Land Use Change By Cellular Automata (CA) – Markov Method

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Abstract. This study examines the simulation of land use changes in transportation node areas, specifically around ports and train stations. The objective is to predict future land use changes in these regions. Several interrelated analytical methods are employed to address the research questions. These include supervised classification analysis using Landsat 8 imagery, overlay analysis to identify land use changes over the past eight years, and prediction of land-use discrepancies in comparison to the Barru Regency spatial plan (RTRW). Additionally, the study uses Cellular Automata (CA)-Markov and artificial neural networks (ANN) methods to forecast land use changes over the next 20 years. The analysis of land changes in transportation node areas provides data on land use before and after the development of these nodes over the past two decades. The results show significant changes, particularly in residential land use, which has increased by 770.51 hectares over the last 20 years. Based on these findings, the study predicts land use changes for the next 20 years, with the total built-up area projected to reach approximately 1,183.75 hectares.

Keywords: Landuse, Markov, Cellular Automata

1 Introduction

This study was done in node transportation in Barru Regency, Indonesia. The transportation node is a harbour and train station. A Harbour is Garonggong Harbor which was built in the year 2008. This harbour activity is about cruise people and on year 2010. Another a node transportation, it is a train station in the regency centre. The train station itself hopefully can facilitate community activities in traveling outside the Regency or City [1]. The change of land use is very high around the node transportation. This land change is important because the development and urban planning based on

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the development surrounding the transportation node [2].

For the literature review, in predicting the direction of change in land use, several methods can be used methods such as cellular automata-Markov (CA-Markov), Land change modeller, and model conversion of land use. It is effects at small regional extent [3]. The method cellular automata-Markov (CA-Markov) is the choice which is appropriate in this study because the method used is easier and has high accuracy presentation [4]. The CA-Markov method itself is an analysis-based pixels which identify and compare images from the year previously. In applying the CA-Markov method, an additional method is needed to do simulation model displacement potential (transition potential modelling) in CA-Markov where in this simulation there are several methods such as artificial neural networks (ANN) [5], [6], weights of evidence, and multi criteria evaluation. Using ANN method on geographic information systems (GIS) gives solution which is good in predicting land use change utilization land, with mark coefficient determination R2 is 0.99 because the higher the R2 value, the higher the influence of the parameters. Thus, choosing the ANN method in CA-Markov will produce better predictions accurately [7].

Based on background behind previously, this study will analyse and evaluate change land use method CA- Markov with ANN to predict the direction of land change in the future. This can be used in taking a policy as well as in evaluating spatial plans which will create space utilization which controlled on period future.

2 Literature Review

To predict land use change, various methods can be employed, including Cellular Automata-Markov (CA-Markov), the Land Change Modeler, and the Conversion of Land Use and its Effects at Small Regional Extent (CLUE-S) model. In this study, the CA-Markov method was chosen due to its simplicity and high accuracy. This method utilizes pixel-based analysis to compare and identify changes between past and present land use images. [8], [9]

In implementing the CA-Markov method, an additional approach is required to simulate transition potential models. Several techniques, such as artificial neural networks (ANN), weights of evidence, and multi-criteria evaluation, can be applied in this simulation. The ANN method has proven to be particularly effective in geographic information systems (GIS) [10], [11], yielding more accurate predictions of land use change. According to Harmoko, the ANN method demonstrated a determination coefficient (R^2) of 0.99, indicating a strong correlation between the parameters and land use shifts. A higher R^2 value reflects greater influence, supporting the conclusion that incorporating ANN into the CA-Markov model enhances predictive accuracy[6], [12].

3 Methods

3.1 Location

The location of this research is around the Garongkong port area and a train station in Barru regency. The location selection was in Barru Regency, precisely in Barru District and Tanete Rilau District due to the construction of a transportation node like Harbors and railroads which I as a researcher aim to see linkages between these transportation nodes to changes in land use happen several last year and some next year.

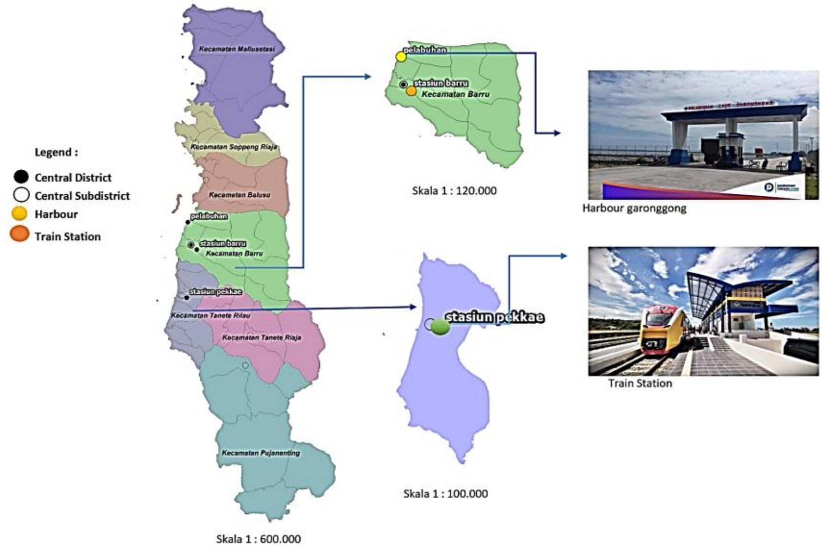

Fig. 1. Study Location

3.2 Step Analysis [5], [8], [9], [10], [11], [13], [14]

1. Overlay Analysis for Evaluating Land Use Over the Last 5 Years Using the Mollusce Plugin in QGIS:
   - At this stage, land cover image data from 2001, 2006, 2011, 2016, and 2023 are used. Once all the land cover raster data and supporting factors are prepared in QGIS, the Mollusce plugin is activated or installed for further analysis.
   - After installing the plugin, the next step involves inputting land use data from the last 5 years.
   - The following stage focuses on analyzing area changes. This stage generates a table detailing the increase or decrease in land use for each category. Additionally, a land use change transition matrix is produced.
   - The process is repeated as the Mollusce plugin can only display two land change matrices at a time.
2. Land Use Prediction Analysis for the Next 10 Years Using the CA-Markov Method. For this stage, the software Terrset is used. Several steps are followed to conduct the CA-Markov analysis with the support of Artificial Neural Networks

(ANN):

- Session Parameters: The first step involves entering initial data, such as land use maps from 2011 and 2016, into the analysis.
- Change Analysis: This step displays the panel and graph of the land use changes that have been input.
- Change Maps: At this stage, various change maps are created, including persistence maps, gains and losses, transitions, and displacements.
- Spatial Trend of Change: This stage helps identify future trends by analyzing previous land use changes, making it easier to determine future patterns of change.
- Running the Transition Sub-Model: Here, all driving data are processed to observe land movement or change potential using the ANN model with a multi-layer perceptron.
- Change Allocation: This stage allocates predicted land use changes across the study area.
- Validation: In this final step, the prediction results are validated to assess the accuracy of the simulation, using the ANN method and driving data. According to Altman (1991), a kappa value of 0.81–1.00 indicates very good agreement, 0.61–0.80 is considered good, 0.41–0.60 is moderate, 0.21–0.40 is less than moderate, and values below 0.21 are deemed poor. This structure outlines the analytical processes involved in evaluating land use over the past 5 years and predicting future land use changes for the next decade.

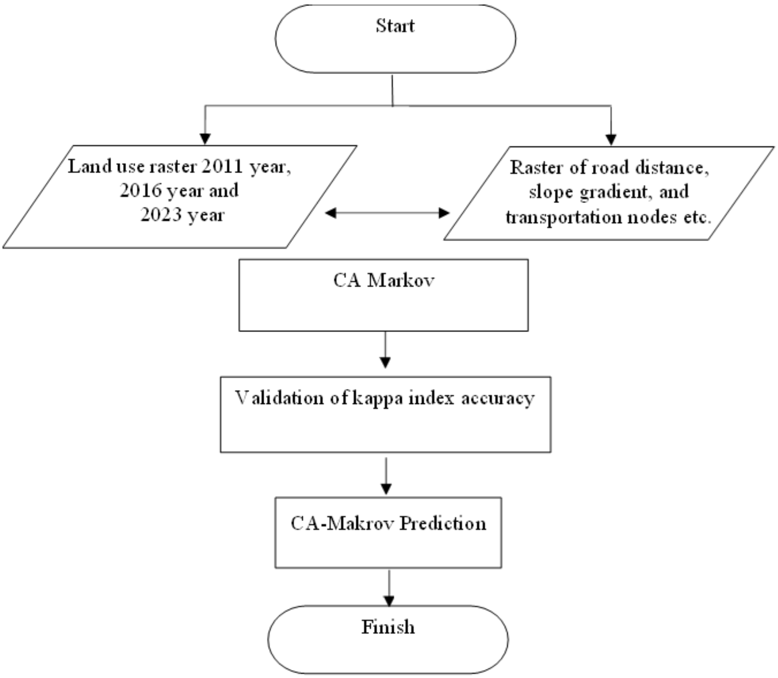

Fig. 2. Step of Analysis

3.3 Data Analysis

The prediction of land use for the next 10 years is carried out using the CA-Markov method, with the analysis performed through the TerrSet software. This process involves several steps, including change analysis, change maps, spatial trend analysis, running transition sub-models, and validation [8], [9], [10].

The validation phase assesses the accuracy of the simulations generated by the ANN (Artificial Neural Networks) method and the choice of driving data. According to the reference, a kappa value between 0.81 and 1.00 indicates a very high level of agreement, 0.61 to 0.80 is considered good, 0.41 to 0.60 is moderate, 0.21 to 0.40 is less than moderate, and any value below 0.21 is considered poor [1], [2], [4].

4 Results and Discussion

4.1 Classification Image

At this stage, Landsat-7 data was obtained directly from EarthExplorer (earthexplorer.usgs.gov). The images underwent geometric corrections to ensure accurate alignment and facilitate the next step: land use classification. The classification was carried out using the supervised classification method, which is based on color patterns in the images and sample points to determine the existing land use types. This process divides land cover into several categories, including forest, water bodies, agricultural land, ponds, and built-up areas.

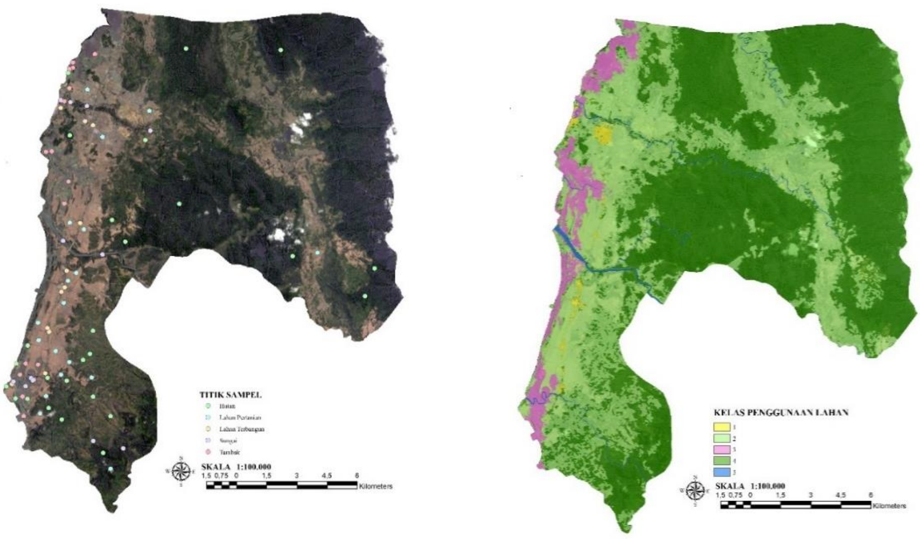

Fig. 3. Point Sample and Class Land Use

As shown in Figure 3, a total of 83 sample points were distributed across different land cover types. These include 26 sample points for forest areas, 18 for agricultural land, 11 for built-up land, 13 for water bodies or rivers, and 15 for ponds.

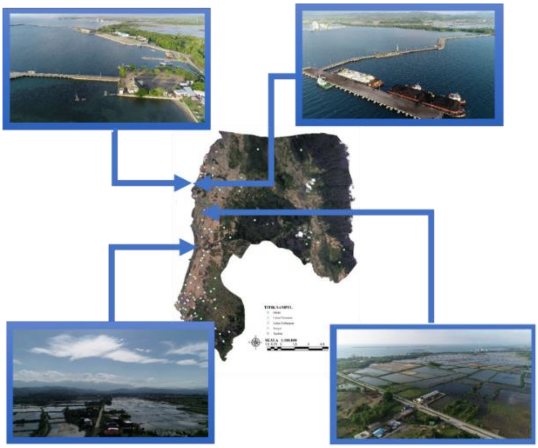

Fig. 4. Supervised Classification Sample

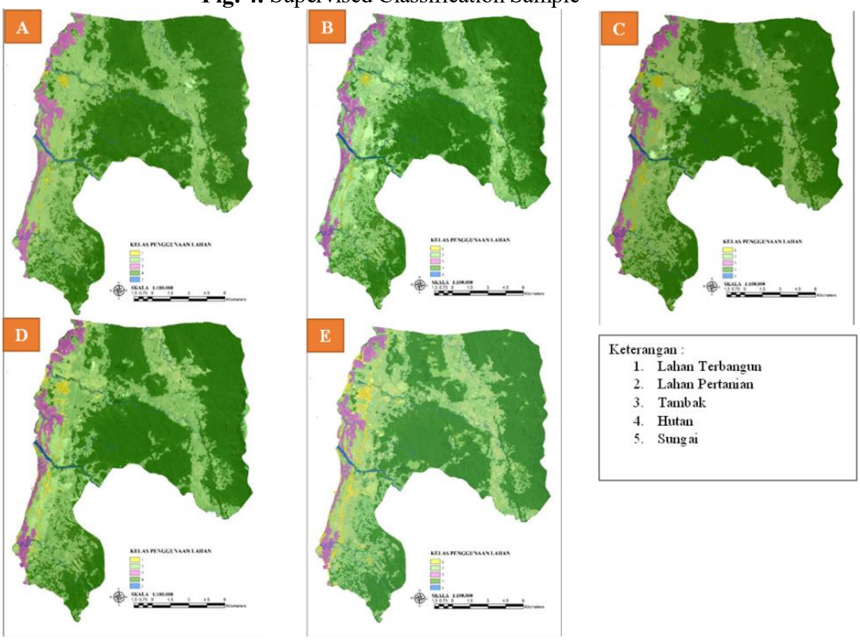

Fig. 5. Land use from 2001 year (A), 2006 year (B), 2011 year (C), 2016 year (D), 2023 year (E)

In Figure 3, the land use in Barru District and Tanete Rilau District is categorized into five classes. These are:

- Class 1: Built-up land
- Class 2: Agricultural land
- Class 3: Ponds
- Class 4: Forest
- Class 5: Rivers

The land use distribution for these areas is detailed in Table 1.

Table 1. Area Map Use Land Results Classification

Class	Year				
	2001 (Ha)	2006 (Ha)	2011 (Ha)	2016 (Ha)	2023 (Ha)
Land awakened	177.66	197.66	327.04	546.09	948.17
Land Agriculture	10936.87	10930.16	10870.4	10706.38	10409.69
pond	1329.32	1329.32	1327.38	1295.06	1210.14
Forest	15174.2	15160.91	15093.23	15070.52	15050.05
River	220.84	220.84	220.84	220.84	220.84
total	27838.89	27838.89	27838.89	27838.89	27838.89

Land use changes are influenced by several factors, including location, socio-economic conditions, and ease of accessibility (Good Nuari, 2014). In Barru Regency, particularly in Tanete Rilau District and Barru District, land use changes were observed over a 20-year period, with data collected and analyzed every 5 years. These changes were assessed using the overlay method with the assistance of the Mollusce plugin in the QGIS application.

Table 2. Land Use Difference Based in 20 Year

No	Class	Year		
		2016 (Ha)	2023 (Ha)	Difference (Ha)
1	Built Up Land	546.09	948.17	402.08
2	Land Agriculture	10706.38	10409.69	-296.69
3	Pond	1295.06	1210,14	-84.92
4	Forest	15070.52	15050.05	-20.47
5	River	220.84	220.84	0
	Total	27838.89	27838.89	

Table 2 clearly shows land use changes over the past 5 years. Specifically:

- The area of built-up land increased by 402.08 hectares.
- Land use changes included a conversion of built-up land to agricultural land, amounting to approximately 296.69 hectares.

The most significant change, as detailed in Table 2, is the substantial increase in agricultural land, contributing 297 hectares to the overall land use changes.

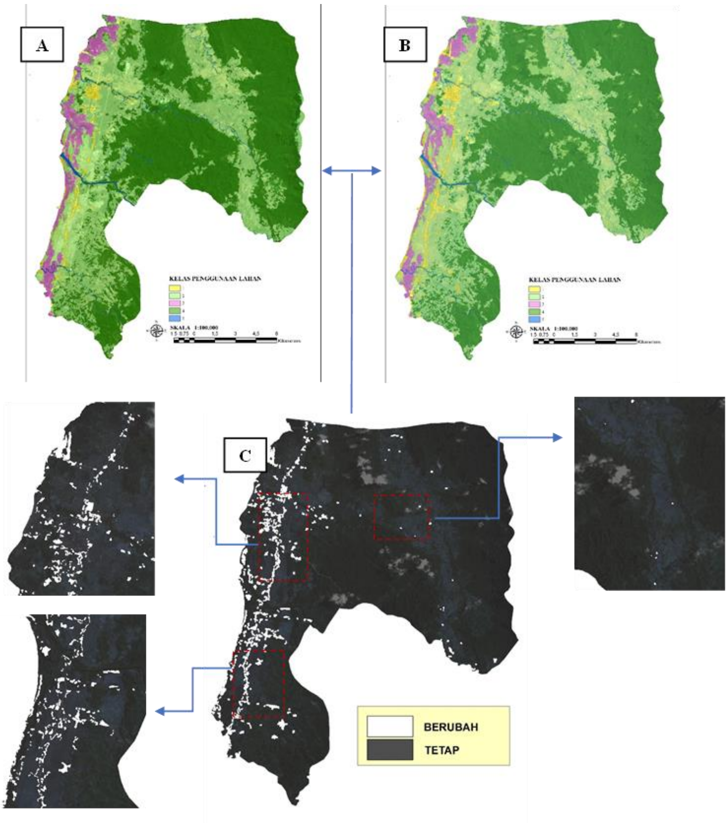

Fig. 6. Map land use 2016 (A), Map land use 2023 (B), Map change land use 2016-2023 (C)

Table 3. Land Use Change Based on Subdistrict Area

No	Subdistrict	Class	Area (Ha)
1	2	3	4
1	Barru Subdistrict	Forest to Land Awakened	9.78
		Land Agriculture to Land Awakened	102.97
		Pond to Land Awakened	34.91
		Total	147.67
2	Tanete Rilau Subdistrict	Forest to Land Awakened	10.05
		Land Agriculture to Land Awakened	181.87
		Pond to Land Awakened	47.11
		Total	239.02

Table 3 shows that the area experiencing the most significant land change is Tanete Rilau District, with a total change of approximately 239.02 hectares. Notably, agricultural land in this district was converted to built-up land, covering an area of 181.87 hectares. The land use changes from 2001 to 2023 reflect substantial transformations over this period.

4.2 Modelling Artificial Neural Network (ANN) and Ca-Markov to Predict Land 2033

Based on the land classification results in the study area (Barru District and Tanete Rilau District), land use is categorized into five classes: built-up land, agricultural land, ponds, forest, and rivers. This classification was processed using **TerrSet** software with the **Land Change Modeler (LCM)** plugin, which helps analyze land changes and predict future land use for the year 2033.

The land prediction using the LCM plugin involves several stages:

- Change Analysis
- Transition Potentials
- Change Predictions

The analysis clearly shows that agricultural land and built-up areas are the most significant contributors to land use changes, with a notable shift towards built-up land. Figure 6 illustrates these changes, highlighting how agricultural and built-up areas are converting into more built-up land.

The results from the land change analysis for 2011 to 2016 provide insights into the ongoing trends. Figure 31 offers a detailed view of these trends, showing how land use patterns have evolved over this period.

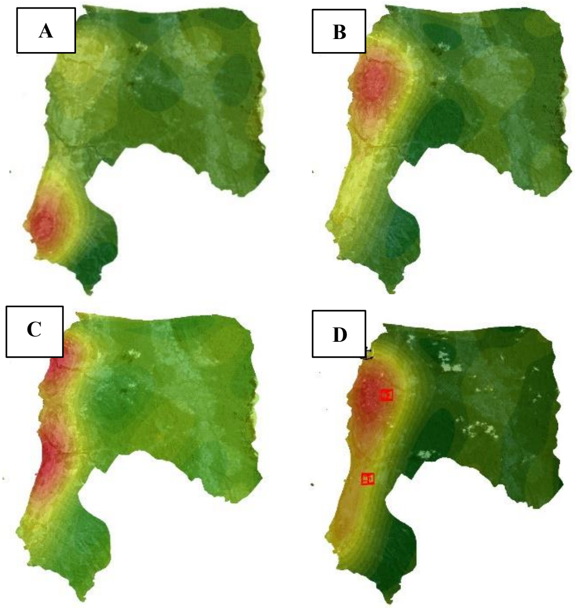

Fig. 7. Direction trend change Forest (A), Direction trend change Agriculture (B), Direction trend change Land Pond (C), Direction changing trends land (D)

In Figure 7:

- Point (A) shows that the trend of land use change for forests is moving strongly towards the southwest, near the coast.
- Point (B) indicates that changes in agricultural land are predominantly shifting towards the northwest.
- Point (C) illustrates that the direction of changes in pond areas is more evenly distributed around the coastal region.
- Point (D) reveals that the overall direction of land change is primarily towards the northwest, particularly around transportation nodes.

4.3 Validation

In this stage, the land use prediction map for 2023 underwent validation. The validation accuracy was found to be over 75%, which is considered acceptable according to Guo et al. (2020). Model validation involves comparing the simulated map with a reference map to identify any discrepancies. Differences between the simulated and reference maps may arise from variations in cell quality (Gharaibeh et al., 2020).

The kappa value for the validation was 97%, indicating a high level of agreement and confirming that the scenario generated is reliable and suitable for replication. After this validation, the next step is to repeat the scenario to obtain the land use prediction for 2033, as shown in Figure 8.

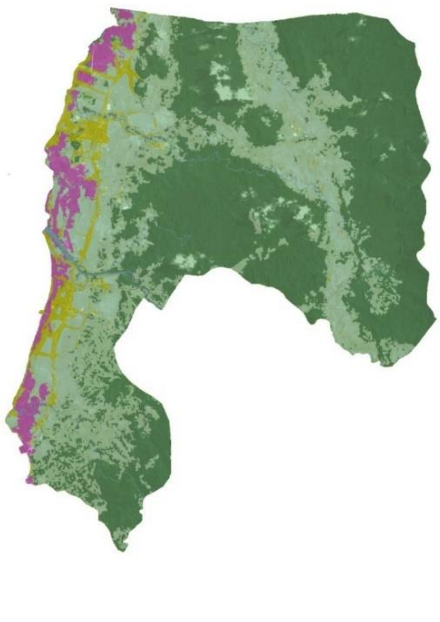

Fig. 8. Prediction map land year 2033

Figure 9 Prediction land 2033 Where there is change which enough significant which happen on land awakened compared to built-up land in 2023. Differences in change land in 2023 and 2033 can be seen in table 4.

Table 4. Land use 2023 year – 2033 year

Class	Year		Difference
	2021	2033	
1	2	3	4
Built Up Land	948.17	1183.75	235.57
Land Agriculture	10409.69	10228.88	-180.81
pond	1210,14	1202.71	-7.42
Forest	15050.05	15002.71	-47.34
River	220.84	220.84	0
	27838.89	27838.89	

From table 4, it can be seen the changes from 2023 to 2033 additional land awakened around 235.57 Ha and land agriculture become land which most lots reduce land agriculture around 180.81 ha.

Fig. 9. Map change land 2021-2033

5 Conclusion

The study addresses three main problem formulations; Land Use Changes in Transportation Node Areas: Over the past 20 years, significant changes have occurred in land use around transportation nodes in Barru Regency. Notably, the area of built-up land has increased by approximately 770.51 hectares. The most substantial land use change occurred in Tanete Rilau Subdistrict, with a notable difference of 104.15 hectares compared to Barru Subdistrict. Agricultural land has become the dominant type of land use change, with an increase of around 289.94 hectares. Trends in Land Use Change: From 2001 to 2016, and continuing through 2011 to 2023, the trend in land use change shows a shift. Initially, the Garonggong Port transportation node in Tanete Rilau District was the center of change. However, as of the more recent period, the focus has shifted to Barru Subdistrict, where built-up land has become the dominant change factor. Future Land Use Predictions: Using Cellular Automata (CA)-Markov and Artificial Neural Networks (ANN) for analysis, the study predicts land use changes for 2033. The results indicate an additional 235.57 hectares of built-up land over the next 20 years. The analysis incorporates various driving factors such as building density, road proximity, DEM data, slope, and service centers, achieving a high accuracy value of 97%, surpassing previous research findings.

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