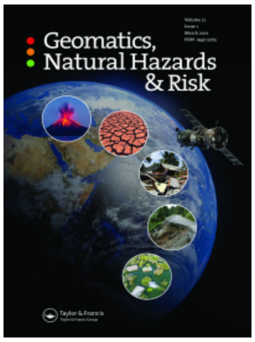

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ABSTRACT

Erosion and sedimentation are global environmental threats that cause land degradation, reduced agricultural productivity and increased flooding risks, leading to the loss of 75 billion tons of fertile soil annually. This study employs advanced remote sensing and machine learning techniques to analyze land use changes and their impacts on erosion and sedimentation at the sub-watershed level. Sentinel-2A images from multiple years were used and classified into 17 distinct land use classes through a supervised classification technique. The baseline land use data served as the foundation for future predictions, with a business-as-usual scenario modelled using cellular automata and artificial neural networks (CA-ANN). Land use factors were incorporated into the USLE model to generate an erosion map and to perform sediment retention analysis using the InVEST model. By 2025, over 35% of the total area is projected to experience significant deforestation, with forested areas being converted into orchards, shrubs, bare land, agricultural dry land and settlements. In 2022, forest area transformation resulted in a 25% increase in erosion and an 18% rise in sedimentation, with these figures expected to climb further by 2025. Our study recommends the CA-ANN model as a tool to predict land use changes and guide interventions, ensuring sustainable management of sub-watershed areas.

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1. Introduction

Global land use change has had dynamics and significantly affected 32% of the world's land surfaces between 1960 and 2019 (Winkler et al). Indonesia has experienced high deforestation rates since 2001 (Austin et al. 2019) and has significant impacts on hydrometeorological disasters, such as erosion (Amundson et al. 2015) and sedimentation (Pawar et al. 2020). Erosion and sedimentation in Indonesia have shown a notable escalation (Yustika et al. 2019), predominantly attributed to anthropogenic influences. The processes of erosion and sedimentation are interdependent since they move and deposit soil particles, forming the earth's surface and topography (Scheingross et al. 2020). This phenomenon leads to decreased infiltration capacities and increased storm flows in small watersheds, resulting in a greater hydrologic response for smaller, more frequent events (Zhang et al. 2014). Erosion and sedimentation cause river shallowing, eutrophication, soil loss and land degradation (Andualem et al. 2023). Understanding these processes is crucial for assessing environmental impacts and implementing effective control measures (Zeleňáková et al. 2019). Conventional techniques for measuring erosivity and sediment load often result in limited or delayed real-time data collection (Senanayake et al. 2020).

Predicting erosion and sedimentation offers several benefits, such as quantifying land erosion, identifying areas with high erosion rates, analyzing land use patterns, determining environmental factors influencing sedimentation rates and supporting the development of effective watershed management strategies (Andualem et al. 2023). The lack of foundational benchmarks for accurately forecasting erosion and sedimentation trends using spatial technology has been highlighted (Medina et al. 2023), alongside recognizing the limitations of existing predictive methodologies. Accurate estimation of environmental trends using remote sensing data requires overcoming challenges related to data calibration, spatial resolution and temporal consistency (Ahmed et al. 2023). Therefore, it is essential to develop a methodology that integrates precise land use analysis to effectively estimate erosion and sedimentation rates.

Markov Chains models are valuable for modelling land use dynamics, such as forest-to-agriculture shifts, which drive erosion and sedimentation. Combining Markov Chains models with cellular automata and artificial neural networks (CA-ANN) allows simulation of land use impacts under a business-as-usual (BAU) scenario. This CA-ANN Markov Chains framework integrates spatial predictions with factors like population density, urban proximity and topography. CA simulate spatial-temporal dynamics, while ANN enhance predictive capabilities, such as modelling overland flow and sediment transport (Zhang and Che 2023). These models can predict how things like land use and erosion will change in the environment, helping us understand and plan for the future (Leta et al. 2021). The integration of CA-ANN models with remote sensing techniques offers a promising avenue for predicting future land use dynamics, erosion and sedimentation. Integrating CA-ANN with remote sensing and GIS techniques enables accurate predictions of land use changes and erosion patterns, aiding in effective management strategies (Leta et al. 2021; Paul and Bhattacharji 2022). This study applies CA-ANN in InVEST to model erosion and sedimentation under BAU scenarios, emphasizing vegetation conservation to mitigate risks. The integration of CA-ANN with InVEST bridges the gap between predictive land use modelling and process-based erosion modelling. CA-ANN generates dynamic, spatial-temporal land use changes and links them to biophysical processes like overland flow (Li and Yeh 2002; Almeida et al. 2008; Islam et al. 2018), allowing InVEST to quantify impacts such as erosion and sedimentation (Hamel et al. 2015; Anley and Minale 2024).

InVEST further enriches this framework by enabling the modelling of ecosystem services, including sediment retention, using spatially explicit inputs such as vegetation and topography (Gashaw et al. 2021). This integration ensures accurate and scalable erosion risk predictions while emphasizing the critical role of vegetation conservation in mitigating significant erosion risks. It serves as a valuable resource for sustainable land management under dynamic scenarios like BAU. The findings highlight preserving vegetation as critical to reducing erosion and sedimentation in the study area. This study offers the following key contributions:

- Comprehensive integration of remote sensing and machine learning
- Development of an erosion and sedimentation analysis framework
- Quantitative predictions of land use and environmental impacts
- Policy-relevant insights for sustainable management

This study contributes to the understanding of land use dynamics and its implications for erosion and sedimentation, providing valuable insights for environmental management and policy-making.

2. Materials and methods

2.1. Study region

The study was carried out in the Sumber Brantas sub-watersheds (165,994 ha) in the Universal Transverse Mercator (UTM) coordinate system of Easting (662741–675301) and Northing (9143393–9124555). Administratively, these sub-watersheds are located in two administrative regions, namely Batu City and Malang Regency, East Java, Indonesia (Figure 1). The study was conducted in the Sumber Brantas sub-watersheds (165,994 ha) within the UTM coordinates Easting (662741–675301) and Northing (9143393–9124555), spanning Batu City and Malang Regency, East Java, Indonesia. The area receives an average rainfall of 2,276 mm year^{-1}, classified as 'Am' under the Köppen system, with temperatures ranging from 11 °C to 20 °C. The site was chosen for its history of erosion, diverse land use, representative topography and agro-tourism development. Sub-watershed boundaries were delineated using an 8.25-m digital elevation model (DEM) from the Indonesian Geospatial Information Agency (https://tanahair.indonesia.go.id/) via ArcSWAT tools (Bharath et al. 2021).

2.2. Image specification and acquisition

The Sentinel-2A data were acquired by the Copernicus portal (https://scihub.copernicus.eu/). The Sentinel-2A carried an optical payload of visible, near-infrared and shortwave infrared sensors comprising 13 spectral bands with up to 10 m spatial

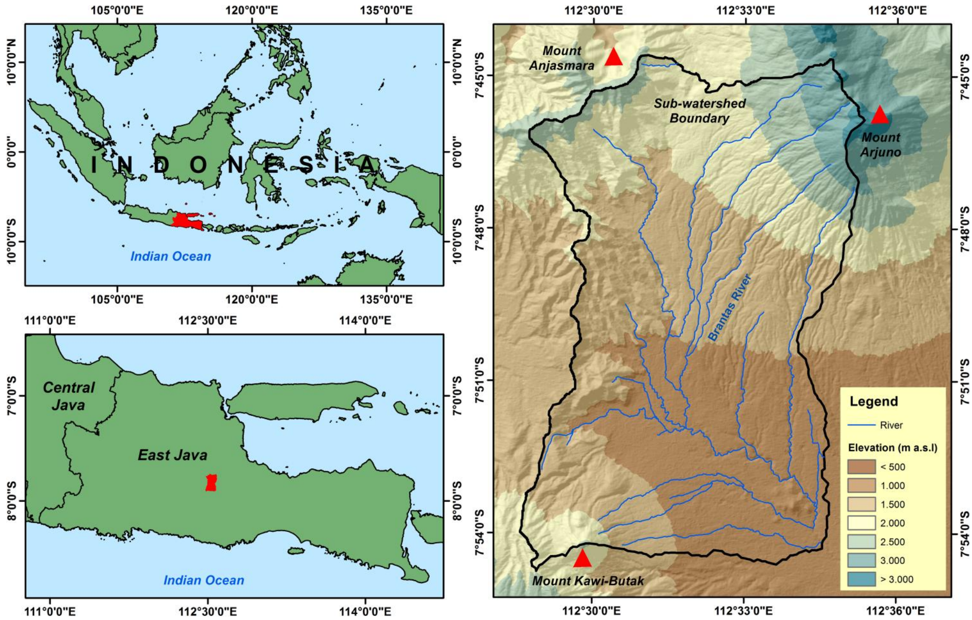

Figure 1. Research location in the Sumber Brantas sub-watersheds, East Java, Indonesia.

resolution and 6 days revisit frequency orbit. To conduct land use change analysis, every 5 days imagery was aggregated to yearly scales to generate 6 years of image recording, namely 1990, 2000, 2010, 2020, 2021 and 2022. Sentinel 2-A, published in 2015, cannot analyze images from 1990, 2000 and 2010. Instead, they are classified from Landsat 5 TM and Landsat 7 ETM (https://earthexplorer.usgs.gov/). To maintain data consistency, the spatial resolution has been increased to 10 m and 17 categories are used for land use categorization.

2.3. Image classification

The Sentinel-2A images from different years (1990, 2000, 2010, 2020, 2021 and 2022) were pre-processed through radiometric correction (Padro et al. 2017), atmospheric correction (Sola et al. 2018) and haze removal (Kganyago et al. 2020) using ArcGIS 10.8 version. All these processes have been carried out by the image provider, and during processing, no further correction is required. The supervised classification technique is used with several training samples per class and maximum likelihood classification at a fixed scale of 1:2,50,000 (Kadavi and Lee 2018). The training area is divided into 17 land uses, each represented by 25 points, resulting in 425 points distributed through purposive random sampling. The image classification results are in the form of land use classes categorized into agroforestry, natural forest, artificial forest, production forest, settlement, orchards, bare land, meadow, rice field, shrub, agricultural dry land and water body (Bangun et al. 2021).

The results of land use classification were examined for accuracy by correlating 100 points of land use classification results in 2022 with the land use results of field checks. The accuracy test aims to quantitatively determine how pixels are grouped into the correct feature class in the observed area (Larbi et al. 2019) and also get precise measurements (Khuwaja et al. 2018). The coordinates of the validation points were recorded using a Garmin 78s GPS. We followed the Indonesian National Standard accuracy assessment using the Kappa analysis method by constructing a confusion matrix (Nita et al. 2020), the most widely applicable and the centrepiece of the accuracy assessment (Foody 2020).

2.4. Business-as-usual prediction

The BAU land use scenario represents land use and land cover development without intervention. Road area data obtained from the Indonesian Geospatial Information Agency (https://tanahair.indonesia.go.id/) and land use using Image Sentinel-2A material for the built-up area extraction in 2022 were used as driving factors for BAU land use projections. In addition to that, the input data of the DEM was processed with fill treatments, while the distance from slope data underwent slope and fuzzy (sigmoidal) treatments. Furthermore, the input data of distance from the city centre were subjected to cost distance fuzzy treatments. Moreover, the data on distance from built-up areas, miscellaneous areas and agricultural areas were treated with fuzzy (linear) methods. Additionally, population density data underwent standard deviation treatments, and distance from road data was processed using fuzzy treatments. The land use projection process was conducted using the CA-ANN Markov Chain method on QGIS 2.18 software by MOLUSCE plugin (Baidya et al. 2021).

The results of land use classification data for 2019 and 2021 and the driving factors (Zhang et al. 2021) of roads and built-up areas were analyzed for BAU land use scenarios. We tested accuracy in 2022 by the ground survey for validations. We only supported the models having Kappa values of >70% (Singh et al. 2022). In this case, the model can continue to predict land use changes in 2025 (Rakuasa et al. 2023), as it can give classifiers a more detailed picture of the performance of models and indicate reliable correspondence (Basu and Das 2021).

2.5. Erosion modelling USLE in InVEST

The InVEST model is spatially explicit, using maps as a source of information and generating maps as output, both in biophysical and economic terms (Hamel et al. 2015) and can be used with limited climate and soil data (Ghazaw et al. 2021). This material applies to small to large watersheds and is essential for identifying erosion hotspot areas and planning land management strategies in data-poor areas (Sharp et al. 2020). The InVEST model has been applied in many countries worldwide to simulate soil loss and sediment yield since its development (e.g. Hamel et al. 2017; Zhou et al. 2019). The model integrates numerous ecosystem functions and includes dozens of sub-models, including water yield, carbon storage, sequestration, habitat quality, plant pollination, water purification, fisheries, crop production, urban flood risk mitigation and offshore wind energy production, among others (Ghazaw et al. 2021). Watershed and sub-watershed delineations are essential, and both were performed in the ArcAPEX model using 8.25 m spatial resolution DEM inputs from the

Indonesian Geospatial Information Agency (https://tanahair.indonesia.go.id/). This study used ArcGIS 10.8 for resampling the spatial resolution of R and K-factors for mapping purposes.

2.6. Sediment delivery ratio modelling in InVEST

The InVEST (Sharp et al. 2020) sediment delivery ratio (SDR) model (i.e. InVEST 3.9.0), which is a spatially explicit model that works on DEM cell sizes, first calculates annual soil loss using a soil loss algorithm (Renard et al. 1997) and then SDR as a function of catchment hydrological connectivity (Vigiak et al. 2012). An index of connectivity (IC) was initially calculated based on its upslope contribution and flow path to the stream (Borselli et al. 2008). The SDR factor maps of the study watersheds were derived from an 8.25 m cell size DEM.

2.7. Runoff and erosion measurement

Field erosion measurements use 200–500 m^2 plots for seasonal crops (e.g. rice fields, dry lands and settlements) and 500–1,000 m^2 plots for annual crops (e.g. orchards, agroforestry and forests) (Madarász et al. 2021). Surface runoff and erosion are measured after rainfall by recording water volume in aprons and storage drums. Total surface runoff (LP) is calculated using the equation:

$$LP = \ a \ VA + b \ VD1 + c \ VD2 + d \ VD3 + e \ VD4 \quad (1)$$

where V_A is the water volume in the apron (litres), VD1–VD4 are the water volumes in drums 1–4 (1–4 L capacity), and a–e are coefficients for water distribution settings (Widianto et al. 2004; Harfia and Prijono 2022).

The dry weight of sediment (Bt) from land erosion is determined by stirring runoff water in aprons and drums, sampling, filtering and weighing the sediment. It is calculated using the equation:

$$\begin{aligned} Bt = {} & (BA \times \ a \ VA) + (BD1 \times \ b \ VD1) + (BD2 \times \ c \ VD2) + (BD3 \times \ d \ VD3) \\ & + (BD4 \ x \ e \ VD4) \end{aligned} \quad (2)$$

where BD is the sediment weight (kg L^{-1}) from the apron, and BD1–BD4 are sediment weights (kg) per litre from drums 1 to 4, corresponding to volumes VD1 to VD4 (1, 2, 3 and 4 L) as defined in the LP equation. This ensures consistency in the calculation pattern. The Universal Soil Loss Equation (USLE) model relies on three main databases as presented by Tomaščík et al. (2023) in Table 1.

The USLE model determines the yearly average loss of soil erosion (A), by the equation:

$$A = \ R \ \times \ K \ \times \ LS \ \times \ C \ \times P \quad (3)$$

where A is the average annual soil loss rate (tons $ha^{-1} year^{-1}$), R is the rainfall erosivity factor (MJ mm ha^{-1} $h^{-1} year^{-1}$), K is the soil erodibility factor

Table 1. Description of factors in the USLE model.

Factor	Description	Unit	Original data source (citation)
Erosivity factor (R)	Derived from climate data including monthly precipitation and temperature.	MJ mm ha^{-1} h^{-1} yr^{-1}	Climate and survey database (Wischmeier and Smith 1978; Arunsurat et al. 2023).
Soil erodibility (K)	Determined through analysis of soil surveys and soil characterization data.	t ha h ha^{-1} MJ^{-1} mm^{-1}	Soil survey and characterization data (Wischmeier and Smith 1978).
Slope length and steepness (LS)	Calculated using contour data to determine slope length and gradient.	Dimensionless	Climate and survey database (Wischmeier and Smith 1978).
Cover management (C)	Computed from crop database reflecting vegetation type and land cover.	Dimensionless	Crop database (Wischmeier and Smith 1978; Arunsurat et al. 2023).

(tons ha^{-1} h^{-1} MJ^{-1} mm^{-1}), LS, C and P are factors of topography, crop management and erosion control practices, respectively (Talchabhadel et al. 2020).

2.8. Sediment delivery ratio measurement in field

Sediment delivery ratio is an indicator to demonstrate the capacity of sediment erosion. SDR can be calculated using the formula SDR = Y/E, where Y is the sedimentation delivery (sediment yield or soil loss) and E is the total amount of sediment erosion in the specified watershed. The equal discharge increment (EDI) method is used to collect sediment samples from a river/canal. The sampling process begins at the midpoint of each sub-cross section, with multiple sub-cross sections determined at specific intervals along the river or canal. The discharge is measured consistently across all sub-cross sections to ensure representative sampling for each river or canal segment. The nozzle diameter typically ranging from 2 to 3 cm, is adjusted to the water flow speed, resulting in a water sample volume ranging from 350 to 400 mL. Sediment load sampling requires a collection tool that adjusts to flow depth and speed, maintains the same speed for lowering and raising, and does not touch the riverbed. The device must store a maximum of 400 mL and a minimum of 350 mL, depending on the measurement method. Sampling locations for floating sediment loads should be unaffected by water structures or backflow, with measurements conducted at discharge locations, even riverbeds, perpendicular cross-sections and a determined collection point. The following formulas were used for this observation:

$$q_i = \frac{Q}{n} \tag{4}$$

$$q_{qi} = \frac{q_i}{2} \tag{5}$$

$$S_{qi} = \sum_{i=1}^{n} q_i + q_{qi} \tag{6}$$

where Q is the discharge in a cross-section m^3/s; q_i is the discharge at each sub-section to I, m^3 s^{-1}; q_{qi} is the central discharge at each sub-cross section to *i*, m^3 s^{-1}; S_{qi}

is the section debit to i, $m^3\ s^{-1}$; I is 1, 2, 3, 4, 5, ... N; i the mark is the cross-section; and n is the number of vertical pick-ups in a cross-section.

2.9. Mechanical and vegetative conservation

The study utilized a survey or observation method, soil samples and soil test methods to classify land capability into eight classes and subclasses based on limiting factors. The classification is represented by Roman numerals I–VIII, with the priority order being erosion (e), water (w), soil (s), climate (c), gradient (g). The direction of land use is determined based on slope, soil type, sensitivity to erosion and rainfall intensity which are analyzed using ArcGIS 10.8 software. The weighting of each of these factors is carried out using a multi-criteria decision analysis approach. This methodology ensures systematic evaluation and is supported by Vaezi et al. (2017).

Land status is categorized into areas within forest zones and those outside forest zones, based on administrative boundaries and land use classifications derived from GIS analysis and official land management policies. Forest zones are further distinguished using satellite imagery and ground verification to identify vegetation cover and legal forest designations. Land status is categorized into areas within forest zones and those outside forest zones, based on administrative boundaries and land use classifications derived from GIS analysis and official land management policies (Rayes 2007). Forest zones are further distinguished using satellite imagery and ground verification to identify vegetation cover and legal forest designations.

3. Results

3.1. Land use baseline

Land use in the Upper Sumber Brantas sub-watershed has changed significantly over the past 32 years, with projections for 2025 offering further insights into future trends. In 2022, the dominant land uses were natural forests (20%), settlements (15%), agricultural dry land (14%) and orchards (10%). The remaining 41% included agroforestry (6%), production forests (10%), bushes (5%), artificial forests (7%), rice fields (6%), meadows (4%) and bare lands (3%). Natural forests declined from 29% in 1990 to 20% in 2022, losing about 1,714 ha, while agricultural dry land increased by 1,931 ha. Settlements and orchards also grew significantly.

Projections for 2025 under the BAU scenario show a further decrease in natural forests to 17%, with agricultural dry land and settlements expanding by 4,457.46 and 3,125.69 ha, respectively. Figure 2 illustrates these changes in land use classifications for 2022 (validation) and 2025 (projection). Agroforestry, which made up about 6% of land use in 2022, is expected to remain stable and continue providing ecosystem services like erosion control and biodiversity preservation. These findings highlight the need for sustainable land management practices by 2025 to mitigate environmental impacts such as soil erosion and sedimentation. Reforestation, agroforestry expansion and improved land use zoning are essential to maintaining ecological and socio-economic balance in the watershed.

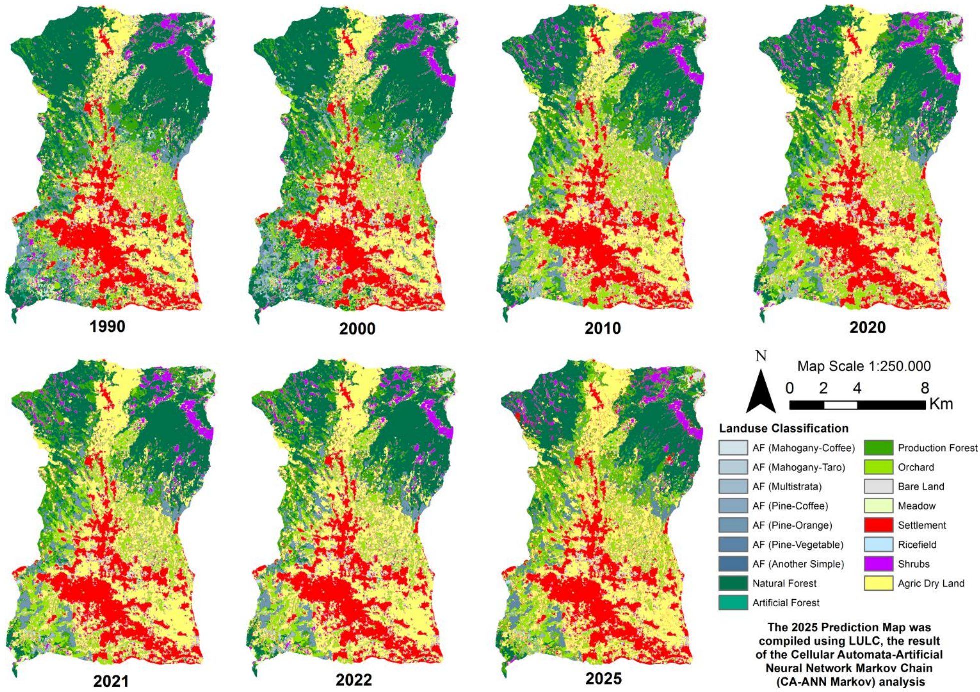

Figure 2. Land use map of Sumber Brantas sub-watersheds for the entire 32 years and land use prediction for BAU (2025).

3.2. Business-as-usual land use prediction

The most significant land use changes projected by 2025, as shown in Figure 3, include an increase in agricultural dry land by 4,457.46 ha, a decrease in natural forest area by 3,243.08 ha, and an expansion of settlement area by 3,125.69 ha. Natural forests continue to decrease, often converting to residential areas. The growing number of settlements has led to agricultural dry lands becoming vital centres for meeting the community's agricultural needs. GIS-based land cover change detection and quantitative land use analysis can be employed to analyze these transformations, reclassifying land cover data over time and calculating landscape indices to assess the impact of urban expansion on agricultural lands (Lee et al. 2023). Agricultural dry land has more area than other land uses due to the shorter cultivation period (3–6 months) compared to agroforestry and production forests (Korwar et al. 2014).

Land use analysis in the Sumber Brantas sub-watershed indicates that natural forests play a critical role in water catchment and mitigating erosion. Dense vegetation and root systems in natural forests reduce surface runoff and soil erosion (Amundson et al. 2015; Puno et al. 2019). From 1990 to 2022, natural forests in the Sumber Brantas sub-watershed declined by 1,000–1,500 ha, while agricultural dry lands and settlements increased by 2,000–4,000 ha annually. These changes are driven by socio-economic factors, such as population growth and increased demand for agricultural and residential spaces. The conversion of forests into agricultural and urban areas has led to land degradation, with a 34% increase in erosion rates from 1990 to 2022, along with higher sedimentation, flood and landslide risks (Karki and Ojha 2021).

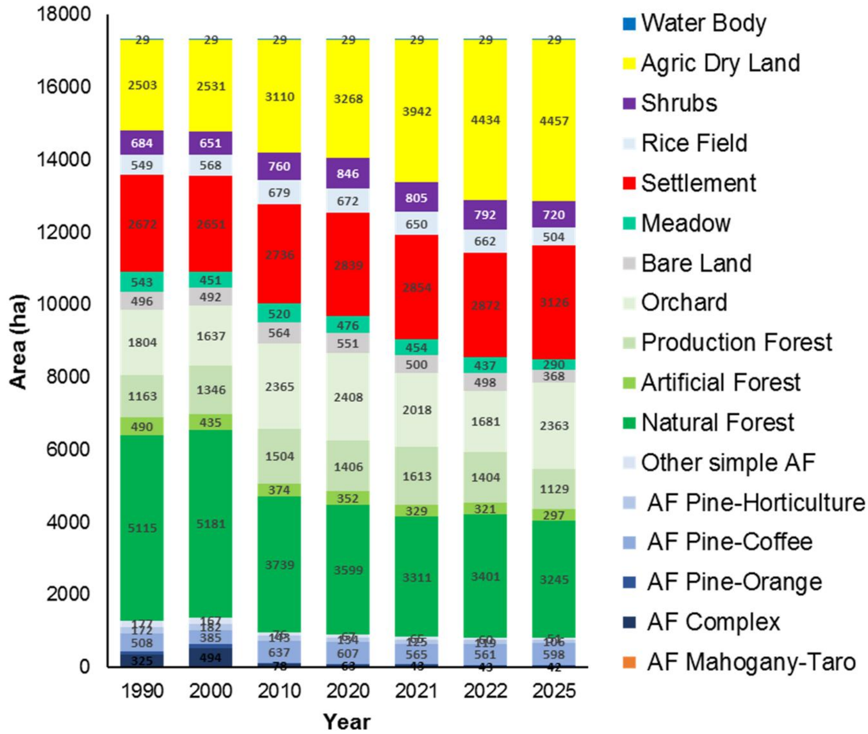

Figure 3. Cellular automata-artificial neural network prediction in business-as-usual scenarios in 2025 and baseline.

Land use change, especially in hilly areas, contributes to soil weathering and slope instability, accelerating landslides (Senanayake et al. 2022).

The accuracy of land use change predictions in this study is location-specific and may vary across regions. The overall accuracy and Kappa coefficient for both methods were found to be 80% and 74%, respectively, exceeding the 60% threshold. These metrics show that the model applied in this study effectively predicts land cover change. According to Yang et al. (2012), Kappa values >60% indicate reliable land cover prediction results, which further validates the suitability of these models for accurate forecasting in the study area.

3.3. Erosion modelling result and validation using field measurement

The Sumber Brantas sub-watershed has seen a significant increase in erosion rates, rising from 62.13 tons ha^{-1} $year^{-1}$ in 1990 to 83.39 tons ha^{-1} $year^{-1}$ in 2022, a 34% increase over 32 years. Projections for 2025 suggest a further increase to 105.39 tons ha^{-1} $year^{-1}$, reflecting a 70% rise since 1990, with an average annual increment of around 2 tons ha^{-1} $year^{-1}$. These findings, visualized in Figure 4, emphasize the need for erosion control measures. Erosion hazard levels are classified into five categories based on soil loss severity: very light (<15 tons ha^{-1} $year^{-1}$), light (15–60 tons ha^{-1} $year^{-1}$), medium (60–180 tons ha^{-1} $year^{-1}$), heavy (180–480 tons ha^{-1} $year^{-1}$),

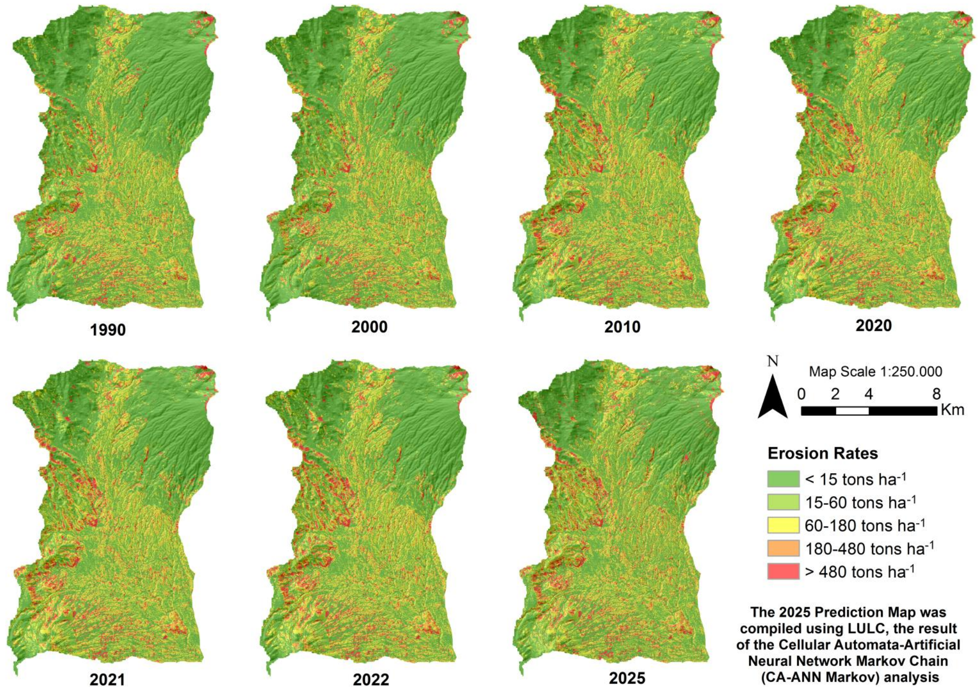

Figure 4. Erosion analysis result using InVEST and the prediction using CA-ANN.

and very heavy (>480 tons ha^{-1} $year^{-1}$). A visual representation of these classes would improve clarity.

To mitigate erosion, conservation measures such as reforestation and agroforestry (e.g. alley cropping, strip planting, cover crops) are recommended. These practices reduce runoff and stabilize soil, as shown in previous studies (Silalahi et al. 2017). The conversion of natural forests to agricultural dry lands and settlements exacerbates erosion by reducing vegetation cover, leading to nutrient loss and soil fertility decline (Preece and Macmillan 1977). Erosion causes topsoil loss, significantly affecting soil fertility if not controlled (Zhang et al. 2021). The three stages of erosion – detachment, transportation and sedimentation – have resulted in a 34% increase in erosion rates in the Brantas sub-watershed, leading to sedimentation in rivers and reservoirs, reducing water storage capacity and disrupting clean water supply (Wu et al. 2018). These findings underscore the urgent need to address land use changes accelerating erosion processes.

3.4. Sediment baseline and prediction modelling result

The SDR in the Sumber Brantas sub-watershed increased from 0.09 tons/ha in 1990 to 0.11 tons/ha in 2010–2022, with the same value projected for 2025. SDR measures the proportion of eroded sediment transported to the river, with values ranging from 0 to 1. Steep slopes (15%–40%) in the sub-watershed facilitate sediment transport and reduce sediment deposition, as discussed by Arsyad (2010). The SDR's increase reflects a moderate rise in sediment transport efficiency, which is projected to reach

11% of eroded material by 2025, indicating increased sediment deposition in downstream reservoirs.

Factors influencing SDR include hydrological inputs (e.g. rainfall), landscape characteristics (e.g. topography, vegetation) and sediment transport dynamics (Zhou et al. 2019; Ayt Ougougdal et al. 2020). The Sumber Brantas sub-watershed's steep slopes and reduced forest cover (from 29% in 1990 to 20% in 2022) amplify runoff and erosion, contributing to higher SDR. The increase in SDR is linked to land use changes, including deforestation and agricultural expansion, which escalate sediment transport. These dynamics can reduce sediment retention, raise sedimentation risks in reservoirs, and intensify flooding and environmental degradation, as evidenced by the rising erosion rates from 62.13 tons ha^{-1} year^{-1}in 1990 to 105.39 tons ha^{-1} year^{-1}in 2025, as visualized in Figure 5.

3.5. Statistical tests for erosion and sedimentation

The paired t-test results for erosion and sedimentation reveal a strong alignment between the modelled outcomes and field observations. Across all tested samples, the t-count was 0.15, significantly lower than the t-table value of 1.73. This minimal difference between the modelled results and actual field conditions confirms the models' high accuracy in predicting erosion and sedimentation patterns. These findings validate the models' reliability and highlight their potential as effective tools for analyzing and managing environmental processes in the region.

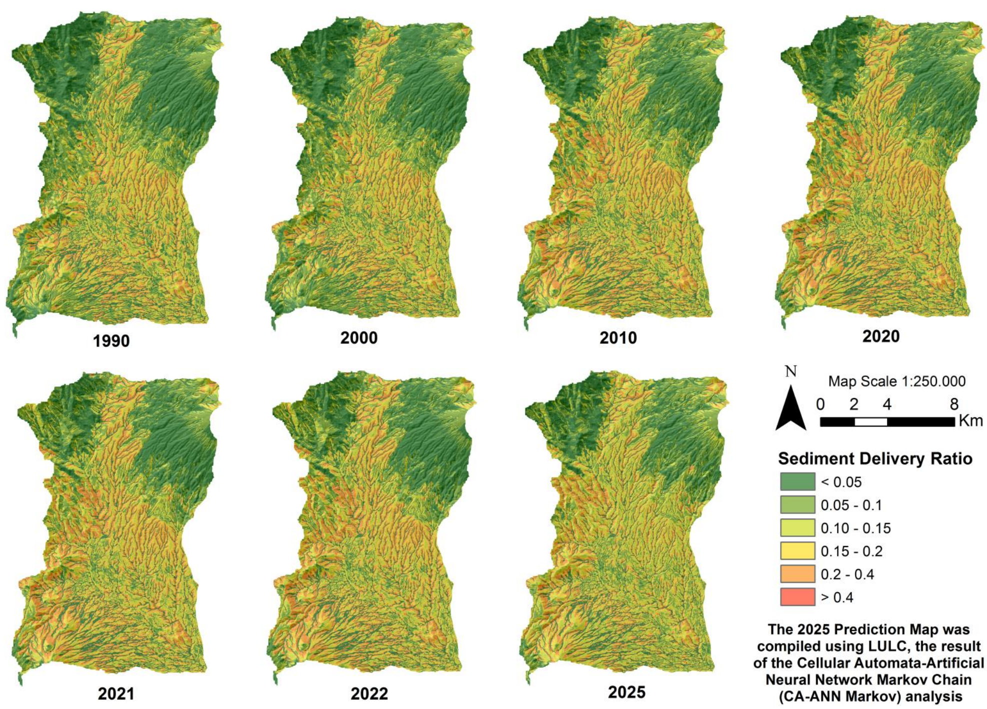

Figure 5. Sediment as a result from erosion causing by land use change.

4. Discussion

4.1. Relationship between land use, erosion and sedimentation

Watershed degradation is driven by factors like population growth, economic development, anti-conservation policies and a lack of public awareness (Surya et al. 2020). In the Sumber Brantas sub-watershed, land use changes have exacerbated erosion and sedimentation. Effective watershed management aims to stabilize the system by addressing its components' interactions (Syafri et al. 2020). Land use should align with land capacity to prevent degradation. Vegetation plays a crucial role in managing erosion and regulating the hydrological cycle by intercepting rainfall, reducing runoff and enhancing soil infiltration, which supports groundwater retention (Kidane et al. 2019; Rammal and Berthier 2020). Rainwater interception by plants decreases erosive impact by lowering raindrop energy, providing time for water to infiltrate and reducing surface runoff (Huang et al. 2023).

The interaction between climate variables, such as temperature and precipitation, and runoff significantly influences sediment transport and erosion, key factors in land use and environmental modelling. Advanced triple cross-wavelet least squares analysis offers a robust method to explore time–frequency relationships between streamflow, temperature and precipitation without requiring resampling or interpolation of data. Findings from the Athabasca River Basin (ARB) demonstrate strong seasonal correlations, with the highest runoff–climate interactions occurring during warm periods, directly affecting erosion patterns (Ghaderpour et al. 2023). The relationship between land use, erosion and sedimentation that occurs in the Sumber Brantas sub-watershed is presented in Figure 6.

Soil erosion occurs through three main mechanisms: soil particle disintegration, transportation by surface runoff and sedimentation in lower-lying areas, leading to both in situ and ex situ damage. These processes reduce the physical, chemical and biological quality of soil, leading to fertility loss (Shi et al. 2012; Kuhwald et al. 2022). Declining fertility limits nutrient availability for crops, resulting in poor plant growth and lower or failed yields. Erosion also increases flood risks as higher surface runoff reduces soil water retention (Hümann et al. 2011; Collentine and Futter 2018). Runoff from fields elevates river discharge and turbidity, degrading water quality, which is especially concerning as river water is often used for domestic purposes. Excessive erosion heightens drought risks by lowering soil water capacity, causing most rainwater to flow away as surface runoff. In the Upper Sumber Brantas sub-watershed, high erosion rates and extensive land conversion exacerbate these challenges, reducing water quality and quantity due to high sediment loads. Implementing effective soil and water conservation measures is essential to control erosion, mitigate its impacts and promote environmental sustainability.

4.2. Strategy strengthening through conservation

The land conditions in the Upper Sumber Brantas sub-watershed are categorized as critical, moderate and non-critical, with projections indicating that moderately critical land will dominate the area, covering approximately 10,264 ha by 2025 (Figure 7).

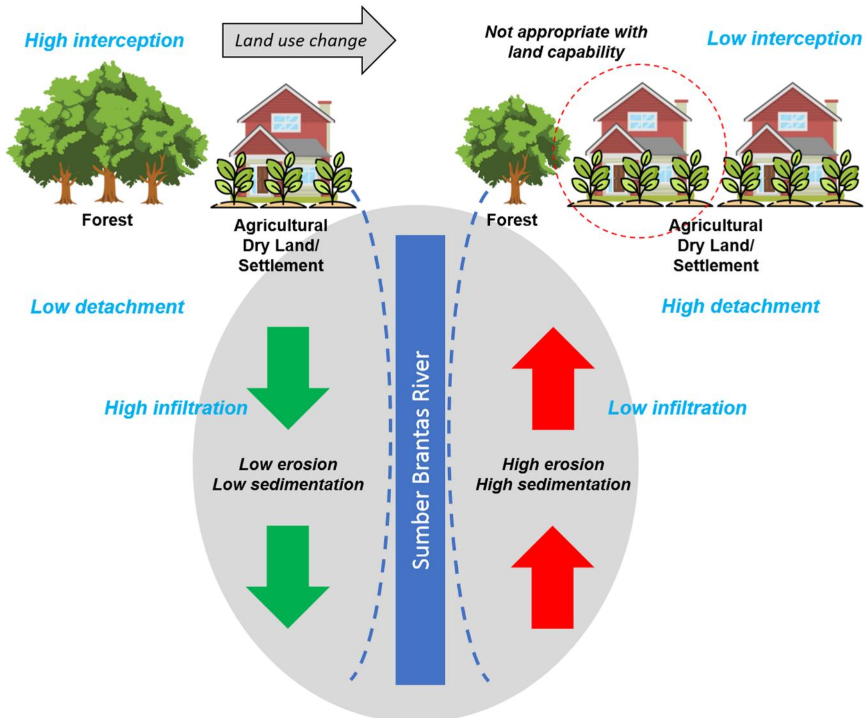

Figure 6. The impact of land use changes in the Sumber Brantas sub-DAS on erosion and sedimentation.

Critical lands, characterized by severe erosion, steep slopes and minimal vegetation cover, exhibit low productivity and are predominantly situated in hilly or steep terrains. The classification of critical land is based on factors such as land cover, slope gradient, erosion risk and land management practices, as stipulated in the Regulation of the Indonesian Ministry of Forestry Number P.32/Menhut-II/2009.

Analysis reveals a significant increase in moderately critical and critical lands within the watershed, with moderate land expanding by 16% and critical land surging by 50% between 1990 and 2025. Concurrently, the area of non-critical land has been steadily declining since 2010. These trends highlight the urgent need for rehabilitation and soil conservation programs (RLKT) to restore critical areas while safeguarding the productivity of non-critical lands. Effective RLKT implementation relies on accurate data to prioritize interventions, ensuring targeted restoration and optimal resource allocation. Sustainable watershed management requires addressing the interconnected impacts of land use changes on soil erosion, hydrology and agricultural productivity. Coordinated and evidence-based strategies among stakeholders are essential to mitigate degradation, enhance ecosystem services and achieve sustainable environmental and socio-economic outcomes (Vittala et al. 2008).

Soil erosion in the Sumber Brantas sub-watershed impacts soil fertility, water quality and drought potential through particle breakdown, surface leakage and sedimentation, leading to reduced soil quality, increased flooding and decreased water storage.

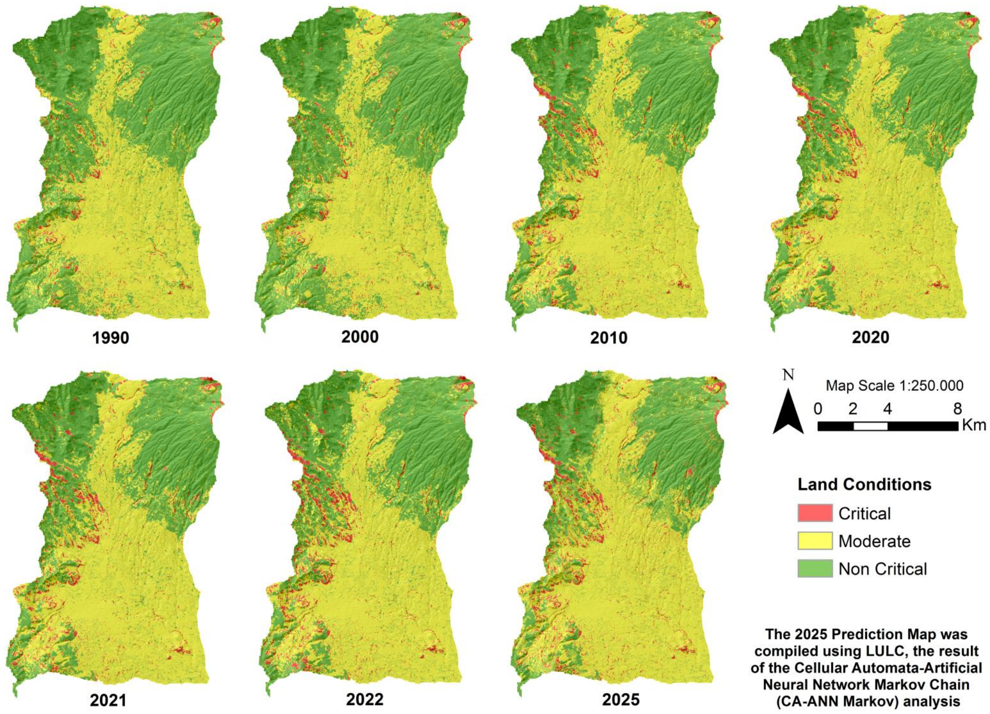

Figure 7. Land conditions in the Upper Sumber Brantas sub-watershed.

Effective soil and water conservation, involving both vegetative and mechanical approaches, is crucial (Weng et al. 2023). Vegetative methods, such as agroforestry, reforestation and terrace plants, help reduce runoff, slow raindrop impact and improve soil infiltration (Dharmawan et al. 2023). Mechanical methods, including mulching, bench terrace construction and sediment retention dams, aim to slow surface flow, enhance infiltration and support plant growth. These conservation efforts, tailored to land conditions, are shown in Figure 8, highlighting their spatial application.

In the Sumber Brantas sub-watershed, vegetative conservation focuses on balancing forest preservation with sustainable agriculture. Key measures include 4,225.1 ha for protected forests, 2,672.6 ha for terrace strengthening and mulching, 2,461.8 ha for crop rotation, and 2,191.5 ha for reforestation. Additionally, 2,015.3 ha will adopt crop rotation with strip planting, 1,668.1 ha will implement agroforestry and 373.5 ha will combine crop rotation with mulching. These efforts aim to reduce erosion while maintaining ecological balance and agricultural productivity.

For mechanical conservation, recommendations include 6,073.2 ha for zero tillage, 2,461.8 ha for improved irrigation, 2,069.9 ha for bench terraces, 2,015.3 ha for contouring, and 1,599 ha for minimum tillage. Further, 602.7 ha will implement bench terraces, 412.6 ha individual terraces, 373.5 ha for settlements and 2.5 ha for river areas. These strategies are crucial for stabilizing soil, managing runoff and reducing sediment transport. The spatial allocation emphasizes the importance of these measures in maintaining the watershed's ecological and hydrological balance.

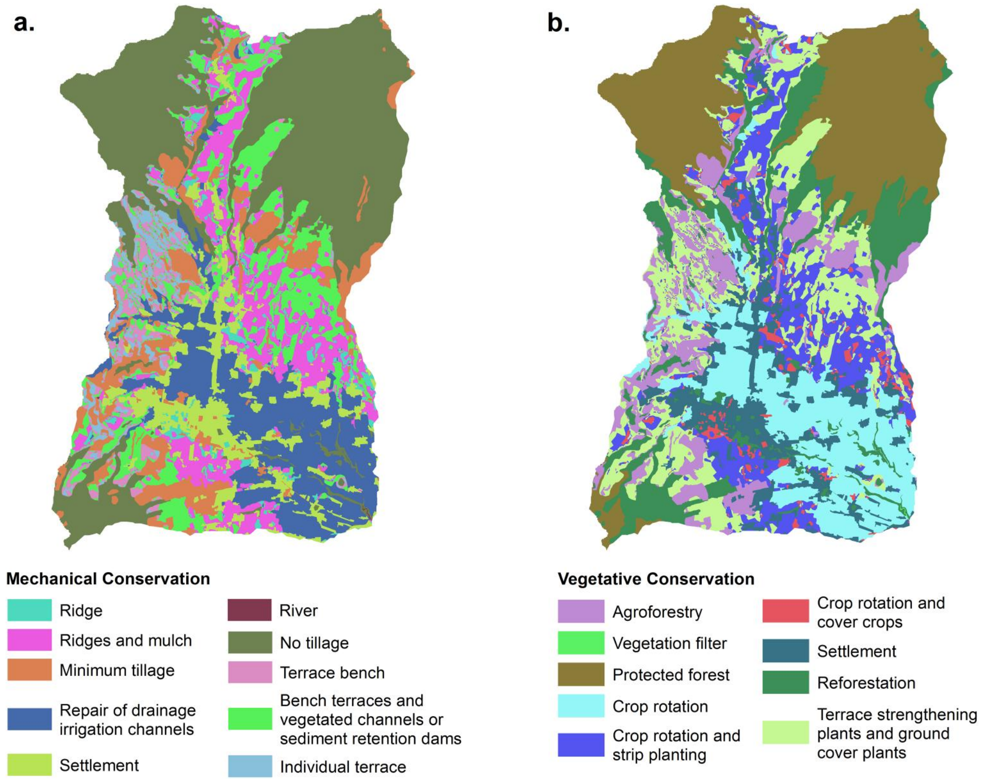

Figure 8. (a) Mechanical and (b) vegetative conservation directions in Sumber Brantas sub-watershed.

4.3. Modelling potential erosion and sedimentation using CA-ANN

Our study identified substantial increases in erosion and sedimentation due to land-use change, with rates projected to rise further by 2025. In the Sumber Brantas sub-watershed, erosion rates increased from 62.13 tons ha^{-1} year^{-1} in 1990 to 83.39 tons ha^{-1} year^{-1} in 2022, marking a 34% rise over 32 years. Projections for 2025 suggest a further increase to 105.39 tonnes/ha/year, representing a 70% increase since 1990, with an average annual rise of approximately 2 tonnes/ha/year. These findings align with results from Suryanta et al. (2022) in the Central Citarum sub-watershed, West Java, Indonesia, where the average erosion rate was 102 tons ha^{-1} year^{-1}, and sediment export was 20.31 tons ha^{-1} year^{-1}. Both studies associated high sedimentation with steep slopes, high rainfall and agricultural expansion. Similarly, Nugroho (2022) identified the Rawa Pening sub-watershed in Central Java, Indonesia, as a critical sediment export zone, with an average rate of 42.9 tons ha^{-1} year^{-1}. While sediment export rates varied due to differences in watershed size, land-use patterns and methodologies, all studies emphasized the significant roles of slope, land management and agricultural practices in sediment transport.

Soil erosion poses a major threat to sustainable land management and ecosystem health, driven by factors such as slope, vegetation cover and land management practices. A study by Mu et al. (2022) in the Pearl River Basin, China, using the RUSLE model and continuous Landsat data (1990–2020), found that areas with slopes >15°, low vegetation cover and poorly managed forests were more prone to erosion. These findings are particularly relevant to our study, which employs the CA-ANN and InVEST models to predict potential erosion and sedimentation. The demonstrated importance of vegetation and land cover underscores the need for high-resolution satellite imagery, such as Sentinel-2A, to improve erosion pattern predictions. Additionally, the use of long-term datasets for monitoring soil erosion trends aligns with our approach of leveraging multi-temporal data to enhance model reliability and accuracy.

Our findings also highlight deforestation and the conversion of forest areas to dry land agriculture and settlements as key drivers of increased sedimentation. Targeted conservation efforts in areas experiencing significant forest loss and erosion are essential for effective watershed management. The consistent findings across these studies emphasize the need to focus sediment management efforts on high-risk areas with steep slopes, agricultural expansion and inadequate vegetation cover. The application of the CA-ANN model in our study provides an effective predictive tool for assessing land-use change and guiding conservation planning, complementing existing frameworks to prioritize soil and water conservation initiatives.

4.4. Limitation and recommendations

This study highlights critical limitations in integrating CA-ANN and InVEST models, particularly related to spatial resolution, temporal coverage and model adaptability. Both models rely heavily on geospatial data, where resolution plays a key role in capturing fine-scale processes. Sentinel-2A imagery (10–20 m resolution) offers improved spatial detail compared to Landsat 5 TM and Landsat 7 ETM (30 m resolution), facilitating better detection of land-use changes. However, the coarse resolution of Landsat may overlook localized features, such as riparian buffers or small-scale erosion hotspots. Incorporating high-resolution datasets, including UAV-derived imagery, offers an opportunity to enhance spatial precision and mitigate this limitation, as demonstrated by He et al. (2023) using sub-pixel mapping for erosion modelling.

Temporal coverage is equally crucial for accurate trend analysis. While Landsat provides a valuable long-term record with its historical archive, its 16-day revisit interval may miss rapid land-use changes. In contrast, Sentinel-2A, with a 5-day revisit cycle, offers higher temporal frequency but lacks the temporal depth of Landsat. Combining these datasets can balance long-term analysis with recent changes, though temporal gaps between sources remain a challenge. He et al. (2022) propose deep-learning-driven super-resolution techniques to enhance both spatial and temporal coherence, potentially addressing this issue and improving mixed-pixel handling in coarser datasets.

Accurately estimating environmental trends using remote sensing data requires addressing challenges related to data calibration, spatial resolution and temporal consistency (Ahmed et al. 2023). As observed in studies involving CA-ANN and InVEST models, integrating multiple satellite datasets introduces difficulties in harmonizing data to detect consistent long-term trends. Additionally, seasonal variability caused by imagery from different time periods can influence the robustness of trend analysis. Future study can benefit from employing advanced data fusion techniques that combine multiple sensor datasets, enhancing both spatial and temporal coverage. Ground-truth validation and machine learning approaches, such as random forest algorithms, are essential to improve predictions of key biophysical parameters, ultimately supporting more precise land-use and erosion modelling.

Model adaptability further constraints broader applicability. The CA-ANN model requires retraining to fit regional land-use dynamics, while InVEST's performance hinges on accurate biophysical parameters, which vary by landscape. Therefore, adaptive calibration and generalized frameworks are necessary for extending model applicability. He et al. (2022) highlight non-uniform kernel architectures and alternating optimization strategies as promising solutions for enhancing model transferability in diverse environments. Future study should focus on developing such frameworks to improve the spatial, temporal and functional accuracy of sediment and erosion predictions, ultimately supporting more effective land management strategies.

5. Conclusion

Between 1997 and 2022, the Sumber Brantas sub-watershed saw a 25% increase in erosion and sedimentation, primarily due to deforestation for agriculture and urban development. These changes have intensified runoff, soil instability, river siltation and water quality degradation. If current land use trends continue, erosion and sedimentation may rise by another 21% by 2025. The study also noted a 0.02 increase in the SDR, signalling more sediment being transported to rivers, exacerbating siltation and increasing maintenance costs for water infrastructure. To address these issues, the study emphasizes the importance of land conservation measures, such as replanting, agroforestry, terracing and check dam construction. These actions, backed by strong policies, institutional support and community involvement, are essential for improving watershed resilience and ensuring its long-term sustainability.

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Data availability statement

The data that support the findings of this study are available from the corresponding author, Aditya Nugraha Putra, upon reasonable request.

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