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Prediction of land use changes via the cellular automata-Markov model in East Luwu Regency

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ABSTRACT

The increasing involuntary demand for land caused by the aggrandization and economic expansion of inhabitants has accelerated land conversion in many developing regions. This study aims to project land use substitutions in East Luwu Regency by 2043 via a CA-Markov modeling approach. Spaceborne imagery from the Landsat 7 ETM+ and Landsat 8 OLI/TIRS datasets was visually interpreted to generate historical land use maps for 2003, 2013, and 2023. The projection analysis involved two key phases: calculating transition probabilities through the Markov chain method, followed by spatial modeling of future land use patterns via a cellular automata framework. Several driving factors were considered, including proximity to roads, settlements, and rivers; elevation; population density; and slope gradient. Projections show that forest areas will continue to decline until 2043 due to increased land conversion by local communities. Conversely, mining, open land, and settlements are projected to expand, especially in areas with high accessibility and high population density. The CA-Markov representation demonstrated a high-pitched Kappa prognostic value of 0.8943 and proved effective in analyzing and forecasting the spatial-temporal kinetics of land-use change. These discoveries accommodate influential perspicacities for community planners and policymakers in underdeveloped sustainable spatial planning and forest management strategies that balance community needs with environmental conservation in East Luwu Regency.

Keywords: land use change, CA-Markov, spatial projection, East Luwu Regency.

INTRODUCTION

Land use modification is a materialization of the enterprising interplay of cognitive semantics between anthropoid movements and characteristic processes [Fahad et al., 2021]. According to the authority of Song et al. [2020], the insufficiency of uninhabited land use in expeditiously underdeveloped citified spaces has led to substantial substitutions in land use, as the limited amount of vacant land forces changes in the function of existing land to meet urban needs. In addition, constituents that result in land use modifications accommodate road access, settlement density, and distance to rivers, with road access being the most dominant factor [Ridha et al., 2023]. This is further emphasized by the findings of Trisnaputra et al. [2023], who highlighted that land use change modeling via Landsat imagery is intended to detect land cover change patterns, examine the driving factors behind them, and estimate future land use and land cover conditions. This implies that modeling serves as a tool to understand actual phenomena and anticipate future land change trends.

In 2020, the gross regional domestic product (GRDP) of the eastbound Luwu rule was recorded at 21.53 trillion rupiah. The mining and quarrying sector was the main contributor, accounting for 44.95% of the total GRDP. Moreover, nonmining sectors such as agriculture, forestry, and fisheries contributed 14.84%, followed by the construction sector, which contributed 10.54% [Central Statistics Agency, 2020]. Supported by these data, the general public of East Luwu Regency has maximized the potential of their land to support the regional economy. The improvement of the regional economy is certainly in line with the utilization of land potential in East Luwu Regency. One example of the conversion of forest areas into mining and settlement areas is the negative relationship between economic expansion and forest sustainability. Therefore, to influence the proportion of land use modifications, a scientific approach was taken through land use projection modeling.

According to the authority of Syaiful et al. [2025], predicting land use incorporation changes via the cellular automata (CA) method helps determine how land cover change occurs and predicts such changes in the future. In addition, researchers around the world are fascinated in studying archetypes and substitutions in land uses that are outstanding because of the substantial consequences of land use processes on environmental sustainability [Hussain et al., 2022]. Ajeeb et al. [2020] revealed that various representations and undergrounds exist in geographical enlightenment organized whole (GIS) and inaccessible senses, euphemistic of which individuals are preowned to foretell citified aggrandizement patterns, such as land use modification detection and countryside matrix analysis. Evaluations have shown that prognostic working models, including Markov concatenation representations and cellular automata, are imperative for compassionate and extenuating the impacts arising from intensified agriculture, forest loss, and citified augmentation of ecosystems [Dey et al., 2021]. Some of these include the CA model, land transformation model (LTM), and logistic regression (LR). However, several previous studies have used prediction and simulation models that focus on land use change via CA-Markov [Selmy et al., 2023], Markov concatenation psychoanalysis [Bashir et al., 2022], and CA-ANN [Ouma et al., 2024]. According to the authority of Mohamed et al. [2020], the application of GIS and inaccessible underground sensors can contribute to the development of future urban planning systems.

This study uses the cellular automata–Markov Chains (CA-Markov) representation to psychoanalyze and accomplish the kinetics of land use modifications occurring in East Luwu Regency and to conduct an environmental carrying capacity analysis via a land capability unit approach. According to Syaiful et al. [2025], the diligence of the Cellular Automata disposition to prognosticate land use incorporates substitutions, resulting in error-free and dependable protuberances for land use provisioning. Furthermore, Nugraheni et al. [2025] showed that the Cellular Automata model successfully predicts land use changes up to 2031 by capturing the complexity of land dynamics even with simple rules. This modeling approach accounts for land use substitutions from individual amplitudes to the coterminous and puts them into practice as a justification for identifying land use substitutions [Leta et al., 2021]. In addition, Fouad et al. [2024] projected land use change over a 20-year period via the CA–Markov method, demonstrating its capability for long-term spatial prediction.

Despite the extensive application of the CA–Markov representation in land use modification research, studies specifically focusing on the spatial dynamics of land transformation in East Luwu Regency are still limited. Most previous studies in Indonesia have concentrated on western regions such as Java and Sumatra, where urbanization and industrialization are the principal drivers of land use transformation. In contrast, East Luwu represents a distinctive case where land change is driven primarily by mining activities, agricultural expansion, and settlement development. This highlights the need for further studies that examine the unique archetypes and impulsive factors of land use modifications in eastern Indonesia.

Understanding these dynamics is essential for anticipating environmental degradation, supporting efficient land resource management, and strengthening evidence-based regional spatial strategic planning. Therefore, this research aims to examine the spatial and temporal dynamics of land use in East Luwu Regency from 2003 to 2023 and to simulate potential land use conditions for 2033 and 2043 through the CA–Markov modeling approach. The results of this study are anticipated to provide scientific insights that can assist local governments in evaluating and reviewing the Regional Spatial Plan (RTRW) of East Luwu Regency, as well as in developing policies for sustainable land management and environmental conservation.

RESEARCH METHODS

Research location

This evaluation was conducted in eastbound Luwu Regency, southbound Sulawesi responsibility, which is geographically located at approximately 119°37’–121°43’ E and -2°20’ – -3°30’ S. Administratively, East Luwu Regency consists of 11 subdistricts, with the capital located in Malili. This region has various topographical characteristics, ranging from lowlands on the coast to hills and mountains in fundamental and blue percentages. The Wu Timur Regency was chosen as the research location for the kinetics of land use modification resulting from accrued economic activity, particularly in the nickel mining sector and residential expansion. This development pressure has the potential to cause changes in land use that impact the ecological balance and environmental carrying capacity. Thus, this area serves as a suitable representation for assessing and forecasting future land use trends through spatial-based analysis. The placement correspondence of the evaluation environment in the eastbound Luwu rule buoy is shown in Figure 1.

Materials and methods

Data sources and LULC classification

A geographical enlightenment transaction psychoanalysis was conducted to obtain historical data on the study area. The analysis was carried out by interpreting satellite images at three different points in time, namely, 2003, 2013, and 2023. The updated Landsat figureurativeness (temporal resolution) of every 16 live buoys is euphemistically preowned to ascertain the up-to-minute land use in an environment [Galiniene et al., 2019]. This process was carried out to distinguish archetypes of land use modifications and understand the dynamics of spatial utilization in East Luwu Regency. The Landsat 7 and Landsat 8 image data used in this study can be seen in Table 1.

The results of image interpretation undergo accuracy testing to determine the error rate in the land use classification process, using the data validation results as an indicator of compartmentalization accuracy, thereby determining the percentage of accuracy of the classification. The faithfulness evaluation to be conducted in this study is the kappa accuracy test with the help of a confusion matrix. The most characteristic and efficacious disposition for measuring the faithfulness of categorized images from remote sensing images is the discombobulation matrix [Morales-Barquero et al., 2019]. The accuracy of classification can be calculated from Kappa faithfulness with the following equation:

$$K = \frac{N\sum_{i=1}^{r} X_{ii} - \sum_{i=1}^{r} X_{i+}X_{+i}}{N^2 - \sum X_{I+}X_{+I}}\, 100\% \qquad (1)$$

where: K is the kappa value, r is the character of strings in the discombobulation matrix, X_{ii}

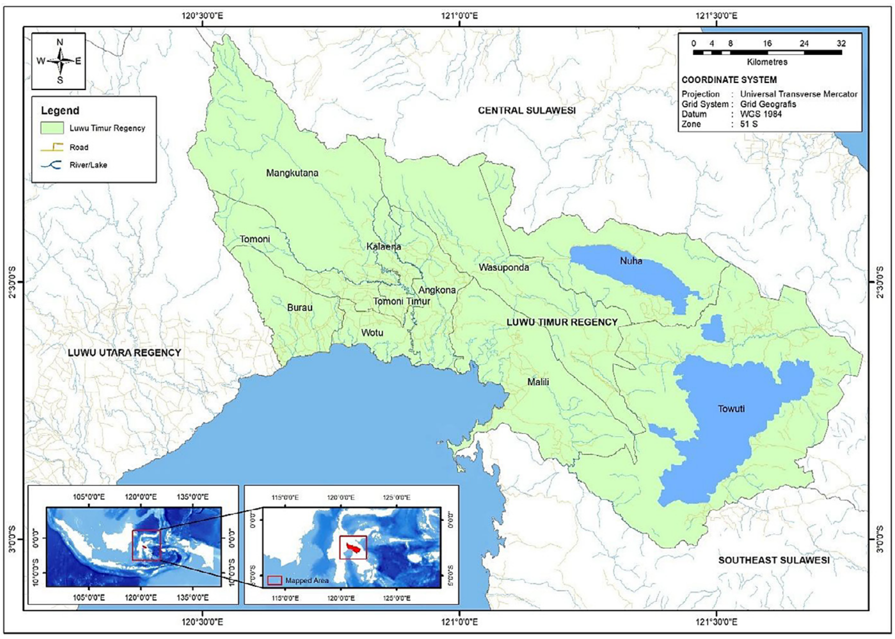


Figure 1. Map of the study area

Table 1. Acquisition details for Landsat 7 and Landsat 8 imagery

Year	Image	Recording time	Path/Row
2003	Landsat 7	10 April 2003	114/62
2003	Landsat 7	10 April 2003	114/61
2003	Landsat 7	21 May 2003	113/62
2013	Landsat 8	27 April 2013	114/62
2013	Landsat 8	27 April 2013	114/61
2013	Landsat 8	20 April 2013	113/62
2023	Landsat 8	15 April 2023	114/62
2023	Landsat 8	01 May 2023	114/61
2023	Landsat 8	15 March 2023	113/62

Note: source - USGS Earth Explorer, 2025.

is the separatrix expenditure of the contingency matrix in string i and borderline i, $X+i$ is the character of pixels in borderline i, $Xi+$ is the character of pixels in string i, and N is the character of pixels in the exemplification. The kappa accuracy suitability categories are presented in Table 2.

Predictions of future LULC dynamics

Similar scenario analyses have been carried out in various studies by applying the Markov chain–cellular automata (CA-Markov) model. In principle, the CA-Markov approach to modeling land use change relies on three essential categories of input data: baseline land cover imagery as the starting condition, transition probability matrices generated from the Markov process, and a series of transition suitability maps that guide the spatial allocation of future land use changes. Together, these components enable the model to simulate both the temporal probabilities of change and the spatial patterns of land transformation [Hyandye and Martz, 2017]. According to Liping et al. [2018], the CA represents the state of affairs in which the sovereign state of a gridiron cellphone is influenced by the kinetics of that cellphone and the kinetics of its neighboring cells. The land use modeling and future projection processes were performed in the Idrisi TerrSet platform via the Markov chain approach. The TerrSet representation put into practice CA-Markov, which is a stochastic modeling of cognitive semantics used to copy editor looking toward substitutions on top of continuance supported by yesteryear substitutions [Fathizad et al., 2015]. The data used in this analysis are land use data collected from 2003 and 2013 to obtain projection data for 2023. In addition, data on the impulsive constituents of land use modifications are also needed. The impulsive constituents of land use modifications, euphemistic preowned therein, include buoys, as shown in Table 3.

Table 2. Kappa accuracy suitability category

Kappa value	Accuracy
<0.2	Poor agreement
0.21–0.40	Fair agreement
0.41–0.60	Moderate agreement
0.61–0.80	Substantial agreement
0.81–1.00	Perfect

Note: Source – McHugh [2012].

After the 2023 land use projection was generated on the basis of the 2003 and 2013 datasets, a validation process was conducted by comparing the simulated 2023 land use data with the actual land use data for the same year. The grandness of representation establishment as an essential stage in the exploitation of a modified prognostication

Table 3. Drivers of land use modification

No.	Driving factors	Processing	Data source
1.	Population density	Overlay	Central Bureau of statistics
2.	Road distance	Euclidean distance	Ina-Geoportal (RBI Data)
3.	Slope	DEM	Ina-Geoportal (DEMNAS)
4.	Settlement distance	Euclidean distance	Classified satellite image
5.	Elevation	DEM	Ina-Geoportal (DEMNAS)
6.	River distance	Euclidean distance	Ina-Geoportal (RBI Data)

representation has been emphasized by industrialists [Eastman, 2012]. The purpose of this validation is to measure the faithfulness of the representation in predicting substitutions in land uses or land cover. Establishment is merely a course of action for assessing the superiority of predicted LULC maps over indication maps [Wang et al., 2016]. This validation is needed to run the 2043 land use projection model. If the results are close to each other, the validation can be accepted, and the 2043 land use projection can be carried out. The validation process was carried out via the kappa coefficient. The kappa coefficient represents a statistical metric that reveals the difference between aggregate inaccuracies and placement inaccuracies on cardinal qualitative maps, providing an all-inclusive valuation of representation accomplishment [Pan et al., 2017]. The kappa coefficient equation can be expressed as follows:

$$Kappa = \frac{P_0 - P_C}{1 - P_C} \quad (2)$$

where: P_0 represents the comparative relation of exactly categorized apartments. P_C indicates the supposititious distinct possibility of correspondence between the thoroughgoing land use correspondence for 2024 and the projected land use correspondence for the corresponding gathering.

The final result of this analysis is a correspondence of projected land use substitutions in 2043, which shows accomplishable substitutions in land uses because of gathering. The 2043 land use projection is obtained by entering the 2003, 2013, and 2023 land use inputs. Model simulation is performed through the application of the Cellular Automata-based simulation framework. This representation foretells the spatial constitution of indefinite land use classifications and scenarios supported by the transformation probability matrix [Li et al., 2015]. The Cellular Automata representation is formulated on the basis of a distinct possibility matrix that defines the distinct possibility of substitutions between land use classifications. The general form of the representation is given as [Eastman, 2024]:

$$S_{(t+1)} = P_{ij} \times S_{(t)} \quad (3)$$

where:

$$P_{ij} = \begin{bmatrix} P_{11} & P_{12} & \cdots & P_{1n} \\ P_{21} & P_{22} & \cdots & P_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ P_{n1} & P_{n2} & \cdots & P_{nn} \end{bmatrix} \quad (4)$$

The transition probabilities P_{ij} satisfy $0 \leq Pij < 1$ and $\sum_{j=1}^{n} P_{ij} = 1$ for $i, j = 1, 2, ..., n$.

This model represents the probability that a cell of land use classification *i* tests modification to classification *j* inside a precondition continuance separation. The evolution of the CA representation over time buoy can be described as follows:

$$S_{(t,\, t+1)} = f[S(t), N] \quad (5)$$

where: $S_{(t)}$ and $S_{(t+1)}$ denote the transaction states at continuance t and $t + 1$, respectively, where N represents the neighborhood configuration, and f denotes the transformation function that governs the transformation of apartments inside an anesthetic spatial circumstance. The variable S indicates the set of discrete and finite land use states, whereas P_{ij} is the transformation distinct possibility matrix that arbitrates the distinct possibility of modification between these states of affairs. The detailed steps and course of action, euphemistically preowned in this context, are illustrated in Figure 2.

RESEARCH RESULTS

Actual land use conditions in 2023

On the basis of the interpretation of images from 2003, 2013, and 2023, 12 land use classes were identified, namely, influential dryland forest, less important dryland forest, mangrove forest, plantations, residential areas, mining, dryland and bush agriculture, rice comedians, scrubland, ponds, open land, and water bodies. A total of 100 samples were taken from all land use classes. The characteristics of the representatives in each land use class varied according to the distribution of each land use class. The confusion matrix for each land use organization for the 2023 buoy is shown in Table 4.

On the basis of the data in Table 4, 92 out of the 100 sample points that had been determined were accurate. From these results, an accuracy test was performed using the kappa accuracy. The kappa accuracy calculation result at the research location was 90.76%, indicating that the image interpretation results were acceptable. According to Table 2, the accuracy test results from image

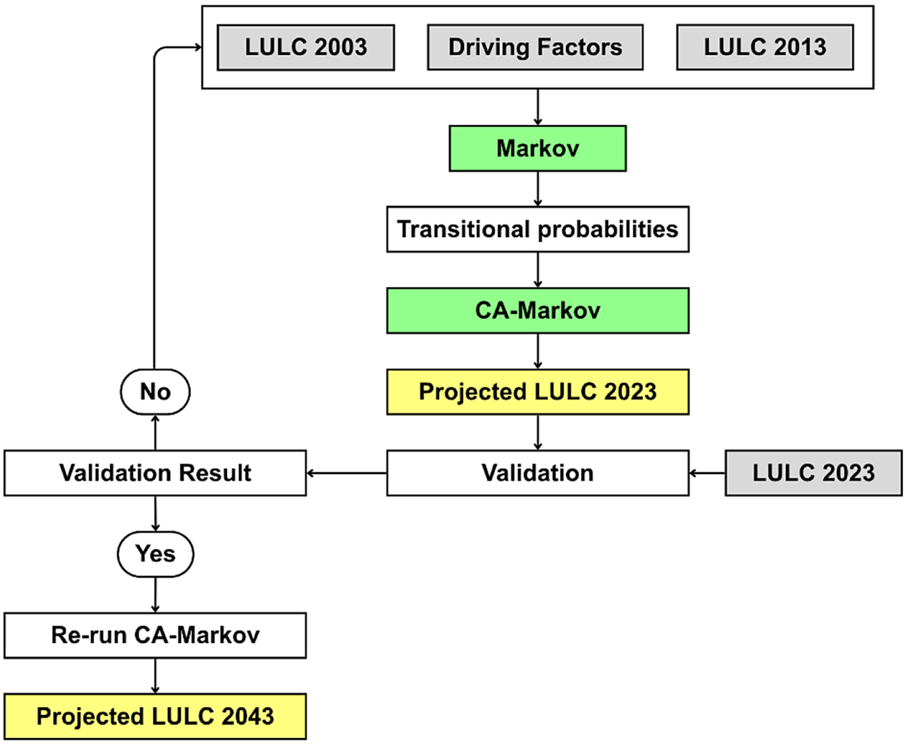


Figure 2. CA-Markov modeling movements to carry through false LULC patterns in 2043

Table 4. Kappa accuracy assessment derived from the confusion matrix

Land use		Ground check data												Grand
		Pri	Sec	Man	Pla	Set	Min	Dry	Ric	Shr	Fis	Ope	Wat	Total
Image interpretation results 2023	Pri	3												3
	Sec		16											16
	Man			4							1			5
	Pla				3	1								4
	Set					4								4
	Min						4							4
	Dry		2					23		1		1		27
	Ric								4					4
	Shr								1	12		1		14
	Fis										7			7
	Ope											3		3
	Wat												9	9
Grand total	3	18	4	3	5	4	23	5	13	8	5	9		100

Note: Pri – primary forest, Sec – secondary forest, Man – mangrove forest, Pla – plantation, Set –settlement, Min – mining, Dry – dryland farming mix shrubs, Ric – ricefield, Shr – shrubs, Fis – fishpond, Ope – open field, Wat – water.

interpretation conducted in this study fall into the perfect category.

Land use change

Supported by the consequences of land use change analysis via satellite imagery data from 2003, 2013, and 2023, East Luwu Regency has experienced substantial substitutions over the last twenty years. The psychoanalysis of land use change was conducted via the overlay method between land use maps from the three time periods to observe shifts in area for each land use class. The land use substitutions in each period to show shifts

Table 5. Area of land use change in 2003, 2013 and 2023

No.	Land use	Area of land use					
		2003		2013		2023	
		ha	%	ha	%	ha	%
1	Primary forest	182,809.12	27.09	179,701.12	26.63	179,061.97	26.53
2	Secondary forest	222,962.54	33.04	215,200.13	31.89	210,441.90	31.18
3	Mangrove forest	9,147.35	1.36	8,565.73	1.27	7,825.94	1.16
4	Plantation	7,096.27	1.05	7,061.50	1.05	7,058.78	1.05
5	Settlement	2,762.34	0.41	4,621.18	0.68	6,548.95	0.97
6	Mining	1,583.75	0.23	2,306.44	0.34	3,234.30	0.48
7	Dryland farming mix shrubs	94,772.48	14.04	99,068.12	14.68	99,954.64	14.81
8	Ricefield	14,102.76	2.09	14,555.34	2.16	14,980.24	2.22
9	Shrubs	48,664.11	7.21	51,944.52	7.70	53,151.79	7.88
10	Fishpond	9,839.81	1.46	10,399.32	1.54	10,940.17	1.62
11	Open field	2,416.82	0.36	2,733.95	0.41	2,958.68	0.44
12	Water	78,704.77	11.66	78,704.77	11.66	78,704.77	11.66
Grand total		674,862.12	100	674,862.12	100	674,862.12	100

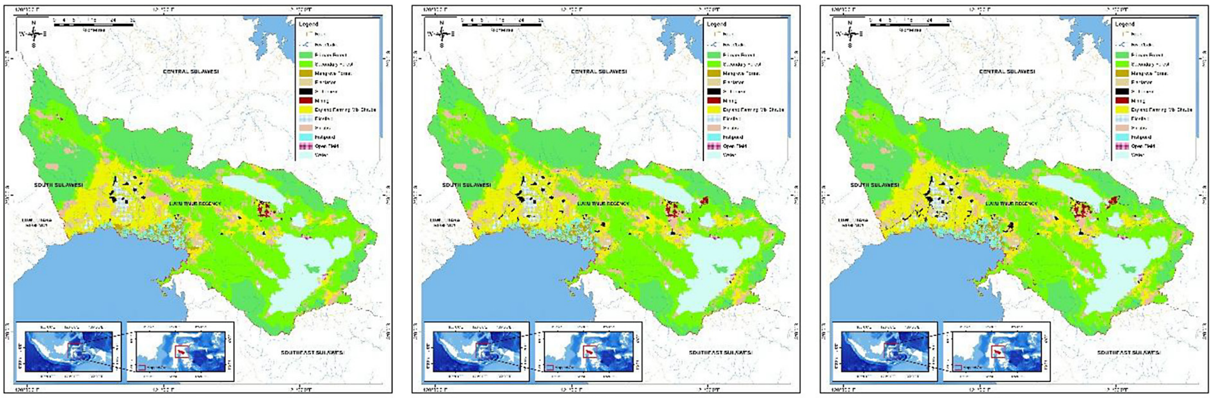
Note: source–processing results, 2025.

in area for each class and the percentage change from the initial area are presented in Table 5. On the basis of the data in Table 5, these substitutions occurred during land use in East Luwu Regency from 2003–2023. The most notable changes were observed in the decline in primary and secondary forest spaces and the increase in agricultural and encampment land use. The primary forest area decreased from 182,809.12 ha (27.09%) in 2003 to 179,061.97 ha (26.53%) in 2023. Similarly, secondary forest decreased from 222,962.54 ha (33.04%) to 210,441.90 ha (31.18%). This decline indicates the changeover of timber land spaces to over-the-counter spaces, which is thought to be related to economic expansion and spatial requirements. This finding aligns with that of El Yousfi et al. [2025], who reported a clear decreasing trend in forests and burdensome vegetation spaces at the expense of paying over-the-counter classes. On the other hand, land use classes such as dryland agribusinesses crossbred with shrubs, rice comedians, and open fields experienced significant increases. The area of dryland farming mixed with shrubs increased from 94,772.48 ha to 99,954.64 ha, whereas the area of rice fields increased from 14,102.76 ha to 14,980.24 ha. The open field class also increased from 2,416.82 ha to 2,958.68 ha, which indicates that land conversion activities were carried out by the community.

The aggrandizement in encampment and mining of land use also reflects the pressure of development on land resources. Settlement land increased from 2,762.34 ha to 6,548.95 ha, whereas mining land increased from 1,583.75 ha to 3,234.30 ha. These consequences are consistent with the evaluation by Bikis et al. [2025], who reported a decrease in forests and an increase in encampments and agricultural land use, which has an impact on the microclimate and local ecosystems. According to the authority of [Supriatna et al., 2020], the decrease in timber land incorporation threatens the existence of endemic species and increases anthropogenic pressure, including settlement and land conversion. On the other hand, Soma et al. [2023] emphasizes that land conversion can occur because of communities' dependence on agricultural land for their livelihoods and population growth, which can lead to a need for land for housing. This may exhilarate residents to transform land use into indefinite classifications of land use incorporation [Hyandye et al., 2015]. The implementation of undeviating security districts in timber land and wetland spaces is a strategical transaction in preserving the ecosystem [Kundu et al., 2024]. A map showing the consequences of land use compartmentalization at the East Luwu Regency buoy is shown in Figure 3.

Drivers of land use modification

Driving factors play a role in explaining the variables that influence the distinct possibility of land use changeover from one category of



(a) (b) (c)

Figure 3. Land use classification in East Luwu Regency in (a) 2003, (b) 2013, and (c) 2023

application to another. Therein is a glance at the impulsive constituents, e.g., preowned accommodations, indifference to roads, slope, inhabitant density, altitude, indifference to settlements, and indifference to watercourses. To gauge the comparative influence of each factor on land use modification, explanatory ratio analysis was used. The explanatory ratio value indicates how strongly a variable influences changes in a particular submodel. The higher the correspondence value is, the better the ability of that factor to explain the archetypes of land use changes. The comparative consequences of each impulsive factor on the land use modification buoy are shown in Figure 4.

On the basis of the results of the average explanatory ratio calculation, an overview of the dominant driving factors influencing the kinetics of land use modification in the context environment was obtained. The highest average value was shown by the population density variable, with an explanatory ratio of 0.7500, followed by the settlement distance of 0.7232 and the road distance of 0.7102. This finding indicates that driving constituents, such as inhabitant compactness, settlement indifference and the course of action indifference, are the main determinants in the process of land use conversion. As stated by Exsan Fadillah and Elysia [2025], population growth is an individual of the principal variables that triggers substitutions in land use, followed by location, economic pressures, and housing needs. The factors with lower average explanatory ratios are distance from river (0.5838), elevation (0.5899), and slope (0.6201). Although they play a role, the contributions of these three factors are relatively smaller than those of population density, settlement distance, and road distance. These results are in line with research Fitri et al. [2025], which revealed that there is a direct relationship

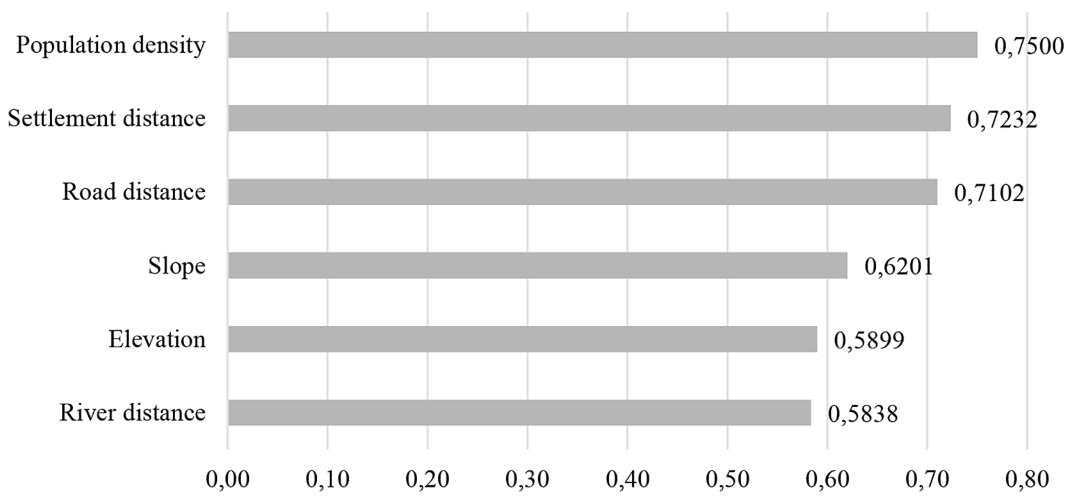


Figure 4. The consequences of each impulsive factor on land use modification

between inhabitant aggrandizement and pauperization for residential land use, leading to the expansion of residential areas and infrastructure, including transport networks.

Land use projections for 2043

Land use substitutions from 2003–2013 to influence land use in 2023 via cellular automata modeling. This stage produced a land use change transition matrix. Transition matrix psychoanalysis is a far-reaching substitute for land use modification modeling. This matrix is designed to establish the distinct possibility of a modification in a land use organization in the representation gathering to another land use organization in the projection year. Each value in the matrix reflects the transition probability from one category to another, with values ranging from 0 to 1. A value of 1 represents an extremely high-pitched distinct possibility that a land class will remain or change to a particular class, whereas values of 0 represent an extremely small distinct possibility. Research by Kesaulija et al. [2021] explains that the use of transformation distinct possibility matrices to determine the likelihood of modification from individual land use organization to another with a matrix dimension of n × n (n = number of cover classes). The transformation matrix resulting from the 2003–2013 land use change model is presented in Table 6.

The transition matrix in Table 6 shows that virtually land use classes have a highly distinct possibility of remaining in their original class (diagonal values close to 1). For example, the Water Body class has a probability of 1.0000 of remaining a water body, as do the Rice Field, Settlement, and Mining classes, which each have a value of 1.0000. This indicates that these classes were relatively stable during the 2003–2013 period, with very low rates of change. However, there are also land use classes that have a probability of transitioning to another class. Dry land agriculture + shrubs has a probability of 0.0174 of changing to settlement, whereas the rest remain in their original class with a probability of 0.9802. This demonstrates the dynamics of dryland agricultural land conversion to residential land in urban areas [Madhusudhan et al., 2024].

The secondary forest class has a fairly high probability of remaining in its class at 0.9512 but also has a chance of conversion to Dryland Agriculture + Scrub at 0.0248 and to Shrubs at 0.0187. This indicates that secondary forestland is vulnerable to degradation. In addition, the mangrove forest class has a probability of 0.9364 of remaining mangrove forest, with a small chance of conversion to open land of 0.0047 and to fish ponds of 0.0589. These findings are consistent with the fact that mangrove areas often experience pressure to convert to fishponds in coastal areas. This is in accordance with an

Table 6. The transition probability matrix used to simulate land use conditions for 2023 was generated from the land use imagery of 2003 and 2013

Land use	Probability to change to											
	Cl.1	Cl.2	Cl.3	Cl.4	Cl.5	Cl.6	Cl.7	Cl.8	Cl.9	Cl.10	Cl.11	Cl.12
Cl.1	**1.0000**	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Cl.2	0.0000	**0.9802**	0.0000	0.0001	0.0000	0.0000	0.0000	0.0000	0.0000	0.0013	0.0174	0.0010
Cl.3	0.0000	0.0000	**0.9830**	0.0170	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Cl.4	0.0000	0.0248	0.0000	**0.9512**	0.0018	0.0000	0.0187	0.0000	0.0000	0.0000	0.0004	0.0031
Cl.5	0.0000	0.0066	0.0000	0.0000	**0.9442**	0.0000	0.0470	0.0000	0.0000	0.0010	0.0012	0.0000
Cl.6	0.0000	0.0000	0.0000	0.0000	0.0047	**0.9364**	0.0000	0.0000	0.0589	0.0000	0.0000	0.0000
Cl.7	0.0000	0.0104	0.0000	0.0000	0.0001	0.0000	**0.9886**	0.0000	0.0004	0.0000	0.0000	0.0005
Cl.8	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	**0.9951**	0.0000	0.0000	0.0049	0.0000
Cl.9	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	**1.0000**	0.0000	0.0000	0.0000
Cl.10	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	**1.0000**	0.0000	0.0000
Cl.11	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	**1.0000**	0.0000
Cl.12	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	**1.0000**

Note: Cl.1 – water, Cl.2 – dryland farming mix shrubs, Cl.3 – primary forest, Cl.4 – secondary forest, Cl.5 – ppen field, Cl.6 – mangrove forest, Cl.7 – shrubs, Cl.8 – plantation, Cl.9 – fishpond, Cl.10 – ricefield, Cl.11 – settlement, and Cl.12 – mining.

evaluation conducted by Suyarso and Avianto [2024], which revealed that the main cause of degradation in mangrove forests is the continued expansion of land clearing for fishponds, with quantitative data supporting land use pressure on the coast. The transition matrix shows that although most land use classes tended to be stable during the 2003–2013 period, several classes experienced significant conversion dynamics, particularly dry agricultural land + shrubs, secondary forests, and mangroves. This is an illustration influenced by the cellular automata process, whereby supported by the explanation of the neighborhood, each pixel has the potential to change the pixels next to it.

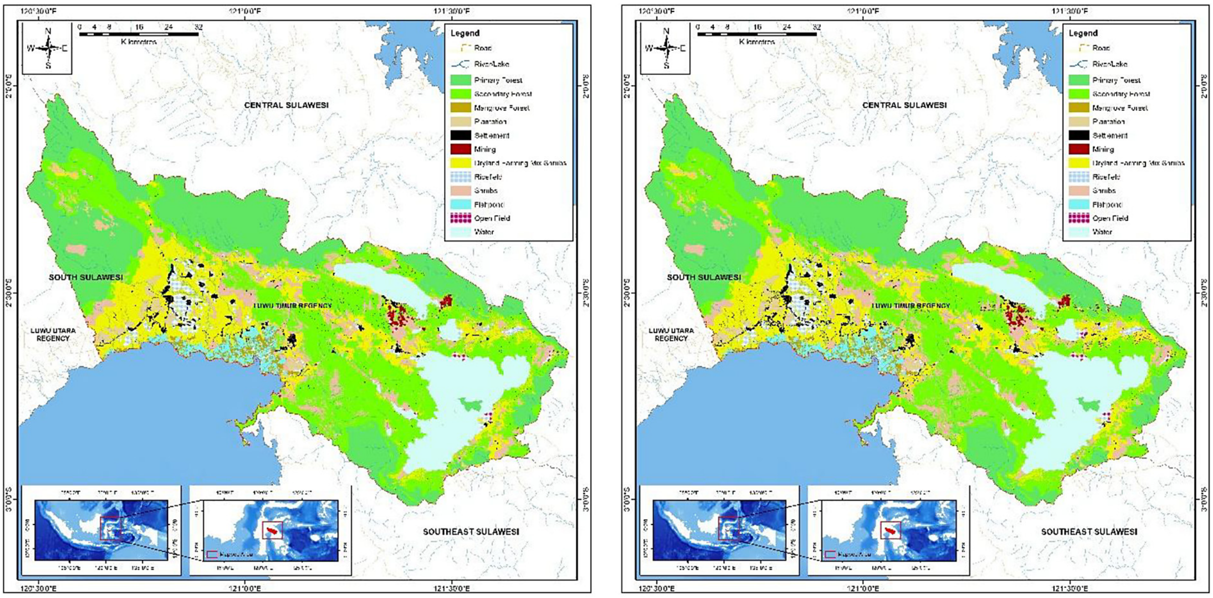
After the 2023 land use projection map was obtained, a validation model was constructed between the actual 2023 land use map and the projection map. The validation process was carried out by comparing the 2023 land use protuberance collections with the thoroughgoing conditions in the same year. The comparison aimed to determine the spatial conformity between the representation consequences and the thoroughgoing collections. The development of the suitability analysis was conducted via the decision support tools available within the Idrisi TerrSet software. The validation results indicate that the Kappa accuracy value reached 0.8943, or approximately 89.43%. This finding demonstrates that the Land Change Modeler model has a fairly high degree of accuracy in projecting land use changes. According to Table 2, this kappa accuracy value falls into the perfect category. This approach involves an evaluation conducted by Tahir et al. [2025], who used the CA-Markov representation to predict land use changes and achieved an overall classification accuracy of more than 90%. The proportions of land use modifications in 2023, projections for 2033, and 2043 buoys are shown in Table 7.

As shown in Table 7, the area of influential timber land is projected to decrease from 179,061.97 ha (26.53%) in 2023 to 177,723.34 ha (26.33%) in 2043. This decline reflects the pressure of land use in forest areas driven by the need for space and community economic activities. Moreover, secondary forests fluctuate, with a slight decline from 210,441.90 ha (31.18%) in 2023 to 188,356.07 ha (27.91%) in 2043. This condition indicates the existence of a natural regeneration and rehabilitation process in some forest areas, but it is not yet strong enough to withstand the rate of conversion that continues to occur in other areas. This is an occupation with an evaluation conducted by Xu et al. [2022], where the use of forestland tends to decrease in the future due to pressure from land use changeover carried elsewhere by the community. On the other hand, the area of settlement increased from 6,548.95 ha (0.97%) in 2023 to 10,103.34 ha (1.50%) in 2043. This increase indicates that the process of urbanization and population growth in East Luwu Regency continues, especially in

Table 7. Land use modification environment in 2023, projections for 2033, and 2043

No.	Land use	Area of land use					
		2023		2033		2043	
		ha	%	ha	%	ha	%
1	Primary forest	179,061.97	26.53	178,148.59	26.40	177,723.34	26.33
2	Secondary forest	210,441.90	31.18	196,701.10	29.15	188,356.07	27.91
3	Mangrove forest	7,825.94	1.16	7,533.71	1.12	7,047.55	1.04
4	Plantation	7,058.78	1.05	6,992.47	1.04	6,957.81	1.03
5	Settlement	6,548.95	0.97	8,311.33	1.23	10,103.34	1.50
6	Mining	3,234.30	0.48	3,602.90	0.53	3,900.51	0.58
7	Dryland farming mix shrubs	99,954.64	14.81	106,775.00	15.82	109,938.77	16.29
8	Ricefield	14,980.24	2.22	15,424.80	2.29	15,802.01	2.34
9	Shrubs	53,151.79	7.88	58,018.70	8.60	61,170.28	9.06
10	Fishpond	10,940.17	1.62	11,403.63	1.69	11,883.04	1.76
11	Open field	2,958.68	0.44	3,245.13	0.48	3,274.63	0.49
12	Water	78,704.77	11.66	78,704.77	11.66	78,704.77	11.66
Grand total		674,862.12	100	674,862.12	100	674,862.12	100

Note: source–processing results, 2025.



(a) (b)

Figure 5. Land use projections in East Luwu Regency for (a) 2033 and (b) 2043

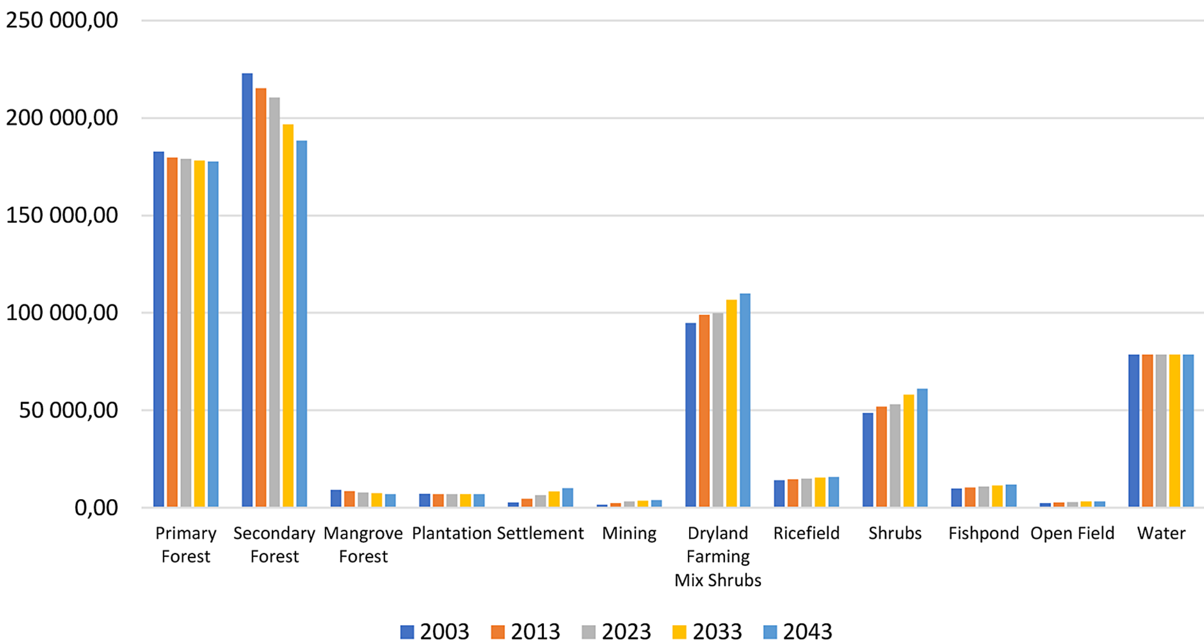


Figure 6. Land use area comparison chart

areas with high accessibility. The area of residential areas or built-up land will continue to increase over time [Ajeeb et al., 2020; Sidiq et al., 2024]. This is further emphasized by Gabisa et al. [2025], who show a direction of land use modification from agriculture to residential and open land with a substantial decrease in the agricultural land use environment and an increase in residential areas, which is consistent with urbanization. In addition to residential areas, the use of mining land also increased from 3234.30 ha (0.48%) in 2023 to 3900.51 ha (0.58%) in 2043. This increase reflects the expansion of the mining sector, which has transformed the landscape and caused significant changes in land use [Sutriadi et al., 2024]. Furthermore, there was an increase in dryland mixed with shrubland agricultural land from 99,954.64 to 109,938.77 hectares. This finding aligns with that of Layuk et al. [2025], who reported a substantial increase in agricultural land use from 399 hectares in 2011 to 519 hectares in 2030. The map showing the projected land use in East Luwu Regency is shown in Figure 5. A comparative graph of land use area buoys is shown in Figure 6.

CONCLUSIONS

This study shows that land use in East Luwu Regency has undergone significant changes from 2003 to 2043. The strongest driving factors influencing these changes are population density, distance to settlements, and distance to roads. Projection results up to 2043 indicate that forest areas, particularly secondary forests, are likely to continue declining due to land conversion for agricultural, residential, and mining activities. In contrast, land use types such as settlements, mining areas, dryland farming mixed with shrubs, and shrubland are projected to increase, especially in areas with high accessibility, high population density, and close proximity to road networks and existing settlements. The application of the CA-Markov model proved effective in representing the spatial and temporal dynamics of land use change, as evidenced by a high validation accuracy with a Kappa coefficient of 89.43%.

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