0	0	0	3	1	0	4	100.00	75.00
Dryland agriculture	0	0	0	0	1	0	1	0	2	50.00	50.00
Water body	0	0	0	0	0	0	0	3	3	100.00	100.00
Number of samples	10	13	5	2	7	3	2	3	45		
Overall accuracy	86.67										
Indeks Kappa	0.84										

Soil characteristics observed from the 18 samples showed variations among the land units. Soil texture comprised clay loam, clay, sandy loam, loam, silt loam, and silty clay loam, with clay loam being the dominant texture class. Organic matter content ranged from 1.52% to 11.66%, while permeability ranged from 0.09 to 93.77 cm h⁻¹. These variations in soil characteristics resulted in differences in soil erodibility (K), with K values ranging from 0.05 to 0.47. Higher K values indicate greater

soil susceptibility to erosion (Barchia et al., 2023). Based on the soil-erodibility classification used in this study, the moderate erodibility class was dominant, occurring in 8 of the 18 soil samples. The low and moderately high classes were each represented by 3 samples, while the very low and high classes were each represented by 1 sample. No samples were classified as having very high erodibility. The complete laboratory analysis results for all soil samples are presented in Table 6.

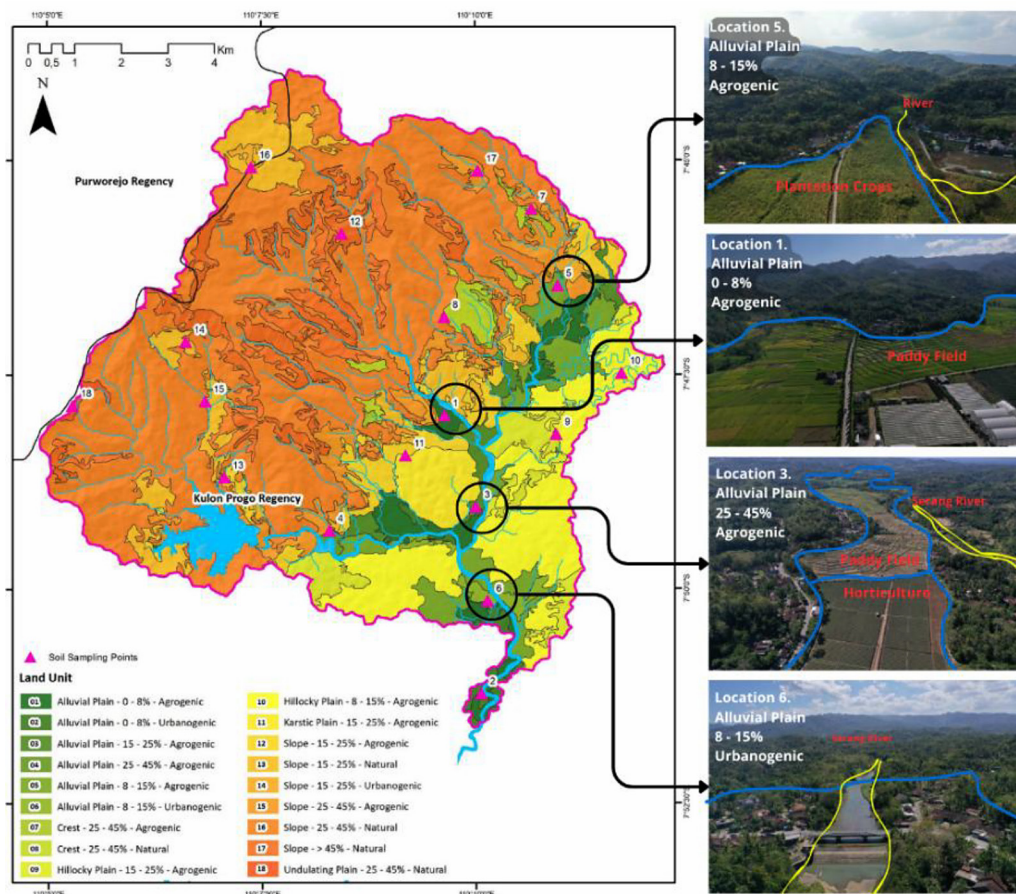


Figure 4. Spatial distribution of soil samples within land units and their field representation

Soil erosion map

The estimated soil erosion in the study area was classified into five erosion classes, ranging from Class I ($< 15 \text{ ton ha}^{-1} \text{ year}^{-1}$) to Class V ($> 480 \text{ ton ha}^{-1} \text{ year}^{-1}$). The dominant erosion class was Class IV, representing high erosion rates of $180\text{--}480 \text{ ton ha}^{-1} \text{ year}^{-1}$ and covering $3,167.97 \text{ ha}$ (30.44%) of the study area. This was followed by Class I, which covered $2,503.57 \text{ ha}$ (24.06%). The smallest proportion was represented by Class II, covering 812.41 ha (7.81%). Overall, the high and very high erosion classes (Classes IV and V) covered $5,445.25 \text{ ha}$ or 52.32% of the study area. The spatial distribution of the USLE factors and soil erosion classes is presented in Figure 5.

The high soil erosion rates observed in the study area are consistent with previous findings indicating that the upstream to middle sections of the Serang Watershed have considerable potential for severe erosion (Arif & Danoedoro, 2017). Considering the USLE model components and the dominance of forest cover within

the study area, the relatively high erosion rates appear to be primarily associated with the physical characteristics of the landscape, particularly steep topography and slope gradients. This condition is reflected in the relatively high LS factor values across several parts of the study area. Higher LS values generally contribute to increased soil loss because longer and steeper slopes increase the velocity and erosive power of surface runoff (Das et al., 2022). In addition to topographic conditions, rainfall erosivity also showed relatively high values across the study area. Rainfall erosivity represents an important driver of soil erosion and is particularly sensitive to changes in rainfall intensity and patterns (Zhu, Qingguo; Yang, Xihua; Ji, Fei; Du, 2025). This factor may become increasingly important under climate change conditions, which can alter rainfall regimes and increase the occurrence of high-intensity rainfall events. Therefore, the combination of steep topography and high rainfall erosivity may explain the extensive distribution of high and very high soil erosion classes in part of the Serang Watershed

Table 6. Soil characteristics and erodibility factor (K) of the soil samples

Sample code	Texture class	Organic matter (%)	Permeability (cm/hour)	K value
01	Clay loam	3.59	1.94	0.30
02	Clay loam	3.30	0.92	0.32
03	Clay	4.03	0.34	0.22
04	Sandy loam	2.08	31.40	0.13
05	Clay	2.97	0.15	0.32
06	Clay loam	2.34	2.13	0.28
07	Loam	2.03	1.76	0.31
08	Loam	3.87	1.73	0.27
09	Clay	11.66	16.61	0.05
10	Clay loam	5.22	0.09	0.15
11	Clay	2.72	0.41	0.30
12	Sandy loam	2.74	6.51	0.18
13	Loam	3.82	59.42	0.26
14	Clay loam	3.22	7.83	0.30
15	Silt loam	1.52	93.77	0.43
16	Silt loam	3.25	62.19	0.36
17	Silty clay loam	3.10	1.95	0.37
18	Silt loam	3.01	2.68	0.47

Critical land map and field-based verification

The critical-land assessment identified five criticality classes in the study area, namely Non-Critical, Potentially Critical, Slightly Critical, Critical, and Highly Critical. Slightly Critical was the dominant class, covering 6,080.44 ha or 58.45% of the study area. In contrast, the Critical and Highly Critical classes covered relatively small areas, accounting for 530.26 ha (5.10%) and 122.04 ha (1.17%), respectively. Together, these two classes represented 6.27% of the total study area. The spatial distribution of critical-land classes is presented in Figure 6.

Although the proportion of Critical and Highly Critical land was relatively small, the dominance of the Slightly Critical class indicates considerable land degradation pressure across the study area. As this class represents an intermediate condition that is one level below the Critical category, these areas may become more vulnerable to further degradation following changes in land cover, inappropriate land and soil management, and external factors that intensify erosion processes. Future changes in rainfall erosivity, particularly under increasingly extreme rainfall patterns associated with climate change, may further increase erosion risks (Sengupta et al., 2023). Similarly, land cover changes

may increase erosion intensity and contribute to land degradation (Biru et al., 2025). Evidence of increasing development pressure is also indicated by previous findings showing that nearly 20% of the Serang Watershed has experienced built-up land development exceeding its land capability (Hidayat et al., 2025).

Field-based verification of critical-land conditions was conducted at 40 observation points distributed across five representative areas classified within the two highest criticality categories, namely Critical and Highly Critical. The field observations were not intended to provide an independent statistical accuracy assessment of the complete five-class critical-land map. Instead, they were conducted to examine whether areas identified by the spatial model as Critical and Highly Critical exhibited observable degradation characteristics consistent with the modelled conditions. The field observations revealed different degradation characteristics across the observation areas, as illustrated by the spatial distribution presented in Figure 6.

Area 1 was located near a river and was identified as critical land. The area was characterized by steep slopes and relatively sparse vegetation cover. These conditions indicate limited protection of the soil surface against rainfall, thereby increasing its susceptibility to erosion (Yu et al.,

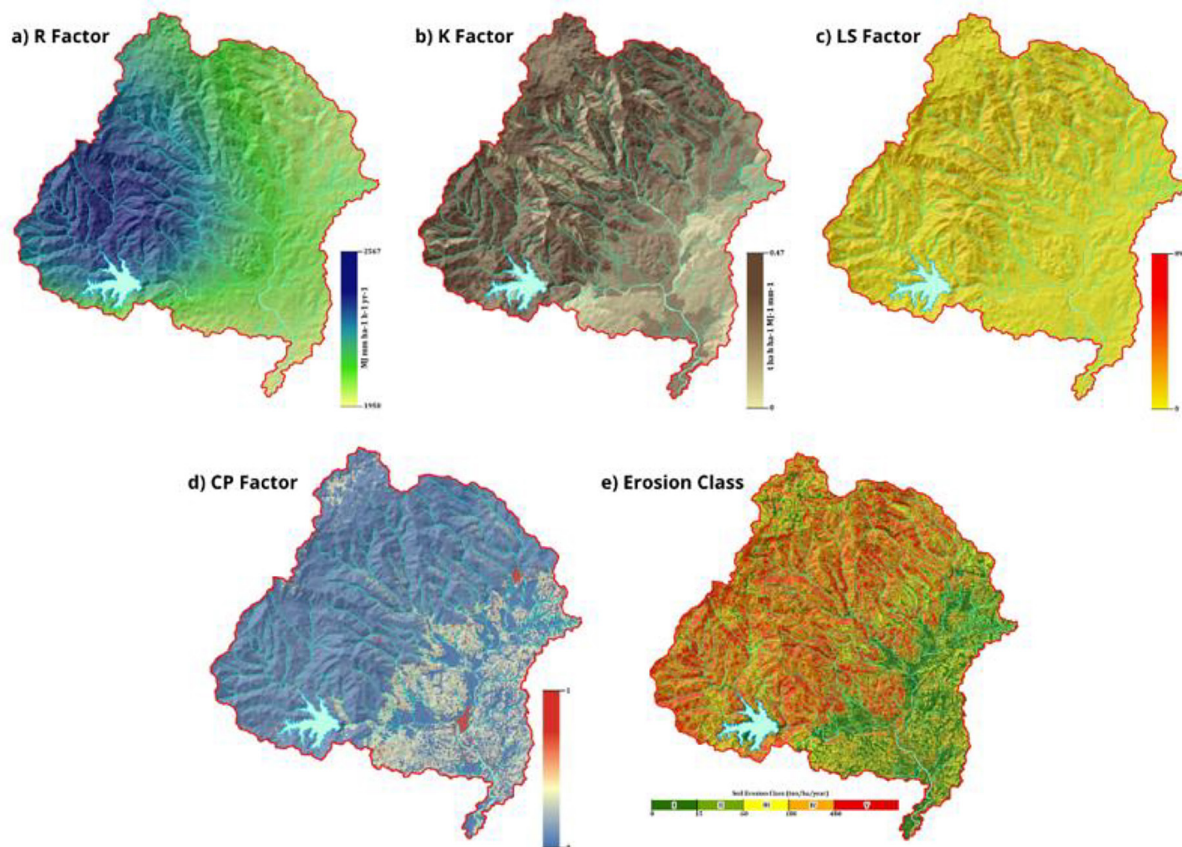


Figure 5. Spatial distribution of use factors and soil erosion classes in part of the Serang watershed: (a) r factor, (b) k factor, (c) ls factor, (d) cp factor, and (e) soil erosion classes

2026). Steep slopes may also increase surface runoff and enhance its capacity to detach and transport soil particles.

Area 2 exhibited more pronounced evidence of land degradation, particularly the presence of gully erosion. Field observations also revealed very shallow soil profiles and the loss of topsoil, with vegetation largely limited to perennial plants. In other locations within this area, karst landscapes showed numerous rill erosion features, indicating surface material removal associated with concentrated surface runoff. These observations provide direct evidence of land degradation processes associated with soil erosion (Gong W, Liu T, Duan X, Sun Y, Zhang Y, Tong X, 2022).

Area 3 was characterized by mining activities occurring on steep slopes in the central part of the study area. Mining activities have altered the land surface and reduced vegetation cover, potentially affecting ecosystem functions (López-osorio et al., 2026; Nahib et al., 2026). According to the critical land model, mining areas were classified as bare land associated with steep slopes and high erosion potential. Field observations confirmed

the contribution of anthropogenic land disturbance to critical land conditions in this area.

Area 4 showed evidence of landslides and fallen vegetation along steep slopes. These conditions indicate slope instability and susceptibility to mass movement. Intensive erosion combined with high rainfall can progressively remove surface soil layers and expose tree roots (Matulewski, 2024). The exposure and loss of supporting soil may reduce slope stability and increase the risk of tree failure.

A different condition was observed in Area 5, where evidence of forest and land rehabilitation activities was identified. The presence of *Dalbergia latifolia* (Sonokeling) indicated vegetation-based rehabilitation efforts, as this species has been used in forest and land rehabilitation programs in Indonesia (Yulita et al., 2025). Rehabilitation signage was also observed at another location, indicating ongoing land restoration efforts.

However, further field observations revealed that some areas were dominated by monoculture cassava cultivation, which provides limited soil protection when not accompanied by appropriate

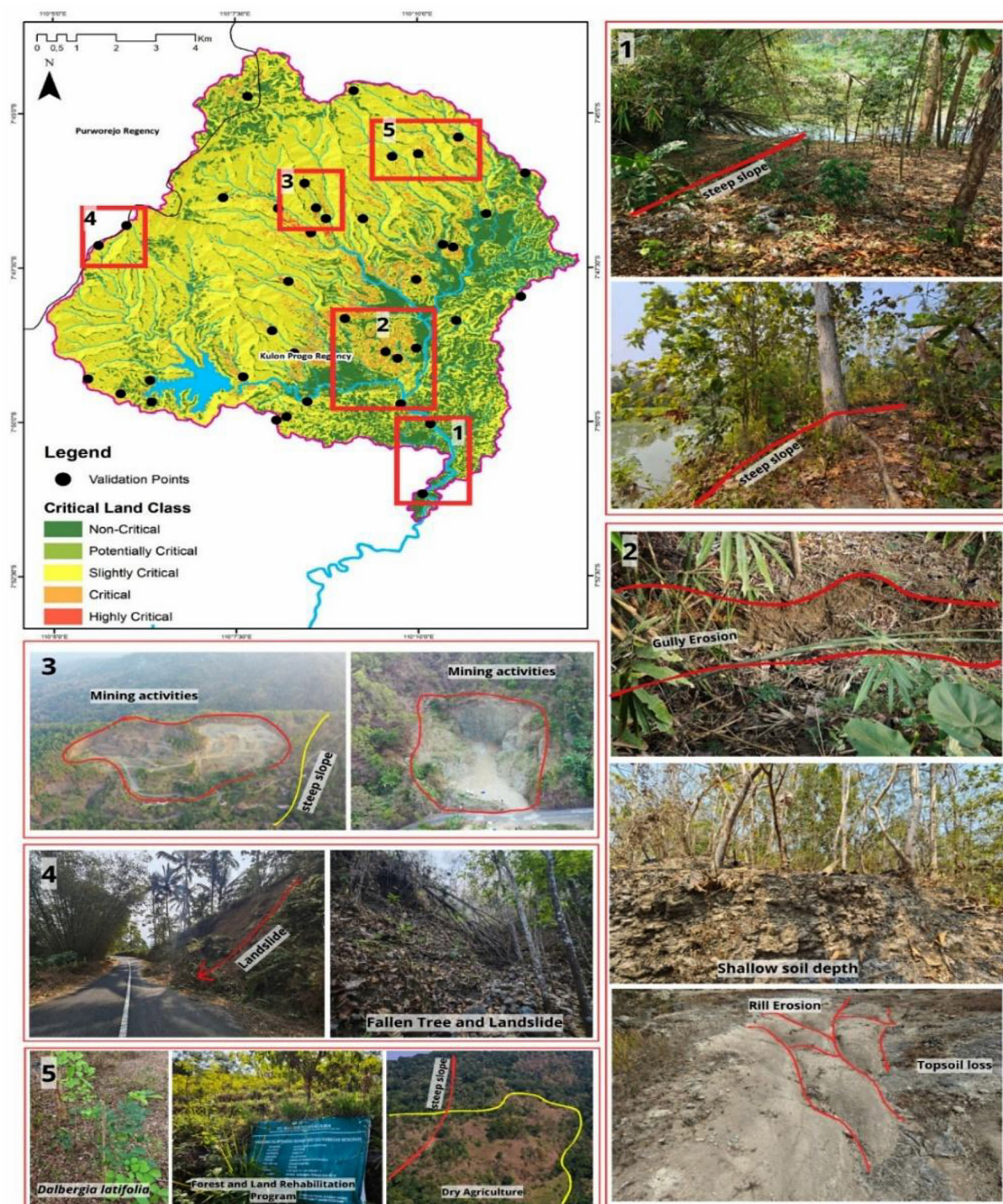


Figure 6. Spatial distribution of critical land classes and field-based verification sites in the study area

conservation practices. Agricultural activities on critical land without adequate management may further contribute to physical and chemical soil degradation (Popradit et al., 2024) and increase sediment transport to downstream areas (Khidzir et al., 2023; Wairiu, 2017). Dryland agriculture was also observed on steep slopes, indicating continuing pressure on land conditions and the need for appropriate soil conservation

measures. These observations demonstrate that critical-land conditions are not necessarily characterized by completely barren surfaces. Critical conditions may also occur in areas undergoing rehabilitation or those that remain actively used for agricultural production.

Overall, the field observations from the 40 verification points provided qualitative evidence on the observable conditions of areas classified by

the spatial model as Critical and Highly Critical. The observed indicators included steep slopes, gully erosion, shallow soil profiles, topsoil loss, landslides, and land-cover disturbances associated with human activities. These observations were generally consistent with the degradation characteristics expected in areas with high criticality and therefore provided supporting evidence for interpreting the critical-land mapping results. However, because the field observations were intentionally concentrated on the Critical and Highly Critical classes, they do not provide a statistical assessment of the accuracy of the complete five-class critical-land classification.

Nevertheless, the interpretation of field-based observations in relation to spatial modelling results is closely related to the quality, scale, and spatial resolution of the input data. Previous studies have demonstrated that differences in data scale and resolution may lead to different spatial modelling results (Comber & Harris, 2022). Therefore, critical-land models may not fully capture the complexity of degradation processes occurring at the site level. Field-based verification can complement spatial modelling by documenting degradation characteristics that may not be fully represented by the modelling parameters. The integration of spatial analysis and field observations is therefore important for improving the interpretation of critical-land conditions, particularly when the results are used as a basis for land management policies and land restoration practices (Kirui et al., 2021).

Implications for soil conservation and land rehabilitation

The degradation conditions identified in critical areas exhibited diverse characteristics; therefore, rehabilitation measures should be adapted to the biophysical conditions and specific forms of degradation occurring at each site. Considering that most of the affected areas are located in the upstream part of the watershed and are characterized by steep slopes, interventions should focus on protecting the soil surface and reducing runoff energy. Increasing permanent and adaptive vegetation cover plays an important role in reducing soil exposure to the kinetic energy of rainfall (Box, James E.; Bruce, 2023) while also improving slope stability (Katzenbach & Werner, 2010). In areas affected by gully erosion, vegetative measures

alone may not be sufficient and should be combined with mechanical approaches, such as check dams and channel protection structures (Higaki et al., 2005).

Dryland agricultural activities observed on sloping land also require particular attention, especially in areas with relatively sparse land cover. The implementation of soil conservation practices, such as agroforestry systems, may provide an alternative for maintaining land productivity while reducing erosion risks. Agroforestry systems can involve combinations such as *Falcataia moluccana* (sengon) with *Arachis hypogaea* (groundnut) or *Anthocephalus cadamba* (jabon) with *Glycine max* (soybean) (Karmini & Karyati, 2021). The Sloping Agricultural Land Technology (SALT) approach may also be applied because it has been shown to significantly reduce erosion while improving key soil properties (Wanniang & Kearney, 2026). SALT integrates perennial crops, food crops, and conservation vegetation arranged along contour lines. In addition to integrating physical and vegetative conservation measures, land rehabilitation may also involve soil amendments to improve soil quality, particularly in areas with shallow soil profiles. Biochar represents one potential amendment because it can improve soil properties, including aggregate formation, root development, and water infiltration. Furthermore, biochar may provide long-term carbon sequestration benefits, contributing simultaneously to land rehabilitation and climate change mitigation (Kuryntseva et al., 2023).

The importance of field-based verification in critical-land assessment extends beyond examining the correspondence between spatial modelling results and observable field conditions. Field observations also provide important information on the characteristics and forms of degradation occurring at individual sites. These findings can support the selection of rehabilitation strategies and soil conservation measures that are adapted to site-specific degradation characteristics. This approach enables critical-land maps to function not only as tools for identifying the spatial distribution of criticality levels but also as a basis for directing more context-specific rehabilitation treatments that address degradation processes observed in the field.

Several limitations should be considered when interpreting the results. The field-based verification of critical-land conditions was

intentionally conducted using purposive observations focused on areas classified as Critical and Highly Critical. Therefore, the 40 field observations were not designed to provide an independent statistical accuracy assessment of the complete five-class critical-land map. In addition, the spatial assessment depends on the quality, spatial resolution, and thematic characteristics of the input datasets, while the USLE-based erosion assessment does not explicitly represent all erosion and land-degradation processes observed in the field, such as gully erosion and landslides. Therefore, the resulting critical-land map should be interpreted as a spatial assessment based on the selected parameters and modelling framework, complemented by field-based observations, rather than as a complete representation of all degradation processes occurring at the site level.

CONCLUSIONS

The spatial integration of biophysical parameters resulted in five critical-land classes in part of the Serang Watershed, dominated by Slightly Critical land (58.45%), while Critical and Highly Critical land accounted for 6.27% of the study area. Field-based verification provided qualitative evidence on the observable degradation characteristics of areas classified as Critical and Highly Critical, including rill and gully erosion, topsoil loss, shallow soil, slope failure, and anthropogenic disturbances. These findings demonstrate that field-based verification can complement spatial modelling by providing site-level information that supports the interpretation of critical-land conditions and the selection of appropriate rehabilitation and soil conservation measures. Therefore, critical-land management should integrate spatial prioritization with site-specific degradation characteristics to support more targeted rehabilitation interventions.

Acknowledgement

The authors would like to express their sincere gratitude to the Faculty of Geography, Universitas Gadjah Mada, for supporting this research. The authors also thank all individuals and institutions involved in facilitating the field surveys, soil sampling, laboratory analysis, and data collection in part of the Serang Watershed.

REFERENCES

1. AbdelRahman, M. A. E. (2023). An overview of land degradation, desertification and sustainable land management using GIS and remote sensing applications. In: Rendiconti Lincei (Vol. 34, Issue 3). Springer International Publishing. <https://doi.org/10.1007/s12210-023-01155-3>
2. Allafta, H. (2022). Soil erosion assessment using the RUSLE model, remote sensing, and GIS in the Shatt Al-Arab Basin (Iraq-Iran). *Applied Sciences*, 12, 7776. <https://doi.org/10.3390/app12157776>
3. Arif, N., & Danoedoro, P. (2017). Raster-based qualitative spatial modelling of soil erosion: A case study of the Serang Watershed, Kulon Progo Regency. *Jurnal Ilmu Lingkungan*, 15(2), 127–134. <https://doi.org/10.14710/jil.15.2.127-134>
4. Biru, M. K., Gadisa, C. W., Dirbaba, N. B., & Nunes, M. R. (2025). Land use changes and their impacts on soil erosion in a fragile ecosystem of the Ethiopian Highlands. *Land*, 1–20. <https://doi.org/10.3390/land14071473>
5. Bols, P. (1978). The Iso-Erodent Map of Java and Madura.
6. Box, James E.; Bruce, R. (2023). The effect of surface cover on infiltration and soil erosion. In: *Soil Erosion, Conservation, and Rehabilitation* (pp. 107–123). CRC Press. <https://doi.org/10.1201/9781003418177-6>
7. Comber, A., & Harris, P. (2022). The importance of scale and the MAUP for robust ecosystem service evaluations and landscape decisions. *Land*, 11(3), 1–17. <https://doi.org/10.3390/land11030399>
8. D’Odorico, Paolo; Ravi, S. (2016). Land degradation and environmental change. In: *Biological and Environmental Hazards, Risks, and Disasters* (pp. 219–227). Academic Press. <https://doi.org/10.1016/B978-0-12-394847-2.00014-0>
9. Danoedoro, P., Widayani, P., Hidayati, I. N., Gupita, D. D., & Salsabila, H. N. (2023). Vegetation structural composition mapping of a complex landscape using forest cover density transformation and random decision forest classifier: a comparison. *Geocarto International*, 38(1). <https://doi.org/10.1080/10106049.2023.2220289>
10. Das, S., Kumar, P., & Ranjit, B. (2022). Estimation of slope length gradient (LS) factor for the sub-watershed areas of Juri River in Tripura. *Modeling Earth Systems and Environment*, 8(1), 1171–1177. <https://doi.org/10.1007/s40808-021-01153-0>
11. Directorate General of Watershed and Protected Forest Management. (2018). Regulation of the Director General of Watershed and Protected Forest Management Number P.3/PDASHL/SET/KUM.1/7/2018 concerning Technical Guidelines for the Preparation of Critical Land Spatial Data.

12. Ekawati, N. L., Danoedoro, P., & Wibowo, S. B. (2026). Erosion rate estimates in relation to land-use change: A case study in Samin Watershed, Central Java, Indonesia. *International Journal of Geoinformatics*, 22(2), 80–96. <https://doi.org/10.52939/ijg.v22i2.4789>
13. Enar, K. A., Ibrahim, M. M., Abdelsamie, E. A., & Shokr, M. S. (2025). Modeling land degradation in drylands of the Nile delta using remote sensing and GIS. *Egyptian Journal of Soil Science*, 65(2), 817–836. <https://doi.org/10.21608/EJSS.2025.360359.1999>
14. Foody, G. M., Pal, M., Rocchini, D., Garzon-lopez, C. X., & Bastin, L. (2016). The sensitivity of mapping methods to reference data quality: Training supervised image classifications with imperfect reference data. *International Journal of Geo-Information*, 5(199). <https://doi.org/10.3390/ijgi5110199>
15. García-álvarez, D., Lloyd, C. D., Delden, H. Van, Teresa, M., & Olmedo, C. (2019). Computers, environment and urban systems thematic resolution influence in spatial analysis. An application to land use cover change (LUCC) modelling calibration. *Computers, Environment and Urban Systems*, 78(April), 101375. <https://doi.org/10.1016/j.compenurbsys.2019.101375>
16. Gong W, Liu T, Duan X, Sun Y, Zhang Y, Tong X, Q. Z. (2022). Estimating the soil erosion response to land-use land-cover change using GIS-based RUSLE and remote sensing. *Water*, 14(5), 742. <https://doi.org/10.3390/w14050742>
17. Gound, R. S. (2022). Validation of ground truth of remotely sensed data from Sentinel-2 (MSI) using supervised classification, after combined cloud and shadow effect removal. *Indian Journal of Computer Science and Engineering*, 13(3), 860–868. <https://doi.org/10.21817/indjcse/2022/v13i3/221303164>
18. Hidayat, W., Sari, C. P., Supriyadi, S., & Himawan, W. (2025). Evaluation of built-up land incompatibility with land capability and its implications for critical land in the Serang Watershed. 02001. <https://doi.org/10.1051/e3sconf/202568202001>
19. Higaki, D., Karki, K. K., & Sekhar, G. C. (2005). Soil erosion control measures on degraded sloping lands: A case study in Midlands of Nepal. *Aquatic Ecosystem Health and Management*, 8(3), 243–249. <https://doi.org/10.1080/14634980500208184>
20. Juwono, P. T., & Subagiyo, A. (2019). Integrated watershed and coastal area management. UB Press.
21. Karmini, & Karyati. (2021). Economic analysis of application two agroforestry combinations in the sloping lands. 9–15. <https://doi.org/10.1088/1755-1315/824/1/012105>
22. Katzenbach, R., & Werner, A. (2010). Slope stability analysis of railway embankments considering the effects of vegetation and capillarity. *Geotechnical Special Publication*, 173–180. [https://doi.org/10.1061/41103\(376\)22](https://doi.org/10.1061/41103(376)22)
23. Kebede, Y. S., Endalamaw, N. T., Sinshaw, B. G., & Atinkut, H. B. (2021). Modeling soil erosion using RUSLE and GIS at watershed level in the upper. *Environmental Challenges*, 2. <https://doi.org/10.1016/j.envc.2020.100009>
24. Khan, M., & Chen, R. (2025). Assessing the impact of land use and land cover change on environmental parameters in Khyber Pakhtunkhwa, Pakistan: A Comprehensive Study and Future Projections. <https://doi.org/10.3390/rs17010170>
25. Khidzir, A. R., Setyawan, C., S.Susanto, & Zaki, M. K. (2023). GIS based monitoring of critical area upstream watershed of Soedirman Reservoir, Central Java, Indonesia. *IOP Conference Series: Earth and Environmental Science*. <https://doi.org/10.1088/1755-1315/1233/1/012059>
26. Kironoto, B. A., Yulistiyanto, B., & Olii, M. R. (2021). *Soil Erosion and Land Conservation* (Siti (Ed.); 1st ed.). Gadjah Mada University Press.
27. Kirui, O. K., Mirzabaev, A., & Braun, J. Von. (2021). Assessment of land degradation ‘on the ground’ and from ‘above’ *SN Applied Sciences*, 3(3), 1–13. <https://doi.org/10.1007/s42452-021-04314-z>
28. Kumar, D., Yadav, R. S., & Kadam, D. M. (2024). Agroforestry Practices: A Possible Way to Achieve Land Degradation Neutrality. In S. Kumar, B. Alam, S. Taria, P. Singh, A. Yadav, & A. Arunachalam (Eds.), *Agroforestry Solutions for Climate Change and Environmental Restoration*. Springer. https://doi.org/10.1007/978-981-97-5004-7_17
29. Kuryntseva, P., Karamova, K., Galitskaya, P., & Selivanovskaya, S. (2023). Biochar functions in soil depending on feedstock and pyrolyzation properties with particular emphasis on biological properties. *Agriculture*, 13(10). <https://doi.org/10.3390/agriculture13102003>
30. Landis, J. R., & Koch, G. G. (1977). The measurement of observer agreement for categorical data. 33(1), 159–174. <https://www.jstor.org/stable/2529310>
31. Lathifah, R. N., Setiawan, M. A., & Widyatmanti, W. (2024). Erosion mapping based on erosion evidence features in the micro watershed of Parangtritis. *Jurnal Penelitian Pengelolaan Sumberdaya Alam Dan Lingkungan*, 13(2), 146–164. <https://doi.org/10.31186/naturalis.13.2.35744>
32. Lees, B. G., Zhi, H., Niel, K. Van, & Laffan, S. W. (2008). The impact of DEM error on predictive vegetation mapping (Qiming Zhou, G. Tang, & B. Lees (Eds.)). Springer. https://doi.org/10.1007/978-3-540-77800-4_19
33. López-osorio, R. F., Pérez-aguilar, L. Y., Avila-aceves, E., Zambrano-medina, Y. G., & Quintero-morales,

- M. A. (2026). Spatial analysis of land cover degradation processes associated with aridity in north-western Mexico using geographically weighted regression. *International Journal of Geo-Information*, 1–20. <https://doi.org/10.3390/ijgi15050200>
34. Matulewski, P. (2024). Catena Scots pine roots (*Pinus sylvestris* L.) as dendrogeomorphological indicators of soil erosion on a hiking trail in the Brodnica Lakeland, Poland NE. *Catena*, 245(August). <https://doi.org/10.1016/j.catena.2024.108316>
35. Ministry of Environment and Forestry of the Republic of Indonesia. (2022). Regulation of the Minister of Environment and Forestry of the Republic of Indonesia No. 10 of 2020 on the Preparation of General Plans for Watershed Forest and Land Rehabilitation and Annual Plans for Forest and Land Rehabilitation.
36. Ministry of Forestry of the Republic of Indonesia. (2009). Decree of the Minister of Forestry of the Republic of Indonesia No. SK.328/Menhut-II/2009 on the Designation of Priority Watersheds for the 2010–2014 Medium-Term Development Plan.
37. Morgan, R. P. C. (2005). *Soil Erosion and Conservation* (3rd ed.). Blackwell Publishing Ltd.
38. Naharuddin, N. (2021). The critical level of mangrove ecosystem in Lariang watershed downstream, West. *International Journal of Sustainable Development and Planning*, 16(5), 841–851. <https://doi.org/10.1051/e3sconf/202020206003>
39. Nahib, I., Wahyudin, Y., Widiatmaka, W., Tarigan, S. D., Ambarwulan, W., Ramadhani, F., Pranoto, B., & Nugroho, N. P. (2026). Spatio-temporal dynamics of land use and land cover change and ecosystem service value assessment in Citarum Watershed, Indonesia: A multi-scenario and multi-scale approach. *Resources*, 1–34. <https://doi.org/10.3390/resources15020024>
40. Narendra, B. . (2019). Critical land mapping for the development of biomass-based energy in East Lombok Regency, Indonesia critical land mapping for the development of biomass-based energy in East Lombok Regency, Indonesia. *IOP Conference Series: Earth and Environmental Science*. <https://doi.org/10.1088/1755-1315/314/1/012072>
41. Popradit, A., Nakhokwik, Y., Robischon, M., & Saiki, S. (2024). Soil degradation and herbicide pollution by repeated cassava monoculture within Thailand's conservation region. *Plos One*, 1–18. <https://doi.org/10.1371/journal.pone.0308284>
42. Putri, K. A., & Handayani, H. H. (2024). Comparison of land cover classification results using artificial neural network (ANN), support vector machine (SVM), and random forest (RF) methods with the R programming language. *Journal of Geodesy and Geomatics*, 19(2), 349–360. <https://doi.org/10.12962/geoid.v19i2.1145>
43. Racca, P.; Zeuner, T.; Jung, J.; Kleinhenz, B. (2010). Model validation and use of geographic information systems in crop protection warning service. In: R. Oerke, E. C.; Gerhards, R.; Menz, G.; Sikora (Ed.), *Precision Crop Protection – the Challenge and Use of Heterogeneity*. Springer. https://doi.org/10.1007/978-90-481-9277-9_16
44. Radoux, J., & Bogaert, P. (2017). Good Practices for Object-Based Accuracy Assessment. *Remote Sensing*, 9(646). <https://doi.org/10.3390/rs9070646>
45. Rajkumar, L.; Arti Sudam, P.; Madhira, M. (2023). Effect of Sample Disturbance on Compressibility Parameters. In B. Muthukkumaran, K.; Jakka, R.S.; Parthasarathy, C.R.; Soundara (Ed.), *Soil Behavior and Characterization of Geomaterials*. Springer. https://doi.org/10.1007/978-981-19-6513-5_5
46. Sengupta, A., Krishna, N., & Indrani, V. (2023). Seasonal variations in the dynamic and thermodynamic response of precipitation extremes in the Indian subcontinent. *Climate Dynamics*, 61(1), 831–848. <https://doi.org/10.1007/s00382-022-06613-6>
47. Taufan, L. B., & Pratomo, R. A. (2022). Implementation of Zoning Regulation Instruments for Addressing Critical Land in the Mahakam Cascade Catchment Area. 10, 151–165. <https://doi.org/10.14710/jwl.10.2.151-165>
48. Thuraipalam, Gladima; Selvaraj, R. (2023). Hybrid deep learning CNN-MCSVM method-based land cover classification of Kanyakumari Region using Sentinel-2A image. *AIP Conference Proceedings*. <https://doi.org/10.1063/5.0166125>
49. Vacca, A., Loddo, S., Melis, M. T., Funedda, A., Puddu, R., Verona, M., Fanni, S., Fantola, F., Madrau, S., Marrone, V. A., Serra, G., Tore, C., Manca, D., Pasci, S., Puddu, M. R., & Schirru, P. (2014). A GIS based method for soil mapping in Sardinia , Italy : A geomatic approach. *Journal of Environmental Management*, 138, 87–96. <https://doi.org/10.1016/j.jenvman.2013.11.018>
50. Wahyunto, & Dariah, A. (2014). Land Degradation in Indonesia: Existing Conditions, Characteristics, and the Harmonization of Definitions to Support the One Map Policy. *Jurnal Sumberdaya Lahan*, Vol. 8, No, 81–93. <https://doi.org/10.2018/jsdl.v8i2.6470>
51. Wairiu, M. (2017). Land degradation and sustainable land management practices in Pacific Island Countries. *Regional Environmental Change*, 17(4), 1053–1064. <https://doi.org/10.1007/s10113-016-1041-0>
52. Wanniang, & Kearney, J. (2026). Sloping Agriculture Land Technology. In *Meghalaya Mirrors: Reflections of Community-Led Environmental Action* (1st ed., pp. 133–146). Taylor and Francis. <https://doi.org/10.4324/9781003735380-10>
53. West, P. W. (2016). Simple random sampling of individual items in the absence of a sampling frame that lists the individuals. *New Zealand Journal of*

- Forestry Science, 1–7. <https://doi.org/10.1186/s40490-016-0071-1>
54. Widyatmanti, W., Murti, S. H., & Syam, P. D. (2018). Critical land mapping for land use suitability analysis in Kulon Progo Regency. *Jurnal Pengabdian Dan Pengembangan Masyarakat*. <https://doi.org/10.22146/jp2m.41024>
55. Windarto, Y. E., Bashit, N., Ristianti, N. S., & Ulfiana, D. (2020). Decision support system for critical land in Klaten Regency determining. *E3S Web of Conferences*, 202, 06003. <https://doi.org/https://doi.org/10.1051/e3sconf/202020206003>
56. Wischmeier, W. H., & Smith, D. D. (1978). Predicting rainfall erosion losses: A guide to conservation planning. In 7th International Congress of Soil Science. United States Government Printing Office.
57. Yu, J., Chen, Z., He, X., & Bao, J. (2026). Catena A modified CSLE for slope-scale soil loss prediction under different vegetation types in China. *Catena*, 270(September 2025), 110216. <https://doi.org/10.1016/j.catena.2026.110216>
58. Yulita, K. S., Atikah, T. D., Wardani, W., Pratama, B. A., Rachmat, H. H., Setyawati, T., & Dwiyantri, F. G. (2025). The present state of the Indonesian rosewood (*Dalbergia latifolia*) from a biological perspective. In: R. R. Warriar, G. Joshi, & A. N. Arunkumar (Eds.), *Handbook of Asian Rosewoods: Materials Horizons: From Nature to Nanomaterials*. Springer. https://doi.org/10.1007/978-981-96-9459-4_5
59. Zachrani, A. O., Rayes, M. L., & Sulaeman, Y. (2024). Critical Land identification at a 1:25,000 scale based on Sentinel-2 Imagery and 8 m resolution DEMNAS: A case study of the Cikapundung Sub-Watershed, West Java. *Jurnal Tanah Dan Sumberdaya Lahan*, 11(2), 327–338. <https://doi.org/10.21776/ub.jtsl.2024.011.2.4>
60. Zhu, Qingguo; Yang, Xihua; Ji, Fei; Du, Z. (2025). Rainfall erosivity projection in south-east australia using the improved regional climate simulations. *International Journal of Climatology*, 45(2). <https://doi.org/10.1002/joc.8702>