p-ISSN 2460-0768 e-ISSN 2597-6044
https://doi.org/10.20961/ge.v12i2.108804

GeoEco, Vol. 12, No 2. July 2026 Page. 678 - 699
https://jurnal.uns.ac.id/GeoEco/article/view/108804

SPATIAL MODELING OF LAND COVER DYNAMICS IN DKI JAKARTA CILIWUNG WATERSHED USING CA-MARKOV APPROACH

Mohamad Mahfudz[1,2*], Baba Barus[3], Asep Sapei[4], Bambang Pramudya Noorachmat[5]
[1]Postgraduate Student of Natural Resources and Environmental Management IPB University, Bogor, Indonesia
[2]Geodetic Engineering Study Program of Pakuan University, Bogor City, Indonesia
[3]Head of P4W Study Center of IPB University, Bogor, Indonesia
[4]Department of Civil and Environmental Engineering of IPB University, Bogor, Indonesia
[5]Department of Natural Resources and Environmental Management IPB University, Bogor, Indonesia

*E-mail: mohamadmahfudz@apps.ipb.ac.id

ARTICLE INFO

Article History
Received : 07/09/2025
Revised : 25/11/2025
Accepted : 04/06/2025

Citation:
Mahfudz. M., Barys, B., Sapei, A., and Noorachmat, B.P. (2026) Spatial Modeling of Land Cover Dynamics in DKI Jakarta Ciliwung Watershed Using CA-Markov Approach. GeoEco. Vol. 12, No. 2.

ABSTRACT

Land use and land cover (LULC) change driven by human activities has become a major factor influencing environmental dynamics, particularly in rapidly urbanizing areas. This study aims to analyze LULC changes in the Ciliwung Watershed, DKI Jakarta, during the period 2010–2025 and to project future trends up to 2030. The study utilizes Landsat imagery with a spatial resolution of 30 meters, combined with a Geographic Information System (GIS) approach and the Cellular Automata–Markov (CA-Markov) model. LULC classification was categorized into six classes, achieving an overall accuracy of 80% and a Kappa coefficient above 75%, indicating strong agreement. The results show a significant increase in built-up areas by 81.83% by 2030, accompanied by a decrease in open land by 18% and forest areas by 13.53%. Agricultural land and shrubland show slight increases of 1.57% and 0.82%, respectively, while water bodies remain relatively stable at 2.07%. The expansion of built-up areas exerts considerable pressure on green spaces and reduces water infiltration capacity, thereby increasing the potential risk of flooding in the study area. These findings highlight the importance of implementing adaptive and sustainable spatial planning policies to control LULC changes and mitigate future environmental impacts.

Keywords: *CA-Markov; ciliwung watershed; DKI Jakarta; GIS; land cover change*

INTRODUCTION

Land use and cover change (LULC) is one of the important indicators in understanding environmental dynamics. The study of LULC is particularly relevant because it can provide a spatial-temporal overview of the impacts of climate change and human activities (Thakur et al, 2020; Ali et al., 2016). Anthropogenic and heavy rainfall-induced changes in land use patterns have been shown to affect surface flow, increase soil erosion and accelerate environmental degradation (Son & Binh, 2020). LULC transformation is an inevitable phenomenon, especially in developing countries that are experiencing rapid economic and demographic growth. However, without an accurate and technology-based analytical approach, projections of LULC change are subject to high uncertainty (Ghalehteimouri et al, 2022). Urbanization is one of the main drivers of LULC change dynamics, including population growth, expansion of built-up areas, and intensification of economic and industrial activities (Rustiadi et al., 2023; Elagouz et al, 2020; Msofe et al, 2019). The need for land for settlements and infrastructure along with population growth encourages massive conversion of agricultural land and green areas (Sanga & Haulle, 2024; Simon et al, 2023; Rustiadi et al., 2018). In the urban context, visualization of land use change and spatial modeling are important to support sustainable and evidence-based planning (Shafizadeh et al, 2013).

Geographic Information Systems (GIS) and remote sensing technologies combined with Markov CA are effective tools for detecting, monitoring and predicting spatial and temporal changes in LULC at both regional and global scales (Mosleh, 2025; Mahfudz et al, 2024; Mahfudz, 2023; Saing et al, 2021)

The Jakarta area is a clear example of very high urbanization pressure, which has a significant impact on land cover dynamics. The Indonesian government through Presidential Regulation No. 6/2020 has stipulated that a minimum of 30% of the district/city area must be green open space. However, data shows that by 2012, the built-up area in Jakarta had reached 69.9%, and increased by 11.1% in 12 years. In fact, all administrative cities in DKI Jakarta have exceeded the 70% built-up area limit since 2014 (Rachma et al., 2022; Rushayati et al., 2018). One of the affected areas is the Ciliwung Watershed (DAS). Intensive urbanization in this area has led to massive conversion of green land into built-up areas, where by 2020, settlements and built-up areas are estimated to have covered around 45-50% of the total area of the Ciliwung watershed (Rajagukguk et al, 2023; Farid et al, 2022). This condition raises concerns about reduced environmental carrying capacity, increased flood risk, and decreased ecosystem quality (Ali et al, 2016). Because the Ciliwung watershed plays an important role in the ecological and socio-economic system of

Jakarta as the center of the national capital. However, in recent decades, the region has experienced considerable pressure due to population growth, uncontrolled urbanization, and intensification of land use. This condition is exacerbated by climate change, which further increases uncertainty in natural resource management and spatial planning of the watershed area. Changes in seasonal rainfall and surface temperature have triggered accelerated land use change, decreased soil infiltration capacity, and increased flood risk and environmental degradation.

This study aims to analyze the dynamics of land use and land cover (LULC) changes in the Ciliwung River Basin, Jakarta, during the period 2010–2025, and to predict future trends up to 2030. In addition, this study seeks to identify the main driving factors influencing land cover changes using an integrated approach of the CA-Markov model and MICMAC analysis. The results of this study are expected to provide a scientific basis for understanding environmental pressures caused by urbanization and to support the formulation of adaptive and sustainable spatial planning strategies in the future.

MATERIALS AND METHODS

1. Location and Research Time

Jakarta is located in the northwestern part of Java Island. Geographically, the city is located between 5°19'12" to 6°23'54" South latitude and 106°22'42" to 107°01'00" East longitude. The Ciliwung watershed runs from the central area of Jakarta to the north (**Figure 1**), through several densely populated areas, such as Central Jakarta, South Jakarta, and East Jakarta. Along this river, there are various human activities including settlements, offices, and industries (Susilowati et al., 2020).

2. Data Source

Data from Landsat 5, 8 and 9 images in 2010, 2015, 2020, 2025 were downloaded from the United States Geological Survey (USGS) website at https://earthexplorer.usgs.gov for LULC derivation, analysis, prediction (**Table 1**). The main objective of the study was to predict the land use change (LULC) of the Jakarta Ciliwung watershed. The Landsat imagery used in this study was selected based on a cloud cover threshold of less than 10% to ensure optimal data quality and minimize atmospheric interference. This threshold was applied to reduce spectral distortion caused by clouds and their shadows, thereby improving the accuracy of LULC classification (Rimal et al., 2017). Consequently, only images with relatively clear atmospheric conditions were utilized to ensure the reliability of the spatial analysis results, in accordance with standard guidelines for Landsat data processing.

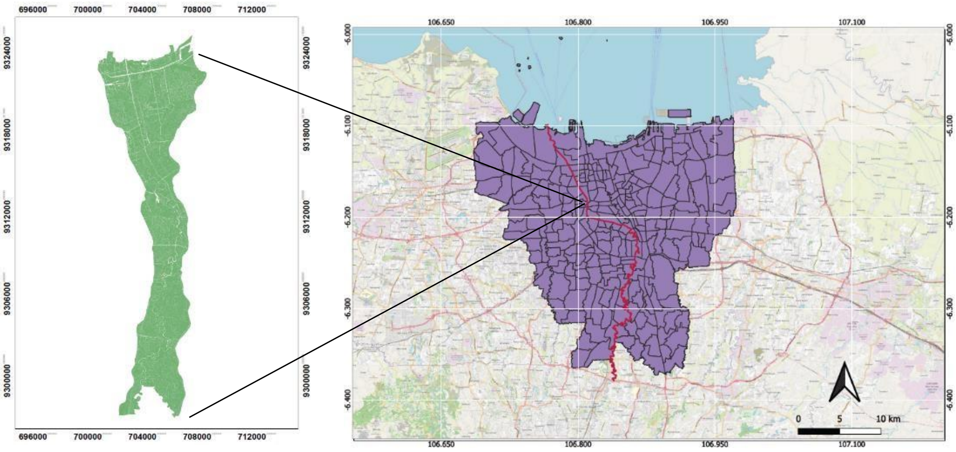

Figure 1. Research Location

Source: Author’s own elaboration (2025)

Table 1. Satellite data

Region	Year	Satellite	Acquisition Data	Sensor
Jakarta Ciliwung Watershed	2010	Landsat 5	September 15, 2010	TM
	2015	Landsat 8	September 17, 2015	OLI TIRS
	2020	Landsat 8	September 17, 2020	OLI TIRS
	2025	Landsat 9	September 20, 2025	OLI TIRS

Source: Author’s own elaboration (2025)

3. Image Processing and LULC Classification

The Landsat TM, ETM+, and OLI datasets were verified, and then the datasets were processed and filtered using a GIS platform (Rimal et al., 2017). All remote sensing image data during the processing stage were subjected to geometry and radiometry corrections to remove distortions (Trevisiol et al. 2024; Rimal et al. 2017). The classification process uses both unsupervised and supervised classification to improve accuracy. Undirected classification with the ISODATA algorithm groups pixels based on natural patterns to identify land cover categories such as: built-up land (LB), open land (LT), agricultural land (LP), forest (H), scrub (B), water body (BA). In addition, supervised classification using a maximum likelihood algorithm with 40–50 field samples collected via stratified random sampling has been shown to improve the accuracy of the results. The combination of these two methods resulted in a more precise LULC map (Paradis, 2022). The classification of land cover change in the Jakarta Ciliwung Watershed area as described in **Table 2**

Table 2. LULC Class Description

LULC class	Class Description
LB	This area includes various types of land uses, such as housing, business areas, industry, transportation, as well as other public facilities
LT	These lands are often natural open spaces that have natural vegetation or ecosystems, such as grasslands, forests, farmlands, or undeveloped vacant land.
H	Forests include a wide range of vegetation types, including trees, shrubs, understory plants and other organisms, and have many layers that support a variety of flora and fauna species.
LP	This land can be paddy fields, fields, gardens, or areas used for the development of other agricultural systems.
B	areas that have been disturbed, such as former farmland, burnt areas, or unmaintained areas
BA	Rivers, consistently flowing open watercourses, lakes, ponds, wetlands, swampy areas, paya, and reservoirs, including year-round and seasonal water sources.

Source: Author's own elaboration (2025)

4. Accuracy Assessment

Accuracy assessment refers to the level of accuracy of the classification compared to the actual field observation data. To calculate user accuracy. The User Error Matrix is used to calculate user accuracy, producer accuracy, overall accuracy, as well as the kappa coefficient (Kafy et al., 2021). The kappa coefficient is calculated using the equation 1:

$$k = \frac{P_0 - P_e}{1 - P_e} \quad (1)$$

where:

Po = observation accuracy (proportion of total correctly classified)

Pe = probability of expected accuracy based on chance

The Kappa coefficient measurement is carried out in accordance with the established standards, while the accuracy is considered adequate if the Kappa coefficient value exceeds 0.75 (Feizizadeh et al., 2022). In addition, this model applies the expected frequency calculation, which is calculated by summing the diagonal and total frequencies of the data using the equation 2:

$$a = \frac{number\ of\ rows\ x\ number\ of\ coloums}{N} \quad (2)$$

where:

Po = observation accuracy (proportion of total correctly classified)

Pe = probability of expected

accuracy based on chance

Therefore, Kappa values exceeding 0.80 indicate a significant level of accuracy for the study area (Feizizadeh et al., 2022).

5. LULC Transition Matrix

Geographic Information System (GIS) was used to analyze the LULC transition matrix. In periods T1 and T2, the matrix consists of rows and columns describing environmental categories. Utilizing GIS, the Land Change Modeler (LCM) was applied to calculate LULC changes (Rimal et al. 2018; Rimal et al. 2017).

6. LULC Projection

The Cellular Automata-Markov method is an effective tool for modeling LULC change, especially in areas with complicated topography where complex interactions between landscape elements pose challenges for in-depth analysis and understanding (Gharaibeh et al. 2020; Meyer et al. 2014). This approach combines Cellular Automata (CA) and Markov Chain to predict future landscapes based on historical data and current spatial configuration. CA simulates local interactions, while Markov calculates transition probabilities between land cover classes. This combination enables accurate landscape change projections and insights for future scenarios (Song et al., 2020) . We added details on the establishment and application of transition rules in the CA-Markov model to clarify the projections. The transition rules, which determine the probability of land cover change, were derived from the transition matrix of the 2010-2025 LULC map and used with the CA component to project future land use patterns (Asif et al., 2023). The CA-Markov methodology is widely used to analyze built-up area growth and landscape change, and supports urban planning and environmental management, including in assessing rapid urbanization (Chu et al., 2018). CA-Markov models provide datadriven projections that support policy and strategic planning for sustainable land use and mitigation of environmental change impacts (Li et al., 2023) . The CA-Markov model process includes the development of LULC maps for 2010-2025, the creation of a transition matrix, and potential transition maps based on associated factors. Simulation accuracy was evaluated using the kappa index before being used to project the future LULC map for 2030. A Markov model approach was applied to create a transition matrix analyzed using GIS. This transition matrix represented the probability of change between land cover categories based on historical trends and supported the CA component in projecting accurate future LULC maps (Fu et al.2024

Hamad et al.,2018) . This process resulted in a LULC map for the year 2030. Details of the procedural framework are shown visually in **Figure 2**, which illustrates the methodological steps in the CA-Markov-based projection.

7. Driving factors of LULC

Land use and land cover change (LULC) is a complex system because it is influenced by various interacting factors. Therefore, the MICMAC (Matrix of Cross Impact Multiplication Applied to Classification) method is used to identify relationships between variables and determine key factors within the system. In MICMAC analysis, the role of each variable is determined based on two main parameters: driving power and dependence. The driving force is calculated as the total influence of one variable on another variable as shown in equation 3.

$$DP_i \sum_{j=1}^{n} V_{ij} \quad (3)$$

DPi = driving power of the i-th variable (influence level), Vij = influence value of the i-th variable on the j-th variable, n = total number of variables in the system.

Meanwhile, dependency shows the level of dependence of a variable on other variables in the system as shown in equation 4.

$$DE_i \sum_{j=1}^{n} V_{ij} \quad (4)$$

DEi = driving power of the i-th variable (influence level), Vij = influence value of the i-th variable on the j-th variable, n = total number of variables in the system.

Based on these two values, variables can be classified to identify the primary drivers of LULC change, thereby supporting the formulation of more effective spatial planning policies (Ariyani et al., 2022). Kappa statistical analysis was used to assess the performance of the model by comparing the 2025 LULC map and the corresponding simulated map. The results show that the model has a stable accuracy rate above 75%, proving its reliability as a predictive tool (Keshtkar et al, 2016; Araya et al, 2010). The transition area matrices from various years, namely 2010, 2015, 2020, and 2025, were utilized to conduct an analysis of land use change over time. This analysis was then used to project the LULC map to 2030, providing a predictive picture of the changes that may occur in the future.

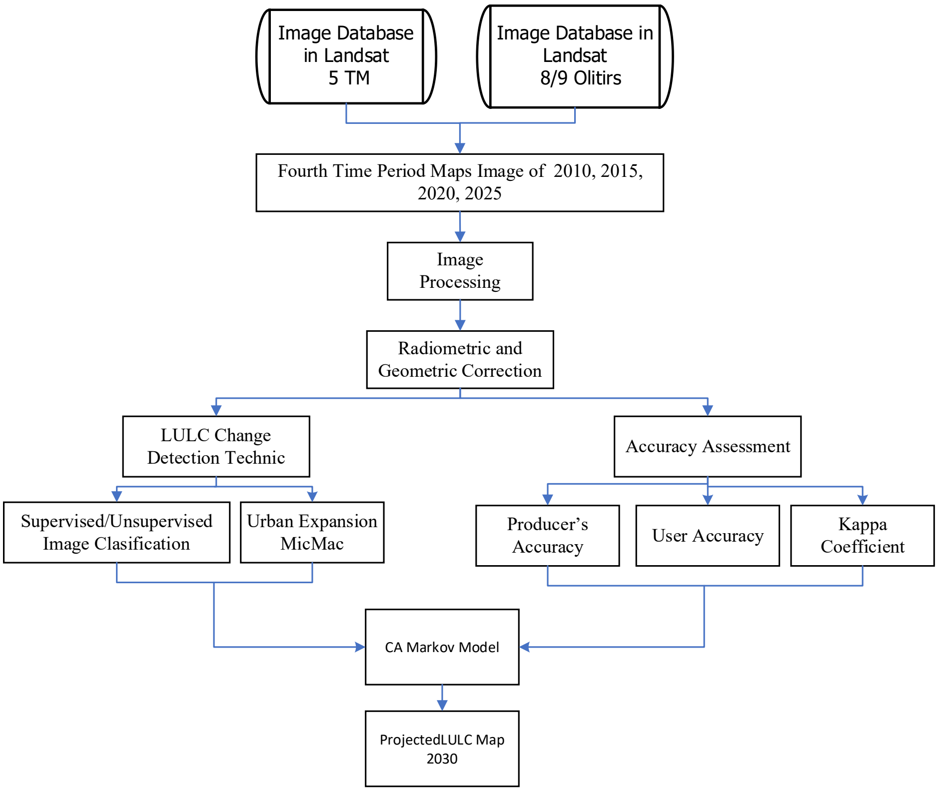

Figure 2. Research methodology framework

Source: Author's own elaboration (2025)

RESULTS AND DISCUSSION

1. LULC Trends 2010 - 2025

The process of identifying land use change utilizing remote sensing technology proved to be a very powerful and effective method in monitoring the dynamics of land use and land cover (LU/LC) change in the study area over the period 2010 to 2025. With the application of this remote sensing technology, six major categories of land cover were accurately identified. These categories include built-up land, open land, forest, farmland, scrub and water bodies, as shown in **Table 3**. Each of the identified categories showed notable changes during the study period, reflecting the dynamics of change occurring in the study area. Furthermore, the analysis results presented in **Figure 3** clearly reveal that the study area underwent significant changes in land use and cover, reflecting the impact of various environmental, social and economic factors that influenced the development of the area over time.

Table 3. Trend of LULC in Jakarta Ciliwung Watershed 2010-2025

LULC	2010		2015		2020		2025	
	Km²	%	Km²	%	Km²	%	Km²	%
LB	83,49	60,53	99,70	72,29	103,69	75,18	112,83	81,80
LT	1,54	1,12	2,83	2,05	0,13	0,09	0,31	0,23
H	50,49	36,61	32,82	23,80	31,65	22,95	18,90	13,70
LP	0,28	0,20	0,27	0,20	0,27	0,20	1,99	1,44
B	0,18	0,13	0,16	0,12	0,28	0,21	1,04	0,75
BA	1,95	1,42	2,14	1,55	1,89	1,37	2,86	2,07
Total	**137,93**	**100**	**137,93**	**100**	**137,93**	**100**	**137,93**	**100**

Source: Author's own elaboration (2025)

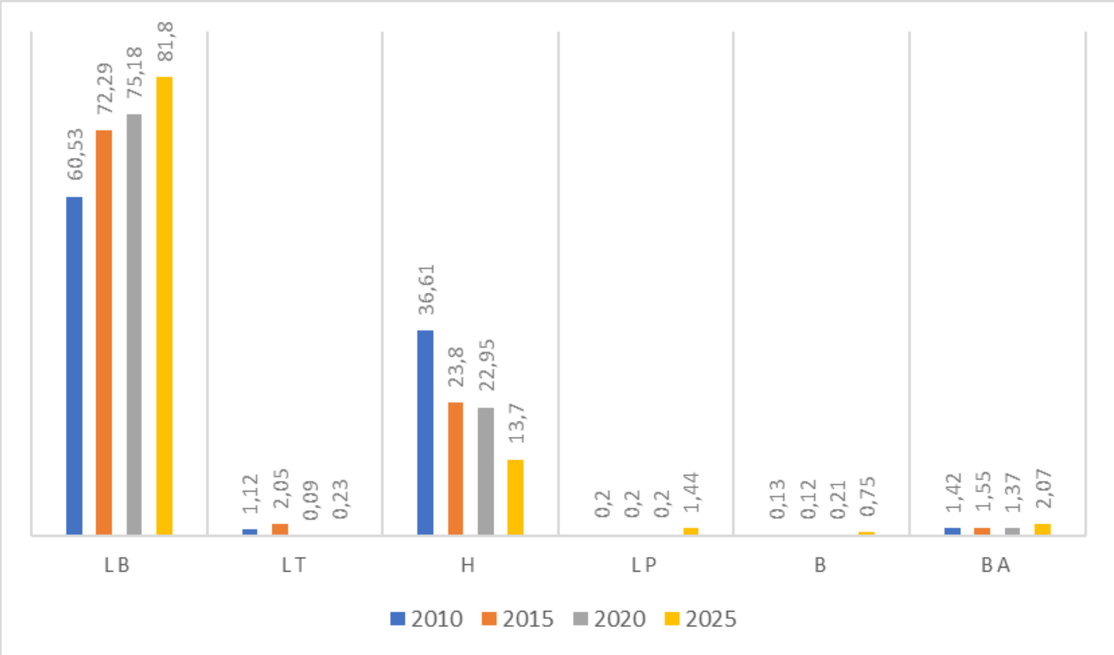

Figure 3. Trend Precent of LULC in Ciliwung watershed Jakarta from 2010 to 2025

Source: Author's own elaboration (2025)

Built-up land shows a significant increase from 60.53% in 2010 to 81.80% in 2025. Urbanization plays a significant role in causing demographic expansion and infrastructure development aimed at meeting the requirements for housing, industry, and public facilities. This phenomenon is in line with previous research which states that urbanization leads to an escalation in the area used to the detriment of green spaces and forests. Open land shows variability as in 2010, its coverage was measured at 1.12%, which increased to 2.05% in 2015, but experienced a marked decrease in the following years, and reduced to

0.23% in 2025. This reduction is a consequence of the transformation of open land into developed areas or alternative uses, such as infrastructure improvements. This decline exemplifies the pressure exerted by urbanization on unoccupied areas. Forest area experienced a significant decrease from 36.61% in 2010 to 13.70% in 2025. This reduction can be attributed to deforestation efforts by urban development, agricultural proliferation, other economic development. The environmental consequences of forest reduction are profound, including habitat destruction, deteriorating air quality, and increased risks associated with climate change. Agricultural land remains relatively constant through 2020, maintaining an estimated area of 0.20%, but increases to 1.44% by 2025. Shrubs show a small increase from 0.13% in 2010 to 0.75% in 2025. This increase is related to natural regeneration processes in certain areas or changes in non-intensive land use classification. Nonetheless, the importance of shrubs in facilitating biodiversity and mitigating climate change challenges remains paramount. Water bodies show an upward trajectory, increasing from 1.42% in 2010 to 2.07% in 2025. This increase is a reflection of the implementation of rehabilitation of previously degraded water systems.

LULC Change 2010-2025 **Figure 4** shows that developed land has increased rapidly accompanied by a significant decrease in forest area, especially in the first two periods and again in 2020-2025. This indicates that the conversion of forest land to built-up areas is the main dynamic in land use change. Other categories such as agricultural land, scrub, and water bodies experienced relatively small changes, indicating that the main impact still revolves around the conversion of forest to built-up areas.

The spatial and temporal patterns of LULC change show significant dynamics throughout the period 2010 to 2025. Based on the data in **Table 3**, there was a substantial increase in the built-up land category from 83.4867 km² in 2010 to 112.8294 km² in 2025. On the other hand, forest areas experienced a drastic decrease in area, which amounted to 23%. Meanwhile, water bodies also showed an increasing trend, with an increase in area reaching 2.8557 km². These changes are clearly visualized in **Figure 5**, which indicates that the expansion of built-up land is the most dominant transformation during the period 2010 – 2025.

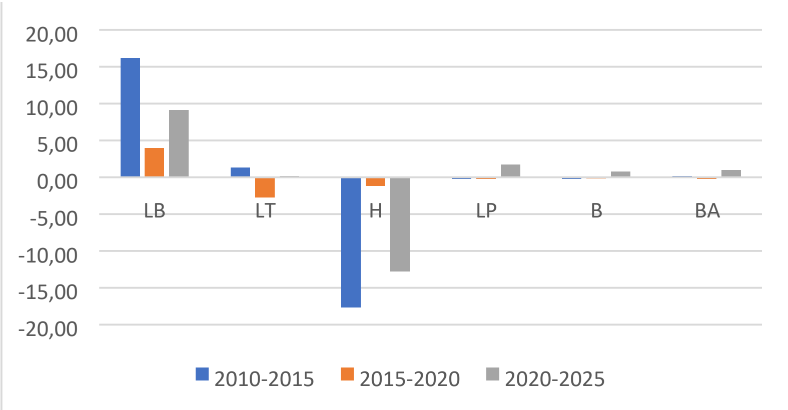

Figure 4. Trend Precent of LULC in Ciliwung watershed Jakarta from 2010 to 2025

Source: Author's own elaboration (2025)

2. Classification Accuracy Assessment

The classification accuracy matrix shows the degree of agreement between the classification results and the reference data, which is reinforced by the Kappa coefficient value as an indicator of statistical accuracy (Verma et al., 2020) . The Kappa value obtained reflects the extent to which the classification results are better than random classification, with the interpretation that the higher the Kappa value, the higher the level of reliability in representing the actual conditions in the field **Table 4**.

Table 4. Accuracy of Classification and Verification for 2010-2025

LULC	2010	2015	2020	2025
Built up land	83,49	99,70	103,69	112,83
Open land	1,54	2,83	0,13	0,31
Forest	50,49	32,82	31,65	18,90
Agricultural land	0,28	0,27	0,27	1,99
Thicket	0,18	0,16	0,28	1,04
Water Body	1,95	2,14	1,89	2,86
Overall Accuracy	**0,80**	**0,86**	**0,84**	**0,89**
Koefisien Kappa	**0,77**	**0,83**	**0,81**	**0,85**

Source: Author's own elaboration (2025)

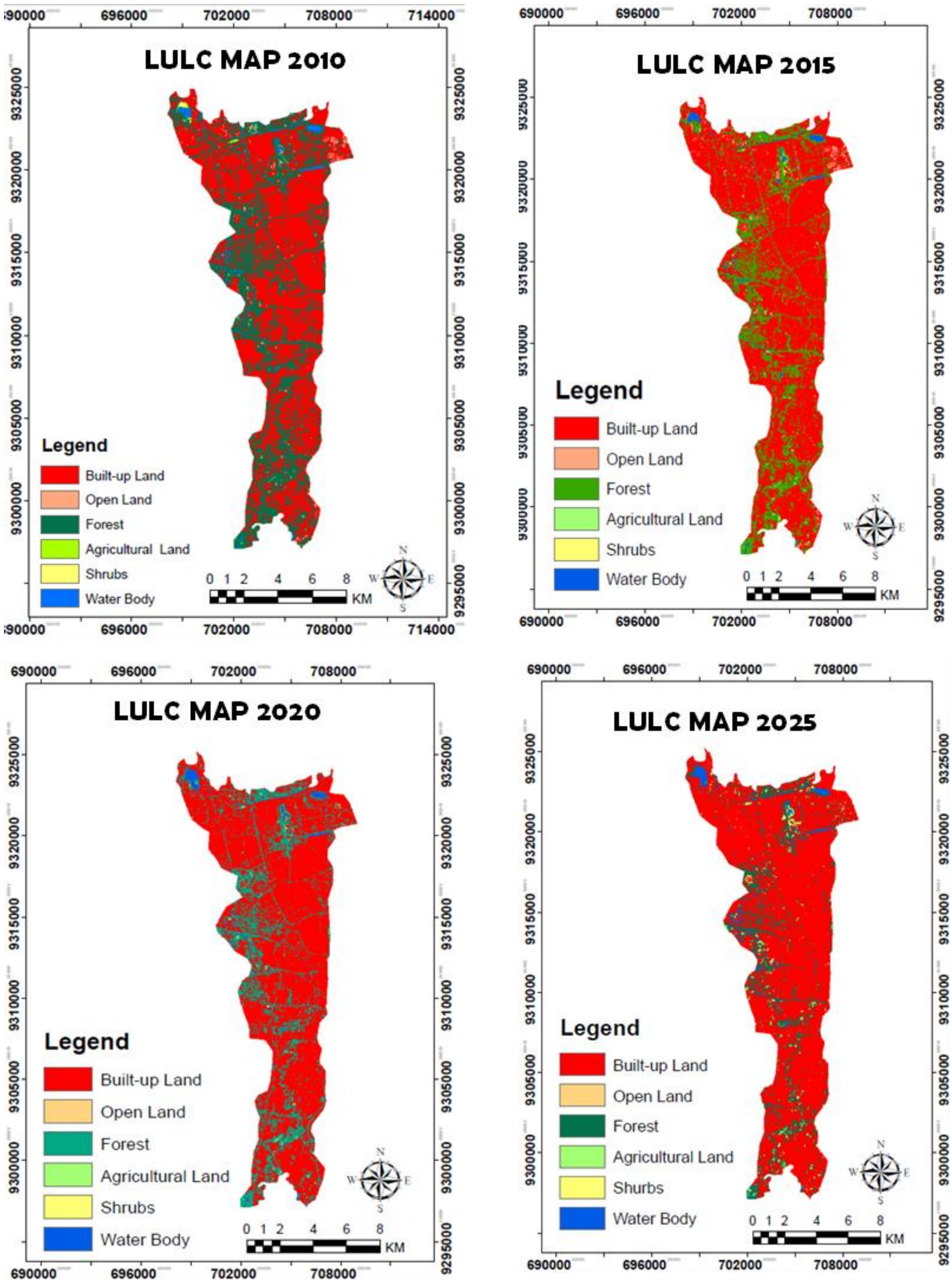

Figure 5. LULC map trends 2010 - 2025

Source: Author’s own elaboration (2025)

3. Drivers of Land Change

Factors influencing land change were analyzed using Micmac software. Micmac is used to determine relationships between variables that serve to identify important factors causing land change (Ariyani et al., 2022). Micmac can map relationships between variables and correlations of variables to explain the system, as well as identify causal relationships of the system (Bashir & Ojiako, 2020). As shown in **Figure 6**, the factors that contribute to land use change show a strong direct influence, especially from the urbanization process. Urbanization clearly drives land use change that is closely related to infrastructure development, increased trade and industrial activities, expansion of residential areas, and the dynamics of spatial planning policies in DKI Jakarta Province. This phenomenon does not occur in isolation, but as part of an interrelated urban process. Concrete evidence of this trend is reinforced by the demographic data in **Figure 7,** which illustrates a significant increase in population over the last decade, especially in the time span between 2014 and 2024. This increase in population is one of the main drivers of pressure on land, driving intensification of space utilization and accelerating the transformation of urban landscapes.

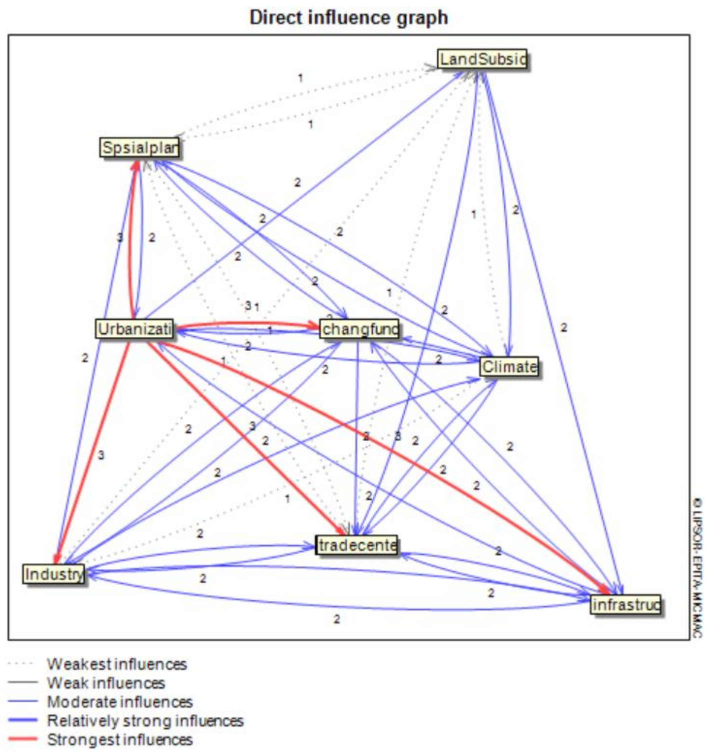

Figure 6. Direct Impact of Land Change
Source: Author's own elaboration (2025)

p-ISSN 2460-0768 e-ISSN 2597-6044
https://doi.org/10.20961/ge.v12i2.108804

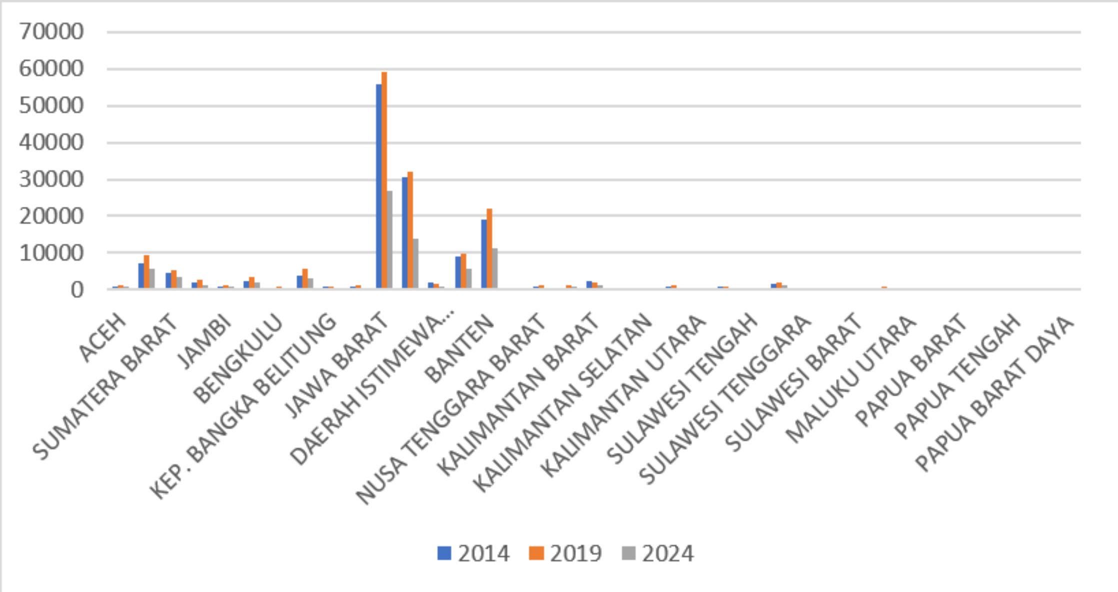

Figure 7. Population Growth 2014-2024

Source: Author's own elaboration (2025)

Figure 7 shows that the number of residents from various provinces in Indonesia living in DKI Jakarta increased from 2014 to 2019, then declined in 2024. This was the result of a policy by the DKI Jakarta government requiring residents domiciled outside the DKI Jakarta region but still holding a Jakarta ID card to update their residency records and register in accordance with their actual place of residence. The largest contribution comes from provinces on the island of Java, such as West Java, Central Java, and East Java, as the primary feeder regions, while provinces outside Java—including Sumatra, Kalimantan, Sulawesi, and Papua—also contribute in smaller numbers. This indicates that DKI Jakarta remains the primary national hub for population migration, driven by factors such as natural growth through birth rates, inbound migration due to economic attractiveness and regional development, as well as improved quality of life leading to a decline in mortality rates (Todaro & Smith, 2020).

4. Predicted LULC Change

Predictions of LULC change are an important part of the analysis to understand the cumulative impacts of human activities and climate change on the ecosystem as a whole, and provide a solid basis for more sustainable land use planning in the future (Wangyel et al., 2021; Rai et al., 2014). During the transition period between 2010 and

2025, there has been a major transformation in land use patterns, which clearly reflects that development is the dominant factor driving land use change, with forests and water bodies being the main land categories converted to meet development needs (**Table 3** and **Figure 3**). Land use transformation is largely dominated by the conversion of green open spaces into densely populated residential areas, commercial activity centers, and industrial areas (Arifasihati & Kaswanto, 2016). This situation results in approximately 81.83% of the Jakarta Cilliwung watershed area turning into built-up areas by 2030 with a high level of density, which significantly reduces the capacity of the area to absorb rainwater (**Table 5** and **Figure 8**). A further impact of this conversion is the increased risk of urban flooding due to decreased water infiltration function and increased surface runoff, in addition to the reduction of green spaces that previously played a role in maintaining ecosystem balance.

Table 5. Predicted LULC 2025 - 2030

Land Cover	2025	2030	2025	2030
	km	km	%	%
LB	112,83	112,87	81,80	81,83
LT	0,31	0,25	0,23	0,18
H	18,90	18,67	13,70	13,53
LP	1,99	2,16	1,44	1,57
B	1,04	1,14	0,75	0,82
BA	2,86	2,85	2,07	2,07
Total	**137,93**	**137,93**	**100**	**100**

Source: Author's own elaboration (2025)

Overall, the prediction results in the data analysis reflect the dynamics of land change in the five-year period, increasing in area from 112.83 km² in 2025 to 112.87 km² in the built-up land category in 2030. Meanwhile, open land decreased in area from 0.31 km² in 2025 to 0.25 km² in 2030. This decrease indicates a reduction in land area that does not have vegetation. Forest area also decreased, although not significantly, only by 0.17% in 2030. Meanwhile, agricultural land and shrubs experienced a slight increase in 2030 of 0.13% for agricultural land and 0.07% for shrubs. While water bodies tend to be stable with the percentage remaining constant at 2.07%, the absence of significant changes indicates that this area is relatively undisturbed.

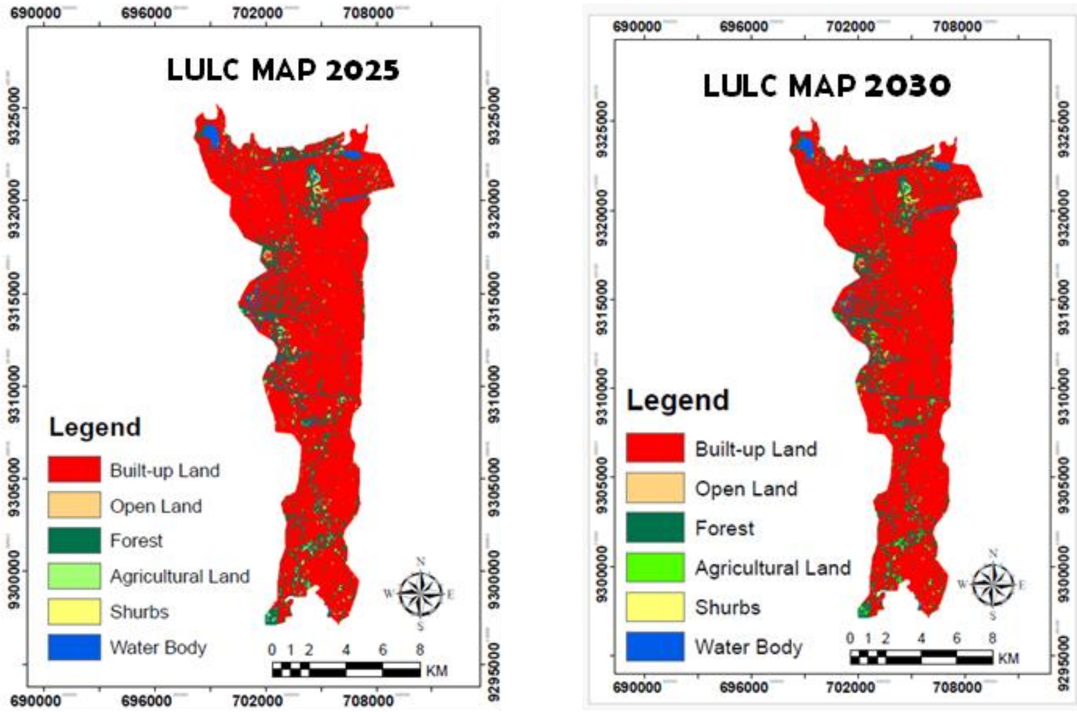

Figure 8. LULC Prediction Map 2025 – 2030

Source: Author's own elaboration (2025)

5. Discussion

The results of the study show that the dynamics of LULC change in the Ciliwung River Basin in DKI Jakarta are dominated by massive built-up land expansion. In 2010, the area of built-up land was recorded at 83.49 km² (60.53%) and increased to 112.83 km² (81.80%) in 2025. Projections using the CA–Markov model show that by 2030, the area of built-up land will reach 112.87 km² or 81.83% of the total study area. In contrast, forest areas experienced a significant decline, from 50.49 km² (36.61%) in 2010 to only 18.67 km² (13.53%) in 2030. Open land also shrinks drastically, from 1.12% in 2010 to 0.18% in 2030, while water bodies remain relatively stable at around 2.07%. This phenomenon reflects the intense pressure of urbanization in the DKI Jakarta area, where the need for housing, industry, and infrastructure has consistently converted forest areas and green open spaces (Rustiadi et al., 2018; Rajagukguk et al., 2023). These changes not only reduce environmental carrying capacity but also increase the potential for urban flooding due to decreased soil infiltration capacity and increased surface runoff (Farid et al., 2022; Ali et al., 2016).

The accuracy results of the classification of Landsat satellite imagery from 2010 to 2025 show a Kappa coefficient value > 0.80, which indicates a high level of reliability in mapping the dynamics of land cover change. The CA–Markov model has proven effective for projecting LULC patterns in the Ciliwung watershed, with consistent validation above 75% (Keshtkar & Voigt, 2016; Sanga et al., 2024). This reinforces previous findings that a combination of spatial analysis and probabilistic-based predictions can accurately represent urbanization trends (Chu et al., 2018; Li et al., 2023). The main implication of these results is that the minimum target of 30% green open space as stipulated in Presidential Regulation No. 6 of 2020 will be difficult to achieve, considering that by 2030, green areas in the Ciliwung River Basin are projected to only remain at around 13%. This condition calls for more adaptive spatial planning policies, stricter control of land use change, and revitalization of green open space to strengthen the carrying capacity of the urban environment (Rachma et al., 2022).

Overall, the results of this study confirm that uncontrolled urbanization in the Ciliwung River Basin has caused significant deforestation, ecosystem degradation, and increased risk of urban flooding. Therefore, it is urgent to implement an ecology-based watershed management strategy that balances development with environmental conservation in this region.

CONCLUSIONS

This study shows that the dynamics of land cover change in the Ciliwung watershed is dominated by the expansion of built-up land, which increased from 60.53% in 2010 to 81.80% in 2025, and is projected to reach 81.83% in 2030. A significant decline occurred in forest area, from 36.61% in 2010 to 13.53% in 2030, which illustrates the rate of deforestation due to urbanization. This process is triggered by population growth, infrastructure needs, and intensification of economic activities in the DKI Jakarta area. The CA-Markov model proved effective in predicting the pattern of LULC change with high accuracy (Kappa coefficient >0.80). The results of this study confirm the need to control land use change, increase green open space, and strengthen spatial policies that are adaptive to urbanization pressures and environmental risks.

This study has several limitations that should be noted. The use of Landsat imagery with a spatial resolution of 30 meters limits the detail of land-use change identification, particularly in complex urban areas. Additionally, the CA-Markov model assumes that future change patterns follow historical trends, and thus does not fully account for policy dynamics, government interventions, or external factors such as climate change. The

MICMAC analysis used is also still qualitative in nature, so it is not yet capable of quantitatively measuring the strength of the influence between variables.

For future research, it is recommended to use data with higher resolution, such as Sentinel or UAV data, to improve spatial accuracy. Model development can also be enhanced by integrating machine learning approaches or hydrological models to make prediction results more comprehensive. Furthermore, it is necessary to incorporate spatial planning policy scenarios and quantitative flood risk analysis so that research results are more applicable in supporting regional planning and decision-making.

ACKNOWLEDGMENTS

I would like to thank the Provincial Government of DKI Jakarta and Pakuan University for supporting the data and costs of this research.

REFERENCES

Ali, M., Hadi, S., & Sulistyantara, B. (2016). Study on Land Cover Change of Ciliwung Downstream Watershed with Spatial Dynamic Approach. Procedia - Social and Behavioral Sciences,227 (November 2015), 52-59. https://doi.org/10.1016/j.sbspro.2016.06.042

Araya, Y. H., & Cabral, P. (2010). Analysis and Modeling of Urban Land Cover Change in Setúbal and Sesimbra, Portugal. 1549–1563. https://doi.org/10.3390/rs2061549

Arifasihati, Y., & Kaswanto. (2016). Analysis of Land Use and Cover Changes in Ciliwung and Cisadane Watershed in three Decades. Procedia Environmental Sciences,33 , 465-469. https://doi.org/10.1016/j.proenv.2016.03.098

Ariyani, D., Purwanto, M. Y. J., Sunarti, E., & Perdinan. (2022). Contributing factors influencing flood disaster using MICMAC (Ciliwung Watershed Case Study). Journal of Natural Resources and Environmental Management,12 (2), 268-280. https://doi.org/10.29244/jpsl.12.2.268-280

Bashir, H., & Ojiako, U. (2020). An integrated ISM-MICMAC approach for modeling and analyzing dependencies among engineering parameters in the early design phase. Journal of Engineering Design,31 (8-9), 461-483. https://doi.org/10.1080/09544828.2020.1817347

Chu, L., Sun, T., Wang, T., Li, Z., & Cai, C. (2018). Evolution and prediction of landscape pattern and habitat quality based on CA-Markov and InVEST model in hubei section of Three Gorges Reservoir Area (TGRA). Sustainability (Switzerland),10 (11). https://doi.org/10.3390/su10113854

M.H. Elagouz, S.M. Abou-Shleel, A.A. Belal, M.A.O. El-Mohandes (2020) Detection of land use/cover change in Egyptian Nile Delta using remote sensing. Egyptian Journal of Remote Sensing and Space Science,23 (1), 57-62. https://doi.org/10.1016/j.ejrs.2018.10.004

Farid, M., Pratama, M. I., Kuntoro, A. A., Adityawan, M. B., Rohmat, F. I. W., & Moe, I. R. (2022). Flood Prediction due to Land Cover Change in the Ciliwung River Basin. International Journal of Technology,13 (2), 356-366. https://doi.org/10.14716/ijtech.v13i2.4662

Feizizadeh, B., Darabi, S., Blaschke, T., & Lakes, T. (2022). QADI as a New Method and Alternative to Kappa for Accuracy Assessment of Remote Sensing-Based Image Classification. Sensors,22 (12), 1-21. https://doi.org/10.3390/s22124506

Fu, F., Jia, X., Zhao, Q., Tian, F., Wei, D., Zhao, Y., Zhang, Y., Zhang, J., Hu, X., & Yang, L. (2024). Predicting land use change around railway stations: An enhanced CA-Markov model. Sustainable Cities and Society,101 (July). https://doi.org/10.1016/j.scs.2023.105138

Gharaibeh, A., Shaamala, A., Obeidat, R., & Al-Kofahi, S. (2020). Improving land-use change modeling by integrating ANN with Cellular Automata-Markov Chain model. Heliyon,6 (9), e05092. https://doi.org/10.1016/j.heliyon.2020.e05092

Ghalehteimouri, K. J., Shamsoddini, A., Mousavi, M. N., Binti Che Ros, F., & Khedmatzadeh, A. (2022). Predicting spatial and decadal of land use and land cover change using integrated cellular automata Markov chain model based scenarios (2019-2049) Zarriné-Rūd River Basin in Iran. Environmental Challenges,6 (July 2021), 100399. https://doi.org/10.1016/j.envc.2021.100399

Hamad, R., Balzter, H., & Kolo, K. (2018). Predicting land use/land cover changes using a CA-Markov model under two different scenarios. Sustainability (Switzerland),10 (10), 1-23. https://doi.org/10.3390/su10103421

Kafy, A. A., Naim, M. N. H., Subramanyam, G., Faisal, A. Al, Ahmed, N. U., Rakib, A. Al, Kona, M. A., & Sattar, G. S. (2021). Cellular Automata approach in dynamic modeling of land cover changes using RapidEye images in Dhaka, Bangladesh. Environmental Challenges,4 (January), 100084. Https://doi.org/10.1016/j.envc.2021.100084

Keshtkar, H., & Voigt, W. (2016). A spatiotemporal analysis of landscape change using an integrated Markov chain and cellular automata models. Modeling Earth Systems and Environment,2 (1), 1-13. https://doi.org/10.1007/s40808-015-0068-4

Li, G., Cheng, G., Liu, G., Chen, C., & He, Y. (2023). Simulating the Land Use and Carbon Storage for Nature-Based Solutions (NbS) under Multi-Scenarios in the Three Gorges Reservoir Area: Integration of Remote Sensing Data and the RF-Markov-CA-InVEST Model. Remote Sensing,15 (21). https://doi.org/10.3390/rs15215100

Mahfudz, M. (2023). Analysis of Settlement Land Change Using Landsat 8 Imagery (Case Study: Cianjur Regency, West Java Province). Engineering Journal | Scientific Magazine of the Faculty of Engineering UNPAK,24 (1), 23-29. https://doi.org/10.33751/teknik.v24i1.7997

Mahfudz, M., Riadi, B., Nurtyaman, R., & Utomo, P. P. (2024). Satellite Image Analysis Approach for Identifying Flood Impacts in DKI Jakarta.

Engineering and Technology Journal,09 (04). https://doi.org/10.47191/etj/v9i04.14

Meyer, S. R., Johnson, M. L., Lilieholm, R. J., & Cronan, C. S. (2014). Development of a stakeholder-driven spatial modeling framework for strategic landscape planning using Bayesian networks across two urban-rural gradients in Maine, USA. Ecological Modeling,291 , 42-57. https://doi.org/10.1016/j.ecolmodel.2014.06.023

Mosleh, M. K. (2025). Integrating the CA-Markov model and geospatial techniques for spatiotemporal prediction of land use/land cover dynamics in Qus District, Egypt. Modeling Earth Systems and Environment,11 (5). https://doi.org/10.1007/s40808-02502479-9

Msofe, N. K., Sheng, L., & Lyimo, J. (2019). Land use change trends and their driving forces in the Kilombero Valley Floodplain, Southeastern Tanzania. Sustainability (Switzerland),11 (2), 1-25. https://doi.org/10.3390/su11020505

Paradis, E. (2022). Probabilistic nsupervised classification for large-scale analysis of spectral imaging data. International Journal of Applied Earth Observation and Geoinformation,107 , 102675. Https://doi.org/10.1016/j.jag.2022.102675

Rachma, T. R. N., Silalahi, F. E. S., & Oktaviani, N. (2022). Monitoring 20 Years of Land Cover Change Dynamics in the Satellite Cities of Jakarta, Indonesia. IOP Conference Series: Earth and Environmental Science,1111 (1). https://doi.org/10.1088/17551315/1111/1/012034

Rai, P. K., Mishra, V. N., & Mohan, K. (2014). Prediction of land use changes based on land change modeler (LCM) using remote sensing: A case study of Muzaffarpur (Bihar),.November. https://doi.org/10.2298/IJGI1401111M

Rajagukguk, J. R., & Pranoto, D. A. (2023). Research on the Impact of Ciliwung River Water on the Surrounding Environment in the DKI Jakarta Area. IOP Conference Series: Earth and Environmental Science,1175 (1). https://doi.org/10.1088/1755-1315/1175/1/012013

Rimal, B., Zhang, L., Keshtkar, H., Sun, X., & Rijal, S. (2018). Quantifying the spatiotemporal pattern of urban expansion and hazard and risk area identification in the Kaski District of Nepal. Land,7 (1). https://doi.org/10.3390/land7010037

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). https://doi.org/10.3390/ijgi6090288

Rushayati, S. B., Shamila, A. D., & Prasetyo, L. B. (2018). The Role of Vegetation in Controlling Air Temperature Resulting from Urban Heat Island. Geography Forum,32 (1), 1-11. https://doi.org/10.23917/forgeo.v32i1.5289

Rustiadi, E., Barus, B., Iman, L. S., Mulya, S. P., Pravitasari, A. E., & Antony, D. (2018). Land use and spatial policy conflicts in a rich-biodiversity rain forest region: The case of Jambi Province, Indonesia. Springer

Geography, January, 277-296. https://doi.org/10.1007/978-981-10-5927-8_15

Rustiadi, E., Pravitasari, A. E., Priatama, R. A., Singer, J., Junaidi, J., Zulgani, Z., & Sholihah, R. I. (2023). Regional Development, Rural Transformation, and Land Use/Cover Changes in a Fast-Growing Oil Palm Region: The Case of Jambi Province, Indonesia. Land,12 (5). https://doi.org/10.3390/land12051059

Saing, Z., Djainal, H., & Deni, S. (2021). Land use balance determination using satellite imagery and geographic information system: case study in South Sulawesi Province, Indonesia. Geodesy and Geodynamics,12 (2), 133-147. https://doi.org/10.1016/j.geog.2020.11.006

Sanga, F., & Haulle, E. (2024). The paradox of the land use/land cover change in Kipengere ranges in southern highlands of Tanzania. Geology, Ecology, and Landscapes,00 (00), 18. https://doi.org/10.1080/24749508.2024.2429206

Shafizadeh Moghadam, H., & Helbich, M. (2013). Spatiotemporal urbanization processes in the megacity of Mumbai, India: A Markov chains-cellular automata urban growth model. Applied Geography,40 , 140-149. https://doi.org/10.1016/j.apgeog.2013.01.009

Simon, O., Lyimo, J., & Yamungu, N. (2023). Land use and cover change in Dar es Salaam metropolitan city: satellite data and CA-Markov chain analysis. GeoJournal,88 (6), 6119-6136. https://doi.org/10.1007/s10708-023-10960-0

Son, N. T., & Binh, N. D. (2020). Predicting land use and climate change scenarios impacts on runoff and soil erosion: A case study in hoa Binh Province, lower da River Basin, Northwest Vietnam. EnvironmentAsia,13 (2), 67-77. https://doi.org/10.14456/ea.2020.30

Song, W., Yunlin, Z., Zhenggang, X., Guiyan, Y., Tian, H., & Nan, M. (2020). Landscape pattern and economic factors' effect on prediction accuracy of cellular automata-Markov chain model at county scale. Open Geosciences,12 (1), 626-636. https://doi.org/10.1515/geo-2020-0162

Susilowati, Y., Kumoro, Y., & Nur, W. H. (2020). Integrated water quality modeling for spatial planning. IOP Conference Series: Earth and Environmental Science,483 (1). https://doi.org/10.1088/1755-1315/483/1/012041

Todaro, M. P., & Smith, S. C. (2020). Economic Development (13th ed.). Pearson.

Thakur, T. K., Patel, D. K., Bijalwan, A., Dobriyal, M. J., Kumar, A., Thakur, A., Bohra, A., & Bhat, J. A. (2020). Land use land cover change detection through geospatial analysis in an Indian Biosphere Reserve. Trees, Forests and People,2 (June), 100018. https://doi.org/10.1016/j.tfp.2020.100018

Trevisiol, F., Mattivi, P., Mandanici, E., & Bitelli, G. (2024). Cross-Sensors Comparison of Popular Vegetation Indexes from Landsat TM, ETM=, OLI, and Sentinel MSI for TimeSeries Analysis over Europe. IEEE Transactions on Geoscience and Remote Sensing,62, 1-16. https://doi.org/10.1109/TGRS.2023.3343071

Verma, P., Raghubanshi, A., Srivastava, P. K., & Raghubanshi, A. S. (2020). Appraisal of kappa-based metrics and disagreement indices of accuracy assessment for parametric and nonparametric techniques used in LULC classification and change detection. Modeling Earth Systems and Environment,6 (2), 1045-1059. https://doi.org/10.1007/s40808-020-00740-x

Wangyel, S., Munkhnasan, L., & Lee, W. (2021). Land use and land cover change detection and prediction in Bhutan's high altitude city of Thimphu, using cellular automata and Markov chain. 2(November 2020). https://doi.org/10.1016/j.envc.2020.100017