LAND COVER CHANGE PREDICTION USING CELLULAR AUTOMATA AND MARKOV CHAIN MODELS

Amandus Jong Tallo [1*]; Maria Gratiana Yudith Tallo [2]; Antonius Leonardo Antjak[3]; Maria Imanuela Doko[4]; Maria Anita Christanti Lodang[5]

Irrigation Design and Coastal Engineering Techniques, Department of Civil Engineering[1,3,4,5]
Business Management, Department of Business Administration[2]
Politeknik Negeri Kupang, Indonesia[1,2,3,4,5]
https://pnk.ac.id/ [1,2,3,4,5]
mandustallo@gmail.com[1*], talloyudith@gmail.com[2], ronaldantjak11@gmail.com[3], ayudoko8@gmail.com[4]
(*) Corresponding Author

Abstract—*This research examines the impact of land use change on mobility. Spatial problems arise due to increased activity, population, and transportation in the same space, necessitating the development of modeling strategies. This aligns with SDG 11 on cities and settlements, as well as the PRN's focus on transportation innovation. The urgency of this research lies in its adaptive and sustainable spatial prediction efforts aimed at controlling future land use. This study aims to analyze land use change patterns using the Cellular Automata Markov Chain (CA-Markov) model in Kupang City until 2043. CA-Markov simulations efficiently evaluate land cover changes and movement. The quantitative research method was conducted based on spatial predictions and spatial configuration. Quantum GIS (QGIS) and GeoSOS-FLUS were used to obtain results from each stage. There are three research stages. First, identification of land cover (land use in 2018 and 2023), driving factors (distance to settlements, airports, highways, elevation, slope, slope orientation, rainfall, population density), and conservation areas. Second, standardisation of spatial data. Third, land cover prediction using GeoSOS software (five-year prediction) to identify patterns of land use change. These findings emphasize the importance of using CA-Markov-based spatial predictions as a foundation for adaptive spatial planning to control land-use conversion and maintain sustainable spatial connectivity in Kupang City until 2043.*

Keywords: *CA-Markov, Room Configuration, Kupang.*

Intisari—Penelitian ini didasari dampak alih fungsi lahan menyebabkan terhambatnya mobilitas pergerakan. Masalah spasial akibat peningkatan aktivitas, penduduk dan transportasi pada ruang yang sama, sehingga membutuhkan strategi pemodelan, ini sejalan dengan SDGS 11 tentang kota dan permukiman, dan fokus PRN pada bidang inovasi transportasi. Urgensi dari penelitian ini sebagai upaya spasial prediksi secara adaptif dan berkelanjutan, guna kontrol penggunaan lahan masa depan. Penelitian ini bertujuan untuk menganalisis pola perubahan penggunaan lahan dengan Cellular Automata Markov Chain (CA-Markov) di Kota Kupang hingga tahun 2043. Simulasi CA-Markov efisien mengevaluasi perubahan tutupan lahan dan pergerakan. Metode penelitian kuantitatif dilakukan dengan berbasis prediksi spasial dan konfigurasi ruang. Pemanfaatan Quantum GIS (QGIS) dan GeoSOS-FLUS, dilakukan guna mendapatkan hasil dari setiap tahapan. Terdapat tiga tahapan penelitian, pertama, identifikasi tutupan lahan (penggunaan lahan tahun 2018 dan tahun 2023), faktor pendorong (jarak ke pemukiman, bandara, jalan raya, ketinggian, kemiringan, orientasi lereng, curah hujan, kepadatan penduduk), area konservasi. Kedua, standarisasi data spasial. Ketiga, prediksi prediksi tutupan lahan dengan software GeoSOS (prediksi 5 tahunan), guna mendapatkan pola perubahan jenis lahan. Temuan ini menekankan pentingnya menggunakan prediksi spasial berbasis CA-Markov sebagai landasan untuk perencanaan spasial adaptif guna mengendalikan konversi penggunaan lahan dan mempertahankan konektivitas spasial yang berkelanjutan di Kota Kupang hingga tahun 2043.

Kata Kunci: *CA-Markov, Konfigurasi Ruang, Kupang.*

PENDAHULUAN

Urban development requires integrating static spatial structures with dynamic human activities and evolving population dynamics. Effective transportation systems and strategic land use planning play a crucial role in enhancing spatial connectivity. Kupang City, located in southern Indonesia, functions as a national activity centre (PKN) and continues to grow in education, government, and trade service sectors (Luwarti et al., 2023; Tallo et al., 2018, 2024). Rapid population growth of 31 percent between 2010 and 2020 has intensified urbanisation, resulting in significant land conversion, particularly of rice fields and mangroves (Angin & Sunimbar, 2021; Kupang, 2020; Statistik, 2023).

These dynamics highlight the need for predictive analysis to support adaptive land use planning, in line with Sustainable Development Goal 11 (SDG 11). Previous studies show that land use change in Kupang has largely affected rice fields, gardens, and mangroves, driven by residential development and educational infrastructure (Angin & Sunimbar, 2021; Pauleit et al., 2005a).

Traffic congestion arises when the volume of vehicles exceeds the designed capacity of transportation infrastructure, resulting in reduced mobility and increased travel times (A. Wadu, A. A. Tuati, 2020). Insufficient drainage capacity and malfunctioning drainage systems significantly worsen traffic conditions during the rainy season The relationship between land use change, population dynamics, and movement connectivity in Kupang City highlights the need for predictive analysis. This study examines how land use predictions can inform strategies to enhance spatial connectivity in Kupang City, given the crucial role of land use planning in directing development according to designated functions.

The GeoSOS-FLUS software was employed to simulate land cover changes using the Cellular Automata-Markov Chain (CA-Markov) method. Land cover data from 2018 and 2023 were analyzed to identify change patterns, providing a foundation for future land cover predictions. The CA-Markov method facilitated both the analysis and modeling of land cover dynamics. (Li et al., 2023; Villamor et al., 2015; Wang et al., 2021). Quantitative drivers are used to evaluate the dynamics of land use and land cover change (Altafinio & Poloni, 2022; Purnama F et al., 2024).

Previous studies using the CA–Markov approach in other Indonesian cities, such as Ambon (Sugandhi et al., 2022) and Banjarmasin (Supriatna et al., 2022), have also demonstrated significant urban expansion at the expense of natural land cover. While the Ambon case emphasised conversion from agricultural to built-up areas, the Banjarmasin study highlighted the decline of wetlands and grasslands. Compared with these cases, Kupang shows both similarities—rapid urbanisation leading to loss of natural vegetation—and differences, particularly the substantial conversion of rice fields and mangroves. These variations are explained by each city's geographic context, demographic pressures, and economic drivers.

Research Gap and Contribution. Most previous studies have focused on other Indonesian cities and relied primarily on the CA–Markov model without integrating advanced validation techniques. This study addresses that gap by applying the CA–Markov model to Kupang City and complementing it with Artificial Neural Network (ANN) validation to enhance the robustness of predictions. By focusing on Kupang—a city with distinct ecological and socio-economic characteristics—this research contributes to a broader understanding of land cover change in Indonesia while advancing methodological innovation in spatial modelling.

This study analyses land cover change patterns in Kupang City from 2018 to 2023 and predicts land cover for the period 2028–2043 in five-year increments. The findings are expected to support both theoretical insights and practical policy tools for adaptive and sustainable spatial planning in Kupang City.

MATERIALS AND METHODS

This study utilizes a quantitative methodology supported by Quantum GIS (QGIS) and GeoSOS-FLUS software. These tools facilitate prediction and visualization of spatial connectivity. A literature review was conducted during the preparation stage to establish the theoretical and empirical framework. The selection of the CA-Markov approach over alternative LULC models was based on methodological considerations specific to data availability and study objectives. Comparative studies demonstrate that while more advanced models like FLUS and PLUS achieve higher accuracy (Kappa >0.76),

CA-Markov provides optimal balance between performance and practical applicability, particularly in data-limited environments typical of intermediate Indonesian cities (Luan & Liu, 2022)). Recent validation studies confirm CA-Markov's reliability with robust performance in complex environments, demonstrating its suitability for sustainable urban planning applications (Tahir et al., 2025)

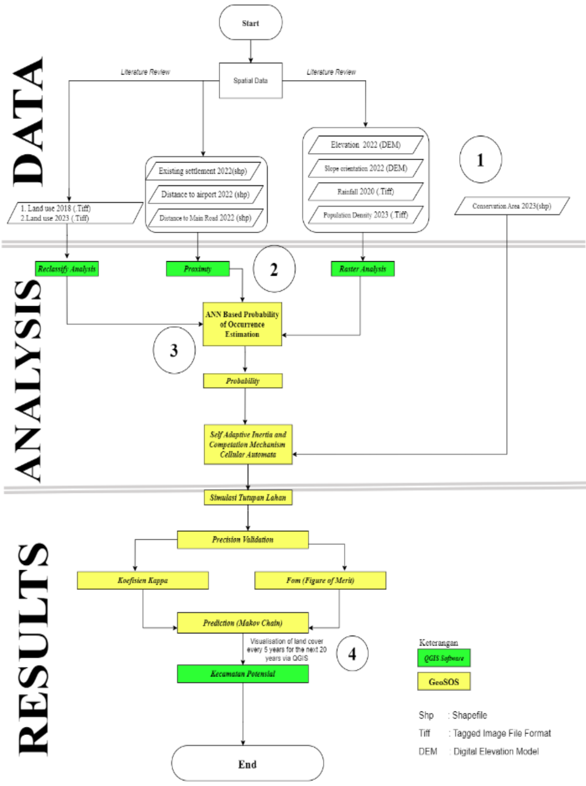
The initial stage consists of preparing spatial data, including land cover, driving factors, and conservation areas. Land cover data is derived from Region of Interest (ROI) imagery of Kupang City for 2018 and 2023, obtained from ESRI–Sentinel-2. GeoSOS-FLUS requires two temporal land cover classifications: the 2018 data serves as the Initial Land Use Map to represent baseline conditions and calculate transition probabilities, while the 2023 data is used as Future Land Use Demand due to the unavailability of 2024 or 2025 data. The land cover data is formatted as vector shapefiles, and resolution standardization between the two years was conducted in QGIS to ensure analytical consistency.

Driving factors refer to variables that influence changes in land cover. Seven datasets were used as driving factors, including vector data such as existing settlements in 2022, distance to the airport, and distance to the main road in the same year. Raster data included the Digital Elevation Model, which provided elevation and slope orientation in 2022, as well as Tagged Image File Format data representing rainfall and population density in 2022.

Conservation areas are defined as regions excluded from modification within the prediction model. These include mangrove areas and water bodies, as identified in the Kupang City Spatial Plan (RTRW) 2011–2031 and the RBI map 2022. The primary criterion at this stage is the compatibility of the current data format for subsequent analysis.

The second stage consists of standardizing land cover data and associated driving factors using QGIS software. Land use data from 2018 and 2023 have been reclassified to align with the Environmental Systems Research Institute (ESRI) classification standards. The classification includes seven categories: water bodies, vegetation, flooded vegetation, agriculture, built-up land, open land, and grasslands. Driving factor data in shapefile (shp) format are analyzed using the Proximity tool, while data in Digital Elevation Model (DEM) and Tagged Image File Format (TIFF) are processed with Raster Analysis. The primary criterion for this stage is the adequacy of the data for progression to the next stage.

The third stage is data processing using GeoSOS-FLUS, which includes two main parts, namely ANN-based Probability-of-Occurrence Estimation and Self-Adaptive Inertia and Competition Mechanism CA (Chen et al., 2022). The basic data used are the land cover data from 2018. In the probability estimation stage, the driving variables and conservation areas are entered and adjusted to the row and column standards (Sugandhi et al., 2022b; Supriatna et al., 2022.



Source:(Research Results , 2025)

Figure 1. Research Flow Chart

The Artificial Neural Network (ANN)-based probability-of-occurrence estimation generates a probability raster that quantifies the likelihood of transitions between specific land cover classes (Durmusoglu & Tanriover, 2017; Liu et al., 2017). In the ANN-based probability estimation stage, the network was configured with eight input neurons corresponding to the driving factors, two hidden layers containing 16 and 8 neurons respectively, and an output layer producing class transition probabilities. Training data comprised 20,000 stratified random samples drawn from the 2018 and 2023 land cover maps, split 75% for training and 25% for validation. These settings ensured the ANN could learn the non-linear relationships between driving factors and land cover transitions effectively.

The probability data generated will be used as input in the next stage, namely the Self-Adaptive Inertia and Competition Mechanism CA, which will produce a confusion matrix, kappa coefficient, overall accuracy, omission error, commission error, producer's accuracy, and user's accuracy The next step is to validate the prediction results using the Kappa coefficient and Figure of Merit (FoM). Kappa measures the agreement between the prediction results and the reference data, taking into account coincidental similarities, while FoM assesses the accuracy of land use change simulations based on comparisons with the reference data (ground truth)(Guo et al., 2025; Han et al., 2024). Land cover change was predicted using the Markov Chain model. This method analyzes historical land cover transitions to produce probability matrices, transition area matrices, and probability maps (Fezzai et al., 2024; Hassanshahi et al., 2023; Ntakirutimana & Vansarochana, 2021; Supriatna et al., 2022). The analysis identified specific subdistricts with a high likelihood of land cover change by 2043. Success at this stage is measured by the generation of land use projections delineated by administrative boundaries.

RESULTS AND DISCUSSION

Baseline Land Cover Map

Kupang City, the capital of East Nusa Tenggara Province, with an area of 159.17 km^2 (15,917.28 Ha), exhibits diverse land cover characteristics. The land cover data used needs to be reclassified so that the land cover classification used is in accordance with standards. In this case, the land cover classification used refers to the ESRI classification, which includes 7 land cover classifications using Sentinel imagery, namely water bodies (BA), vegetation (VGT), flooded vegetation (SV), agriculture (AGL), built-up areas (BUA), open land (OL), and grasslands (GRL).

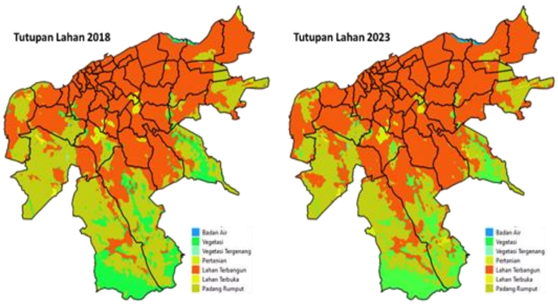
The accuracy of the land cover classification was tested using 10% of the total valid pixels randomly selected as a validation sample. The Kappa coefficient was found to be sufficiently strong, indicating that the classification results are suitable for further research (Rwanga & Ndambuki, 2017). Based on the error matrix analysis in this study, the Kappa accuracy was 0.81, and the overall accuracy was 86%. These values indicate that the interpretation of satellite images falls into the very good category, making the interpretation results suitable for further analysis.

The land cover map of Kupang City, based on the results of classification in 2018 and 2023, serves as the Initial Land Use Map to illustrate the initial conditions and is presented in Figure 2. Furthermore, Figure 3 illustrates significant changes in land cover in Kupang City from 2018 to 2023. One of the most significant changes is seen in the built-up area (BUA) category, which increased in size from 8,626.81 hectares to 10,339.08 hectares. This trend suggests that the urbanization process in Kupang City is progressing rapidly, likely driven by population growth, housing needs, and the expansion of urban infrastructure.

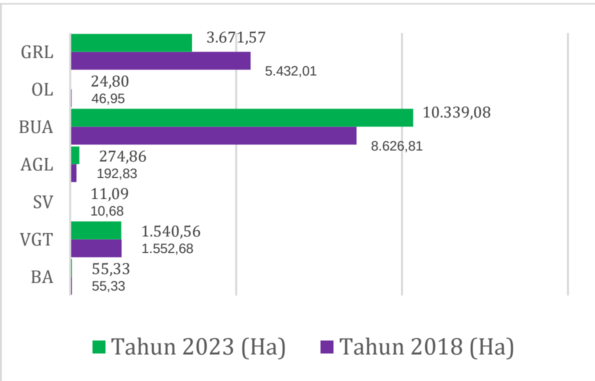
On the other hand, open land (OL) decreased from 46.95 hectares to 24.80 hectares. This decline reflects significant land conversion, likely caused by increased construction activities or land use changes for residential purposes, intensive agriculture, or other infrastructure development.

Agricultural land (AGL) increased from 192.83 hectares to 274.86 hectares. Water bodies (BA) showed stability in area, remaining at 55.33 hectares. The absence of changes in area indicates that water bodies in the area are relatively protected from land conversion pressures.

The submerged vegetation (SV) category increased from 10.68 hectares to 11.09 hectares, presumably due to rising water levels that expanded the shallow water area. Meanwhile, natural vegetation (vegetation/VGT) experienced an insignificant increase from 1,552.68 hectares to 1,540.56 hectares.



Source:(Research Results , 2025)
Figure 2. Changes in Land Cover between 2018 and 2023



Source:(Research Results , 2025)

Figure 3. Changes in Land Cover in Kupang City in 2018 and 2023

Notes: BA = Water Agency, VGT = Vegetation, SV = Flooded Vegetation, AGL = Agriculture, BUA = Built-up Land, OL = Open Land, GRL = Grassland

Land Cover Prediction Simulation

This study aims to examine the dynamics of land cover change using two reference points in time, namely 2018 as the initial condition and

2023 as the final condition of the study. Land cover change predictions were made using one type of model, namely Business as Usual (BAU), which assumes that future land cover changes will follow the historical patterns that occurred in the previous period. The predictive method used to estimate land cover conditions from 2028 to 2043 in five-year intervals adopts the Markov Chain approach.

This land cover change simulation is based on several driving factors that influence the prediction results. These factors include the presence of existing settlements, distance to airports, proximity to main roads, elevation, slope orientation, rainfall intensity, population density, and the existence of conservation areas and water bodies that serve as boundaries or exclusive areas that remain unchanged. The results of this simulation are expected to provide a spatial overview of the direction of future land cover development, thereby serving as an important reference in the formulation of spatial planning policies, land use control, and sustainable environmental management strategies.

Tabel 1 Projected Land Use Change from 2020 to 2043 in Five-Year Intervals

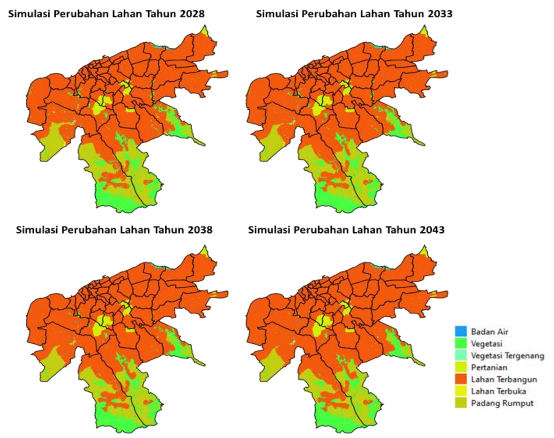
Land Cover	2018 (Ha)	2023 (Ha)	2028 (Ha)	2033 (Ha)	2038 (Ha)	2043 (Ha)	Δ2018–2043 (Ha)	Δ (%)
BA	55,33	55,33	55,33	55,33	55,33	55,33	0	0.0%
VGT	1.552,68	1.540,56	1.528,24	1.528,24	1.421,45	1.368,98	-183,7	-11.8%
SV	10,68	11,09	11,43	11,43	11,45	11,46	0,79	7.4%
AGL	192,83	274,86	366,68	366,68	412,98	422,50	229,67	119.1%
BUA	8.626,81	10.339,08	11.452,00	11.452,00	11.879,93	12.006,31	3.379,50	39.2%
OL	46,95	24,80	11,96	11,96	2,94	2,42	-44,52	-94.8%
GRL	5.432,01	3.671,57	2.491,63	2.491,63	2.133,19	2.050,27	-3.381,74	-62.3%

Source:(Research Results , 2025)

Note: BA = Water Agency, VGT = Vegetation, SV = Flooded Vegetation, AGL = Agriculture, BUA = Built-up Land, OL = Open Land, GRL = Grassland

The results of land cover change simulations from 2018 to 2043 show significant shifts in land use patterns. One of the most notable changes occurred in the settlement category (BUA), which increased in area by 3,379.50 hectares or around 39.2%. This increase suggests rapid growth in built-up areas, likely due to increased demand for housing and infrastructure. In addition to residential areas, agricultural land (AGL) has also shown significant expansion, increasing by 229.67 hectares, or more than double (119.1%) compared to 2018. On the other hand, several types of land cover experienced a significant decline. Grassland (GRL) decreased by 3,381.74 hectares or 62.3%, while open land (OL) nearly disappeared, decreasing by 94.8%. This decline indicates a shift from natural land to more intensive use.

Land vegetation (VGT) also declined, although not as significantly as the previous two categories, by 183.70 hectares or 11.8%. Meanwhile, flooded vegetation (SV) actually increased slightly, which is likely related to rising water levels or changes in aquatic environmental conditions. Water bodies (BA) remained stable throughout the period, with no significant changes in area. Overall, this pattern of change reflects a trend toward land conversion from natural ecosystems to developed and cultivated areas. Moreover, the accuracy of the CA–Markov model in this study (Kappa 0.81) aligns well with results reported in previous studies, such as Sugandhi et al. (2022) in Ambon, which achieved a Kappa of 0.8593 with urban expansion from 1,011.71 ha to 1,281.49 ha, and Supriatna et al.,(2022) in Banjarmasin, with a Kappa of 0.906 and significant land-cover changes including deforestation of 356 km^2. These comparisons demonstrate consistent performance of the CA–Markov approach across different Indonesian urban contexts, reinforcing its reliability in predicting land cover dynamics, despite variations in local characteristics and development pressure



Source:(Research Results , 2025)

Figure 4. Land Change Simulation 2028-2043

The simulation presented above illustrates projected land use changes in the study area from 2028 to 2043. Results indicate a substantial annual increase in built-up land area, represented in orange. This expansion consistently replaces regions previously classified as natural vegetation, agriculture, and grasslands, especially within the central and northern sections of the study area. These trends indicate significant pressure resulting from urbanisation and infrastructure development. The land use changes identified in the simulation are further detailed using a land cover transition matrix. This matrix quantifies the transfer of land area, measured in hectares, between different land use categories and highlights the predominant conversion types for each original land category. Cross-tabulation techniques were employed to systematically identify and calculate the area converted between land cover classes.

Tabel 2 Dominant Transition Matrix

Origin	**→ BA**	**→ VGT**	**→ SV**	**→ AGL**	**→ BUA**	**→ OL**	**→ GRL**	**Total Conversion (Ha)**	**Dominant Changes**
BA	-	0	0	0	0	0	0	0,00	→ BA
VGT	0	-	0	0,86	237,94	0	41,06	279,86	→ BUA
SV	0	0	-	0,00	0,00	0	0,00	0,00	→ SV
AGL	0	0	0,00	-	14,39	0	0,16	14,55	→ BUA
BUA	0	17,32	0,01	233,76	-	0,15	69,69	320,93	→ AGL
OL	0	0	0	0	38,51	-	8,61	47,12	→ BUA
GRL	0	78,84	0,78	9,60	3.409,60	2,44	-	3.501,25	→ BUA

Source:(Research Results , 2025)

Notes: BA = Water Agency, VGT = Vegetation, SV = Flooded Vegetation, AGL = Agriculture, BUA = Built-up Land, OL = Open Land, GRL = Grassland

The matrix quantifies land use change in hectares, including both inter-category transitions and areas that remain unchanged. The transition matrix highlights that the most substantial change was from grassland (GRL) to built-up area (BUA), totaling 3,409.60 hectares. Additional significant transitions include 237.94 hectares of flooded vegetation (VGT) transitioning to built-up land (BUA) and 14.39 hectares of agriculture (AGL) transitioning to built-up land (BUA). Conversely, built-up land was converted to agricultural land (AGL) over 233.76 hectares and to grassland (GRL) over 69.69 hectares. Grassland (GRL) experienced the highest total conversion, amounting to 3,501.25 hectares.

Analysis of average land cover change demonstrates that conversion to built-up areas (BUA) is the most prevalent. Vegetation and grassland categories contribute most to this increase, whereas water bodies exhibit minimal change. This trend persists throughout all analysis periods, with transitions to BUA consistently exceeding those to other categories. The results indicate a pronounced trend of urbanisation in the study area and a corresponding reduction in non-built-up land.

Subdistricts with Potential for Settlement Development

The analysis of land cover changes indicates a predominant conversion of non-built-up land to built-up land. This trend serves as an initial indicator of future settlement expansion. Accordingly, subdistricts exhibiting the highest increases in built-up land were identified.

Period	**Alak**	**Maulafa**	**Kelapa Lima**
2018–2023	3.224,03	3.223,33	1.473,25
2023–2028	4.068,38	3.503,69	1.473,48
2028–2033	4.237,19	3.572,92	1.470,82
2033–2038	4.354,31	3.667,60	1.469,98
2038–2043	4.429,41	3.723,32	1.469,34

Source:(Research Results , 2025)
Note: In hectares (Ha)

The results of the analysis of built-up area (BUA) changes in Kupang City show that of all sub-districts, Alak, Maulafa, and Kelapa Lima recorded the highest rates of change throughout the projection period. Alak sub-district ranked first with a very significant increase in BUA in each period, reaching more than 4,400 hectares at the end of the projection. This rate of change reflects the rapid growth of new residential areas, particularly in outlying areas that are beginning to connect with the city centre through road infrastructure and access to basic services. Maulafa ranks second with a stable upward trend, while Kelapa Lima is third with relatively small changes but still showing signs of development dynamics. These findings confirm that the three districts are the primary centres of developed land expansion, directly correlated with the direction of future residential area expansion. This pattern reflects the concentration of developed area growth, which has the potential to drive residential expansion along specific corridors.

CONCLUSION

The Cellular Automata–Markov Chain (CA-Markov) model demonstrated high predictive accuracy for land cover changes in Kupang City, achieving an overall accuracy of 86% and a Kappa coefficient of 0.81. Simulations for the 2018–2043 period identified a predominant conversion of non-built-up land, especially grasslands and vegetation, into built-up land. Built-up land is projected to increase by 3,379.50 hectares (39.2%), while grasslands and open land are expected to decline by 62.3% and 94.8%, respectively. The districts of Alak, Maulafa, and Kelapa Lima are anticipated to experience the most rapid residential expansion. This pattern reflects significant urbanisation pressure and a concentration of development within specific corridors. The results highlight the necessity of employing CA-Markov-based spatial predictions to inform adaptive spatial planning, thereby supporting controlled land use conversion and sustainable spatial connectivity in Kupang City through 2043.

ACKNOWLEDGMENTS

This manuscript presents research funded by the National Grant for Early Career Faculty Research, supported by the Directorate General of Higher Education, Research, and Technology (Ditjen Diktiristek), Ministry of Higher Education, Science, and Technology of the Republic of Indonesia, under Contract Number 173/C3/DT.05.00/PL-BATCH II/2025 (Main Contract) and 107h/PL23/PPK.1/KU/LT/2025 (Subcontract). The research, entitled 'Prediction of Land Cover Changes Using Cellular Automata-Markov Chain to Improve Spatial Connectivity in Kupang City,' acknowledges the support provided by the Director of Kupang State Polytechnic, the Centre for Research and Community Service (P3M), the Directorate General of Higher Education, Research, and Technology (Ditjen Diktiristek), and all contributing parties.

REFERENCES

A. Wadu , A. A. Tuati, M. R. S. (2020). Strategy To Reduce Traffic Jams On Piet A. Tallo Street, Kupang City. *Ukarst : Universitas Kadiri Riset Teknik Sipil*, *4*(2), 139–150. https://doi.org/10.30737/ukarst.v3i2

Altafini Diego; Poloni, F. M. B. B. D. C. V. (2022). Markov-Chain based centralities and Space Syntax' Angular Analysis: an initial overview and application. *13th International Space Syntax Symposium, SSS 2022*, 1–22.

Angin, I. S., & Sunimbar. (2021). Analysis of Land Use Change in Kupang City, East Nusa Tenggara 2010-2018 (Case Study in Kelapa Lima, Oebobo, and Kota Lama Subdistricts). *Geoedusains Journal*, *2*(1), 36–52.

Chen, X., He, X., & Wang, S. (2022). Simulated Validation and Prediction of Land Use under Multiple Scenarios in Daxing District, Beijing, China, Based on GeoSOS-FLUS Model. *Sustainability (Switzerland)*, *14*(18). https://doi.org/10.3390/su141811428

Durmusoglu, Z. O., & Tanriover, A. A. (2017). Modelling land use/cover change in Lake Mogan and surroundings using CA-Markov Chain Analysis. *Journal of Environmental Biology*, *38*(5(SI)), 981–989. https://doi.org/10.22438/jeb/38/5(SI)/GM-15

Fezzai, S., Hassanshahi, G., Soltani, A., Roosta, M., Askari, S., Colaço, R., de Abreu e Silva, J., Güller, C., Toy, S., Stevens, Q., Thai, H. M. H., Sun, M., Meng, Q., Miura, S., Yoshida, M., Nakamura, F., Wongwiriya, P., Tanaka, S., Ariyoshi, R., … Yenen, Z. (2024). Improving Urban Planning Using Land Use Analysis and Traffic Network Optimization: A Case Study of Da Nang City. *Frontiers in Earth Science*, *13*(1), 386–404. https://doi.org/10.1016/j.foar.2023.09.001

Guo, Q., Albarrán, I., Alonso-González, P. J., & Grané, A. (2025). Well-being horizons for silver and golden ages: an application of traditional and fuzzy Markov chains. *Humanities and Social Sciences Communications*, *12*(1). https://doi.org/10.1057/s41599-025-04555-y

Han, L., Qu, Y., Liang, S., Shi, L., Zhang, M., & Jia, H. (2024). Spatiotemporal Differentiation of Land Ecological Security and Optimization Based on GeoSOS-FLUS Model: A Case Study of the Yellow River Delta in China Toward Sustainability. *Land*, *13*(11). https://doi.org/10.3390/land13111870

Hassanshahi, G., Soltani, A., Roosta, M., & Askari, S. (2023). Walking as soft mobility: A multi-criteria GIS-based approach for prioritizing tourist routes. *Frontiers of Architectural Research*, *12*(6), 1080–1096. https://doi.org/10.1016/j.foar.2023.09.001

Kupang, B. P. S. K. (2020). *Laju Pertumbuhan Penduduk NTT 2020*. Kota Kupang Dalam Angka 2022. https://kupangkota.bps.go.id/site/chartResultTab

Li, Y., Wang, N., Tong, Z., Liu, Y., An, R., & Liu, Y. (2023). The Nonlinear Influence of Street Quality on Housing Prices Based on Random

Forest Model: A Case Study of Guangzhou. *Tropical Geography*, *43*(8), 1547–1562. https://doi.org/10.13284/j.cnki.rddl.003724

Liu, X., Liang, X., Li, X., Xu, X., Ou, J., Chen, Y., Li, S., Wang, S., & Pei, F. (2017). A future land use simulation model (FLUS) for simulating multiple land use scenarios by coupling human and natural effects. *Landscape and Urban Planning*, *168*(July 2016), 94–116. https://doi.org/10.1016/j.landurbplan.2017.09.019

Luan, C., & Liu, R. (2022). A Comparative Study of Various Land Use and Land Cover Change Models to Predict Ecosystem Service Value. *International Journal of Environmental Research and Public Health*, *19*(24). https://doi.org/10.3390/ijerph192416484

Luwarti, Y., Kangkan, A. L., Tallo, I., & Lima, K. K. (2023). *Analisis Laju Perubahan Garis Pantai Di Kecamatan Kelapa Lima Kota Kupang*. 59–68.

Ntakirutimana, A., & Vansarochana, C. (2021). Assessment and prediction of land use/land cover change in the national capital of burundi using multi-temporary landsat data and cellular automata-markov chain model. *Environment and Natural Resources Journal*, *19*(5), 413–426. https://doi.org/10.32526/ENNRJ/19/202100023

Pauleit, S., Ennos, R., & Golding, Y. (2005). Modeling the environmental impacts of urban land use and land cover change—a study in Merseyside, UK. *Landscape and Urban Planning*, *71*(2–4), 295–310. https://doi.org/10.1016/j.landurbplan.2004.03.009

Purnama F, M. M., Pramatana, F., Aini, Y., & Soimin, M. (2024). Analisis Tutupan Lahan Menggunakan Penginderaan Jauh ei Kecamatan Kupang Tengah, Kabupaten Kupang, Provinsi Nusa Tenggara Timur. *Jurnal Kehutanan Papuasia*, *10*(1), 96–106.

Statistik, B. P. (BPS). (2023). *Kota Kupang Dalam Angka 2023* (D. K. Ayuningtyas, Ed.; 1st ed.). BPS Kota Kupang.

Sugandhi, N., Supriatna, S., Kusratmoko, E., & Rakuasa, H. (2022a). Prediksi Perubahan Tutupan Lahan di Kecamatan Sirimau, Kota Ambon Menggunakan Celular Automata-Markov Chain. *JPG (Jurnal Pendidikan Geografi)*, *9*(2). https://doi.org/10.20527/jpg.v9i2.13880

Sugandhi, N., Supriatna, S., Kusratmoko, E., & Rakuasa, H. (2022b). Prediksi Perubahan Tutupan Lahan di Kecamatan Sirimau, Kota Ambon Menggunakan Celular Automata-Markov Chain. *JPG (Jurnal Pendidikan Geografi)*, *9*(2). https://doi.org/10.20527/jpg.v9i2.13880

Supriatna, Mukhtar, M. K., Wardani, K. K., Hashilah, F., & Manessa, M. D. M. (2022a). CA-Markov Chain Model-based Predictions of Land Cover: A Case Study of Banjarmasin City. *Indonesian Journal of Geography*, *54*(3), 365–372. https://doi.org/10.22146/IJG.71721

Supriatna, Mukhtar, M. K., Wardani, K. K., Hashilah, F., & Manessa, M. D. M. (2022b). CA-Markov Chain Model-based Predictions of Land Cover: A Case Study of Banjarmasin City. *Indonesian Journal of Geography*, *54*(3), 365–372. https://doi.org/10.22146/IJG.71721

Tahir, Z., Haseeb, M., Mahmood, S. A., Batool, S., Abdullah-Al-Wadud, M., Ullah, S., & Tariq, A. (2025). Predicting land use and land cover changes for sustainable land management using CA-Markov modelling and GIS techniques. *Scientific Reports*, *15*(1). https://doi.org/10.1038/s41598-025-87796-w

Tallo, A. J., Alraouf, A. A., & Wibowo, C. A. (2024). Multi-scenario location-allocation in decision-making for improving educational facility services in Kupang City. *ARTEKS : Jurnal Teknik Arsitektur*, *9*(1), 121–128. https://doi.org/10.30822/arteks.v9i1.3264

Tallo, A. J., Arianti, S. P., Abdillah, F., Bahri, A. S., Heryanto, S., Fassa, F., Prihandrijanti, M., & Anshory, B. J. (2018). Typology Analysis and Leading Sector of East Nusa Tenggara Province in 2017. *Journal of Physics: Conference Series*, *1114*(1). https://doi.org/10.1088/1742-6596/1114/1/012122

Villamor, G. B., Akiefnawati, R., Van Noordwijk, M., Desrianti, F., & Pradhan, U. (2015). Land use change and shifts in gender roles in central Sumatra, Indonesia. *International Forestry Review*, *17*(4), 61–75. https://doi.org/10.1505/146554815816002211

Wang, W., Xu, Z., Sun, D., & Lan, T. (2021). Spatial-optimization-of-megacity-fire-stations-based-on-multisource-geospatial-data-A-case-study-in-beijingISPRS-International-Journal-of-GeoInformation.pdf. *International Journal of Geo-Information*, *10*(282), 1–19.