https://jurnal.unimed.ac.id/2012/index.php/geo/article/view/48121
https://doi.org/10.24114/jg.v16i1.48121 - (Vol 16, No 1 – 2024)
available at http://jurnal.unimed.ac.id/2012/index.php/geo
e-issn (2549-7057) & p-issn (2085-8167)

Modeling of Land Cover Changes in Banjarbaru City South Kalimantan Province

Aswin Nur Saputra[1*], M Wahyu Saputra[1], Hendy Fatchurohman[2], Prama Ardha Aryaguna[3]
[1] Geography Education Study Program, Universitas Lambung Mangkurat, Indonesia
[2]Department of Geography, Faculty of Social and Historical Science, University College London, North West Wing, Gower Street, London
[3]Department of Survey and Mapping, Esa Unggul University, Indonesia

ARTICLE INFO
Article History:
Received: June 27, 2023
Revision: March 15, 2024
Accepted: March 15, 2024

Keywords:
Land Cover
Land Change Modeller
Cellular Automata
Markov Chain

Corresponding Author
E-mail: aswin.saputra@ulm.ac.id

ABSTRACT
Urban areas often experience land cover changes. Banjarbaru is one of several cities in Indonesia that has experienced land changes. The relocation of the administrative center of Banjarmasin City to Banjarbaru City led to the development of settlements. One spatial analysis carried out to examine the phenomenon of land change is remote sensing techniques. The method that can be used is the Land Change Modeler from MOLUSCE in QGIS. This model uses the CAM (Cellular Automata Markov) method to identify land cover change and predict land cover distribution. CAM can understand and predict land change patterns by considering land use, vegetation, and cell spatial interactions. This modeling is based on land cover data for 2015 and 2020 and several supporting parameters such as DEM data and distance to roads. Based on the modeling results from 2015 and 2020, Banjarbaru City experienced a change in built-up land, with most of it occurring in the center of Banjarbaru City. Based on the Markov Chain method by looking at land changes in the previous year, the development of built-up land increased by about 8% of the Banjarbaru City area of 32917.41 hectares. Based on the prediction results, the development of built-up land is centered in the middle of Banjarbaru City, such as North and South Banjarbaru Districts, due to the development of residential development.

INTRODUCTION

Land cover change is a complex phenomenon based on complex relationships, interactions between different land cover classes, the diversity of variations, and factors that cause land cover change (Lambin et al., 2003; Mahmood et al., 2014). Urban areas often experience changes in land cover. Development activities cause changes in land cover (Cervero, 2013; Kosasih et al., 2019). Rapid development causes changes in land cover, where built-up land increasingly dominates and forces natural land to change its function (Arisanty et al., 2021; Hermon, 2012; Wu et al., 2013). Altering a region's land cover can shift its functions from their original purposes, adversely affecting the environment and the land's potential. Factors such as population growth, the development of new cities and large manufacturing projects, increased job opportunities, and improved transportation access may drive changes in land cover (Nurhanifah, 2021; Putri & Wicaksono, 2021). One of the cities in Indonesia that have experienced significant land cover change is Banjarbaru City (Muhaimin & Ramali, 2021; Supriatna et al., 2022). Changes in land cover that occurred in Banjarbaru resulted in the locking of the center of government from Banjarmasin to Banjarbaru in 2012, so construction took place.

The increase in railroad construction was caused by the large number of residents who urbanized to Banjarbaru (Maryati et al., 2021). In 2015, the original population was

227,500 in 2014 to 234,371 in 2015, around 6,871 people who experienced an increase (Erlina & Suherty, 2019). The population increase continues until 2020, with around 253,442 people based on BPS 2021. This increase in population affects the area of sellers' land. The increase in land area in 2015-2020 is a reference for knowing changes in land cover in 2025. The growth of urban areas and a rise in population could reduce the amount of fertile agricultural land available (Sadali, 2018).

Identifying land-cover changes manually in the field is feasible for small-scale changes but becomes challenging when changes occur on a larger scale. Different attempts have been made to find the appropriate method, with one approach involving remote sensing technology (Febrianti et al., 2023). Satellite imagery offers an alternative solution to many problems associated with LCLU changes and their impacts on society and the environment (Indarto et al., 2020).

Spatial approaches such as remote sensing are used to analyze data changes. Spatial modeling related to land cover change is widely used in analyzing land cover change, such as Markov Chain, Cellular Automata, and empirical models (Rimal et al., 2017). Information on changes in land cover was obtained using Landsat 8 OLI/TIRS satellite image data. Landsat 8 OLI/TIRS imagery is based on each channel used to determine land cover classification (Estoque & Murayama, 2015).

Changes in land cover that occurred in 2015 and 2020 are exciting topic issues for research, as well as the extent of changes in land cover in those two years and the potential changes that will occur in 2025. The purpose of this research is explained in the topic of the problem: to analyze the extent of land cover change in 2015 and 2020 and the potential for land cover change to occur in 2025.

This research will collect historical land cover data, satellite imagery, and accessibility indicators to calibrate the CAM (Cellular Automata Markov) model. The model will then simulate future land cover changes based on different scenarios and urban development policies. By applying CAM to study urban expansion dynamics, this research seeks to provide valuable insights into the drivers of land cover change in developing cities. The findings could help urban planners and policymakers make informed decisions regarding sustainable land use planning, infrastructure development, and environmental conservation efforts. Additionally, the study may contribute to the advancement of spatial modeling techniques for predicting land cover changes in dynamic urban environments.

RESEARCH METHODS

This research was conducted in Banjarbaru, South Kalimantan Province. The location was chosen because Banjarbaru is one of the cities that has experienced rapid development since the move of the government center to Banjarbaru. The effect of displacement has not least caused several land conversions, such as reduced vegetation land to become built-up land or bare land. The data used in this study include Landsat 8 OLI/TIRS imagery, Digital Elevation Model (DEM), and distance to road maps. The tools used are a set of laptops with ArcGIS software for the initial processing of vector data, ENVI to perform digital land cover classification, QGIS to model land cover changes and mobile GPS for field surveys.

Remote sensing techniques are used in this study to interpret land cover and classification processes. Interpretation using Landsat 8 OLI/TIRS imagery for coverage in the dry season assuming lower cloud cover. The images used are Landsat 8 on 13 August 2015 and 5 May 2020. The classification process uses supervised classification with the maximum likelihood classification method (Aryaguna & Saputra, 2020a; Khatami et al., 2016). Determination of classification using land cover classification from Anderson with four land cover classes that can be found in this study according to Table 1.

Table 1. Land Cover Class

No	Land Cover Class	Information
1	Built up	Housing, offices, industry, infrastructure, and development facilities
2	Bare land	Bare land, landfills, and mining area
3	Vegetation	Forests, rice fields, agriculture, and plantations
4	Waterbody	Rivers, lakes, swamps, and reservoirs

(Source: Anderson 1979 in (Aryaguna & Saputra, 2020b)

In the early stages of this research, radiometric and geometric corrections were made to Landsat 8 OLI/TIRS images before being used for the classification process. Radiometric correction is done to correct image errors due to atmospheric phenomena when recording and converting digital number values into reflectance values (Arisanty et al., 2019; López-Serrano et al., 2016; Pons et al., 2014). The geometric correction is carried out to adjust the georeferenced image conditions with the existing georeferenced on the earth's surface.

For the image that has been corrected, the land cover classification is carried out according to Table 1. The land cover change classification results are analyzed based on the land cover data obtained by digital classification using maximum likelihood. The number of samples used in digital processing classification is 100 points spread across the administrative area of Banjarbaru. The results of the classification obtained land cover maps for 2015 and 2020. The results of the classification were tested for accuracy using a confusion matrix. The 2015 land cover accuracy test used images from Google Earth with 2015 coverage, while the 2020 land cover accuracy test was conducted with a field survey.

Land cover data tested for accuracy is used for the land cover change modeling stage. The land cover change modeling phase uses land cover data for 2015 and 2020 as the primary data and altitude data and distance to roads as supporting data in the modeling process. Modeling uses the help of QGIS software with MOLUSCE plugins at the construction stage (Muhammad et al., 2022) The modeling results are in the form of the latest land cover data with an accuracy test carried out in the field.

RESULTS AND DISCUSSION

The results of a land cover classification in 2015 and 2020 using supervised classification using maximum likelihood in ArcGIS software can be seen in Figures 1 and 2. The land cover classification results were tested for accuracy with the confusion matrix table, and the results were 87% for 2015 and 96 % for 2020. The accuracy test results can be seen in Tables 2 and 3. The accuracy test process aims to determine the accuracy of land cover data for 2015 and 2020 before being used for modeling land cover change in Banjarbaru.

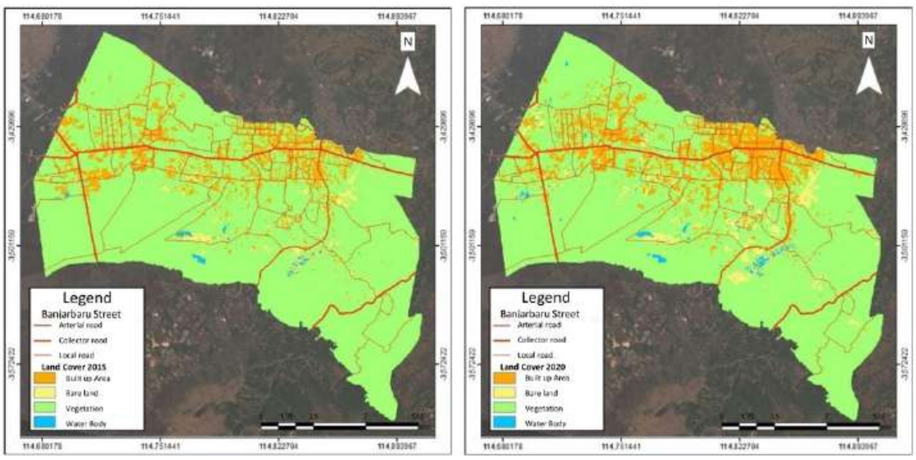

Figure 1. (a) Land cover in 2015; (b) Land cover in 2020 (Source: Data Processing, 2023)

Table 2. Accuration test of land cover in 2015

	Land Cover 2015	Classified values: Built up area	Bare land	Vegetation	Waterbody	Total	User accuracy	Total class area (Ha)
Thematic raster	Built up area	5302	39	1150	0	6491	0.82	584.19
	Bare land	26	1102	453	26	1607	0.69	144.63
	Vegetation	0	0	22734	0	22734	1.00	2046.06
	Water body	1	0	0	289	290	1.00	26.10
	Total	5329	1141	24337	315	31122		2800.98
	Producer accuracy	0.99	0.97	0.93	0.92		0.87	
	Overall Accuracy				0.87			

(Source: Data Processing, 2023)

Table 3. Accuration test of land cover in 2020

	Land Cover 2020	Classified values: Built up area	Bare land	Vegetation	Waterbody	Total	User accuracy	Total class area (Ha)
Thematic raster	Built up area	1431	12	49	0	1492	0.96	134.28
	Bare land	17	686	43	12	758	0.91	68.22
	Vegetation	123	62	31456	4	31645	0.99	2848.05
	Waterbody	2	7	3	392	404	0.97	36.36
	total	1573	767	31551	408	34299		3086.91
	Producer accuracy	0.91	0.89	1.00	0.96		0.96	
	Overall Accuracy				0.96			

(Source: Data Processing, 2023)

Data on altitude and distance to roads are also used for land cover modeling (Puertas et al., 2014). Elevation and distance to roads can have significant influences on land cover change. Studies have shown that as the distance to roads increases, there are fewer changes in land use and land cover change (Patarasuk & Binford, 2012). Elevation, on the other hand, can affect land cover change through its impact on vegetation and soil conditions (Liu et al., 2021) The results of the altitude and distance to the road can be seen in Figures 3 and 4. The altitude in Banjarbaru is included in the lowland category with an altitude of 0-380 meters. The altitude of the place in Banjarbaru has increased to the east around the Cempaka District area.

Banjarbaru City's Roads have adequate mobility access for the influence of development with the main road route around Jl. Ahmad Yani. Distance to road analysis results using Euclidean Distance in ArcGIS software shows results of 0-3918.07 meters. The results of the distance to the road explain the effect of the shortest distance to the road (Leta et al., 2021). The shortest distance to the road starts from 0, and the longest distance is at 3918.07.

The relationship between the altitude data and the distance to the road is used for the land cover modeling process. The influence of altitude and distance data on the road was analyzed in evaluation correlations using the Pearson correlation technique (Al-Najjar et al., 2019). The results of the Pearson correlation between the altitude data and the Euclidean distance of the road is 0.1 or the correlation is very weak. Pearson correlation results can be seen in Table 4.

Table 4. Relationship of Altitude Data and Distance to the Road

No	Class	Distance to Road	Altitude
1	Distance to Road	0	0.11114
2	Altitude	0	0

(Source: Data Processing, 2023)

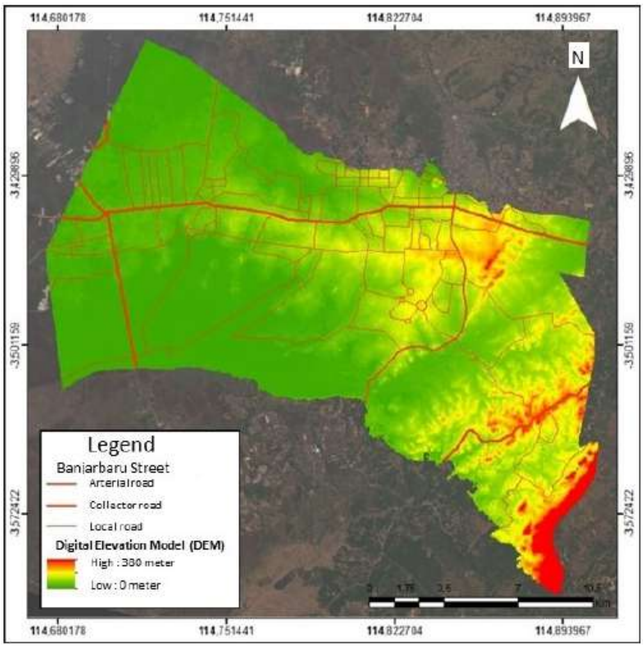

Figure 2. Digital Elevation Model in Banjarbaru (Source: Data Processing, 2023)

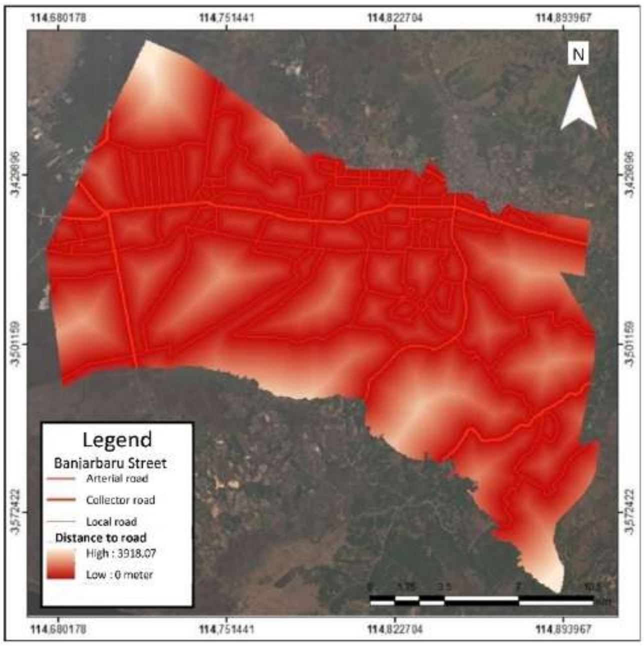

Figure 3. Distance to Road (Source: Data Processing, 2023)

Table 5. Land Cover Changes in 2015 and 2020

Class Statistic		Area (Ha)			Percentage		
No	Class	2015	2020	Δ	2015%	2020%	Δ %
1	Built up area	3593.61	4639.95	1046.34	10.92	14.10	3.18
2	Bare land	603.9	1407.69	803.79	1.83	4.28	2.44
3	Vegetation	28597.68	26630.55	-1967.13	86.88	80.90	-5.98
4	Waterbody	122.22	239.22	117	0.37	0.73	0.36
	Total	32917.41	32917.41		100	100	

(Source: Data Processing, 2023)

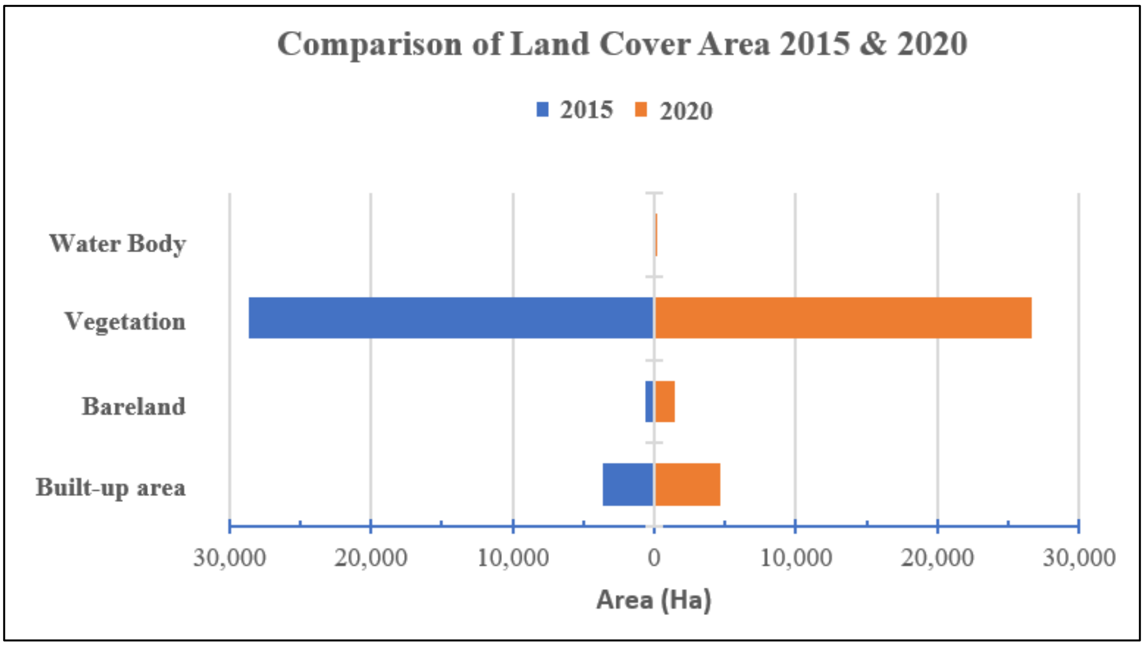

Figure 4. Comparison of the land cover area in 2015 and 2020 (Source: Data Processing, 2023)

The results of the 2015 and 2020 land cover analysis show the level of change over five years. According to Anderson, the effect of changes is based on land cover class parameters. The results of the land cover analysis can be seen in Table 5. The percentage of changes in land cover that occurred over five years from 2015 and 2020 saw a significant increase in built-up land with a percentage of 3.18%. A significant decrease in the rate of change in land cover occurred in vegetation types where the rate of decline was at -5.98% of the total area of 32917.41 Ha. Changes in land cover in 2015 and 2020 are also explained in profit and loss diagrams, which can be seen in Figure 4.

The distribution of land cover changes resulting from land cover data for 2015 and 2020, supported by altitude and distance to roads, shows that several land cover classes have changed. The distribution of land cover changes can be seen in Figure 6. The distribution results are supported by a transition matrix table for the distribution of land cover changes which can be seen in Table 6.

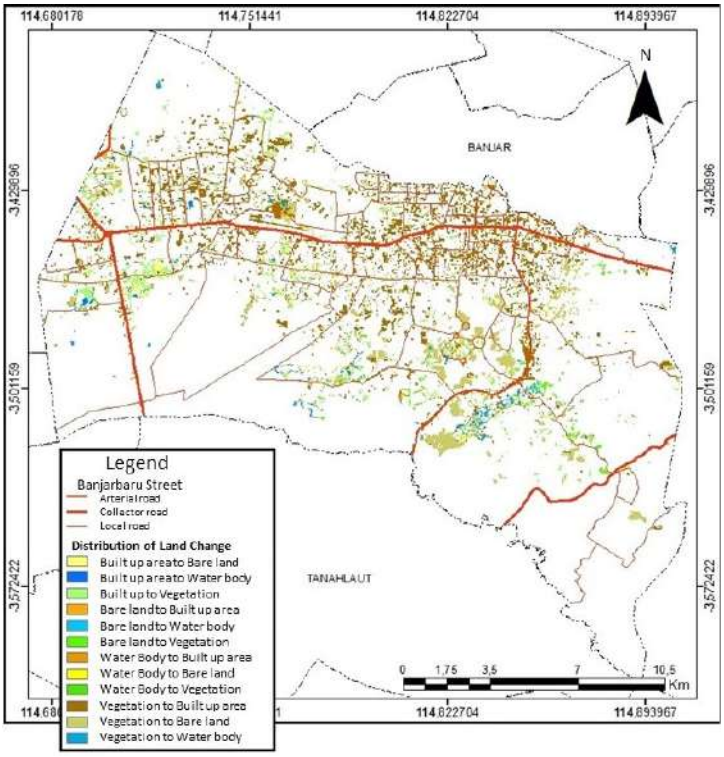

Figure 5. Distribution of Land Cover Change (Source: Data Processing, 2023)

Table 6. Land Cover Change Distribution Transition Matrix

Transition Matrix	Built up area	Bare land	Vegetation	Waterbody
Built up area	0.73571	0.03827	0.21516	0.01087
Bare land	0.07779	0.56915	0.30179	0.05127
Vegetation	0.06807	0.03205	0.89716	0.00273
Waterbody	0.02136	0.08174	0.15096	0.74595

(Source: Data Processing, 2023)

Table 7. Distribution Area of Land Cover Change

No	Class	Area (Ha)	Percentages (%)
1	Built up area	2643.84	8.03
2	Built-up area to Bare land	137.52	0.42
3	Built-up area to Vegetation	773.19	2.35
4	Built-up area to Waterbody	39.06	0.12
5	Bare land to Built up area	46.98	0.14
6	Bare land	343.71	1.04
7	Bare land to Vegetation	182.25	0.55
8	Bare land to Water body	30.96	0.09
9	Vegetation to Built up area	1946.52	5.91
10	Vegetation to Bare land	916.47	2.78
11	Vegetation	25656.66	77.94
12	Vegetation to Water body	78.03	0.24
13	Water body to Built up area	2.61	0.01
14	Water body to Bare land	9.99	0.03
15	Water body to Vegetation	18.45	0.06
16	Waterbody	91.17	0.28
	Total	32917.41	100.00

(Source: Data Processing, 2023)

The distribution area of land cover changes based on the distribution of land cover changes shows several areas that have changed, such as the area of bare land that became the built-up area of 46.98 Ha or the area of vegetation that became built-up area of 1946.52 Ha. The results of the distribution area of land cover change can be seen in Table 7.

The results of land cover distribution are used to determine the transition potential model. The potential transition model uses Artificial Neural Network (ANN) and Logistic Regression (LR) as analytical media in determining land cover change predictions (Sajan et al., 2022). The results of the Artificial Neural Network (ANN) method show a kappa index validation level of 0.76 for the potential transition of land cover change prediction. The Logistic Regression method shows the opposite value related to the potential transition effect of 0.92 Pseudo R-squared or how well the level of the equation model is formed.

The results of the potential transition model are simulated into predictions of land cover change in 2025. Land cover in 2025 is generated from the Markov chain model with the variable land cover prediction in 2015 and 2020 in the QGIS plugins MOLUSCE software. The 2025 land cover model was validated based on the 2020 simulation model. The model simulation results for the 2020 land cover validated the overall kappa level or kappa index at 90%. The results of land cover in 2025 can be seen in Figure 5.

The results of land cover in 2025 are then carried out by field accuracy tests to determine the accuracy of the predictions determined. The results of the field accuracy test can be seen in Table 8. The accuracy test for land cover in 2025 shows 90% results. The 2025 land cover results show that Banjarbaru will experience changes in land cover. Changes in land cover that occurred in Banjarbaru were concentrated in built-up land with a total built-up area of 4991.67 Ha, and areas with high potential for built-up land were in North and South Banjarbaru District due to the concentration of settlements in North and South Banjarbaru. The bare land area is around 1779.84 Ha, compared to the 2020 area of around 1407.69 Ha, with areas with high potential in Cempaka District.

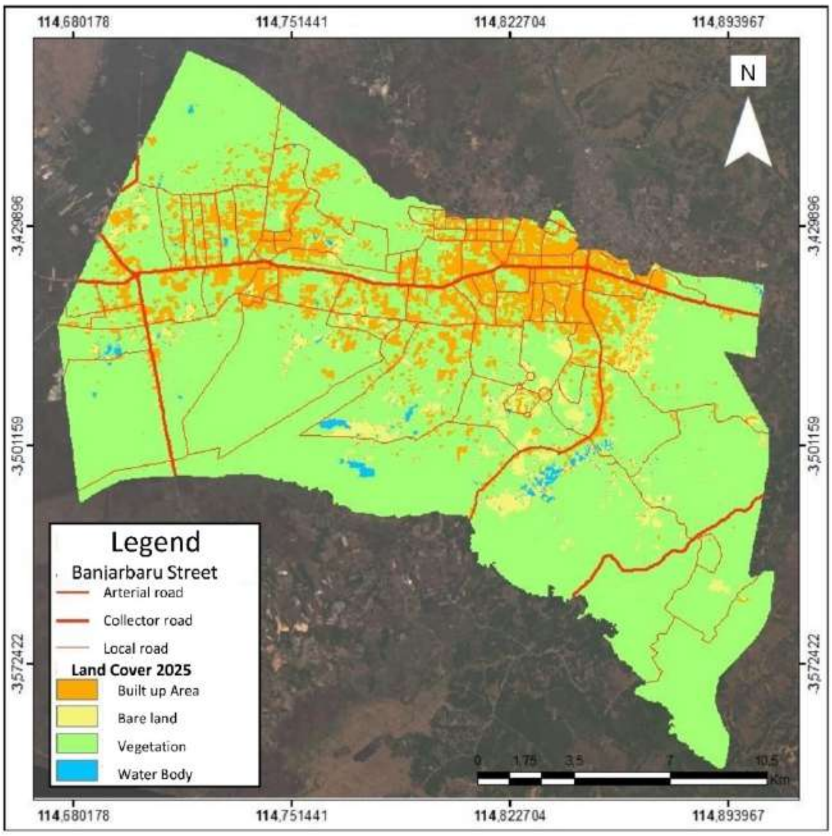

Figure 6. Land Cover Prediction Map in 2025 (Source: Data Processing, 2023)

Table 8. Land Cover Accuracy Test in 2025

	Land Cover in 2025	Classified values						
		Built up area	Bare land	Vegetation	Waterbody	Total	User accuracy	Total class area (Ha)
Thematic raster	Built up area	10	0	0	0	10	1.00	4991.67
	Bare land	1	8	0	0	9	0.89	1779.84
	Vegetation	0	0	12	1	13	0.92	25870.23
	Water body	0	1	1	6	8	0.75	279.72
	total	11	9	13	7	40		32921.46
	Producer accuracy	0.91	0.89	0.92	0.86		0.90	
	Overall Accuracy				0.90			

(Source: Data Processing, 2023)

CONCLUSION

Changes in land cover that occurred in 2015 and 2020 show the level of change where the built-up land area is around 3583.61 Ha to 4539.95 Ha, and the bare land area is around 603.9 Ha to 1407.69 Ha. The body of water is around 122.22 Ha to 239.22 Ha, while the area of vegetation has decreased from 28597.68 Ha to 26630.55 Ha. The potential for changes in land cover in 2025 can be seen in the fact that built-up land will increase from 4640.31 Ha in 2020 to 4991.67 Ha and the bare land area from 1407.69 Ha to 1779.84 Ha. Areas with the potential to experience land change occur in North and South Banjarbaru District as built-up land and Cempaka District as bare land. North Banjarbaru District is connected to Martapura City, which is the capital of Banjar Regency, and is planned for a new residential area so that it has the potential to become a built-up area in the next few years. Whereas in Cempaka District, the potential for bare land in the next few years is based on active community mining activities.

The results of this study can serve as a basis for conducting further simulation processes to model land cover change. Elevation parameters and distance to the road are proven to influence the distribution of land cover, especially in urban areas. The CAM (Cellular Automata Markov) method in the MOLUSCE instrument in QGIS can provide information on land cover change and model future land cover forecasting.

ACKNOWLEDGMENT

The author thanks the Geography Education FKIP, University of Lambung Mangkurat students who have assisted in conducting field surveys in this research.

REFERENCES LIST

Al-Najjar, H. A. H., Kalantar, B., Pradhan, B., & Saeidi, V. (2019). Conditioning factor determination for mapping and prediction of landslide susceptibility using machine learning algorithms. In K. Schulz, K. G. Nikolakopoulos, & U. Michel (Eds.), Earth Resources and Environmental Remote Sensing/GIS Applications X (p. 19). SPIE. https://doi.org/10.1117/12.2532687

Arisanty, D., Adyatma, S., Muhaimin, M., & Nursaputra, A. (2019). Landsat 8 OLI TIRS Imagery Ability for Monitoring Post Forest Fire Changes. Pertanika Journal of Science & Technology, 27(3).

Arisanty, D., Anis, M. Z. A., Putro, H. P. N., Hastuti, K. P., & Angriani, P. (2021). Social Vulnerability of Land Fires in Banjarbaru. https://doi.org/10.2991/assehr.k.210222.042

Aryaguna, P. A., & Saputra, A. N. (2020a). Land change modeler for predicting land cover change in Banjarmasin City, South Borneo (2014 - 2022). IOP Conference Series: Earth and Environmental Science, 500, 012002. https://doi.org/10.1088/1755-1315/500/1/012002

Aryaguna, P. A., & Saputra, A. N. (2020b). Land change modeler for predicting land cover change in Banjarmasin City, South Borneo (2014 - 2022). IOP Conference Series: Earth and Environmental Science, 500(1). https://doi.org/10.1088/1755-1315/500/1/012002

Cervero, R. (2013). Linking urban transport and land use in developing countries. Journal of Transport and Land Use, 6(1), 7–24. https://doi.org/10.5198/jtlu.v1.425

Erlina, & Suherty, L. (2019). Pengaruh Jumlah Penduduk, Penduduk Miskin dan Pengangguran Terbuka Terhadap Pertumbuhan Ekonomi di Kota Banjarbaru. JIEP: Jurnal Ilmu Ekonomi Dan Pembangunan, 2(4), 852. https://doi.org/10.20527/jiep.v2i4.1219

Estoque, R. C., & Murayama, Y. (2015). Classification and change detection of built-up lands from Landsat-7 ETM+ and Landsat-8 OLI/TIRS imageries: A comparative assessment of various spectral indices. Ecological Indicators, 56, 205–217. https://doi.org/10.1016/j.ecolind.2015.03.037

Febrianti, N. K. O., Danoedoro, P., & Widayani, P. (2023). Land-Cover Change Detection in Batur Catchment Area Using Remote Sensing. Jurnal Geografi, 15(1), 64. https://doi.org/10.24114/jg.v15i1.32670

Hermon, D. (2012). Dinamika Cadangan Karbon akibat Perubahan Tutupan Lahan menjadi Lahan Permukiman di Kota Padang Sumatera Barat. Forum Geografi, 26(1), 45. https://doi.org/10.23917/forgeo.v26i1.5049

Indarto, I., Mandala, M., Febrian Arifin, F., & Lukman Hakim, F. (2020). Aplikasi Citra Sentinel-2 untuk Pemetaan Tutupan dan Peruntukan Lahan pada Tingkat Desa. JURNAL GEOGRAFI, 12(02), 189. https://doi.org/10.24114/jg.v12i02.16970

Khatami, R., Mountrakis, G., & Stehman, S. V. (2016). A meta-analysis of remote sensing research on supervised pixel-based land-cover image classification processes: General guidelines for practitioners and future research. Remote Sensing of Environment, 177, 89–100. https://doi.org/10.1016/j.rse.2016.02.028

Kosasih, D., Buce Saleh, M., & Budi Prasetyo, L. (2019). Visual and Digital Interpretations for Land Cover Classification in Kuningan District, West Java. Jurnal Ilmu Pertanian Indonesia, 24(2), 101–108. https://doi.org/10.18343/jipi.24.2.101

Lambin, E. F., Geist, H. J., & Lepers, E. (2003). Dynamics of Land-Use and Land-Cover Change in Tropical Regions. Annual Review of Environment and Resources, 28(1), 205–241. https://doi.org/10.1146/annurev.energy.28.050302.105459

Leta, M. K., Demissie, T. A., & Tränckner, J. (2021). Modeling and Prediction of Land Use Land Cover Change Dynamics Based on Land Change Modeler (LCM) in Nashe Watershed, Upper Blue Nile Basin, Ethiopia. Sustainability, 13(7), 3740. https://doi.org/10.3390/su13073740

Liu, Z., Yang, Y., Ji, S., Dong, D., Li, Y., Wang, M., Han, L., & Chen, X. (2021). Effects of Elevation and Distance from Highway on the Abundance and

Community Structure of Bacteria in Soil along Qinghai-Tibet Highway. International Journal of Environmental Research and Public Health, 18(24), 13137. https://doi.org/10.3390/ijerph182413137

López-Serrano, P., Corral-Rivas, J., Díaz-Varela, R., Álvarez-González, J., & López-Sánchez, C. (2016). Evaluation of Radiometric and Atmospheric Correction Algorithms for Aboveground Forest Biomass Estimation Using Landsat 5 TM Data. Remote Sensing, 8(5), 369. https://doi.org/10.3390/rs8050369

Mahmood, R., Pielke, R. A., Hubbard, K. G., Niyogi, D., Dirmeyer, P. A., McAlpine, C., Carleton, A. M., Hale, R., Gameda, S., Beltrán-Przekurat, A., Baker, B., McNider, R., Legates, D. R., Shepherd, M., Du, J., Blanken, P. D., Frauenfeld, O. W., Nair, U. S., & Fall, S. (2014). Land cover changes and their biogeophysical effects on climate. International Journal of Climatology, 34(4), 929–953. https://doi.org/10.1002/joc.3736

Maryati, S., Humaira, A. N. S., Afriana, A., Roekmi, R. A. K., & Suhartini, N. (2021). Developer behavior in local infrastructure provision in Indonesia: Implications for policy. Utilities Policy, 70, 101183. https://doi.org/10.1016/j.jup.2021.101183

Muhaimin, M., & Ramali, A. (2021). Development of Leading Sectors and Competitiveness of Animal Husbandry Commodities in Banjarbaru City 2010-2016. https://doi.org/10.2991/assehr.k.210222.066

Muhammad, R., Zhang, W., Abbas, Z., Guo, F., & Gwiazdzinski, L. (2022). Spatiotemporal Change Analysis and Prediction of Future Land Use and Land Cover Changes Using QGIS MOLUSCE Plugin and Remote Sensing Big Data: A Case Study of Linyi, China. Land, 11(3), 419. https://doi.org/10.3390/land11030419

Nurhanifah, N. (2021). Description and Mapping of Urbanization Development in Sumatera Utara. JURNAL GEOGRAFI, 13(2), 251. https://doi.org/10.24114/jg.v13i2.23206

Patarasuk, R., & Binford, M. W. (2012). Longitudinal analysis of the road network development and land-cover change in Lop Buri province, Thailand, 1989–2006. Applied Geography, 32(2), 228–239. https://doi.org/10.1016/j.apgeog.2011.05.009

Pons, X., Pesquer, L., Cristóbal, J., & González-Guerrero, O. (2014). Automatic and improved radiometric correction of Landsat imagery using reference values from MODIS surface reflectance images. International Journal of Applied Earth Observation and Geoinformation, 33, 243–254. https://doi.org/10.1016/j.jag.2014.06.002

Puertas, O. L., Henríquez, C., & Meza, F. J. (2014). Assessing spatial dynamics of urban growth using an integrated land use model. Application in Santiago Metropolitan Area, 2010–2045. Land Use Policy, 38, 415–425. https://doi.org/10.1016/j.landusepol.2013.11.024

Putri, L. M., & Wicaksono, P. (2021). Mapping of Land Use Changes in The Core Zone of Parangtritis Sand Dunes Using OBIA Method 2015-2020. JURNAL GEOGRAFI, 13(1), 109. https://doi.org/10.24114/jg.v13i1.21465

Rimal, B., Zhang, L., Keshtkar, H., Wang, N., & Lin, Y. (2017). Monitoring and Modeling of Spatiotemporal Urban Expansion and Land-Use/Land-Cover

Change Using Integrated Markov Chain Cellular Automata Model. ISPRS International Journal of Geo-Information, 6(9), 288. https://doi.org/10.3390/ijgi6090288

Sadali, M. I. (2018). Ketahanan Pangan Berkelanjutan di Kabupaten Sukoharjo. JURNAL GEOGRAFI, 10(1), 86. https://doi.org/10.24114/jg.v10i1.8493

Sajan, B., Mishra, V. N., Kanga, S., Meraj, G., Singh, S. K., & Kumar, P. (2022). Cellular Automata-Based Artificial Neural Network Model for Assessing Past, Present, and Future Land Use/Land Cover Dynamics. Agronomy, 12(11), 2772. https://doi.org/10.3390/agronomy12112772

Supriatna, S., Hashilah, F., Mukhtar, M. K., & Wardani, K. K. (2022). Determinant of Land Use Change in South Kalimantan: An Evidence from Banjarbaru City and Banjar Regency. Forest and Society, 6(1), 422–435. https://doi.org/10.24259/fs.v6i1.18469

Wu, K., Ye, X., Qi, Z., & Zhang, H. (2013). Impacts of land use/land cover change and socioeconomic development on regional ecosystem services: The case of fast-growing Hangzhou metropolitan area, China. Cities, 31, 276–284. https://doi.org/10.1016/j.cities.2012.08.003