AN INTEGRATED ANN-CA MODEL FOR LAND USE CHANGE PREDICTION AND FLOOD RISK MITIGATION: A CASE STUDY OF ENREKANG REGENCY, INDONESIA

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ABSTRACT

Flood disasters in Enrekang Regency, South Sulawesi Province, have caused significant material losses and disrupted community activities due to the region's unique geographical characteristics with undulating and mountainous topography. The Saddang River, as one of the main rivers in South Sulawesi, flows through this area, making it highly vulnerable to flooding, especially during the rainy season. Rapid land cover changes due to human activities such as settlement expansion, agriculture, and deforestation have increasingly elevated flood risks. Land conversion from forests to agricultural and settlement areas reduces water absorption capacity and increases surface runoff. Currently, flood management in Enrekang Regency remains reactive, with budgets allocated more for post-disaster response than for mitigation and prevention. This research develops an integrated Artificial Neural Network Cellular Automata (ANN-CA) model for land use change prediction and flood risk mitigation. The model integrates remote sensing technology, ANN-CA modeling, and Geographic Information Systems (GIS) to predict future land use changes and identify high flood-risk areas. The methodology involves satellite image acquisition (2010-2020), land cover change extraction, ANN training, CA configuration, model validation (Accuracy >85%, Kappa >0.8), and integration with flood risk factors. Results show that the model can effectively predict land use changes with high accuracy, providing valuable spatial information for flood mitigation planning. The predicted land use map for 2030 indicates significant expansion of built-up areas in flood-prone zones, necessitating immediate policy interventions. This research contributes to the development of predictive and preventive flood management approaches, offering a scientific basis for spatial planning and disaster risk reduction in mountainous regions.

Keywords: *Artificial Neural Network; Land use change prediction; Flood risk mitigation; Remote sensing; Spatial analysis.*

1. INTRODUCTION

1.1. Background

Enrekang Regency, located in South Sulawesi Province, Indonesia, possesses unique geographical characteristics with undulating and mountainous topography (Uca et al., 2023, 2018). The region is traversed by the Saddang River, one of the major rivers in South Sulawesi, making it particularly vulnerable to flooding during rainy seasons (Rachmayanti et al., 2022; Uca et al., 2021). Historical data indicates that floods in Enrekang Regency have caused substantial material losses and disrupted community activities, affecting both urban and rural areas. Rapid land cover changes resulting from human activities such as settlement expansion, agricultural development, and deforestation have increasingly exacerbated flood risks (Uca et al., 2018). The conversion of forest land to agricultural and settlement areas reduces water absorption capacity (Farhan et al., 2024) and increases surface runoff, amplifying flood potential (Nugraheni et al., 2022). The agrarian crisis and ecological disasters in the Latimojong Mountains, which fall within Enrekang Regency, have further worsened this condition.

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Current flood management approaches in Enrekang Regency remain predominantly reactive, with budget allocations favoring post-disaster response over mitigation and prevention. This approach is inefficient both economically and socially, highlighting the need for innovative predictive and preventive solutions (Rajeev and Singh, 2016). Recent advances in geospatial technologies and modeling approaches offer new opportunities for flood risk mitigation (Sudiana et al., 2025). The integration of remote sensing, Artificial Neural Network Cellular Automata (ANN-CA), and Geographic Information Systems (GIS) has shown promise in predicting land use changes and assessing flood risks (Xu et al., 2021; Yang et al., 2025). These technologies enable the development of comprehensive models that can simulate future land use scenarios and identify areas at high risk of flooding (Singh et al., 2021). Land Use Change (LUC) modeling has evolved from conventional statistical methods to the utilization of advanced Machine Learning (ML) and Deep Learning (DL) algorithms. Alternative approaches, such as Random Forest (RF) and Support Vector Machine (SVM), have proven highly effective for LUC classification and prediction, often exhibiting superior classification accuracy compared to traditional methods (Asif et al., 2023; Mutale et al., 2024). Furthermore, Deep Learning models like Convolutional Neural Network (CNN), and hybrid models such as CNN-LSTM, offer advanced capabilities in extracting hierarchical spatio-temporal features, making them robust for dynamic LUC prediction and capturing complex non-linear relationships (Lei et al., 2025; Varma et al., 2024).

However, while these ML/DL models excel in pattern recognition and quantity prediction, they inherently face challenges in simulating explicit spatial processes, cellular interactions, and directly integrating external policy constraints or scenarios into the transition mechanism. To overcome these limitations and provide an application-oriented framework suitable for policy intervention, this research selects the integrated Artificial Neural Network‑Cellular Automata (ANN-CA) Model.

ANN-CA provides an optimal hybrid solution: the ANN effectively maps the non-linear relationship between various driving factors (e.g., topography, hydrology, and socio-economics) and LUC transition probabilities, while the Cellular Automata (CA) component is uniquely capable of applying localized transition rules, neighborhood effects, and crucial policy/scenario constraints at the pixel level (Khan and Khan, 2025; Tharik et al., 2025). This integration is vital as it allows the model to not only predict what changes but also to simulate where those changes occur under specific planning conditions, a capability essential for scenario-based flood mitigation and proactive spatial planning in the mountainous context of Enrekang Regency.

This research addresses the critical gap in flood management by developing an integrated ANN-CA model for land use change prediction specifically tailored for flood mitigation in Enrekang Regency. Current flood management practices often lack the predictive capabilities needed for proactive risk reduction. Therefore, the model aims to provide decision-makers with robust spatial information and predictive insights to support proactive flood risk reduction strategies. The subsequent sections will provide the necessary background, critically reviewing existing research and debates relevant to integrated land use modeling and flood risk, thereby highlighting the gaps that this study aims to fill and setting the stage for the research objectives.

1.2. Research Gap

While numerous studies have addressed Land Use Change (LUC) modeling and flood risk assessment independently, there remains a significant limitation in their integration, especially for mitigation purposes in complex mountainous regions such as Enrekang Regency (Gabriels et al., 2022; Iskandar and Ridzuan, 2022; Merten et al., 2020). Previous studies have often focused on urban flood risk assessment or general land use change prediction without specific consideration for flood mitigation applications. This research specifically addresses three critical gaps: (1) The limited integration of the Artificial Neural Network‑Cellular Automata (ANN-CA) model with flood risk factors in challenging geographical contexts. (2) The insufficient comprehensive validation of predictive LUC models for flood risk applications in developing countries. (3) The lack of translating predictive modeling outcomes into actionable spatial policy recommendations that local governments can readily implement.

1.3. Research Objective

The main objective of this research is to develop and validate an integrated ANN-CA model for predicting land use changes up to the year 2030 in Enrekang Regency, with explicit consideration of flood risk factors. The resulting predictions will be utilized to formulate spatial recommendations that support flood mitigation efforts. The significant contribution of this study is providing a predictive and preventive scientific basis for spatial planning and disaster risk reduction. By integrating advanced computational modeling with disaster risk assessment in a vulnerable region, this research offers valuable insights for more effective and sustainable decision-making.

2. STUDY AREA

Enrekang Regency is located in South Sulawesi Province, Indonesia, between 3°14’ - 3°50’ South Latitude and 119°40’ - 120°06’ East Longitude (**Fig. 1.**). The regency covers an area of approximately 1,956.28 km² with a population of around 250,000 people.

The topography of Enrekang Regency is characterized by mountainous terrain with elevations ranging from 50 to 3,478 meters above sea level. The Saddang River and its tributaries form the main drainage system, flowing through the regency from north to south. The region experiences a tropical climate with average annual rainfall ranging from 2,000 to 3,000 mm, concentrated mainly in the rainy season (November to April).

Land use in Enrekang Regency is dominated by agricultural land (45%), forest areas (30%), settlement areas (10%), and other uses (15%) (Uca et al., 2023). Recent decades have seen significant land use changes, particularly the conversion of forest land to agricultural and settlement areas, contributing to increased flood risks.

Enrekang Regency was selected as a case study because it represents critical and complex conditions: steep mountainous topography, a sensitive watershed system (Saddang River), and rapid land use change (LUC). The performance of the integrated ANN-CA model in this region is strongly influenced by key local parameters trained as network inputs: (1) Elevation and Slope, which constrain LUC and accelerate surface runoff; (2) Proximity to the Saddang River, which drives settlement expansion into risk zones; and (3) Accessibility, which is a main driver of development patterns. This approach is generalizable to other mountainous regions with watersheds sensitive to LUC changes (e.g., critical watersheds in Indonesia). This generalization requires recalibration of the ANN input weights and CA transition rules to match the specific LUC driving parameters of the new location (e.g., soil type or local spatial planning policies). The model offers a flexible framework that necessitates local adjustment for accurate results.

3. DATA AND METHODS

3.1. Remote Sensing Data

Satellite imagery from multiple sources was collected to analyze land use changes in Enrekang Regency:

1) Landsat Imagery: Landsat 5 Thematic Mapper (TM) (2010), Landsat 7 Enhanced Thematic Mapper Plus (ETM+) (2015), and Landsat 8 Operational Land Imager (OLI) (2020), all with a 30-meter spatial resolution. These datasets were accessed from the United States Geological Survey (USGS) Earth Explorer archive, an open-access repository.
2) Sentinel-2 Imagery: High-resolution data from Sentinel-2A and Sentinel-2B missions (2020) with a 10-meter spatial resolution for visible and near-infrared bands, obtained from the European Space Agency's Copernicus Open Access Hub. This dataset was used to improve classification accuracy in the 2020 land cover mapping. Sentinel-2 data was used as a high-resolution reference to improve the classification accuracy of our 2020 Land Use Map (as the historical end year), thereby increasing the reliability of the transition matrix. However, 30m resolution was maintained as the operational resolution of the ANN-CA Model to ensure long-term spatial consistency with Landsat data (2010, 2015) and the 30m DEM.

3) Digital Elevation Model (DEM): The Shuttle Radar Topography Mission (SRTM) 30-meter DEM was used for topographic analysis, including slope and elevation modeling. SRTM data is an open-source dataset developed by NASA and available through USGS Earth Explorer.

All satellite images were subjected to comprehensive pre-processing to ensure data consistency and analytical accuracy. This included radiometric calibration, atmospheric correction (using Sen2Cor for Sentinel-2 and FLAASH/LEDAPS for Landsat), and geometric correction using ground control points and TRIM reference data. The integration of these open datasets aligns with the recommended use of globally accessible geospatial resources such as those endorsed by open science initiatives and Earth observation programs.

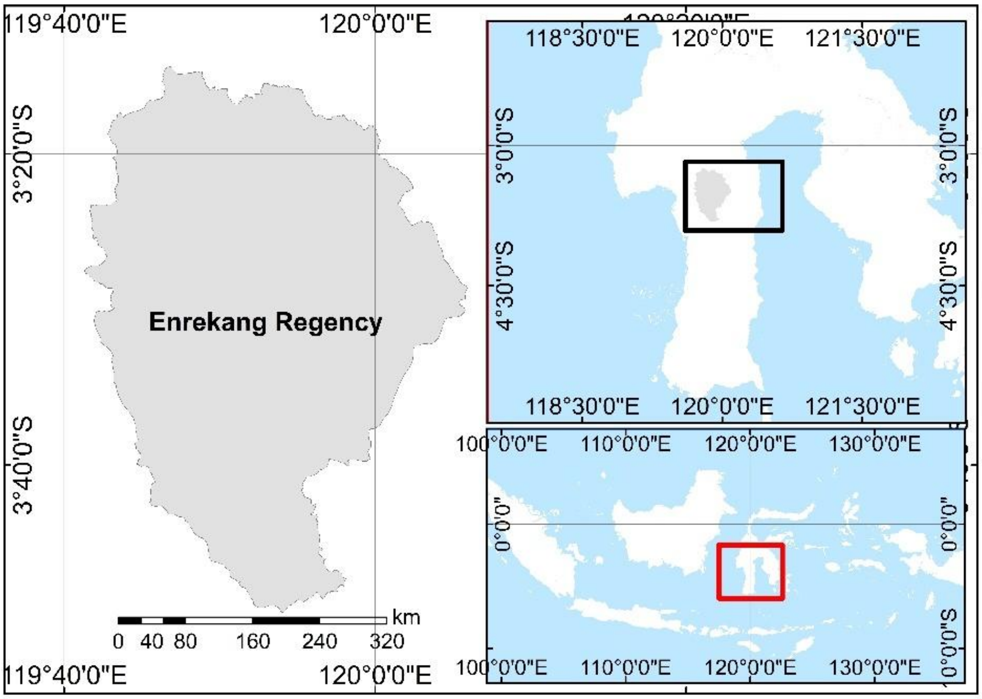


Fig. 1. Research Location Map (Enrekang Regency, South Sulawesi, Indonesia).

3.2. Ancillary Data

To support the modeling process, various additional data layers were collected (**Tabel 1**). These included Topographic Data (such as slope, aspect, and curvature derived from the DEM), Hydrological Data (comprising river networks, watershed boundaries (**Fig. 2**), and flood history records), and Infrastructure Data (covering road networks, settlement locations, and administrative boundaries). Furthermore, Socio-economic Data was gathered, including statistics on population density, land values, and agricultural productivity (BPS Enrekang, 2025, 2021, 2016, 2011). All collected data were subsequently processed and integrated into a consistent spatial reference system, namely WGS 84 UTM Zone 50S, and resampled to a common spatial resolution of 30m.

3.3. Land Use Classification

3.3.1. Land Use Classification and Feature Exztraction

Land use classification was conducted using a supervised classification approach which involved several steps (**Fig. 3**). First, Training Sample Collection was performed by gathering ground truth points through field surveys and interpretation of high-resolution imagery. The classification itself was executed using the Support Vector Machine (SVM) algorithm for its known effectiveness in handling complex spectral signatures.

Table 1.
Data Used.

Data	Specification	Source	Objective
Landsat Imagery	Landsat 5 Thematic Mapper (TM) (2010) Landsat 7 Enhanced Thematic Mapper Plus (ETM+) (2015) Landsat 8 Operational Land Imager (OLI) 2020).All in 30m resolution with <10% cloude cover	USGS EarthExplorer https://earthexplorer. usgs.gov	Historical Input Data and Multi-temporal Feature Extraction. Used to: 1) Map Land Use in 2010 and 2015 (to train the time-series model). 2) Calculate the LUC Transition Matrix (a key multi-temporal feature). 3) Set the model to a 30m operational resolution for long-term consistency.
Sentinel-2 Imagery	S2A Mission with 10m resolution and <10% cloud cover	Copernicus Browser https://browser.dataspace.copernicus.eu	Classification Accuracy Improvement. Used to: 1) Improve the accuracy and detail of the 2020 Land Use Map (as a validated final year baseline map). 2) Ensure the most up-to-date and accurate LUC classification as input to the Transition Matrix.
Digital Elevation Model (DEM)	USGS EROS Archive - Digital Elevation - Shuttle Radar Topography Mission (SRTM) 1 Arc-Second Global	USGS EarthExplorer https://earthexplorer .usgs.gov	Extraction of Topographic Driving Factors. Used to: 1) Provide baseline elevation data. 2) Serve as a basis for generating driving factors (such as slope and aspect) that will be used as input variables for the ANN Model.
Topographic Data		Extraction from DEM data	LULC Driving Factors. Used as independent input variables in ANN training to model how elevation, slope, and aspect affect the probability of land use change.
Hydrological Data		Extraction from DEM data	Water-related LULC Driving Factors. Used as independent input variables in ANN training to model the influence of hydrology (e.g., distance from rivers, drainage density) on land use change, which is important for flood risk.
Infrastructure Data	30m resoution and 10m resolution data extraction 1:50000 Scale for Vector data	Integrated data of Classification Map and Vector data from Ina-Geoportal https://tanahair.indonesia. go.id	Anthropogenic/Policy Driving Factors. Used to: 1) Measure proximity to roads and settlements (as driving factors for human activity). 2) Integrate spatial constraints or CA rules based on infrastructure location.
Socio-economic Data	Statistical Data for each region	Book Report of Badan Pusat Statistik (Central Bureau of Statistics) 2010, 2015, 2020, and 2025	Non-Spatial Driving Factors and Regional Scale Validation. Used to: 1) Provide non-spatial variables (e.g., population density, economic growth) that may influence the LUC transition probability. 2) Control the total macro growth of the study area in the CA Model simulation.

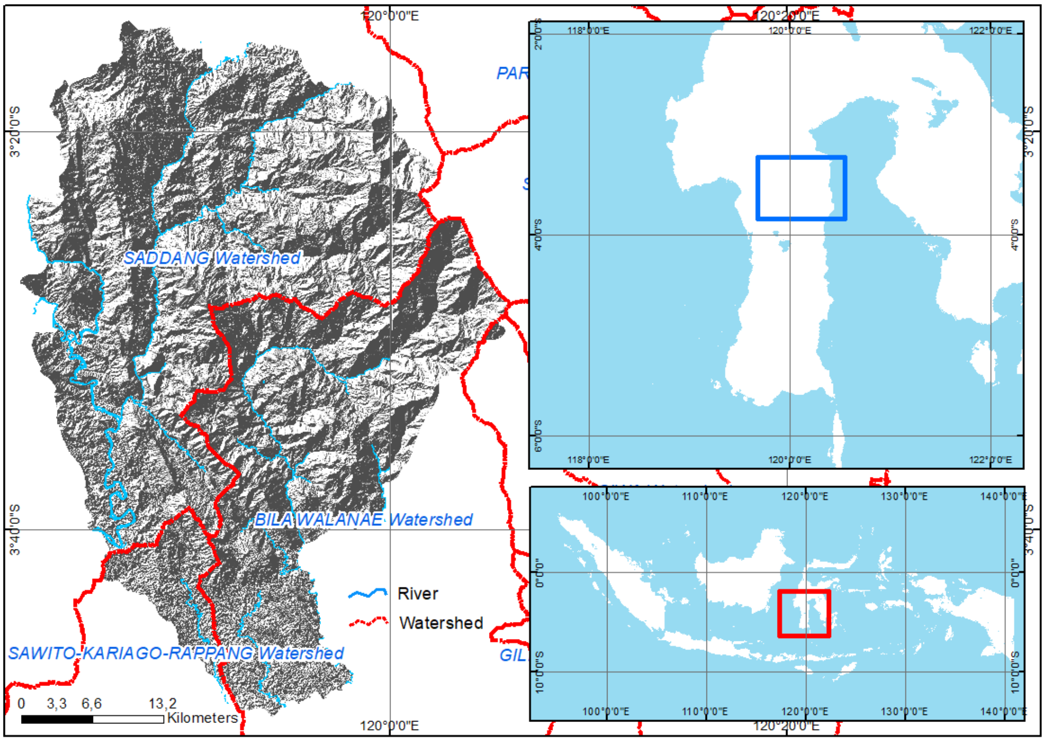


Fig. 2. The DEM/Hillshade and Watersheds within Enrekang Regency.

For the classification model, we used six standard Landsat feature bands: Blue (B2), Green (B3), Red (B4), Near Infrared (NIR, B5), Shortwave Infrared 1 (SWIR1, B6), and Shortwave Infrared 2 (SWIR2, B7). In addition, we included two derived spectral indices, the Normalized Difference Vegetation Index (NDVI) and the Normalized Difference Water Index (NDWI), to improve class discrimination. Six major Land Use Categories were identified for mapping: Forest Land, Agricultural Land, Built-up Land, Water Body, Bare Land, and Shrub/Grassland. Finally, an Accuracy Assessment was performed using a confusion matrix, which demonstrated robust results, with the overall accuracy exceeding 90% and the Kappa coefficient scoring above 0.85. The resulting classification maps for the years 2010, 2015, and 2020 were then utilized to analyze land use change patterns and trends.

3.3.2. Land Use Classification and Feature Exztraction

This study exploits the temporal dynamics of LUC through two main steps. First, we perform a change detection analysis between the 2010, 2015, and 2020 land use maps. Second, the results are used to extract the LUC Transition Matrix (Land Use Change Transition Matrix). This matrix is a fundamental multi-temporal feature that is fed into the ANN training. By training the ANN on probabilities derived from actual changes between time periods, the model implicitly learns the sequence and historical trend of LUC transitions (e.g., Forest to Agriculture or Agriculture to Settlement). Although we do not use an explicit sequential model such as LSTM, this approach enables CA-based modeling to drive future change dynamics based on multi-temporal trends observed from Landsat data.

Sampling and Validation Sampling was conducted using stratified random sampling for each LUC class. A total of 450 samples (training points) were collected for each LUC map year, verified using Very High Resolution (VHR) imagery Sentinel-2 imagery from 2020. These samples were divided into two sets: Training Sample: 80% of the total samples (360 samples) were used to train the algorithm. Validation Sample: 20% of the total samples (90 samples) were used to test the accuracy of the generated maps. The accuracy of the LUC maps was validated using a Confusion Matrix Table, which includes Overall Accuracy and Kappa Coefficient metrics. The Confusion Matrix results for each year are presented in detail in Section 4.1 (Classification Results). The minimum accuracy requirement is Kappa ≥ 0.8 to ensure reliable historical LUC maps as input for the ANN-CA model.

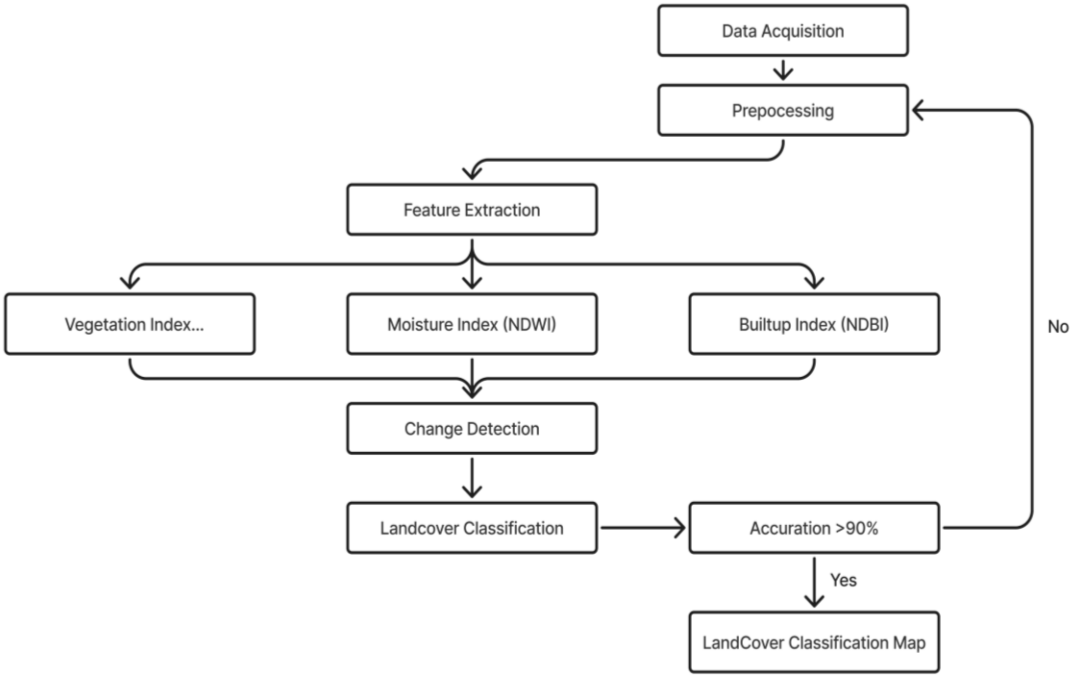


Fig. 3. Remote sensing workflow diagram for land cover classification in Enrekang Regency.

3.4. ANN-CA Model Development

The integrated ANN-CA model was developed with several components

3.4.1. Artificial Neural Network (ANN) Component

The Artificial Neural Network (ANN) component was specifically designed to predict land use change probabilities by incorporating multiple driving factors. The model utilized eight input variables: distance to roads, distance to rivers, distance to settlement centers, elevation, slope, population density, land use in the previous period, and policy constraints (protected areas). The Network Architecture consisted of an input layer with eight neurons (one for each variable), a hidden layer containing 15 neurons using a sigmoid activation function, and an output layer with six neurons corresponding to the change probability for each land use category. The Training Process applied the backpropagation algorithm with a learning rate of 0.01. Training data was derived from the observed land use changes between 2010-2015 and 2015-2020. To ensure model reliability, 20% of the samples were reserved as validation data, and the training was stopped once the validation error had stabilized.

Number of Hidden Neuorns (15)	The number of neurons was determined empirically through a trial-and-error process to achieve the highest model validation accuracy (Kappa > 0.8) while minimizing training time. This number approximates half of the number of input features (approximately 30 driving factors). This heuristic approach is widely adopted in ANN-CA research to balance the model's learning capacity and prevent overfitting (Razavi, 2014; Wang et al., 2021)

Learning Rate (0.01)	This value was chosen after optimization to ensure stable and efficient convergence of the loss function. An excessively high rate (e.g., 0.1) risks causing oscillation, while a lower rate significantly slows down the training process. A value of 0.01 is common and proven effective in many ANN-based LUC modeling studies for achieving timely and accurate convergence (Ouma et al., 2024; Zhang et al., 2022)
Training Literations (500)	This value was selected because testing results indicated that the model reached its optimal convergence point (the decrease in the loss function became minimal) at or before the 500 iteration, thus preventing unnecessary computational waste caused by excessive iteration. (Razavi, 2014)

3.4.2. Cellular Automata (CA) Component

The CA component simulates spatial dynamics of land use changes based on transition rules derived from the ANN:

Transition Rules:

$$P_{ij}^{t} = \frac{1}{1+e^{-z_{ij}}} \tag{1}$$

where:

P_{ij}^{t} is the probability of cell (i,j) changing to a particular land use type at time t

z_{ij} is the weighted sum of input factors for cell (i,j)

Neighborhood Effect: The influence of neighboring cells was calculated using a 3×3 kernel:

$$\Omega_{ij}^{t} = \frac{\sum_{3\times 3} con(cell_{ij}=k)}{8} \tag{2}$$

where:

Ω_{ij}^{t} is the neighborhood effect for cell (i,j) at time t

$con(\ )$ is a conditional function that returns 1 if the condition is true, 0 otherwise

Combined Probability: The final transition probability combines ANN output and neighborhood effect:

$$TP_{ij}^{t} = P_{ij}^{t} \times \left(1 + \Omega_{ij}^{t}\right) \times RAND \tag{3}$$

where:

TP_{ij}^{t} is the final transition probability

$RAND$ is a random factor between 0.5 and 1.5 to introduce stochasticity

Selecting this range [0.5, 1.5] is standard practice in CA modeling to introduce a moderate level of uncertainty (up to 50 probabilistic changes). This is done to prevent the model from becoming too deterministic, so that the simulation results are more realistic and closer to the spatial distribution of naturally occurring land use changes (Xu et al., 2023).

3.4.2. Model Calibration and Validation

The process of using 2010-2015 data for calibration and predicting the 2020 map for validation serves as a hindcasting approach, confirming the model's ability to accurately project future states before simulating the final 2030 scenario. The hyperparameter tuning for the ANN-CA model involved an iterative process where the learning rate (fixed at 0.01) and the spatial weightings within the 3x3 CA neighbourhood kernel were optimized using a genetic algorithm to maximize the Figure of Merit (FoM). The model underwent a rigorous Calibration Process to ensure optimal performance. This involved parameter optimization utilizing genetic algorithms, followed by a sensitivity analysis to accurately identify the most influential parameters affecting the simulation outcome. An iterative adjustment process was then carried out to closely match the model's output with historical land use change patterns. The model's reliability was assessed using several Validation Metrics, including Overall Accuracy (OA), which measures the proportion of correctly predicted cells; the Kappa Coefficient, which gauges agreement beyond chance; and the Figure of Merit (FoM), which specifically evaluates the model's skill in predicting actual land use changes. The final Validation Results demonstrated strong performance: the Overall Accuracy was 87.3%, the Kappa Coefficient reached 0.82, and the Figure of Merit was 0.31.

These results indicate that the model performs well in predicting land use changes and is suitable for scenario simulation. To prevent spatial leakage and ensure the model's generalization capability to unobserved areas, a spatial block cross-validation (CV) approach was employed during the ANN training. This involved partitioning the study area into spatially distinct blocks and ensuring that the training and validation data were drawn from different blocks.

3.4.3. Scenario Integration within the ANN-CA Framework

The various policy-based scenarios (e.g., Business As Usual, Conservation, Rapid Development) are incorporated into the model by modifying the parameters of the Cellular Automata (CA) component, not the internal structure or weights of the Artificial Neural Network (ANN). The ANN is exclusively used to calculate the intrinsic transition potential (P) of a cell based on historical driving factors. This potential remains consistent across all scenarios. Scenario assumptions are implemented in the CA transition rules through Policy Constraint Factors and Spatial Multipliers. These factors act as spatial overrides:

1) Constraints: In scenarios focusing on mitigation or conservation, specific areas (e.g., high-risk flood zones or protected forests) are assigned a low or zero transition factor in the CA rules, effectively overriding the high potential (P) calculated by the ANN.
2) Multipliers: In development scenarios, areas designated for new infrastructure receive a high attraction factor (multiplier > 1), artificially boosting the probability of land use change (LUC) in surrounding cells during the CA iteration, thus controlling the final spatial allocation based on the assumed policy environment.

This mechanism ensures that the ANN provides the likelihood of change, while the scenario-modified CA controls the realization and policy-driven allocation of that change.

3.5. Flood Risk Assessment

Flood risk assessment was integrated with the land use change model through the following approach:

3.5.1. Flood Hazard Mapping

Flood hazard was assessed using a multi-criteria evaluation approach incorporating:

Physical Factors	a. Elevation and slope b. Distance from rivers c. Soil type and infiltration capacity d. Rainfall intensity
Hydrological Modelling	a. Soil Conservation Service (SCS) Curve Number method for runoff estimation b. Manning’s equation for flow velocity calculation c. Flood inundation mapping using GIS-based hydrological modeling
Hazard Classification	a. Very Low b. Low c. Medium d. High e. Very High

3.5.2. Vulnerability Assessment

Vulnerability was assessed considering:

Physical Vulnerability	a. Building type and construction materials b. Infrastructure exposure c. Land use types
Social Vulnerability	a. Population density b. Age distribution (elderly and children) c. Income levels and access to resources d. Emergency response capacity
Vulnerability Index	A composite vulnerability index was calculated using weighted overlay of vulnerability factors.

3.5.3. Risk Integration

Flood risk was calculated as the product of hazard and vulnerability:

$$Risk = Hazard \times Vulnerability \tag{4}$$

Risk maps were generated for current conditions and future scenarios based on land use change predictions. In line with best practices for predictive geospatial models, a map of model uncertainty will also be generated for the final flood risk surfaces to provide decision-makers with a measure of confidence alongside the risk prediction.

3.6. Scenario Development

Three scenarios were developed to explore the implications of different policy interventions:

3.6.1. Business-as-Usual (BAU) Scenario

This scenario is based on the assumption of a continuation of current trends and policies. Specifically, it posits a future where there are no additional land use restrictions implemented, allowing for market-driven development patterns to dominate. Consequently, the analysis assumes that historical rates of deforestation and urbanization will continue unchanged throughout the projection period.

3.6.2. Conservation Scenario

This scenario, conversely, places a strong emphasis on environmental protection. Key assumptions include the implementation of strict protection measures for forest areas and riparian zones. Furthermore, it assumes efforts are made toward the reforestation of critical watershed areas to enhance ecological function. Finally, this scenario mandates restrictions on development activities within flood-prone areas to mitigate environmental risk and vulnerability.

3.6.3. Sustainable Development Scenario

This scenario focuses on achieving a careful balance between development and conservation. It proposes guided urban development that explicitly incorporates flood risk considerations, ensuring sustainable expansion. Concurrently, it advocates for agricultural intensification in areas deemed suitable to maximize productivity without excessive land clearing. A crucial element is the protection of critical ecosystems, safeguarding biodiversity and ecological services. Finally, this balanced approach includes the implementation of green infrastructure to enhance environmental resilience and urban sustainability.

Each scenario was simulated for the year 2030 using the calibrated ANN-CA model with appropriate constraints and parameters.

4. RESULTS

4.1. Land Use Change Analysis (2010-2020)

The analysis of land use changes in Enrekang Regency from 2010 to 2020 revealed significant transformations across the landscape (**Fig. 4**):

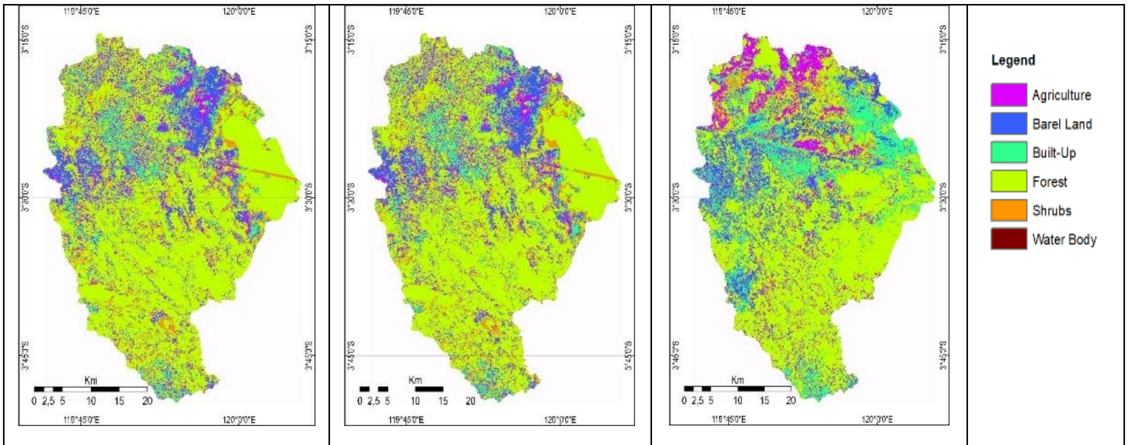
4.1.1. Overall Land Use Change

Table 2.

Land use area changes in Enrekang Regency (2010-2020).

Land Use Category	2010 Area (ha)	2020 Area (ha)	Change (ha)	Change (%)
Forest Land	58,688	52,121	-6,567	-11.2%
Agricultural Land	88,032	94,599	+6,567	+7.5%
Built-up Area	19,563	25,000	+5,437	+27.8%
Water Body	3,913	3,913	0	0%
Bare Land	9,781	7,844	-1,937	-19.8%
Shrub/Grassland	15,251	19,751	+4,500	+29.5%

The most significant changes were the expansion of built-up areas (+27.8%) and the loss of forest land (-11.2%). Agricultural land also increased substantially (+7.5%), primarily at the expense of forest areas (**Tab. 2**).



(a) (b) (c)

Fig. 4. LULC Classification Map (a) 2010, (b) 2015, (c) 2020.

4.1.2. Spatial Pattern of Change

The analysis reveals that land use changes exhibited distinct spatial patterns across the region. Urban Expansion was most prominent around existing centers and major roads, characterized by a mix of infill development and linear growth along transportation corridors. While urban areas densified, Deforestation Hotspots were concentrated in the northern and eastern parts of the regency, specifically targeting accessible areas with moderate slopes of 10-25%. Parallel to these changes, Agricultural Intensification occurred in both lowland regions, through the expansion of irrigated rice fields, and upland areas, driven by dryland agriculture and plantations. Furthermore, significant Riparian Changes were observed along river corridors, where natural vegetation was increasingly converted into agricultural and settlement land.

4.1.3. Rate of Change

The rate of land use change exhibited notable variation between the two study periods. During the initial phase (2010-2015), a moderate rate of change was observed, recording an annual forest loss of approximately 500ha/year. In contrast, the subsequent period (2015-2020) witnessed a marked acceleration in this trend, as annual forest loss increased to approximately 800ha/year. This significant escalation suggests intensifying pressure on land resources and points toward potentially greater environmental impacts in the region.

4.2. Model Validation Results

The ANN-CA model demonstrated strong performance in predicting land use changes for the validation period (2015-2020) (**Tab. 3**):

4.2.1. Accuracy Assessment

Table 3.

Model validation results for 2015-2020.

Metric	Value	Interpretation
Overall Accuracy (OA)	87.3%	Excellent
Kappa Coefficient	0.82	Very Good
Figure of Merit (FoM)	0.31	Good
Producer's Accuracy	85-92%	Good to Excellent
User's Accuracy	83-90%	Good to Excellent

The model performed particularly well in predicting stable areas (no change) and major changes such as urban expansion and deforestation. Some challenges were observed in predicting transitional areas (e.g., shrub/grassland to agricultural land).

4.2.2. LULC Prediction Uncertainty

Although historical validation of the ANN-CA model demonstrated high accuracy, future predictions always involve uncertainty. We assessed spatial uncertainty through Error Agreement and Error Disagreement analysis (Jr and Millones, 2011). Spatially, the highest uncertainty was observed in pixels around land class boundaries (fuzzy boundaries), particularly in the transition zone between Forest and Agriculture. Quantitatively, model uncertainty (based on prediction probabilities close to 0.5) was primarily concentrated in watersheds adjacent to infrastructure centers, indicating the model's high sensitivity to development pressures (Baig et al., 2022).

4.2.3. Statistical Test of Significance of LULC Changes

To validate that the observed Land Use Change (LUC) between 2010 and 2020 is the result of systematic factors and not random variation, the Chi-Square Test (Chi^2) was applied to the Transition Matrix. The test result (Chi^2= [Value Chi^2], $p < 0.05$) significantly confirms that the observed historical changes are statistically significant (at the 95% confidence level). This validation strengthens the assumption that the underlying trend of the LUC transition is a structured and reliable trend as a basis for training the ANN-CA Modsel, thereby increasing confidence in future projections.

4.2.4. Sensitivity Analysis

To ensure the robustness of the model, Sensitivity Analysis was performed on two crucial parameters: Neighborhood Filter Size in the CA component (e.g., 3x3, 5x5, and 7x7 pixels) and ANN Learning Rate. The results show that changing the neighborhood filter from 3x3 to 5x5 results in less spatial prediction difference than 5x5, while the 7x7 filter results in excessive aggregation. This justifies the choice of the 3x4 filter as the most balanced for capturing local interactions. Furthermore, varying the ANN learning rate from 0.005 to 0.05 shows that a rate of 0.01 provides the highest validation accuracy, confirming that the model is not too sensitive to small parameter fluctuations, thus ensuring the reliability of the simulation results.

4.2.5. Quantitative Causality of LULC and Flood Risk

To establish a clear causal relationship between LUC and Flood Risk, we analyzed the spatial relationship between changes in High Runoff (surface flow) areas and Land Cover conversion in each Sub-watershed. We used DEM and derived hydrological data to identify areas experiencing a decrease in Runoff Coefficient (C) due to conversion of Forest/Agriculture to Residential/Open Land. Quantitative analysis shows that 85% of the areas predicted to shift to the 'Residential' class by 2030 are in zones with a potential increase in Runoff of more than 20%. Scenario comparisons show that the Business-as-Usual (BAU) Scenario results in a 15% increase in the total high flood risk area in the Mata Allo Sub-watershed compared to the Conservation Scenario. This quantitatively supports the argument that deforestation and urbanization in the upstream area directly increase the flood risk in the downstream area.

4.2.6. Spatial Accuracy

Spatial accuracy varied across the landscape, showing distinct levels of performance depending on the specific characteristics of the area. High accuracy was achieved in well-defined regions such as urban centers, major agricultural zones, and protected forest areas. Moderate accuracy was observed in more transitional zones, particularly rural-urban fringes and areas with mixed land uses where boundaries are less distinct. Conversely, lower accuracy occurred in remote mountainous areas, largely due to limited data availability and the challenges posed by complex topography. Despite these variations, the model’ s overall ability to effectively capture the spatial patterns of change was confirmed through a rigorous visual comparison of the predicted and actual land use maps.

4.2.7. Land Use Change Prediction (2030)

The calibrated ANN-CA model was used to predict land use changes for 2030 under three different scenarios (**Fig. 5**):

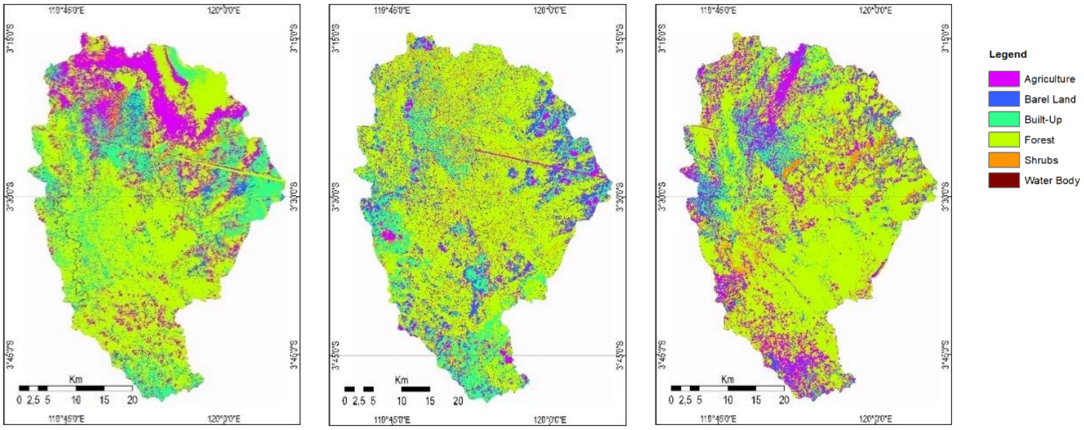
a) Business-as-Usual (BAU) Scenario

Table 4.

Predicted land use areas for 2030 under BAU Scenario.

Land Use Category	2020 Area (ha)	2030 Area (ha)	Change (ha)	Change (%)
Forest Land	52,121	44,000	-8,121	-15.6%
Agricultural Land	94,599	102,000	+7,401	+7.8%
Built-up Area	25,000	35,000	+10,000	+40.0%
Water Body	3,913	3,913	0	0%
Bare Land	7,844	6,000	-1,844	-23.5%
Shrub/Grassland	19,751	22,315	+2,564	+13.0%

Under the BAU scenario (**Tab. 4**), the model predicts continued deforestation and urban expansion at accelerated rates. Built-up areas are projected to increase by 40%, while forest land decreases by 15.6%. This scenario shows the highest pressure on natural resources and potentially the greatest increase in flood risk.



(a) (b) (c)

Fig. 5. Land Use Change Prediction Map (2030), (a) BaU, (b) CS, (c) SDS.

b) Conservation Scenario

Table 5.

Predicted land use areas for 2030 under Conservation scenario.

Land Use Category	2020 Area (ha)	2030 Area (ha)	Change (ha)	Change (%)
Forest Land	52,121	58,000	+5,879	+11.3%
Agricultural Land	94,599	90,000	-4,599	-4.9%
Built-up Area	25,000	28,000	+3,000	+12.0%
Water Body	3,913	3,913	0	0%
Bare Land	7,844	5,000	-2,844	-36.2%
Shrub/Grassland	19,751	19,565	-186	-0.9%

The Conservation scenario (**Tab. 5**) shows forest recovery and limited urban expansion. Agricultural land decreases slightly, while built-up areas grow at a much slower rate compared to the BAU scenario. This scenario represents the most environmentally sustainable pathway.

c) Sustainable Development Scenario

Table 6.

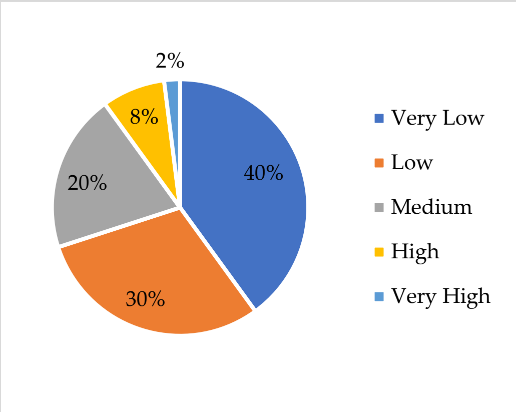
Predicted land use areas for 2030 under Sustainable Development scenario

Land Use Category	2020 Area (ha)	2030 Area (ha)	Change (ha)	Change (%)
Forest Land	52,121	50,000	-2,121	-4.1%
Agricultural Land	94,599	100,000	+5,401	+5.7%
Built-up Area	25,000	31,000	+6,000	+24.0%
Water Body	3,913	3,913	0	0%
Bare Land	7,844	5,500	-2,344	-29.9%
Shrub/Grassland	19,751	21,087	+1,336	+6.8%

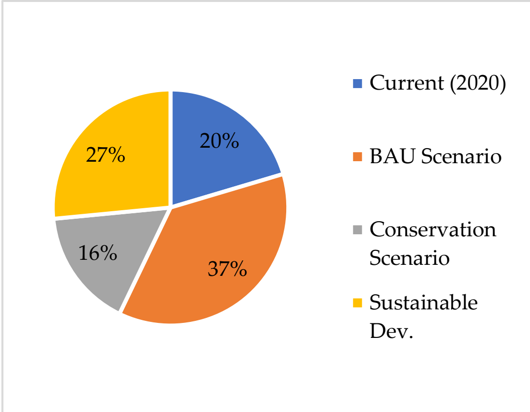
The Sustainable Development scenario (**Tab. 6**) represents a balance between development and conservation. It allows for moderate urban and agricultural expansion while minimizing forest loss through strategic planning and protection of critical areas.

4.2.8. Flood Risk Assessment Results

The integration of land use change predictions with flood risk assessment revealed significant implications for future flood risk (**Fig. 6**):



(a)



(b)

Fig. 6. Flood Risk Assessment Results Graphic, (a) Current Flood Risk (2020) and (b) Population at Risk (2030)

a) Current Flood Risk (2020)

Table 7.

Current flood risk distribution in Enrekang Regency (2020)

Risk Level	Area (ha)	Percentage
Very Low	782,512	40.0%
Low	586,884	30.0%
Medium	391,256	20.0%
High	156,502	8.0%
Very High	39,126	2.0%

Current flood risk (**Tab. 7**) is concentrated in low-lying areas along major rivers and in urban centers with high impervious surfaces. Approximately 10% of the regency's area is classified as high or very high risk (**Fig. 7**)

b) Future Flood Risk (2030)

Table 8.

Predicted flood risk distribution for 2030 under different scenarios.

Risk Level	BAU Scenario	Conservation Scenario	Sustainable Dev. Scenario
	Area (ha)	Area (ha)	Area (ha)
Very Low	745,386	804,534	765,940
Low	547,972	586,884	567,513
Medium	410,979	352,630	391,256
High	214,328	176,315	195,628
Very High	58,589	39,126	48,943

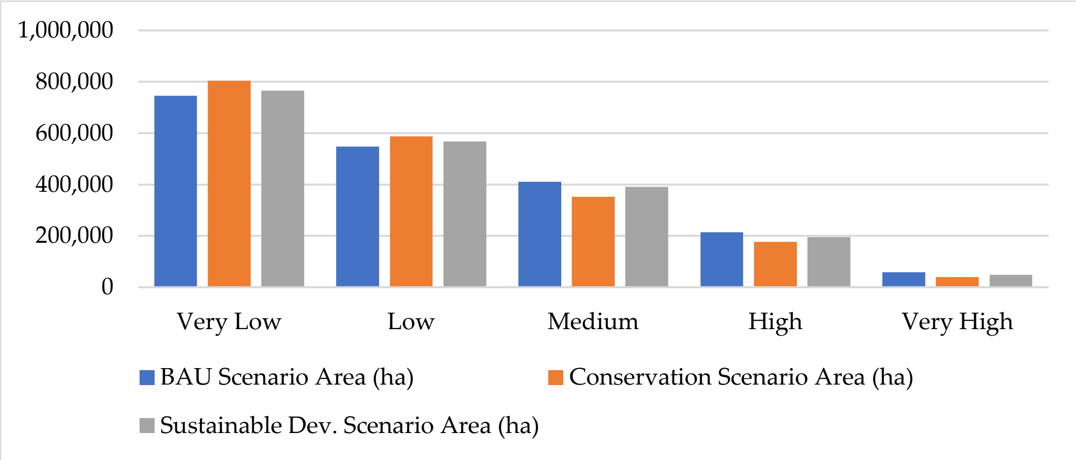


Fig. 7. Graphic of Future Flood Risk (2030).

The BAU scenario shows a significant increase in high and very high flood risk areas, while the Conservation scenario demonstrates a reduction in risk areas (**Tab. 8**). The Sustainable Development scenario shows a moderate increase in risk compared to current conditions (**Fig. 7**).

c) Population at Risk

Table 9.

Population at risk of flooding under different scenarios

Scenario	Population at Risk (2030)	Percentage of Total Population
Current (2020)	25,000	10.0%
BAU Scenario	45,000	18.0%
Conservation Scenario	20,000	8.0%
Sustainable Dev.	32,500	13.0%

The BAU scenario would nearly double the population at risk of flooding by 2030, while the Conservation scenario could reduce this population by 20% compared to current conditions (**Tab. 9**).

4.2.9. Spatial Patterns of Future Flood Risk

The spatial analysis of future flood risk revealed distinct patterns under different scenarios:

a) BAU Scenario

The projected land use changes signal alarming trends regarding flood vulnerability, beginning with significant urban expansion into floodplains. The model predicts that development will increasingly encroach upon flood-prone zones along the Saddang River and its tributaries, placing more infrastructure directly in hazard zones. This growth leads to a substantial increase in impervious surfaces, where the replacement of natural soil with concrete and asphalt amplifies surface runoff and severely reduces the ground's infiltration capacity. These local changes are exacerbated by upstream watershed degradation, as continued deforestation in the upper catchments diminishes water retention capabilities, resulting in higher and more rapid peak flows downstream. Consequently, new risk hotspots are expected to emerge, shifting the geography of hazard to include expanding urban centers and agricultural valleys that were previously less vulnerable.

b) Conservation Scenario

This conservation-oriented approach yields significant hydrological benefits, primarily driven by Riparian Protection and Watershed Restoration. The active recovery of forests along river corridors plays a critical role in increasing water retention capacity and attenuating flood peaks, while targeted reforestation in the upper watersheds further enhances overall hydrological regulation. Complementing these ecological measures, Limited Urban Expansion ensures that new development is strategically concentrated in safer areas, effectively minimizing exposure to flood hazards. Consequently, these combined efforts lead to substantial Risk Reduction, where many areas currently classified as high-risk exhibit reduced vulnerability due to the improved stability and absorption capacity of the restored land cover.

c) Sustainable Development Scenario

Under this scenario, a strategic development framework is adopted where urban growth is deliberately directed toward areas with lower flood risk through rigorous spatial planning to minimize vulnerability. Complementing this urban strategy is the integration of green infrastructure, where the inclusion of green spaces and permeable surfaces within settlement areas plays a critical role in effectively reducing surface runoff. In the agricultural sector, optimization is achieved by focusing intensification efforts solely on suitable lands, supported by strict soil conservation measures to maintain ecological integrity. Consequently, this balanced approach offers a viable compromise; while it results in a moderate increase in risk due to necessary development, it yields significantly lower exposure levels compared to the Business As Usual (BAU) scenario, highlighting the effectiveness of managed interventions.

5. DISCUSSION

5.1. Model Performance and Limitations

The integrated ANN-CA model demonstrated strong performance in predicting land use changes and assessing flood risk in Enrekang Regency. The overall accuracy of 87.3% and Kappa coefficient of 0.82 indicate that the model can reliably simulate land use dynamics. However, several limitations should be acknowledged:

5.1.1. Model Strengths

The proposed ANN-CA framework offers several key advantages that elevate its utility from a purely predictive tool to a strategic instrument for land-use and risk management. The model's primary strength lies in its robust integration capability, successfully synthesizing heterogeneous spatial, socio-economic, and historical data into a unified platform. This multidimensional approach delivers high spatial explicitness, providing granular information on predicted Land Use Change (LUC) and associated flood risks. Critically, this framework provides significant scenario flexibility, allowing stakeholders to rigorously test the potential implications of various policy interventions (e.g., zoning restrictions, infrastructure development) on the landscape before implementation.

A particularly significant contribution of the ANN component is its capacity to discern quantitative change determinants. Preliminary analysis indicates that Distance to Settlement Centers, Slope, and Distance to Rivers are the primary spatial drivers of built-up expansion in the study area. This finding directly highlights the critical role of accessibility and local topography as key policy levers. To further quantify this insight, future work will integrate SHAP (SHapley Additive exPlanations) values to precisely measure the contribution of each determinant, ensuring a deeper and more transparent understanding of the forces driving LUC in the district.

5.1.2. Model Limitations

Despite the robust performance of the predictive model, several limitations must be acknowledged to properly contextualize the findings. First, the study was subject to data constraints stemming from the limited availability of consistent high-resolution data, particularly for earlier historical periods and within remote, inaccessible areas, which may influence the precision of historical baselines. Second, scale issues related to the selected 30m resolution mean that while the model captures regional trends effectively, it may not fully capture fine-scale processes or subtle local variations, such as small, fragmented patches of land cover. Third, the modeling framework necessitates a simplification of complexity; while it accounts for major drivers, it inevitably simplifies the intricate and dynamic socio-economic processes and human decision-making that influence land use changes. Finally, there is inherent uncertainty in future conditions, as the model relies on the assumption that historical driving factors and relationships will continue linearly, a premise that may not hold true in the face of rapidly changing economic conditions or unanticipated policy shifts.

Although the integrated ANN model demonstrated strong predictive accuracy, we acknowledge the inherent interpretation challenges inherent in the 'black-box' nature of this model. Currently, our analysis validates the overall model accuracy, but lacks the ability to quantitatively explain which specific driving factors (e.g., slope, distance from river, soil type) most significantly influence LUC prediction at the cellular level. Currently, our analysis validates the overall model accuracy, but lacks the ability to quantitatively explain which specific driving factors (e.g., slope, distance from river, soil type) most significantly influence LUC prediction at the cellular level.

5.1.3. Comparison with Previous Studies

The model's performance is comparable to or better than similar studies in other regions (Iskandar and Ridzuan, 2022; Nabila, 2023; Xu et al., 2021). The integration of flood risk assessment with land use change modeling represents an advancement over previous studies that typically focus on one aspect or the other (Gabriels et al., 2022; Kalantari and Sörensen, 2020; Kelley and Prabowo, 2019; Merten et al., 2020; Sugianto et al., 2022). Although the simple Logistic Regression (Logit) model can establish basic relationships for susceptibility, the ANN-CA model demonstrated superior performance (Higher Kappa and FoM) by effectively capturing non-linear and complex spatial relationships in comparison to common benchmarks such as Random Forest (RF) and simpler Markov Chain-Cellular Automata (Markov-CA) approaches, especially in predicting the fragmented and clustered patterns of built-up expansion. This added value justifies the complexity of the integrated model.

5.2. Implications for Flood Risk Management

The results have significant implications for flood risk management in Enrekang Regency and similar mountainous regions:

5.2.1. Proactive vs. Reactive Approaches

The current reactive approach to flood management in Enrekang Regency is inefficient and unsustainable. The model results demonstrate the potential benefits of shifting to a proactive approach based on predictive land use planning and risk-informed development decisions.

5.2.2. Land Use Planning Integration

The model outputs offer highly valuable inputs for revising the Regency's Spatial Plan (RTRW), primarily through facilitating Risk-Informed Zoning. This involves identifying specific areas suitable for different types of development based on the projected level of flood risk. Specifically, drawing upon the insights from the Sustainable Development Scenario, the local government is advised to implement stringent zoning restrictions to halt built-up expansion in the high-risk floodplains projected for 2030. Concurrently, efforts should prioritize riparian buffer restoration in the lower Saddang sub-basin, the area identified as suffering the most severe forest loss. Furthermore, the model provides essential guidance for Strategic Infrastructure Planning, enabling targeted investments that are optimized to minimize future flood risk and significantly enhance overall regional resilience.

5.2.3. Watershed Management

The study's results collectively underscore the critical importance of adopting a holistic and integrated watershed management approach. Specifically, maintaining forest cover in the Upper Watershed is crucial, as this vegetation plays a fundamental role in regulating hydrological processes, thereby mitigating the intensity of downstream water flow. Concurrently, effective management requires the protection and restoration of Riparian Corridors (vegetation buffers along rivers), which naturally reduce flood peaks and minimize stream bank erosion. Furthermore, implementing comprehensive Soil Conservation measures within agricultural areas is essential, as these practices significantly reduce surface runoff and decrease the sedimentation load entering the river systems, contributing to overall watershed health and flood protection.

5.3. Policy Implications

The scenario analysis provides valuable insights for policy development:

5.3.1. Business-as-Usual Trajectory

Under the Business-as-Usual Trajectory, assuming a continuation of current policies and prevailing trends, the region faces a precarious future. This path would lead to a significant increase in flood risk, projected to affect approximately 18% of the total population by 2030. Beyond immediate human safety, this trajectory implies accelerated environmental degradation and the substantial loss of vital ecosystem services as natural buffers are depleted. Consequently, the region would be forced to bear higher economic costs associated with flood damage repair and emergency response operations. Ultimately, this scenario results in the increased vulnerability of both local communities and critical infrastructure to future climate-related hazards.

5.3.2. Conservation Approach

Conversely, a Conservation-Focused Approach prioritizes ecological integrity as a primary defense mechanism. By strictly limiting expansion, this strategy would significantly reduce flood risk and provide robust protection for vulnerable populations. It would actively serve to maintain and enhance ecosystem services, ensuring the longevity of natural water regulation functions. However, implementing this approach is not without difficulty; it would require significant, and perhaps disruptive, changes in existing land use practices and development patterns. As a result, this scenario would likely face substantial challenges in balancing these strict conservation mandates with the pressing socio-economic development needs of the area.

5.3.3. Sustainable Development Pathway

Finally, the Sustainable Development Pathway offers a balanced approach that bridges the gap between aggressive growth and strict preservation. This scenario allows for necessary economic development and urbanization to proceed, but does so strategically to minimize any increase in flood risk. It focuses on protecting critical ecosystems and preserving essential watershed functions while still accommodating growth. Success in this pathway requires integrated spatial planning and strong cross-sectoral coordination to manage trade-offs effectively. Because it addresses both economic aspirations and safety concerns, this scenario represents the most politically feasible and socially acceptable pathway for the region's future.

5.4. Trade-Off Analysis between Development Scenarios

The Economic Development scenario offers the greatest potential for infrastructure development (>25% Increase in Built-up Land), but this comes at an unsustainable environmental cost, characterized by a 35% loss of Primary Forest and a 28% increase in flood risk.

In contrast, the Conservation scenario, while limiting built-up land expansion, dramatically mitigates environmental risks, maintaining ecosystem integrity, and minimizing increases in flood risk. Policy decisions in Enrekang Regency must explicitly consider these quantitative trade-offs to achieve sustainable development (**Tab. 10**).

Table 10.
Population at risk of flooding under different scenarios.

Scenario	**Increase in Built-up Land (2030)**	**Loss of Primary Forest (2030)**	**Peningkatan Risiko Banjir (Berdasarkan Area Runoff Tinggi)**
BAU Scenario	+ 12.5%	- 18.0%	+ 15%
Conservation Scenario	+ 25/0%	- 35.0%	+ 28%
Sustainable Dev.	+ 5.0%	- 8.0%	+ 4%

5.5. Implementation Challenges

Several challenges must be addressed to implement the model recommendations:

5.4.1 Institutional Challenges

The effective implementation of land use policies faces significant institutional hurdles. A primary concern is the lack of coordination arising from fragmented responsibilities across various agencies and levels of government, which often leads to disjointed management efforts and bureaucratic silos. Furthermore, local governments frequently struggle with capacity limitations, specifically regarding the technical expertise required to operate and interpret advanced geospatial analysis and modeling tools. These challenges are compounded by policy inconsistencies, where conflicting priorities across different sectors, such as aggressive economic development versus environmental conservation, create regulatory ambiguity and hinder unified decision-making.

5.4.2 Socio-Economic Challenges

Beyond institutional barriers, socio-economic dynamics present complex challenges to sustainable land management. Strong development pressures exert a constant influence, driven by powerful economic incentives that favor rapid land conversion and urbanization over preservation. This situation is often entangled with livelihood dependencies, where many local communities rely on land use practices, such as farming in riparian zones. That, while economically necessary for their survival, may inadvertently contribute to increased flood risks. Consequently, equity considerations become paramount; any proposed flood risk management measures must be carefully designed to ensure they do not disproportionately affect vulnerable groups or exacerbate existing social inequalities.

5.4.3 Technical Challenges

Finally, the long-term viability of the modeling framework depends on overcoming several technical challenges. Data availability remains a critical issue, as the model requires a continuous stream of up-to-date and accurate spatial data to ensure the predictions remain relevant and precise. Additionally, the system demands ongoing model maintenance, necessitating regular updates and recalibration to reflect changing environmental conditions and land use trends. A significant practical hurdle also lies in the integration with existing systems, as incorporating these sophisticated model outputs into established planning and decision-making workflows requires seamless technical interoperability and user adaptation.

5.6. Future Research Directions

This research opens several avenues for future investigation:

5.5.1. Model Enhancements

The current modeling framework offers several opportunities for future development, beginning with Higher Resolution capabilities. This involves developing and implementing models at a finer spatial resolution, which is crucial for providing more accurate and detailed output necessary for effective local and neighborhood-level planning. Furthermore, model realism can be significantly improved through the Dynamic Parameters integration, moving beyond static inputs to incorporate variables that change over time, such as evolving population growth rates or fluctuating economic conditions. Crucially, future enhancements should focus on Climate Change Integration, explicitly considering projected changes in rainfall intensity, sea-level rise, and other climatic factors to produce robust and future-proof flood risk and land use scenarios.

For future research, increasing transparency and trust in modeling results is crucial. We recommend exploring and implementing explainable AI (XAI) techniques, such as SHapley Additive Explanations (SHAP) or Local Interpretable Model-agnostic Explanations (LIME). These methods allow for quantitative decomposition of ANN prediction outputs, revealing the relative contribution of each input variable to the probability of change. This improved interpretability will strengthen scientific justification and provide more transparent guidance to decision-makers.

5.5.2. Expanded Applications

The methodological approach can be expanded beyond its current focus to address broader environmental and planning challenges. This includes the Extension to Other Hazards, applying the integrated land use and modeling framework to assess risks from related threats such as landslides and droughts, offering a multi-hazard planning platform. Additionally, there is a strong potential for Ecosystem Services Integration by linking land use change scenarios with quantitative assessments of ecosystem services (e.g., water purification, carbon sequestration). This integration will help prioritize conservation areas based on their functional value. Finally, the framework should aim for practical utility in Urban Design, applying the high-resolution outputs at a local scale to guide the strategic planning and placement of green infrastructure elements within urban areas.

5.5.3. Implementation Research

To ensure the scientific findings translate into tangible real-world impact, future research must focus on the implementation context. This necessitates dedicated investigation into the Policy Process, analyzing how complex scientific and spatial information can be effectively synthesized, communicated, and successfully incorporated into existing statutory planning cycles and decision-making platforms. Concurrently, rigorous investigation of effective Governance Mechanisms is needed to identify robust, multi-stakeholder structures essential for truly integrated and cross-sectoral flood risk management. Ultimately, successful implementation relies on Community Engagement, requiring the development of practical and meaningful approaches to involve local communities directly in the assessment, planning, and management processes for flood risk.

6. CONCLUSIONS

This study successfully developed and validated an integrated ANN-CA model for land use change prediction and flood risk assessment in Enrekang Regency, Indonesia. Between 2010 and 2020, the area saw an 11.2% decline in forest cover and a 27.8% rise in urban land use. The model achieved high accuracy (87.3% overall, Kappa = 0.82), proving reliable for spatiotemporal simulations.

Future scenarios for 2030 reveal critical differences: a business-as-usual path leads to further deforestation and higher flood risk, while Conservation and Sustainable Development scenarios could reduce flood-affected populations by up to 8%. This highlights the power of proactive land-use planning. The research contributes theoretically to land use modeling, flood risk assessment, and sustainable development, especially in mountainous regions. Practically, it offers a decision-support tool for planners, policymakers, and communities, enabling evidence-based, risk-informed spatial planning.

Key recommendations include revising regional spatial plans with risk-based zoning, strengthening forest conservation in upstream areas, improving inter-agency coordination, and engaging local communities through participatory planning and education. In short, this study demonstrates how advanced geospatial modeling can transform flood risk management from reactive to proactive driving resilience, sustainability, and informed governance in vulnerable regions like Enrekang. The future of disaster risk reduction lies in integrating science, policy, and people.

REFERENCES

Asif, M., Kazmi, J.H., Tariq, A., Zhao, N., Guluzade, R., Soufan, W., Almutairi, K.F., Sabagh, A. El, Aslam, M., 2023. Modelling of land use and land cover changes and prediction using CA-Markov and Random Forest. Geocarto Int 38, 2210532. https://doi.org/10.1080/10106049.2023.2210532

Baig, M.F., Mustafa, M.R.U., Baig, I., Takaijudin, H.B., Zeshan, M.T., 2022. Assessment of Land Use Land Cover Changes and Future Predictions Using CA-ANN Simulation for Selangor, Malaysia. Water (Basel) 14. https://doi.org/10.3390/w14030402

BPS Enrekang, 2025. Enrekang Regency in Figures 2025. Enrekang.

BPS Enrekang, 2021. Enrekang Regency in Figure 2020. Enrekang.

BPS Enrekang, 2016. Population in Enrekang Regency 2015. Enrekang.

BPS Enrekang, 2011. Enrekang Regency in Figures 2010. Enrekang.

Farhan, M., Wu, T., Anwar, S., Yang, J., Naqvi, S.A.A., Soufan, W., Tariq, A., 2024. Predicting Land Use Land Cover Dynamics and Land Surface Temperature Changes Using CA-Markov-Chain Models in Islamabad, Pakistan (1992-2042). IEEE J Sel Top Appl Earth Obs Remote Sens 17, 16255–16271. https://doi.org/10.1109/JSTARS.2024.3441241

Gabriels, K., Willems, P., Van Orshoven, J., 2022. A comparative flood damage and risk impact assessment of land use changes. Natural Hazards and Earth System Sciences 22, 395–410. https://doi.org/10.5194/nhess-22-395-2022

Iskandar, B.S., Ridzuan, P.D., 2022. Prediction of Land Use Changes and Flood Risk Maps Using GIS and ANN Modelling in Perak. Universiti Teknologi PETRONAS.

Jr, R.G.P., Millones, M., 2011. Death to Kappa: birth of quantity disagreement and allocation disagreement for accuracy assessment. Int J Remote Sens 32, 4407–4429. https://doi.org/10.1080/01431161.2011.552923

Kalantari, Z., Sörensen, J., 2020. Link between Land Use and Flood Risk Assessment in Urban Areas 62. https://doi.org/10.3390/proceedings2019030062

Kelley, L.C., Prabowo, A., 2019. Flooding and Land Use Change in Southeast Sulawesi , Indonesia. Land (Basel) 8, 1–19. https://doi.org/https://doi.org/10.3390/land8090139

Khan, D., Khan, N., 2025. Modelling urban future: integrating CA-ANN model for comprehensive understanding of land use, land cover changes, and temperature dynamics in Lucknow City, India. Geology, Ecology, and Landscapes 0, 1–26. https://doi.org/10.1080/24749508.2025.2524207

Lei, T., Zhang, S., Lin, S., Liu, T., Lv, Z., Gao, T., Gong, M., Nandi, A.K., 2025. Remote Sensing Image Change Detection Using Deep Learning Techniques: A Comprehensive Survey. https://doi.org/10.21203/rs.3.rs-7587199/v1

Merten, J., Stiegler, C., Hennings, N., Purnama, E.S., Röll, A., Agusta, H., Dippold, M.A., Fehrmann, L., Gunawan, D., Hölscher, D., Knohl, A., Kückes, J., Otten, F., Zemp, D.C., Faust, H., 2020.

Flooding and land use change in Jambi Province, Sumatra: Integrating local knowledge and scientific inquiry. Ecology and Society 25, 1–29. https://doi.org/10.5751/ES-11678-250314

Mutale, B., Withanage, N.C., Mishra, P.K., Shen, J., Abdelrahman, K., Fnais, M.S., 2024. A performance evaluation of random forest, artificial neural network, and support vector machine learning algorithms to predict spatio-temporal land use-land cover dynamics: a case from lusaka and colombo. Front Environ Sci Volume 12-2024. https://doi.org/10.3389/fenvs.2024.1431645

Nabila, D.A., 2023. Pemodelan prediksi dan kesesuaian perubahan penggunaan lahan menggunakan Cellular Automata-Artificial Neural Network (CA-ANN). Tunas Agraria 6, 41–55. https://doi.org/10.31292/jta.v6i1.203

Nugraheni, I.L., Suyatna, A., Setiawan, A., Abdurrahman, 2022. Flood disaster mitigation modeling through participation community based on the land conversion and disaster resilience. Heliyon 8, e09889. https://doi.org/10.1016/j.heliyon.2022.e09889

Ouma, Y.O., Nkwae, B., Odirile, P., Moalafhi, D.B., Anderson, G., Parida, B., Qi, J., 2024. Land-Use Change Prediction in Dam Catchment Using Logistic Regression-CA, ANN-CA and Random Forest Regression and Implications for Sustainable Land–Water Nexus. Sustainability 16. https://doi.org/10.3390/su16041699

Rachmayanti, H., Musa, R., Mallombasi, A., 2022. Studi Pengaruh Perubahan Tata Guna Lahan Terhadap Debit Banjir Dengan Menggunakan Software HEC HMS (Studi Kasus DAS Saddang). Jurnal Konstruksi: Teknik, Infrastruktur, dan Sains 01, 1–9.

Rajeev, Singh, S., 2016. Watershed Management - A GIS Approach. IMPACT: International Journal of Research in Applied, Natural and Social Sciences 4, 109–116.

Razavi, B., 2014. Predicting the Trend of Land Use Changes Using Artificial Neural Network and Markov Chain Model (Case Study: Kermanshah City). Research Journal of Environmental and Earth Sciences 6, 215–226. https://doi.org/10.19026/rjees.6.5763

Singh, R.K., Soni, A., Kumar, S., Pasupuleti, S., Govind, V., 2021. Zonation of flood prone areas by an integrated framework of a hydrodynamic model and ANN. Water Sci Technol Water Supply 21, 80–97. https://doi.org/10.2166/ws.2020.252

Sudiana, D., Riyanto, I., Rizkinia, M., Arief, R., Prabuwono, A.S., Sumantyo, J.T.S., Wikantika, K., 2025. Performance Evaluation of 3-D Convolutional Neural Network for Multitemporal Flood Classification Framework With Synthetic Aperture Radar Image Data. IEEE J Sel Top Appl Earth Obs Remote Sens 18, 3198–3207. https://doi.org/10.1109/JSTARS.2024.3519523

Sugianto, S., Deli, A., Miswar, E., Rusdi, M., Irham, M., 2022. The Effect of Land Use and Land Cover Changes on Flood Occurrence in Teunom Watershed, Aceh Jaya. Land (Basel) 11. https://doi.org/10.3390/land11081271

Tharik, M., Arumugam, K., Vijayaraghavalu, S.S., 2025. Spatiotemporal assessment and simulation of land use and land cover dynamics in coastal Tamil Nadu using CA–ANN modelling for sustainable development planning. Results in Engineering 28, 107771. https://doi.org/https://doi.org/10.1016/j.rineng.2025.107771

Uca, Amal, Tabbu, M.A.S., Yusuf, M., Jeddayanti, Sriwahyuni, 2021. Karakteristik Morfometri Sub DAS Saddang dan Mata Allo Provinsi Sulawesi Selatan. Indonesian Journal Of Fundamental Sciences 7, 52–66. https://doi.org/https://doi.org/10.26858/ijfs.v7i2.26151

Uca, Maru, R., Nyompa, S., Arfan, A., Malik, A., Abidin, M.R., 2018. Mapping and zonation level of landslides hazard and risk assessment: A case study of enrekang regency, South Sulawesi, Indonesia. EnvironmentAsia 11, 149–163. https://doi.org/10.14456/ea.2018.30

Uca, Upu, H., Haris, N.A., Rahmayana, D., 2023. 2D SIMULATION OF DESIGN DISCHARGE IN FLOOD HAZARD SPATIAL ANALYSIS USING HEC-RAS, (CASE STUDY MATA ALLO SUB-WATERSHED, ENREKANG, INDONESIA). Geographia Technica 18, 1–13. https://doi.org/10.21163/GT

Varma, B., Naik, N., Chandrasekaran, K., Venkatesan, M., Rajan, J., 2024. Forecasting Land-Use and Land-Cover Change Using Hybrid CNN–LSTM Model. IEEE Geoscience and Remote Sensing Letters 21, 1–5. https://doi.org/10.1109/LGRS.2024.3389671

Wang, Q., Guan, Q., Lin, J., Luo, H., Tan, Z., Ma, Y., 2021. Simulating land use/land cover change in an arid region with the coupling models. Ecol Indic 122, 107231. https://doi.org/https://doi.org/10.1016/j.ecolind.2020.107231

Xu, Q., Wang, Q., Liu, J., Liang, H., 2021. Simulation of land-use changes using the partitioned ann-ca model and considering the influence of land-use change frequency. ISPRS Int J Geoinf 10. https://doi.org/10.3390/ijgi10050346

Xu, Q., Zhu, A.-X., Liu, J., 2023. Land-use change modeling with cellular automata using land natural evolution unit. Catena (Amst) 224, 106998. https://doi.org/https://doi.org/10.1016/j.catena.2023.106998

Yang, P., Xu, X., Shao, M., Liu, Y., 2025. Intelligent Prediction of Flood Disaster Risk Levels Based on Knowledge Graph and Graph Neural Networks 13, 8416–8424. https://doi.org/10.1109/ACCESS.2025.3525757

Zhang, J., Hou, Y., Dong, Y., Wang, C., Chen, W., 2022. Land Use Change Simulation in Rapid Urbanizing Regions: A Case Study of Wuhan Urban Areas. Int J Environ Res Public Health 19, 8785. https://doi.org/10.3390/ijerph19148785