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Research Article

Using Neural Networks for Sustainable Land Use Prediction in Sumbawa Regency, Indonesia

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Abstract

Agriculture is vital to Sumbawa Regency's economy, with key activities such as rice cultivation, corn production, onion farming, and cattle rearing. This study applies artificial neural networks (ANN) to predict land cover changes, focusing on agricultural land expansion. Using land cover datasets from ESRI, digital elevation model, and topographical maps, we analyzed land cover changes from 2017 to 2023 and generated future projections for 2050 with the MOLUSCE plugin in qGIS. The predictive model achieved an 85% accuracy rate when comparing 2023 actual data with predictions. Results indicate a significant increase in agricultural land cover by 2050. The key finding is that over a long-term period, the simulation of land use and land cover (LULC) change in Sumbawa reveals an increase of crop areas in the Lunyuk and Labangka Districts. This study highlights the effectiveness of ANN in land cover prediction and emphasizes the need for sustainable practices to balance agricultural expansion. AI-driven insights can aid policymakers in optimizing resource allocation and ensuring long-term environmental and economic stability in Sumbawa Regency. Future research should refine models and incorporate additional factors for improved accuracy.

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Introduction

Agriculture constitutes a fundamental economic activity in Sumbawa Regency, significantly supported by rice cultivation, corn production, onion farming, and cattle rearing, all of which benefit from the region's favorable tropical climate and diverse geographical features. The application of artificial intelligence (AI) technologies has the potential to optimize both irrigated and dryland agricultural practices, enabling more efficient adaptation to seasonal variations and thereby enhancing crop yields. Scholarly research underscores the pivotal role of AI in advancing sustainable farming practices and the adoption of precision agriculture technologies, which collectively bolster productivity and resilience against climatic fluctuations [1]. The integration of AI-driven solutions is essential for ensuring long-term food security and economic stability in Sumbawa Regency.

Agriculture necessitates land as a critical component for its production processes, providing the essential space and natural resources required for cultivating crops and raising livestock. The availability and quality of arable land directly influence agricultural productivity, determining the types of crops that can be grown and the methods of cultivation that can be employed. Furthermore, land management practices, including soil conservation, irrigation, and crop rotation, play a vital role in sustaining

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agricultural output and mitigating the impacts of environmental challenges. Effective land use planning and sustainable agricultural practices are imperative to optimize land resources and ensure long-term food security and environmental health [2].

Monitoring and controlling land cover change is crucial due to the limited available area in the regency. Land cover change, including deforestation, urbanization, and agricultural expansion, can significantly impact local ecosystems, biodiversity, and agricultural productivity. Effective land use management is essential to balance development needs with environmental conservation, ensuring sustainable use of the finite land resources. Advanced geospatial technologies, such as remote sensing and GIS, play a vital role in tracking land cover changes and informing policy decisions aimed at sustainable land management [3–4].

Predicting land use and land cover (LULC) is essential for sustainable development planning because it provides a detailed understanding of how land is utilized and how it changes over time. Before the advent of neural networks and artificial intelligence, several widely-used methods for predicting land use change were employed, such as Markov model [5]. These methods generally involved statistical, econometric, and spatial modeling approaches. This paper aims to investigate the application of artificial neural networks in predicting land cover changes within Sumbawa Regency. It will particularly focus on scenarios projecting an increase in agricultural land cover in the future. The resulting predictions are intended to provide objective guidance for local government authorities regarding the allocation of suitable areas for agricultural expansion. By utilizing these predictive insights, policy-makers can make informed decisions to optimize resource allocation and promote sustainable agricultural development in the region.

Materials and methods

1) Area description

Sumbawa Regency (Figure 1), is one of the ten administrative regions in West Nusa Tenggara Province, is located at the western tip of Sumbawa Island, Indonesia [6]. Following the division of Sumbawa Regency into two separate regions in 2003, Sumbawa Regency itself comprises 24 sub-districts. Geographically, it is bordered by West Sumbawa Regency to the west, Dompu Regency to the east, the Flores Sea to the north, and the Indian Ocean to the south. Notably, Sumbawa Regency stands out in Indonesia for including Saleh Bay, an enclosed ecosystem within its territory.

This unique geographical positioning of Sumbawa Regency, encompassing diverse ecosystems and bordering significant marine environments, underlines its ecological and economic importance. Saleh Bay, in particular, offers a unique enclosed marine ecosystem that supports various aquatic species and contributes to the local economy through fishing and tourism. The distinct sub-districts within the regency display varied land use and cover dynamics, reflecting broader trends in agricultural expansion, urbanization, and environmental conservation.

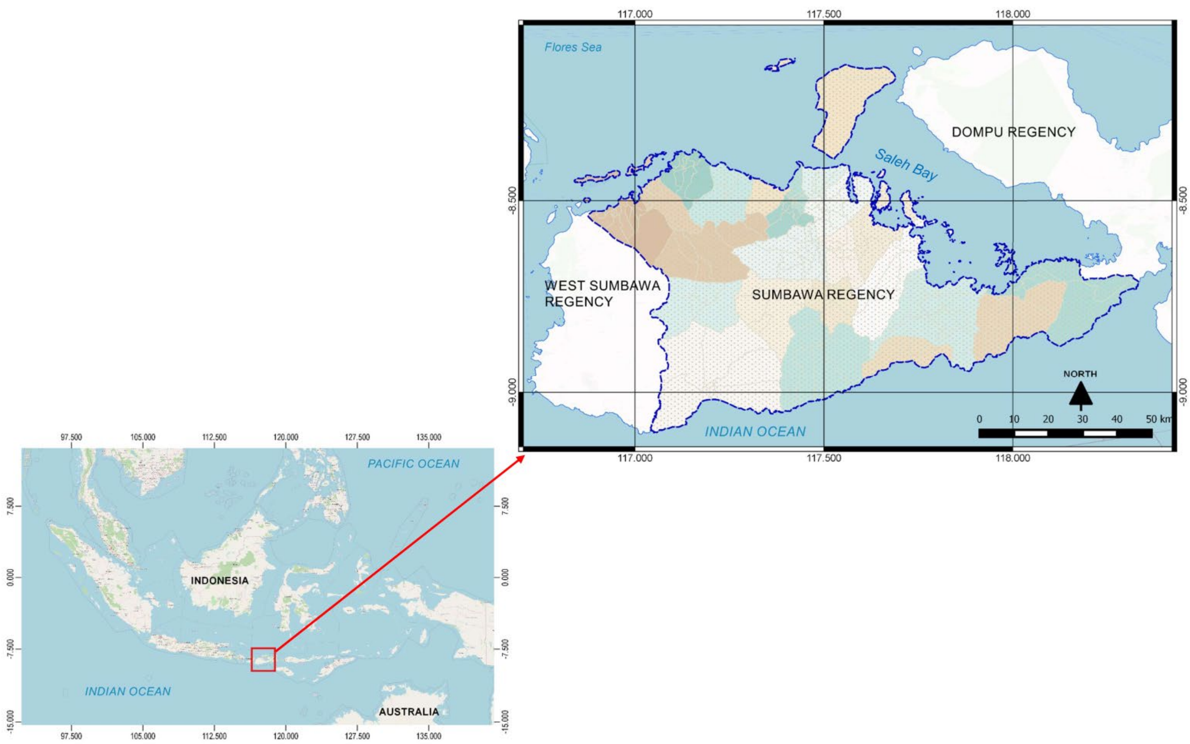

Figure 1 Sumbawa Regency map.

Sumbawa Regency experiences a tropical climate characterized by distinct rainy and dry seasons. In 2023, the maximum temperature peaked at 38°C in September, while the minimum temperature dropped to 19.8°C, also in September. The average humidity in 2023 reached its highest point at 95 percent in February. Throughout the year, there were a total of 102 recorded rainy days. The highest rainfall of 263.3 mm was observed in January [5].

According to data from BPS-Statistics Sumbawa Regency, in September 2022, the population of Sumbawa was reported as 527,607 thousand people, with a slightly higher number of males than females. The population density of Sumbawa Regency in the same year was recorded at 79 people per square kilometer. Among the 24 sub-districts within the regency, there was significant variation in population density. Notably, Sumbawa Sub-district had the highest density at 1499 people per square kilometer, while Orong Telu Sub-district had the lowest at 12 people per square kilometer. The population growth from 2011 to 2023 can be seen in Figure 2a.

In 2023, Sumbawa saw a notable increase in onion production across all its 24 subdistricts (Figure 2b), with a collective rise of 325,951 tons compared to the previous year. Livestock numbers also witnessed significant figures, notably native chickens, Bali cattle, and broiler chickens, with respective totals of 808,215, 562,013, and 288,300. Fisheries production in 2023 amounted to 688,033 tons, marking a substantial uptick from the preceding year. The rich potential of Sumbawa's fishery resources is evident, spanning marine fisheries, public waters, freshwater, brackish water aquatic resources, and marine aquaculture, indicating diverse opportunities and sectors for development and sustainability initiatives.

2) Data and materials

To analyze land use and land cover change using MOLUSCE plug-in qGIS version 2.8, the first step was to ensure that all relevant data layers were imported (Table 1). This included the ESRI LULC dataset, providing detailed land use and land cover information in Sumbawa Regency for year 2017–2023 (Figure 3), digital elevation model at National Level (DEMNAS) dataset sourced from the Indonesian Geospatial Information Agency (BIG) for elevation data (Figure 4a), the road network layer obtained from the Topographical Map of Indonesia (RBI Map) (Figure 4b), and the administrative boundaries layer, also from the RBI Map, delineating the study area's administrative divisions. The ESRI LULC dataset is derived from ESA Sentinel-2 satellite imagery with 10-meter spatial resolution and produced from 6 spectral bands. The annual maps from this dataset in the range of 5 years from 2017–2023 which has 8 classes of LULC classification were used as one of the inputs, classes details can be seen in Table 2.

Once all datasets were loaded into qGIS, the MOLUSCE plugin was activated. Within the MOLUSCE interface, the input layers were specified, including the ESRI LULC data (Table 2), DEMNAS, road network, and administrative boundaries layers. Configuration settings and parameters were adjusted as per the analysis requirements. Subsequently, the analysis was initiated, with MOLUSCE processing the input data to generate outputs such as land use/land cover change maps, statistical analyses, and comprehensive reports. These outputs facilitated a detailed assessment of land use dynamics and patterns within the study area, providing valuable insights for land management and planning purposes.

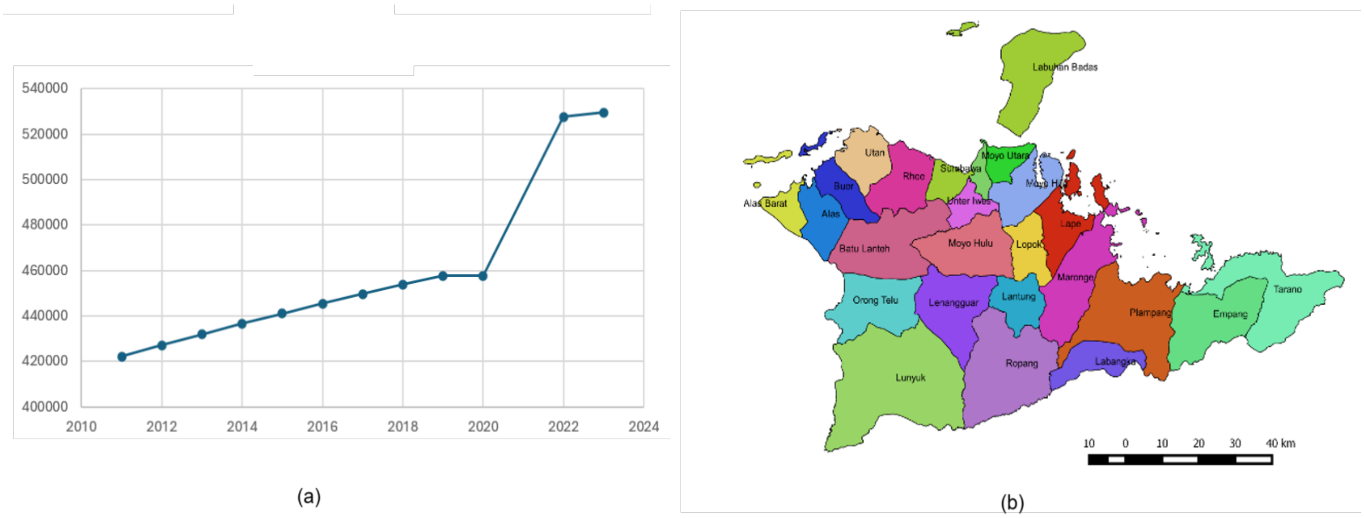

Figure 2 (a) Population growth in Sumbawa Regency and (b) sub-districts in Sumbawa Regency.

Table 1 data that used for this study

Data type	Data source	Resolution/scale	Time
Sumbawa land cover	https://livingatlas.arcgis.com/landcover/, ESRI	10 m	2017– 2023
Digital elevation model	https://tanahair.indonesia.go.id/demnas/, DEMNAS-BIG	5–10 m	2018
Road network	https://tanahair.indonesia.go.id, RBI Map	1:25.000	2017
Administrative boundaries	https://tanahair.indonesia.go.id, RBI Map	1:25.000	2017

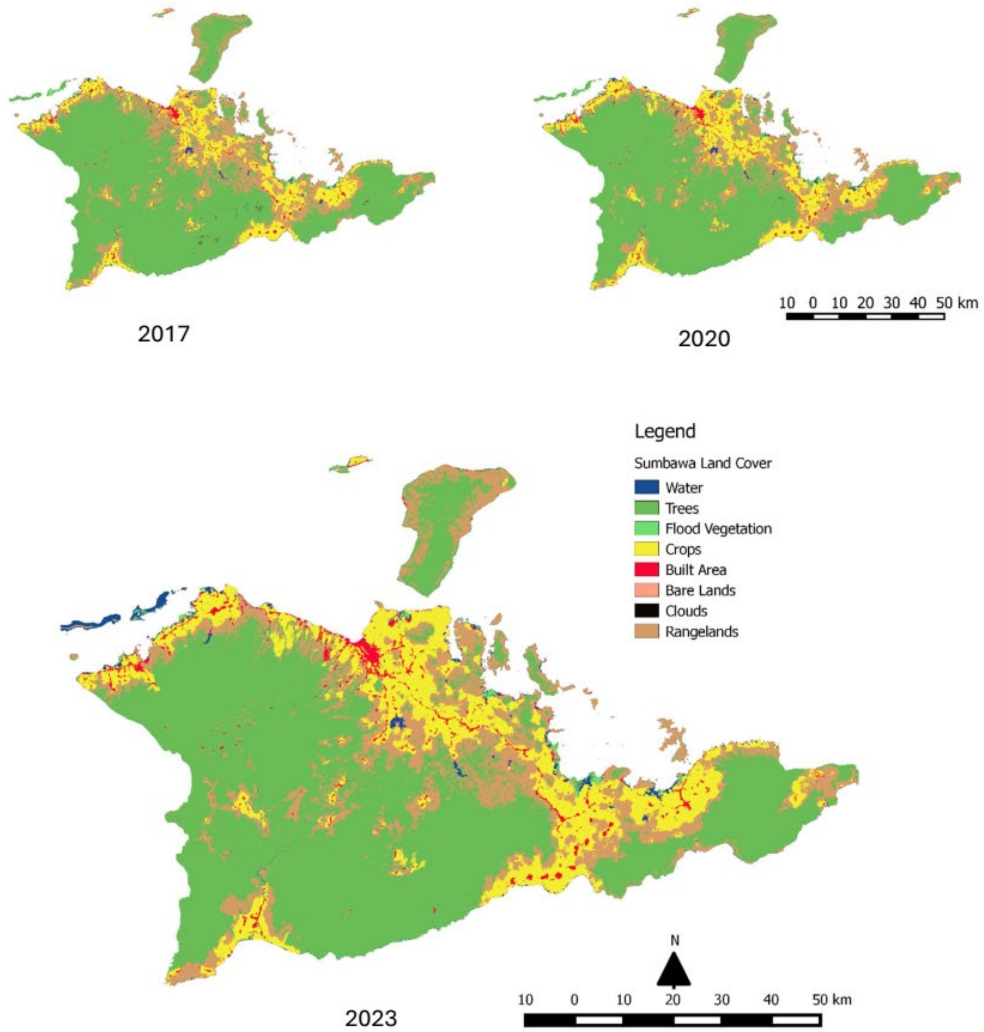

Figure 3 Sumbawa land cover.

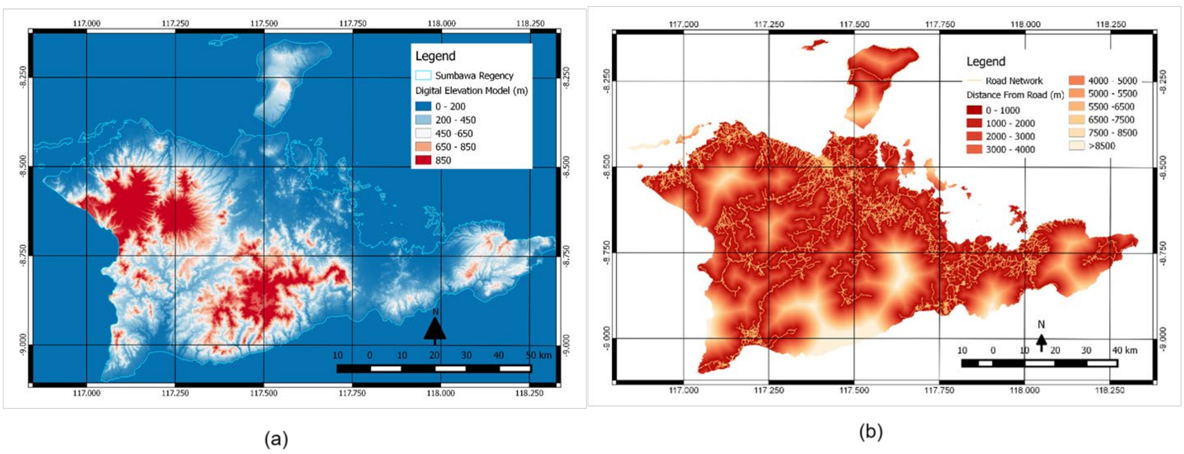

Figure 4 (a) Digital elevation model and (b) proximity map from road network.

Table 2 LULC classification based on ESRI [7]

No.	Class	Description
1	Water	Areas with permanent bodies of water; do not encompass locations with fleeting or ephemeral water presence; scarce vegetation, rocks, or human-constructed structures such as docks are absent; examples include rivers, lakes, oceans, and salt plains that are inundated.
2	Trees	Area with a high concentration of tall and dense vegetation (around 15 m or more). A closely knit canopy typically characterizes these; examples: are forests, areas with densely packed tall plants in savannas, plantations, swamps, and mangroves (locations with abundant vegetation and water that is obscured by the thickness of the canopy).
3	Flood vegetation	Areas where vegetation and water coexist throughout the year. Areas that experience periodic flooding have a combination of grass, shrubs, trees, and bare ground. Examples are mangroves inundated with water, plants growing in water, rice paddies, and other agricultural lands with heavy water management and inundation.
4	Crops	Agricultural lands with crops grown by humans, not reaching the height of trees; examples: corn, wheat, soy, structured land without crops.
5	Built Area	Man-made structures; major roadways and railway networks; large surfaces that don't absorb water, like parking lots, office buildings, and houses; examples: houses, urban areas, paved roads, asphalt.
6	Bare ground	Areas with rocks or soil and minimal to no vegetation yearround; vast regions of sand and deserts with scarce vegetation; examples: exposed rock or soil, deserts, sand dunes, dry salt flats, dried lake beds, mines.
7	Clouds	Areas where persistent cloud cover makes it impossible to determine the land cover.
8	Rangeland	Open areas covered with uniform grass with limited tall vegetation; wild cereals and grasses without human cultivation (not a farmed field); examples: natural meadows and fields with scarce tree cover, open savannas with few trees, parks, golf courses, lawns, pastures.

3) LULC change analysis

To calculate the spatiotemporal change data from the LULC classification maps, the area analysis tool of the Modules for Land-Use Change Simulation (MOLUSCE), a free and most widely used plugin for urban modeling and future scenario simulations through qGIS was used [8–13]. The data was calculated for the study intervals of (2017 to 2020) to generate change maps on which further ANN modelling was done.

4) Artificial neural network modeling and validation measures

The ANN model is a reliable tool that has been used in numerous research studies for future LULC predictions [14-16]. The purpose of the model is to generate a transitional potential map using different computational intelligence aspects. The strategy of the model is to handle enormous amounts of uncertain data. ANN incorporates fuzzy logic, by describing the terrain on a continuous range from 0 to 1. The alteration of the weight connections between geographically linked neurons is an important element of ANN [17]. They are dependent on the computation power offered [18]. Nevertheless, it is highly suitable for urban growth modeling as it can connect well between the complex relationship of huge data fed and extracted.

LULC maps of 2017 and 2020 and the spatial variables were used to predict the map of 2023. MOLUSCE plugin also offers validation of the simulated and actual map to approve the accuracy of the model using % of correctness and Kappa validation coefficients. In the transition potential modeling module of MOLUSCE [19], based on satisfactory results it was concluded that the ANN model for the study data training was better with a neighborhood value of 1×1 pixels, the learning rate of 0.001, maximum iterations set to 100, with 10 hidden layers, and the momentum value of 0.001 [20] as shown in Figure 5. Then in the cellular automata simulation module, using an iteration value of 1, the LULC map of 2023 was simulated. Afterward, in the validation module, the simulated LULC map of 2023 was validated with the reference ESRI-based LULC map of 2023. The performance of the algorithms was also assessed by confusion matrix derivatives such as classification accuracy and Kappa statistics. In addition, the accuracy of the prediction was assessed by root mean square error (RMSE) [20]. After obtaining satisfactory results, as shown in Figure 6, the process was repeated for simulation prediction of the LULC map of 2050 from the LULC maps 2017 along with the thematic layers. The transition map generated by MOLUSCE for this prediction of future LULC can be seen in Figure 7. While the map of Sumbawa land cover prediction for the year 2050 is presented in Figure 8.

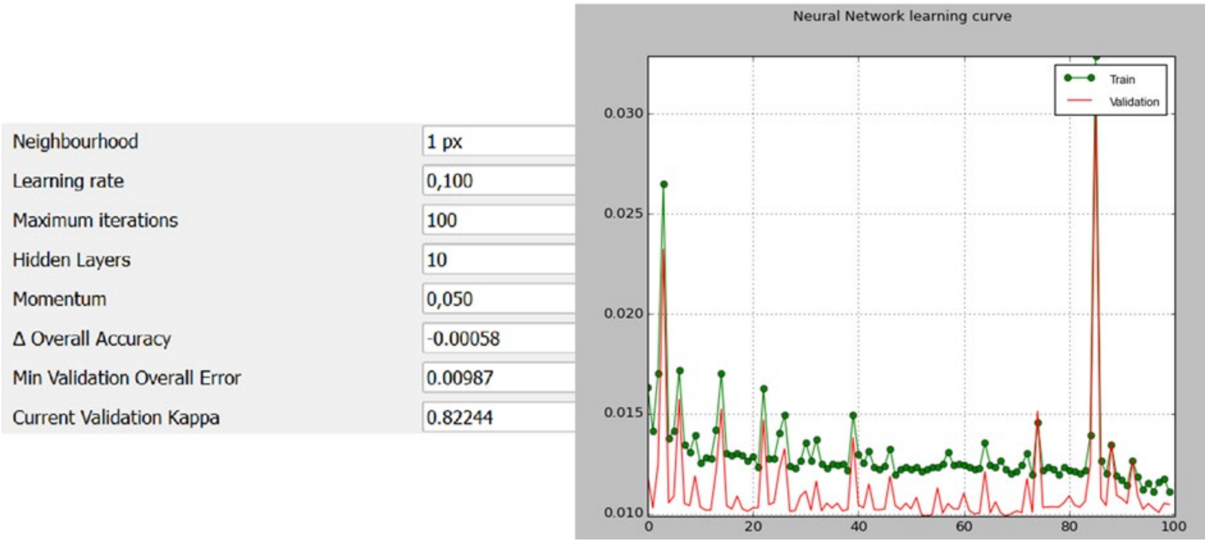

Figure 5 Artificial neural network parameters and process using MOLUSCE plug-in qGIS.

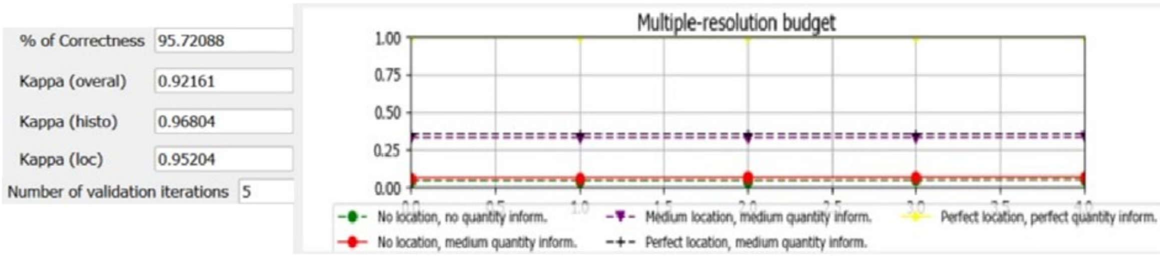

Figure 6 Validation parameters and process using MOLUSCE plug-in qGIS.

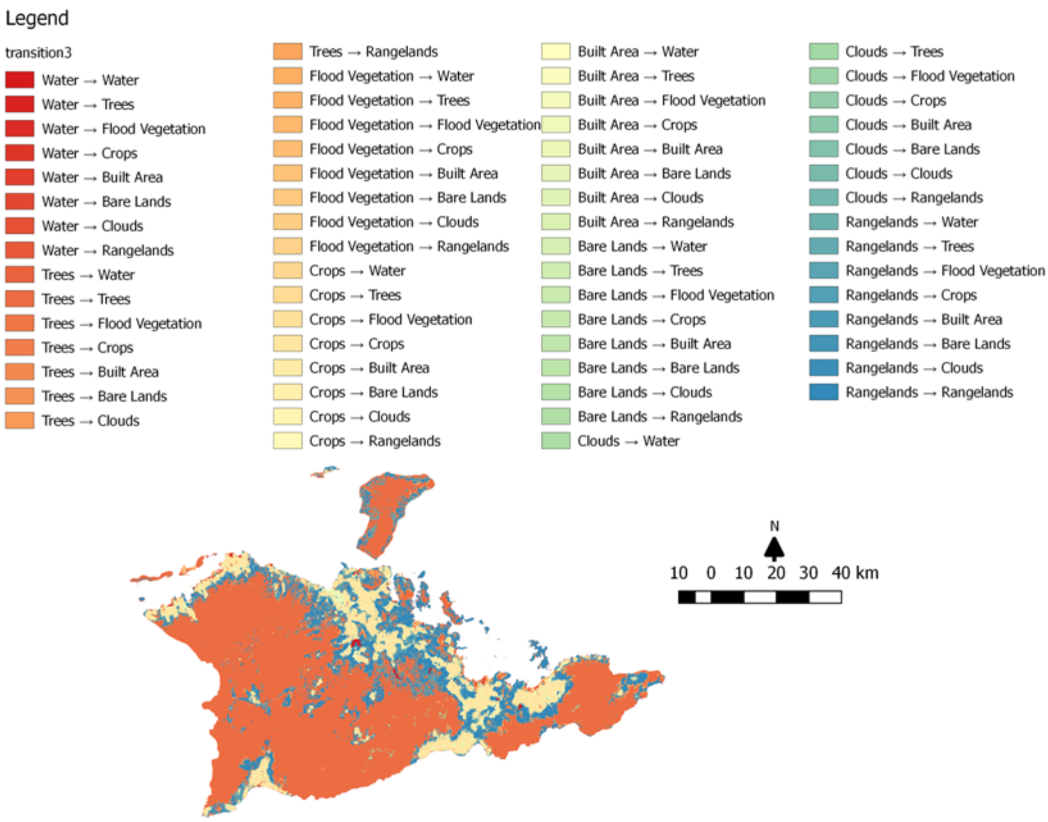

Figure 7 Transition map generated by MOLUSCE for prediction of future LULC.

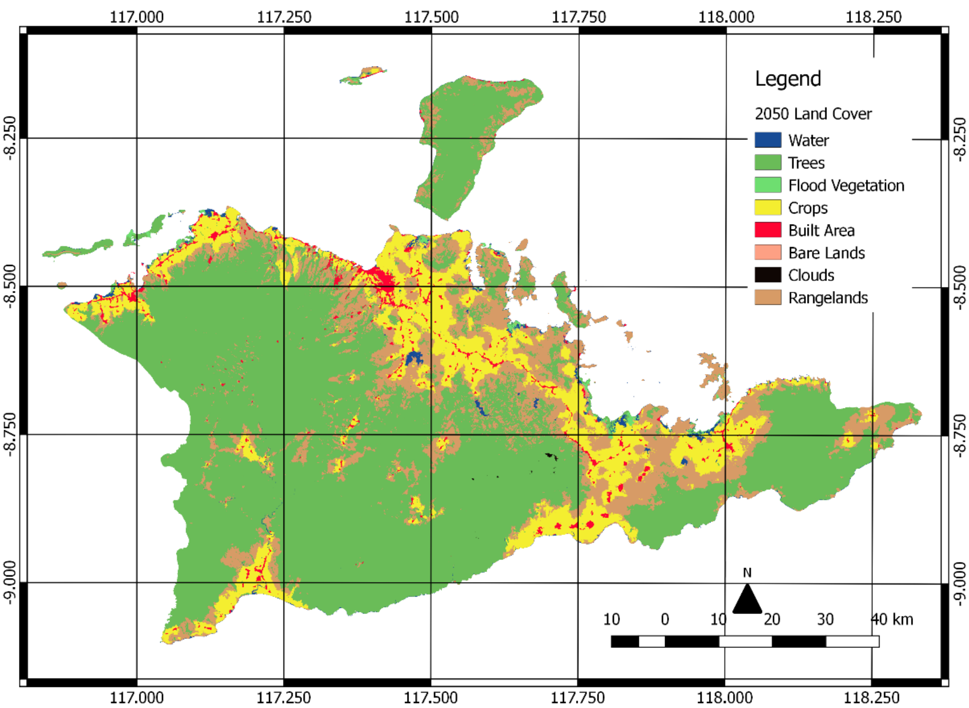

Figure 8 Land cover prediction in year 2050.

Results and discussion

1) Data analysis

The analysis of land use changes between 2017 and 2020 in the given dataset (Table 3) highlights significant transformations in various land cover types. Water bodies increased by 5.88 km^2 (0.09%), while areas covered by trees slightly decreased by 2.40 km^2 (-0.04%). There was a notable reduction in flood vegetation (-3.40 km^2, -0.05%) and bare ground (-4.47 km^2, -0.07%). Conversely, crop areas expanded significantly by 153.00 km^2 (2.30%), indicating a shift towards agricultural development. Built-up areas also grew by 21.73 km^2 (0.33%), reflecting urbanization trends. The rangeland experienced a decline of 161.63 km^2 (-2.43%), highlighting a transition from natural landscapes to other land uses.

These changes align with global trends observed in land use and cover, where urban expansion and agricultural intensification are prominent. Studies like the one by Achu et al. [22] using Landsat data reveal similar patterns of increased cropland and built-up areas globally, often at the expense of natural vegetation and water bodies. Additionally, research on the impacts of land use change on water and carbon budgets, such as that by Sun et al. [23], underscores the environmental implications of these shifts, including changes in water consumption and carbon storage dynamics. These references provide a broader context for understanding the local changes observed in your dataset, emphasizing the interconnected nature of land use change and its environmental impacts.

The provided matrix on Table 4 represents the land cover transition probabilities between different land cover types within a specified area. Each cell in the matrix represents the likelihood of transitioning from one land cover type (row) to another (column) over a given time period. For instance, the value at row "Water" and column "Trees" (0.016762) indicates the probability of transitioning from water to trees. Similarly, the value at row "Crops" and column "Built Area" (0.030102) represents the probability of transitioning from crops to built areas.

These transition probabilities provide valuable insights into the dynamics of land cover change within the study area, informing land management strategies, environmental planning, and conservation efforts. Analyzing the matrix can help identify trends, hotspots of change, and potential areas for intervention or protection. With using this transition matrix, the MOLUSCE qGIS give a prediction of LULC of Sumbawa District in the year of 2023. The prediction land use of 2023 then compare with the ESRI LULC in 2023, the result shown in Figure 5. that the kappa validation number is quite satisfying with number of 0.82244. Then we use the parameters to predict the LULC of Sumbawa District in 2050.

Table 3 Land cover change from 2017- 2020

	2017 (km²)	2020 (km²)	Δ (km²)	2017%	2020%	Δ%
Water	51,97	57,86	5,88	0,78	0,87	0,09
Trees	4263,21	4260,82	-2,40	64,20	64,16	-0,04
Flood vegetation	25,25	21,85	-3,40	0,38	0,33	-0,05
Crops	801,05	954,05	153,00	12,06	14,37	2,30
Built area	99,34	121,07	21,73	1,50	1,82	0,33
Bare ground	7,87	3,40	-4,47	0,12	0,05	-0,07
Clouds	10,05	1,33	-8,72	0,15	0,02	-0,13
Rangeland	1382,21	1220,58	-161,63	20,81	18,38	-2,43

Table 4 Transition matrix, land cover change from 2017 – 2020

	Water	Trees	Flood vegetation	Crops	Built Area	Bare ground	Clouds	Rangeland
Water	0,863793	0,016762	0,015297	0,050950	0,014229	0,005629	0,000000	0,033339
Trees	0,000184	0,951976	0,000295	0,004985	0,001168	0,000002	0,000281	0,041110
Flood vegetation	0,127389	0,151842	0,668771	0,030684	0,000930	0,001453	0,000000	0,018931
Crops	0,004504	0,003079	0,000707	0,898510	0,018231	0,000035	0,000000	0,074934
Built area	0,011137	0,003369	0,000942	0,030102	0,941752	0,002420	0,000003	0,010275
Bare ground	0,214641	0,001371	0,131873	0,103098	0,046070	0,346590	0,000114	0,156241
Clouds	0,000000	0,975769	0,000000	0,004587	0,002159	0,000000	0,011951	0,005533
Rangeland	0,001888	0,133861	0,000873	0,148857	0,004910	0,000049	0,000006	0,709556

The future of crops area appears relatively stable based on graph on Figure 9. With an 80% probability that existing cropland will remain as such in 2050. However, notable transitions include an 8.18% likelihood of cropland converting to water, likely due to issues such as flooding or irrigation practices. Additionally, there is a 2.73% chance of crops transitioning to trees, which may result from reforestation or natural succession, and a 2.84% probability of urban expansion encroaching on agricultural land. These transitions highlight the need for effective water management, careful urban planning, and the promotion of agroforestry to mitigate the loss of cropland. According to Pete et al. [24], competition for land resources is intensifying, making such interventions crucial to ensure sustainable agricultural practices.

Conversely, the matrix indicates that some land currently not used for crops may be converted into cropland in the future. Specifically, there is a 10% probability of flood vegetation being transformed into cropland through drainage and land reclamation efforts. Furthermore, water areas have a 5.33% chance of becoming cropland, likely through agricultural development and irrigation initiatives. Although bare lands show a minor 1.14% probability of conversion to crops, this suggests potential opportunities for expanding agricultural activities through soil improvement. These transitions emphasize the importance of sustainable land reclamation projects and environmental impact assessments to ensure the productive and ecological viability of new croplands. As for Foley et al. [25] discussed solutions for cultivated planet scenarios, emphasizing the balance needed between expansion and sustainability of croplands.

The analysis of land use and cover across various sub-districts reveals distinct trends (Figure 10). Water coverage remains relatively stable in most areas, with notable increases in some sub-districts, such as Alas Barat, where it peaked at 16.64% in 2023, and Plampang, which reached 7.74% the same year. Conversely, areas like Sumbawa and Rhee experienced a decreasing trend in water coverage. Tree coverage is mostly on a decline, with Lunyuk showing a decrease from 676.51 to 648.94 by 2023, and Moyo Hilir witnessing a significant reduction. Despite this, some areas like Batu Lanteh have stable tree coverage with only minor fluctuations. Crop areas generally show an upward trend, reflecting agricultural expansion, with significant increases seen in Empang, Moyo Hulu, and Plampang by 2023. This pattern aligns with findings by Pete et al. [24] which emphasize the global trend of agricultural expansion at the cost of other land covers.

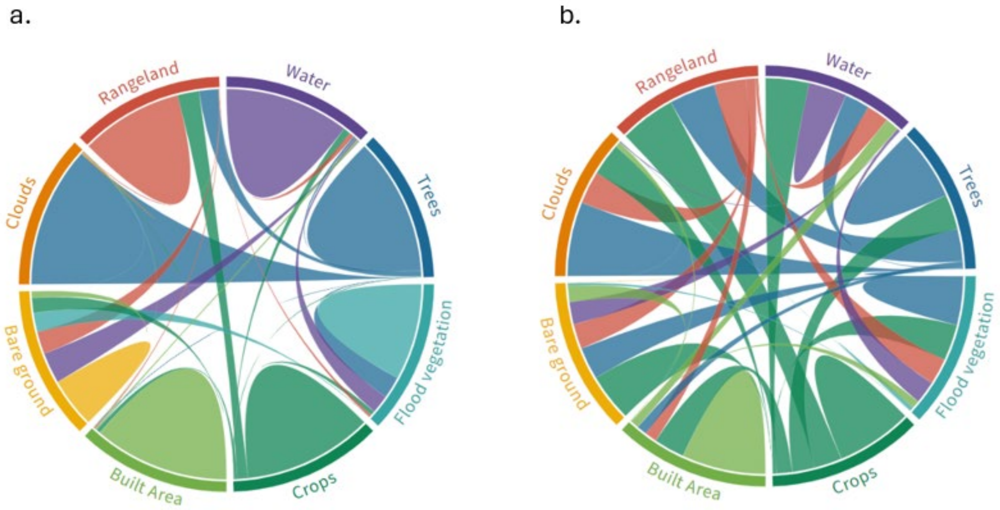

Figure 9 Graphical change between each land cover: (a) from 2017-2020 and (b) from 2017-2050.

Figure 10 Crops land cover change in each sub-district.

Urbanization is evident from the gradual increase in built areas across all sub-districts, peaking in places like Sumbawa and Moyo Hilir in 2023. Rangeland usage fluctuates significantly, with some sub-districts like Lunyuk and Lenangguar reaching peaks in 2023, while others such as Sumbawa and Empang show a decreasing trend. The minimum water coverage is consistently reported as minimal and stable in sub-districts like Ropang, Unter Iwes, and Batu Lanteh. These trends indicate ongoing shifts in land use, driven by factors such as deforestation, agricultural expansion, and urbanization, highlighting the dynamic nature of these regions' landscapes. Pete et al. [24] discuss similar dynamics, noting the increasing competition for land resources as urban and agricultural needs grow.

Conclusions

The study demonstrated the utility of the ANN-CA model in monitoring and predicting LULC changes in Sumbawa Regency from 2017 to 2050. By incorporating satellite-based LULC maps and thematic layers, the research validates the model's accuracy through the MOLUSCE plug-in, providing a reliable basis for future projections. The visual assessment of agricultural land further elucidates the patterns of area sprawl, offering crucial insights into the dynamics of agricultural development. The findings underscore the significant role of advanced modeling techniques in understanding and managing LULC changes, which are critical for sustainable agricultural planning and development.

The research highlights the urgent need for revising agricultural development plans to incorporate predicted trends and prevent potential chaotic scenarios. Recommendations for promoting sustainable agricultural development through societal planning, environmental considerations, and controlled growth policies are crucial for guiding future agricultural expansion. The study serves as a valuable resource for policymakers, agricultural planners, and administrative authorities, providing a comprehensive view of current and future agricultural sprawl. For future research, the incorporation of satellite data at shorter intervals and additional variables is suggested to enhance the accuracy and depth of LULC change analysis, offering new avenues for exploration and improvement.

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