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Analysis and Prediction of Land Cover Change in Palangka Raya City Using a Cellular Automata–Neural Network Model Based on MOLUSCE

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ABSTRACT

Land cover change represents a dynamic phenomenon driven by human activities and rapid regional growth, particularly in Palangka Raya City. This study aimed to analyze the historical dynamics of land cover changes during the 2016–2020 period and predict development trends for 2028 and 2040. The methodology integrated Cellular Automata and Artificial Neural Network (CA-ANN) models utilizing the MOLUSCE plugin within Geographic Information System software. Several driving factors were incorporated into the modeling process, including distance from road networks, distance from rivers, slope, elevation, and population density. The analysis revealed a significant transition from natural vegetated areas, such as peat swamp forests and shrublands, into anthropogenic land uses, specifically oil palm plantations and built-up areas. Model validation was performed using the Kappa coefficient test, which yielded a high level of accuracy, thereby confirming the reliability of the model for spatial projection purposes. The prediction results for 2028 and 2040 provided critical spatial insights regarding the potential continuous expansion of built-up areas. These findings were intended to serve as a crucial reference for local governments in formulating sustainable spatial planning policies to mitigate future environmental degradation.

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1. INTRODUCTION

The main text format is a flat left-right column on A4 paper (quarto). The margin text Land cover change is one of the most dynamic phenomena that reflects the complex interaction between human activities and the spatial distribution of natural resources [1], [2], [3]. Globally, these changes are driven by the intensification of anthropogenic processes such as agricultural development, deforestation, and urban expansion that can hinder ecosystem sustainability and degrade nature's ability to provide ecosystem services [4], [5]. In many developing countries, including Indonesia, the high rate of population growth and the urbanization process that takes place without careful planning have been the main factors in environmental degradation [6]. This condition is also felt significantly on the island of Kalimantan, which is currently under serious pressure due to land use change. Activities such as forest logging, oil palm plantation expansion, and peatland fires have contributed greatly to reduced forest cover [3], [7]. In the last two decades, the conversion of forest areas into settlements, agricultural land, and open areas in Kalimantan has reached 32.8%, indicating an increasingly alarming rate of land cover change [8]. Palangka Raya City, as the capital of Central Kalimantan Province, continues to experience population growth at an average rate of 2.8% per year and a significant increase in land investment [9]. Historical data shows that deforestation in Palangka Raya City reached 7,810 ha in the 2006-2011 period and increased sharply to 17,452 ha in the 2011-2016 period, with the conversion of forests to shrubs as the highest trend [9]. The development of Palangka Raya as the first independent city designed by the sons of the nation has unique characteristics where the city grew on the banks of the Kahayan River (Pahandut Village) [10]. However, rapid development has resulted in a shift in regional orientation from river-based to mainland cities (*Landfront City*), which if left unchecked will exacerbate the degradation of peat swamp forest ecosystems that are critical as carbon sinks and maintain global climate balance [10], [11].

To anticipate the adverse effects of uncontrolled physical development, modeling instruments that are able to simulate future conditions as the basis for adaptive and sustainable spatial planning are needed [4], [12]. The Artificial Neural Network (ANN) method has the advantage of capturing non-linear relationships between factors driving land change such as distance from road networks, activity centers, and elevation with the probability of land transition [13], [14]. On the other hand, Cellular Automata (CA) is a dynamic model that is very powerful in reading spatial and temporal change patterns by considering the influence of neighboring environments (*neighborhood effects*) [1], [15]. The CA-ANN combination has been shown to be more efficient and has higher accuracy than traditional regression models in simulating complex spatial phenomena [13], [16]. The CA-ANN method has been successfully applied in various regions in Southeast and South Asia with a validation accuracy rate of 80-90% [4], [13], [16], [17], [18], [19]. The study in Kupang

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City used the CA-Markov model with an overall accuracy of 86% and a Kappa coefficient of 0.81 for the simulation period 2018-2043 [12].

This study utilizes QGIS software with *Stuart T* MOLUSCE (*Modules for Land Use Change Evaluation*) that provides ANN and CA algorithms to evaluate potential transitions and perform spatially explicit prediction simulations [16]. In addition, the image data used is satellite image data from the MapBiomas Indonesia Platform. MapBiomas Indonesia is a multi-institutional initiative that produces annual maps of Indonesia's land cover and use using a machine learning-based automated classification process [8]. MapBiomas Indonesia's 4.0 collection includes data for the period 1990-2024 with 13 land cover classes classified using Random Forest and Deep Learning, processed by *cloud computing* based *Google Earth Engine* [8]. The data from MapBiomas has been extensively validated and shows high accuracy with Kappa coefficients ranging from 0.75-0.85.

Although research on monitoring land cover change has been widely conducted in Indonesia, special research using MapBiomas data with the CA-ANN methodology to predict land cover change is still limited. Most studies focus on the regional level, while research with an urban-level prediction focus in Central Kalimantan is still minimal. In addition, systematic integration between multi-sensor data and sophisticated machine learning has not been widely carried out in developing cities in Kalimantan. This study aims to analyze the patterns and dynamics of land cover change in Palangka Raya City from historical data as well as identify and analyze the driving factors of land cover change in Palangka Raya, develop a robust CA-ANN hybrid prediction model to predict land cover changes from 2028 to 2040. and validate the accuracy of the model the Kappa coefficient.

2. RESEARCH METHOD

2.1. Research Areas, Tools and Materials

This research was conducted in Palangka Raya City (Figure 1), Central Kalimantan Province, Indonesia. Geographically, the study area is located at the coordinates of 1°35' – 2°24' South Latitude and 113°30' – 114°07' East Longitude with an area of approximately 2.853 km². The selection of the location is based on the dynamics of massive land use due to the expansion of settlements and plantations in peat swamp forest ecosystems. Data processing and modeling are carried out with a combination of GIS and computing software as follows:

1) QGIS 3.x Used as the main platform for data pre-processing, spatial analysis, and visualization
2) The MOLUSCE (Modules for Land Use Change Evaluation) plugin is used as a single instrument for all stages of prediction modeling, which includes Transition Potential Modeling: Using Artificial Neural Network (ANN) algorithms to train models based on driving factors; Cellular Automata (CA) Simulation to simulate the spatial

distribution of future land cover; Validation to calculate the Kappa Coefficient and *Overall Accuracy*.

3) ArcGIS is optional to assist with final map layout and vector data analysis if needed

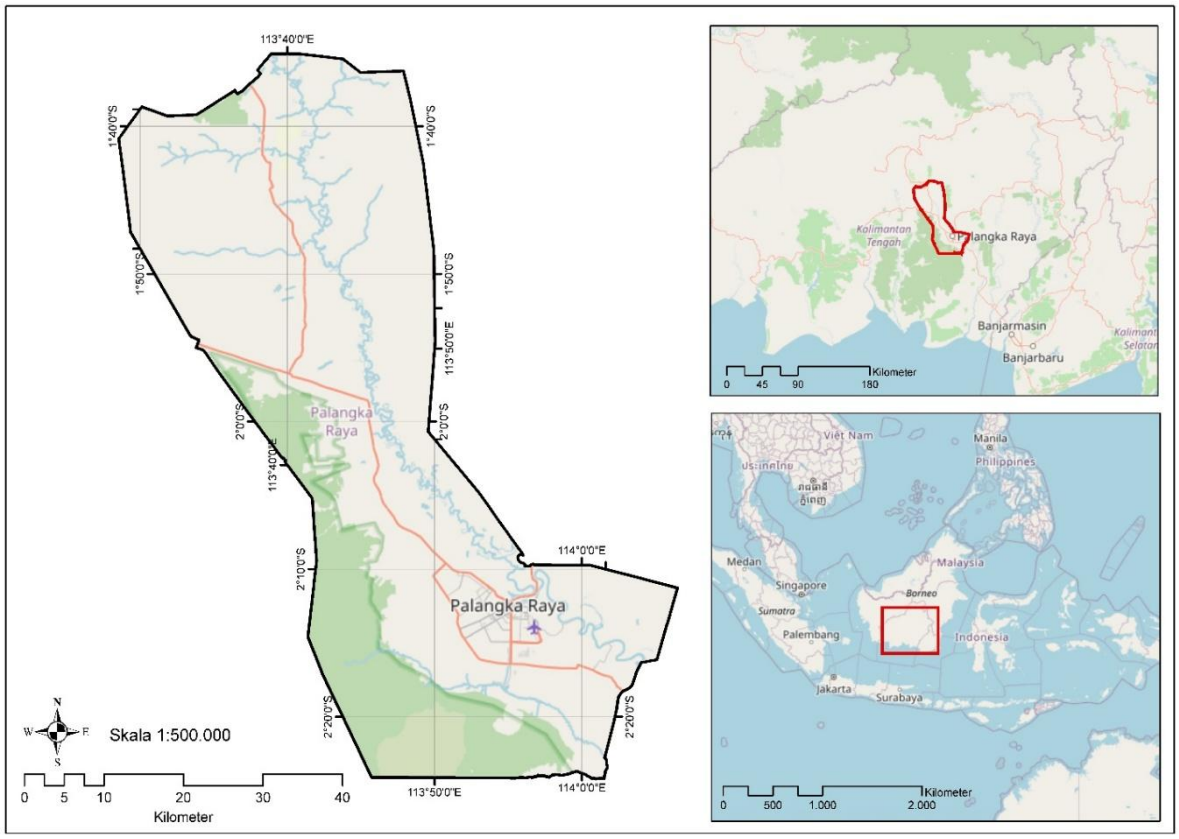

Figure 1. Research Location

This study utilizes multitemporal land cover data from MapBiomas Indonesia. Land cover maps from MapBiomas Indonesia were obtained through the Landy platform (collection 4.0) with a temporal range of 1990–2024 and a spatial resolution of 30 m on the WGS84 projection system (EPSG:4326 The data used are annual, specifically utilizing land cover maps from 2016 and 2020 for the modeling basis, 2024 for validation, and projecting development trends for 2028 and 2040. MapBiomas provides 13 classes of land cover, including: swamp formation forests, natural forests, plantation forests, restoration, savannas/grasslands, annual agriculture, seasonal agriculture, pastures, mines/pits, urban/built areas, open areas, water bodies, and clouds. MapBiomas' classification method reportedly uses Random Forest for the majority of classes and a deep learning approach for specific classes (e.g. specific commodities).

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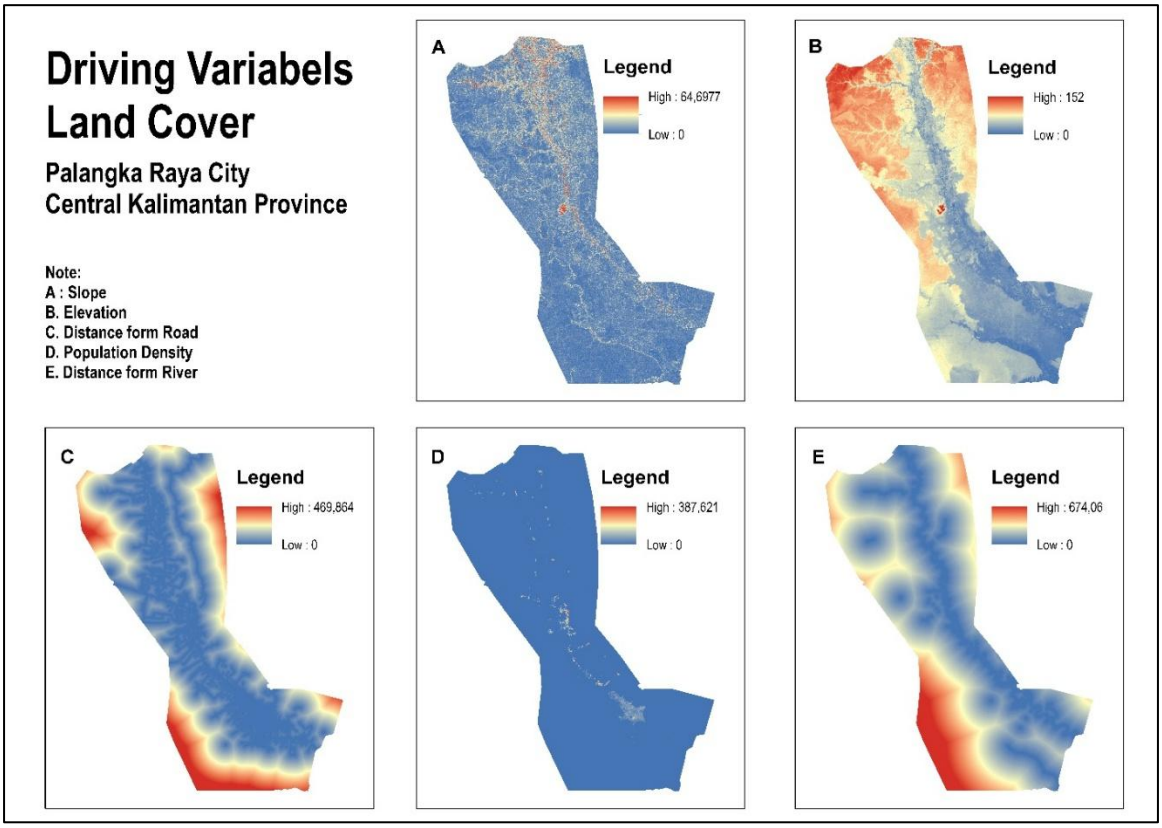

Figure 2. Map of Land Cover Supporting Factors

The selection of the driving variables in this study is based on a literature review and adjustments to specific spatial dynamics in Palangka Raya City. These factors were chosen to represent aspects of accessibility, resources, biophysical conditions, as well as demographic pressures that trigger landscape transformation [16], [19]. The use of this variable is chosen so that the model *Artificial Neural Network* (ANN) can capture the non-linear relationship between human activity and land change. The independent variables (Figure 2) used in this modeling include:

1) Distance to Roads using data *OpenStreetMap* and infrastructure maps. Road accessibility is a key determinant that attracts the expansion of built-up areas and increases the economic value of land [16], [19], [20].
2) Topographic Conditions (Elevation and Slope): Derived from DEMNAS data (resolution of 7.5 m). The elevation and slope of the slope determine the physical suitability of the land as well as the efficiency of construction costs, especially in the Palangka Raya area which varies from swampy lowlands to highlands [19], [21].
3) Population Density: Obtained from statistical data interpolated into a raster grid. This variable represents the most obvious anthropogenic pressure, where the population

growth of Palangka Raya which reaches 2.8% per year encourages a massive increase in the need for space [9], [12], [19].

4) Distance to the River: The focus is on the Kahayan River. This variable is very significant for Palangka Raya because the city grows on the banks of the river, where water accessibility affects the patterns of organic settlements and the primary activities of the community.

All variables were calculated using distance analysis *Euclidean* through the QGIS application to capture the spatial influence gradation of each driving factor [19], [20]. The rationalization of the selection of these variables is rooted in the principle that infrastructure and activity centers increase the chances of land conversion, while the proximity of rivers influences traditional life patterns and local economies. This integration of physical and socio-economic variables allows the MOLUSCE plugin to generate an accurate map of transition potential to simulate the prediction of Palangka Raya's land cover in 2028 and 2040 [6], [13], [16].

2.2. Research Methodology

This study applies a land cover change modeling approach based on Cellular Automata–Artificial Neural Network (CA–ANN) (Figure 3). The workflow includes data preparation, analysis of historical changes, preparation of transition probabilities, development of ANNs for potential transitions, CA-based spatial simulations, and validation of model results. The initial stage began with the acquisition of multi-year land cover data from MapBiomas Indonesia. The entire dataset is then clipped following the administrative boundaries of the study area to ensure consistency of the analysis area. Furthermore, the re-classification of land cover classes is carried out in accordance with the references that have been provided by MapBiomas Indonesia so that the transition is more statistically stable and interpretation is more operational.

Re-classification is carried out with a GIS tool (QGIS/ArcGIS) using *the reclassify* function and *raster calculator*. To ensure spatial compatibility between layers and inter-temporals, all data is standardized on the same projection system (WGS84) and co-registered so that each pixel is proportional from year to year. Positional accuracy is limited to a limited extent using ground control points or other available spatial references. The driving factor map is prepared through a rasterization process (for road, river, and other feature vector data) at a resolution of 30 m so that it is consistent with the land cover map. All driving factors are then normalized to the range of 0–1 using min–max normalization to facilitate integration into the ANN model. This study uses an integrated spatial modeling approach by utilizing the MOLUSCE (Modules for Land Use Change Evaluation) plugin in QGIS software. The research workflow is divided into four main stages as follows:

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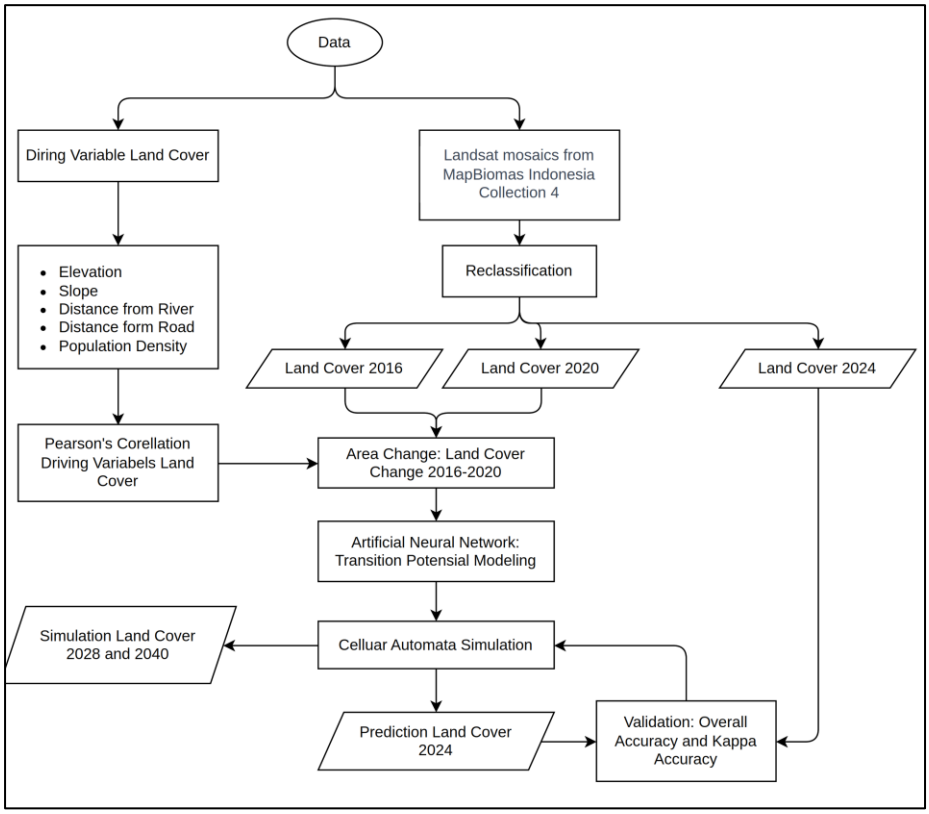

Figure 3. Research Flow Chart

2.2.1. Evaluating Correlation Variables

The initial stage after data preparation is to evaluate the relationship between the driving factors used, such as distance from roads, rivers, settlements, and topographic factors. The Pearson's Correlation method is used to measure the linear correlation between these continuous variables. This evaluation is crucial to ensure that these variables are free from autocorrelation problems. Based on scientific standards, variables with correlation coefficients above 0.7 must be re-evaluated or excluded from the model to maintain the stability of the simulation results.

2.2.2. Area Change and Transition Matrix

The second stage is to analyze historical land cover changes between two time periods (e.g. 2016 and 2020). This process results in a Transition Matrix that describes the pixel ratio that changes from one land cover class to another. This matrix presents a change probability value (in the range of 0 to 1) that serves as a quantitative basis for the model to predict future land use trends. In addition to the matrix, this stage also produces statistics on area change and a change map that identifies significant transition locations.

2.2.3. Transitional Potential and CA Simulation)

At this stage, a map of the transition potential is made using the Artificial Neural Network (ANN) algorithm, specifically the Multi-layer Perceptron (MLP) type. ANN trains models to study complex non-linear relationships between driving factors and land transition patterns that have occurred. The ANN parameters that are set include neighborhood (1 px), learning rate (0.001–0.1), maximum iterations (1000), and momentum (0.05). After the transition potential map was formed, the Cellular Automata (CA) algorithm was used to simulate the spatial allocation of land cover in 2028 and 2040. CA works by considering neighborhood effects, where the state of a cell in the future is affected by the condition of the cell and the surrounding cells currently. The simulation was carried out iteratively to project the spatial distribution of land cover up to the target year.

2.2.4. Model Validation

The final stage is validation to measure the reliability and accuracy of the simulation model. Validation was carried out by the hindcasting method, which is to compare the map of the simulation results of the historical target year with the actual land cover map in the same year. The main metrics used are the Kappa Coefficient (including Kappa Standard, Kappa Location, and Kappa Histogram) and Percentage of Correctness. A Kappa value above 0.70 or 0.80 indicates a strong level of agreement between the model and the real conditions on the ground, so the model is considered valid to predict the dynamics of land cover in Palangka Raya City in 2028 and 2040.

3. RESULTS AND DISCUSSION

3.1. Evaluating Correlation Variables

The initial stage in modeling land cover change is to evaluate the linear relationships between the driving variables using Pearson's Correlation method. This analysis aims to ensure that each variable is independent and free from autocorrelation or multicollinearity issues that can disrupt the stability of the Artificial Neural Network (ANN) algorithm. Statistically, the Pearson correlation coefficient has a value range between -1 to 1, where values close to 0 indicate a weak relationship. Based on scientific standards, variables with correlation values above 0.7 (both positive and negative) are considered to have too strong a relationship and should not be used simultaneously in the model [16].

Based on the results of testing five driving variables (Elevation, Road Distance, Slope Slope, Population Density, and River Distance) all pairs of driving variables had a correlation coefficient value below the threshold of 0.70 (Table 1). This indicates that all of these variables are free of autocorrelation problems and have good statistical reliability to be used as independent variables in the transition potential modeling stage. The highest

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positive correlation value was found in the relationship between Road Distance and River Distance of 0.6149. This value indicates a moderate spatial dependency, where areas far from the accessibility of the main road tend to be also far from the river flow in the study area.

Table 1. Pearson's Correlation Value of Variables

Variable	Elevation	Distance from Road	Slope	Population Density	Distance from River
Elevation	--	0.16806	0.06564	-0.07682	0.25591
Distance from Road		--	-0.15940	-0.11145	0.61495
Slope			--	0.02020	-0.22567
Population Density				--	-0.09079
Distance from River					--

The weakest linear relationship was found between the variables of Slope Slope and Population Density with a value of only 0.0202. This represents that the level of land slope has almost no linear influence on the distribution of population density, which is likely due to the relatively uniform topographic characteristics of the area in residential areas. The strongest negative relationship occurred between the variables of Slope Slope and River Distance with a value of -0.2256. These negative values indicate an inverse relationship, where the increase in slope slope (steeper regions) tends to correlate with a closer distance to a particular river body at the study site

3.2. Broad Change Analysis and Transition Matrix

Analysis of changes in land cover in the study area showed significant transition dynamics between natural vegetation and anthropogenic land over a four-year period. Overall, Peat Swamp Forests remain the most dominant land cover class, covering almost half of the total area, but have experienced a percentage decline of 0.97%, from 50.89% in 2016 to 49.92% in 2020 (Figure 4). This decline confirms that peat ecosystems in Central Kalimantan continue to experience degradation pressures due to human activities and environmental factors [22], [23].

Table 2. Land Cover Transition Matrix 2016-2020

Class	2016 (Ha)	2020 (Ha)	Change (Δ)
Forest Formation	10148.61	9619.65	-528.96
Shrubland	98018.01	92979.15	-5038.86
Dryland Agriculture	5732.12	8488.51	2756.39
Settlement/Built-up Area	6890.32	8021.85	1131.53
Open Land	20605.45	20129.78	-475.67
Mining Area	633.28	425.25	-208.03

Water Body	13236.72	13077.20	-159.52
Oil Palm Plantation	5396.72	11143.68	5746.96
Rice Paddy	161.19	137.44	-23.76
Peat Swamp Forest	167044.93	163844.86	-3200.07

Anthropogenic land expansion was the main driver of change in this period. The highest increase was recorded in the Oil Palm class, which grew by 1.75%, followed by Dryland Agriculture by 0.85%. This upward trend is in line with historical data in Palangka Raya City which recorded a massive surge in oil palm plantations to meet global commodity demand [9]. In addition, Settlements/Built Land experienced a growth of 0.35%, triggered by an average population growth rate of 2.8% per year and the need for urban infrastructure space. Dryland Agriculture experienced a growth of 0.85%. This increase reflects the expansion of the cultivation activities of local communities which often encroach on natural vegetation areas to meet food needs.

On the other hand, the Bush class recorded the largest percentage decrease compared to other classes, which was reduced by 1.54%. Technically, this decline in shrub area is often related to the process of conversion to productive agricultural land or oil palm plantations, as shrubland is considered easier to clear than primary forest [16]. A small decrease was also observed in the Forest Formation (0.15%) and Open Land (0.15%) classes, indicating ongoing gradual deforestation activities in the region.

In the 2016–2020 period, Palangka Raya City experienced a significant shift in land use from protected areas such as peat swamp forest and forest formations to productive land such as oil palm plantations, shrublands, as well as open land and settlement/built-up areas, reflecting anthropogenic pressures for economic development and urbanization. This trend is in line with the historical record of deforestation in Palangka Raya City which recorded a spike in forest loss of up to 17,452 ha in the 2011–2016 period [9].

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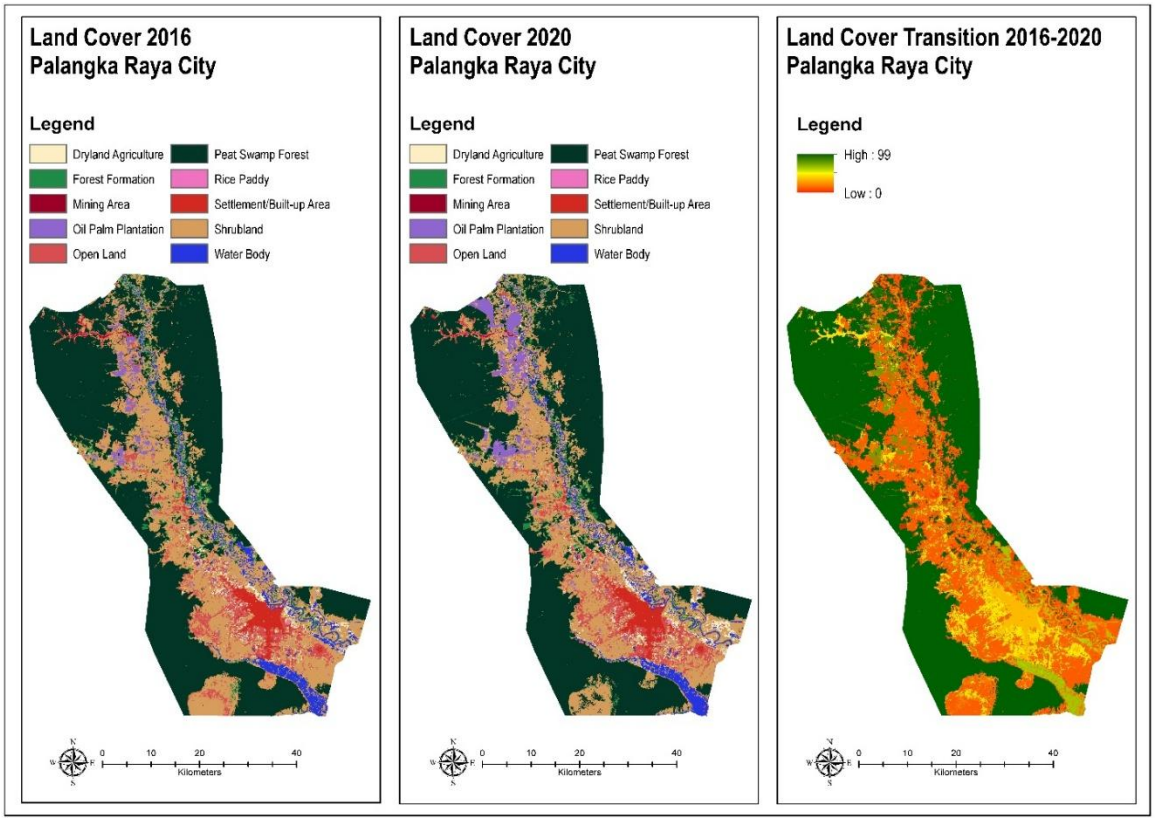

Figure 4. Land Cover 2016, 2020 and Transition

Analysis of the land cover transition matrix of Palangka Raya City for the 2016–2020 period shows that this area is still dominated by wetland ecosystems but is experiencing dynamic conversion pressure. Peat Swamp Forest is the most dominant land cover class, covering 50.48% of the total area. Followed by Shrubland (Shrubland) at 28.27%. These two classes are the ecological backbone as well as the area's most vulnerable to changes in land use due to human activities and natural succession.

The level of land stability in this region is relatively high, which can be seen from the diagonal elements of the transition matrix. The Peat Swamp Forest shows very strong persistence with an area of 158,074.62 ha that has not changed during the period. Similar stability is also seen in the Settlements/Built Land (6,514.11 ha) and Oil Palm Plantations (5,273.14 ha) sectors. This indicates that once land is converted into built-up areas or monoculture plantations, the area tends to be permanent and very rarely returns to natural forest function.

Significant land change (deforestation and degradation) is driven by two major transitions. First, the Peat Swamp Forest has shrunk into Oil Palm Plantations (2,706.13 ha) and Bushes (2,973.40 ha). Second, the bushes are massively transformed into Open Land (5,881.08 ha) and Oil Palm Plantations (2,244.61 ha). This pattern confirms that oil palm

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plantation expansion and land clearing are the main drivers of landscape change in Palangka Raya, which often goes through an intermediate stage in the form of shrubs or open land before finally becoming productive land.

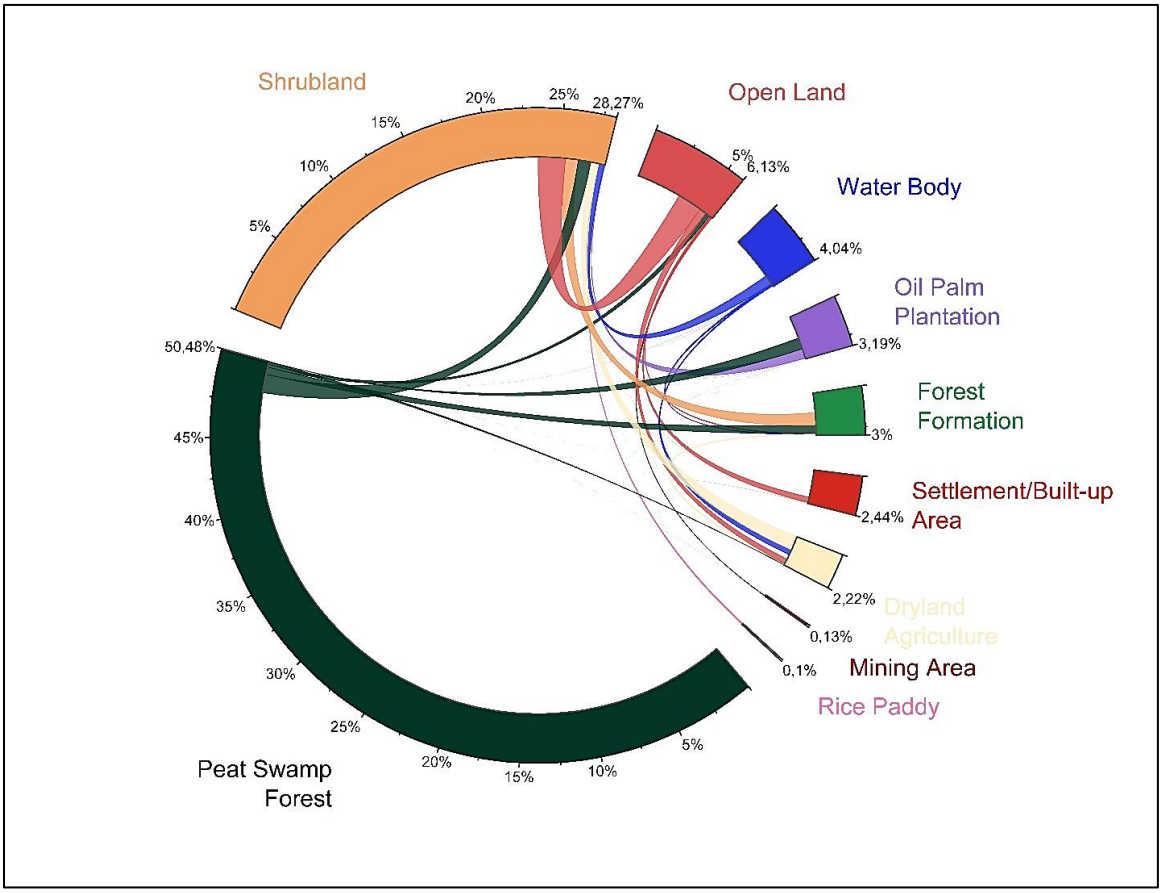

Figure 5. Chord Graphics for Land Cover Transition 2016-2020

On the other hand, the development of urbanization can be seen from the conversion of Open Land into Settlements of 1,238.39 ha, which shows the existence of planned physical development on land that has previously been cleared. Meanwhile, the food sector such as Dryland Agriculture and Rice Fields has a very small proportion, only 2.22% and 0.1%, respectively. This low figure, coupled with the conversion of rice fields into shrubs, emphasizes that the direction of development in Palangka Raya City in this period is more focused on the industrial plantation sector and the expansion of residential areas than the development of the agricultural and food sector.

The graph in Figure 5 illustrates this dynamic, where Shrubland dominates 18.75% of the transition flows as an intermediate area towards the economic sector, while the Forest Formation (16.46%) and Peat Swamp Forest (9.17%) experience shrinkage due to conversion to Mining Area (11.91%) and Oil Palm (8.49%). The expansion of Open Land

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(11.78%) and Settlements (8.32%) was driven by flows from various natural classes, confirming massive urbanization, while Dryland and Rice Field Agriculture remained small (<5%), indicating the dominance of extractive industries and plantations over food land.

3.3. Transition Potential Modeling and Validation (CA-ANN)

This study applies the Artificial Neural Network (ANN) method with Multi-Layer Perceptron (MLP) architecture to model non-linear patterns and relationships between variables in the spatial analysis process. The model was developed using learning parameters in the form of a learning rate of 0.005, a maximum of 1000 iterations, the number of hidden layers of 10 neurons, and a momentum value of 0.010 (Figure 6). This configuration is designed to achieve a balance between the speed of convergence and the stability of the training process, so that the model can capture the complexity of the data without experiencing numerical instability. Based on the test results, a Kappa Coefficient value of 0.6 was obtained. A Kappa value above 0.75 is categorized as a good or strong agreement [16], [24]. In fact, a value above 0.61 is often considered an "Excellent" category in certain contexts [25]. Although it has not yet reached the level of 'Almost Perfect' (>0.80), this value is scientifically considered feasible and acceptable to predict changes in land cover or deforestation in the study area [16], [25].

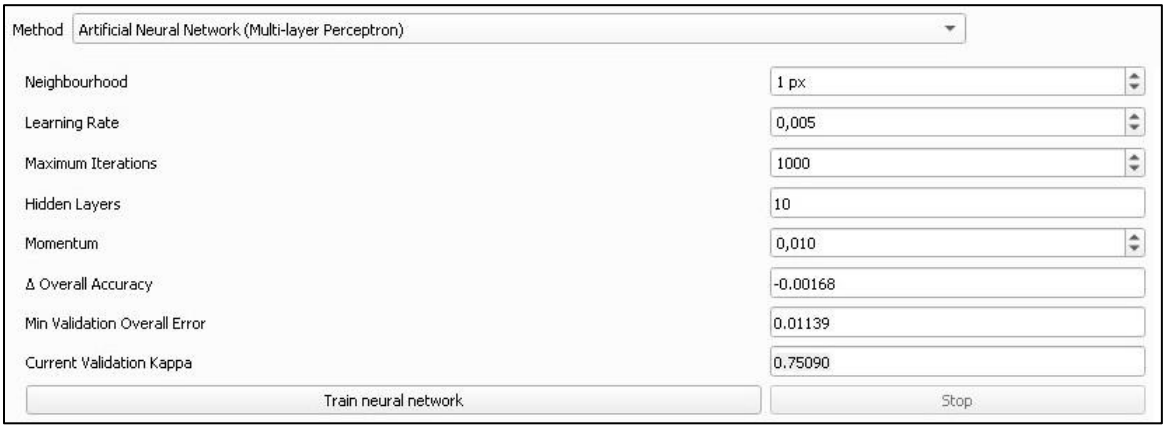

Figure 6. Artificial Neural Network (ANN)

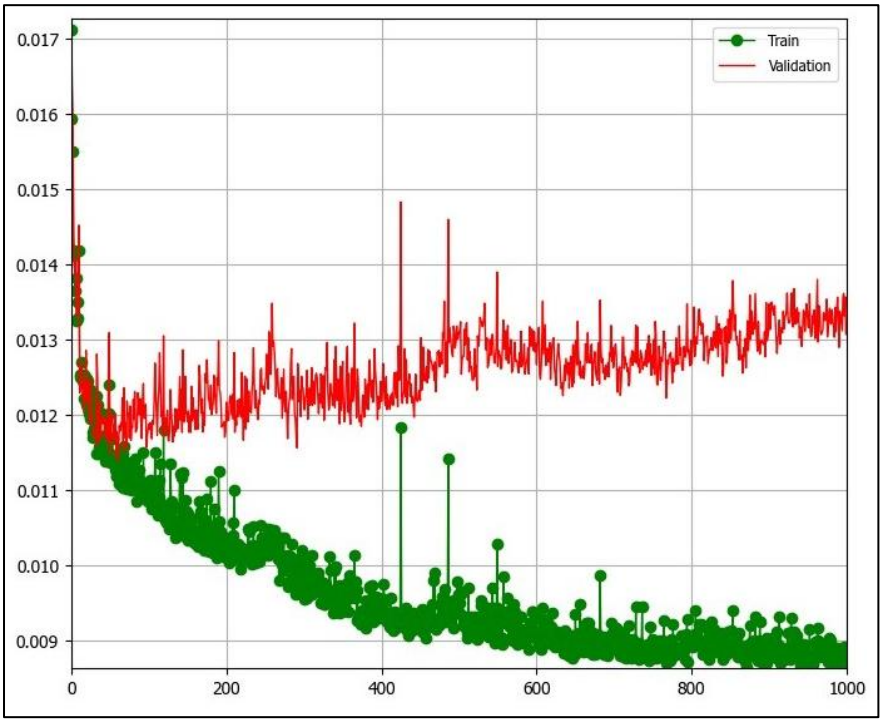

Figure 7. Neural Network Learning Curve

The results showed that the value of the training error decreased significantly in the initial phase of the iteration and then gradually decreased until it approached the convergence point. At the beginning of the process, the error was in the range of ±0.017 and gradually dropped until it reached about 0.009 by the end of the 1000th iteration. This pattern shows that the model successfully learns the structure of training data progressively and stably. The learning curve shows a consistent downward trend in the train data, which indicates that the optimization process is going well.

In contrast, the validation curve shows a relatively stable pattern with small fluctuations in the range of ±0.012–0.013. The Minimum Validation Overall Error value was recorded at 0.01139, while the Current Validation Kappa value reached 0.75090. A Kappa value close to 0.75 indicates a strong level of model agreement (substantial agreement), so the model can be categorized as having good predictive performance in classifying or modeling changes based on validation data. However, the trend difference between the steadily declining training curve and the relatively stagnant validation curve indicates a mild overfitting. This can be seen from the decrease in errors in the training data without being followed by a significant decrease in validation errors. However, the small error difference and high Kappa values indicate that this model is considered valid and has sufficient reliability to simulate future land cover predictions.

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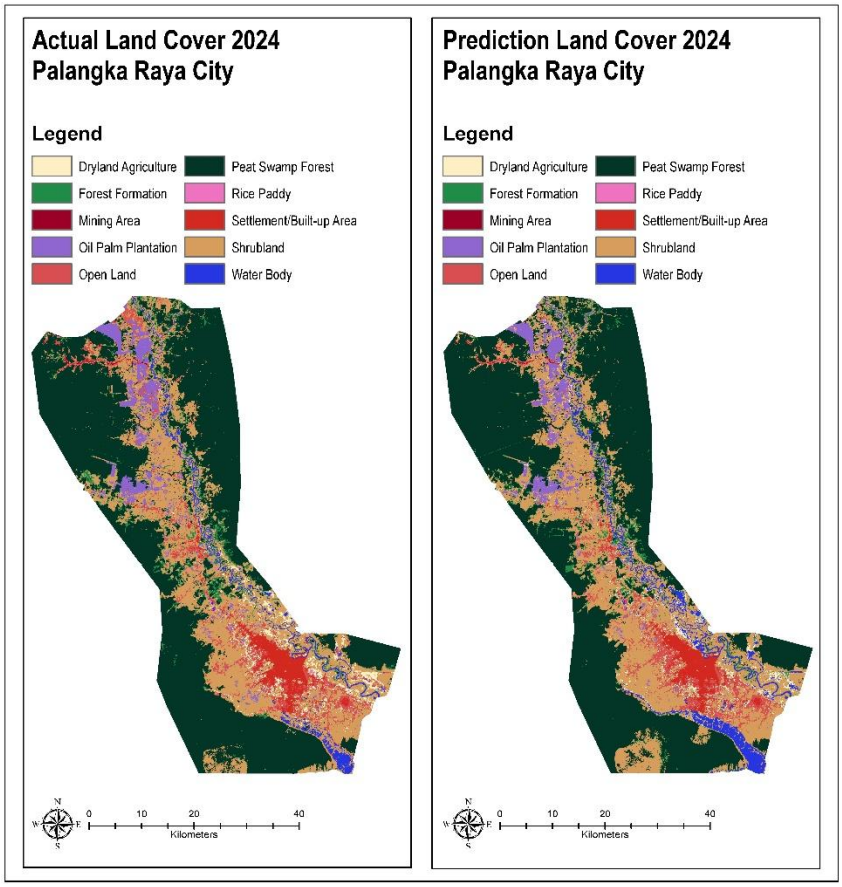

Figure 8. Validation Map between Actual Land Cover 2024 and Land Cover Prediction 2024

Simulation of land cover change in Palangka Raya City was carried out using the Cellular Automata (CA) method through *Stuart T* MOLUSCE. The simulation results showed a spatial distribution consistent with the characteristics of the study area, where the Peat Swamp Forest class dominated the western and eastern landscapes, while the residential areas (*Settlement/Built-up Area*) concentrated in the central-southern part of the city. This pattern reflects the dynamics of physical urban growth that has historically been fueled by population growth and land investment, which often comes at the expense of the surrounding swamp forest ecosystem[9], [21].

% of Correctness	85.84915
Kappa (overall)	0.78346
Kappa (histogram)	0.96025
Kappa (location)	0.81589

Figure 9. Validation Kappa

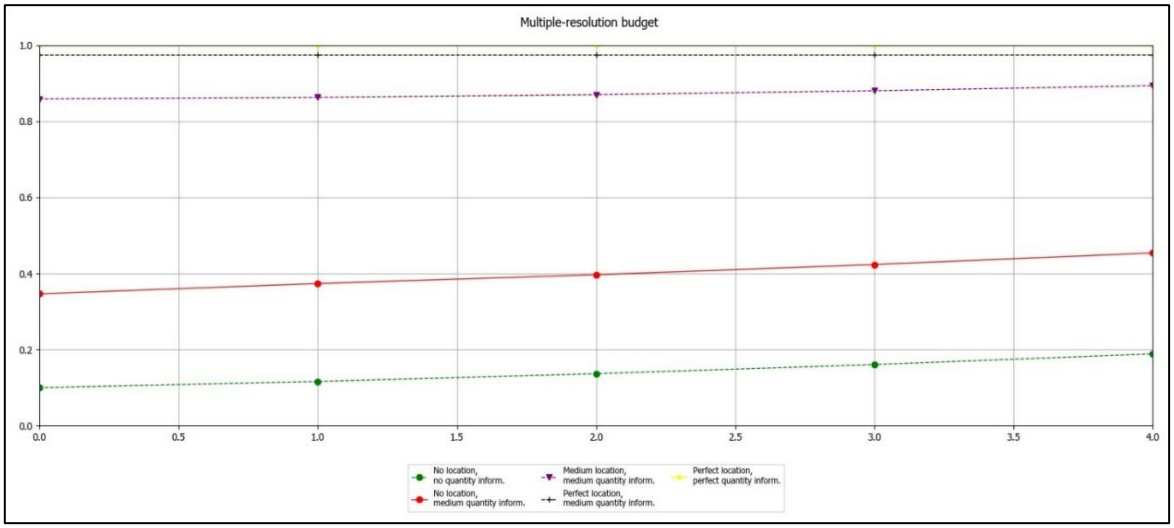

Figure 10. Multiple-Resolution Budget

Model validation was carried out by comparing the simulation map to the actual reference map of 2024 using a spatial validation module. The validation results gave a % of Correctness value of 85.84% (Figure 9), which indicates a very high level of accuracy as it has exceeded the minimum eligibility threshold of 80% in the spatial modeling study [9], [12]. The reliability of this model is reinforced by a Kappa (overall) value of 0.783, belongs to the category of "Good" or has a strong agreement level (*strong agreement*). This performance is greatly affected by ANN parameter settings such as *learning rate*, *hidden layers*, and the number of iterations that allow the model to optimally study the non-linear relationships between the driving variables.

More in-depth accuracy assessments are done through specific Kappa metrics to separate quantity and location aspects. A Kappa value (histogram) of 0.960 reflects a very high quantity accuracy, which means that the proportion of area of each land cover class on the prediction map is very close to the reference condition. On the other hand, Kappa (location) of 0.816 is in the "Very Good" category (0.81–1.00), which proves the ability of the CA algorithm to predict the spatial position of land changes with a high degree of geographical precision. The use of this integrated model allows for more realistic simulations than conventional linear models because it takes into account the influence of *neighborhood effects*.

Analysis through *the Multiple-Resolution Budget graph* (Figure 10) confirms that the actual simulation curve is well above the random model with no location information (*no location, no quantity*), which proves the effectiveness of the driving variables used. The consistency of the performance curve at various spatial resolutions shows that the model is able to accurately capture the spatial patterns of land transitions. With a combination of

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satisfactory accuracy values and high validity, this hybrid model is declared feasible and reliable to be used to project land cover scenarios in 2028 and 2040

3.4. Predicted Land Cover of Palangka Raya City in 2028 and 2040

The results of the simulation using Cellular Automata (CA) project the expansion of the built-up area that will continue from 2028 to 2040. The projected land cover of Palangka Raya City until 2040 shows a transition trend influenced by anthropogenic activities and the dynamics of natural land succession. As an area in a province with a high deforestation rate, Palangka Raya continues to experience pressure on its natural ecosystem, although models show stabilization in certain land classes.

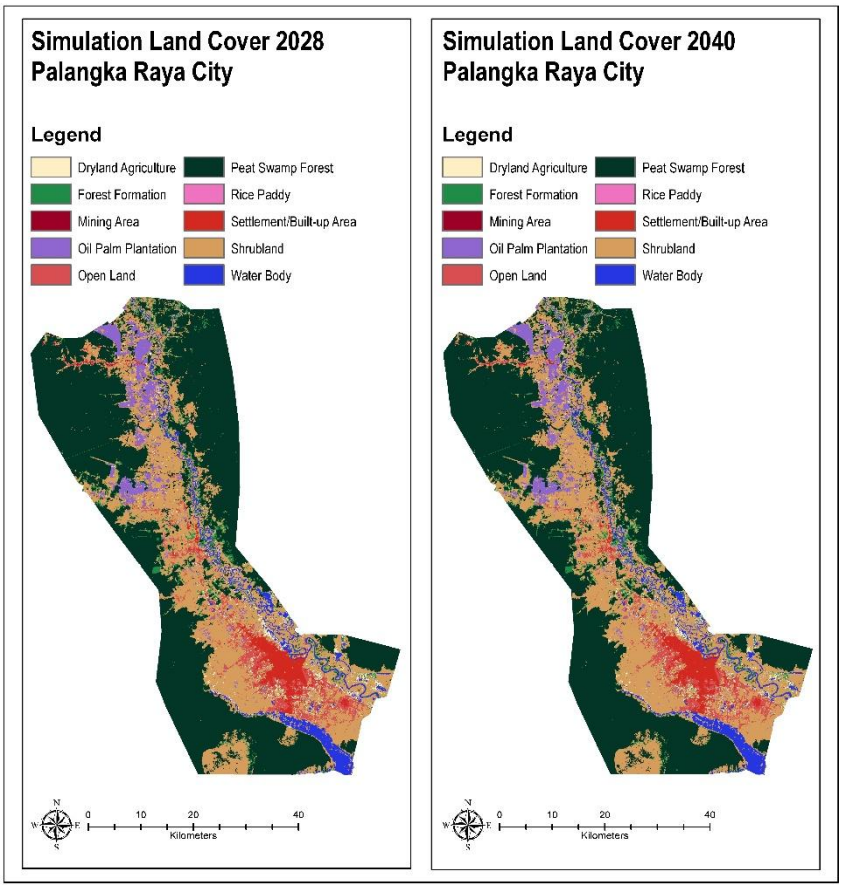

Figure 11. Land Cover Prediction in 2028 and 2040

Peat Swamp Forest land cover remains the most dominant land cover class in Palangka Raya City. However, the data shows a gradual downward trend from 167,044 ha in 2016 to 163,752 ha in 2040 (Table 3). The decline of approximately 3,292 ha reflects the vulnerability of peat ecosystems to land conversion and degradation that is often triggered

by drainage or historical forest fires, as occurred in 2015 [9], [23]. Given its role as a major carbon store, the stability of this area until 2040 (which is predicted to remain at 163 thousand ha) is crucial for local climate change mitigation [9], [11]. One of the most striking trends is the increase around the Bush, which is predicted to reach 102,556 ha by 2040. up from 94,431 ha in 2024. Increasing bush growth in Kalimantan is often an indicator of disturbed forest succession or the result of land that has been taken for timber and abandoned. This suggests that some fragmented forest areas are turning into shrubland that ecologically have opportunities for regeneration but remains vulnerable to fire.

Table 3. Land Cover Changes from 2016, 2020, 2024, 2028 and 2040

Land Cover	Years (hectar)				
	2016	2020	2024	2028	2040
Forest Formation	10,148.61	9,619.65	11,380.28	10,429.82	10,684.66
Shrubland	98,018.01	92,979.15	94,431.09	100,273.99	102,556.64
Dryland Agriculture	5,732.12	8,488.50	7,391.16	5,785.14	4,691.63
Settlement/Built-up Area	6,890.32	8,021.85	8,670.55	8,196.29	8,233.35
Open Land	20,605.45	20,129.78	18,143.37	14,669.55	13,126.88
Mining Area	633.28	425.25	455.30	348.05	323.77
Water Body	13,236.72	13,077.20	8,018.54	13,207.03	13,307.96
Oil Palm Plantation	5,396.72	11,143.68	12,316.95	11,147.87	11,145.69
Rice Paddy	161.19	137.44	164.96	48.95	44.44
Peat Swamp Forest	167,044.93	163,844.85	166,895.18	163,760.68	163,752.35

On the other hand, after experiencing a massive surge from 2016 (5,396 ha) to 2024 (12,316 ha), the area of oil palm plantations is predicted to stabilize at 11,145 ha in 2040 (Table 3). This pattern suggests that the intensive expansion phase is likely to slow down towards 2040. in line with existing spatial or land saturation control policies. Likewise in Settlements/Built Land where in 2028 (Figure 11), residential areas/buildings will be built and open land will expand, especially in the central to southern part of the city which is currently the center of urban activities. This expansion appears to follow the road and river network, indicating a tendency to concentrate growth towards transportation corridors and riverbanks. In 2040 (Figure 11), the pattern that appears in 2028 will be even stronger, namely residential zones and open land will be denser and more spread from the city center to the north-south along rivers and roads. The area of settlements has relatively increased compared to 2016–2020 and then tends to be stable, but the intensity and density of buildings in the city core and riverbanks appear to be much higher where it is predicted to remain stable in the range of 8,233 ha in 2040 (Table 3). The tendency to expand settlements and open land to the south and along rivers signals increased pressure on peat swamp ecosystems and forests around urban areas. Although Palangka Raya's population growth

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has reached 2.8% per year, simulation models show a consolidation of built-up areas in existing activity centers, especially in the central-southern part of the city.

In the Decline of Agricultural Land and Open Land The downward trend can be seen in Dryland Agriculture which shrank from 8,488 ha (2020) to 4,691 ha (2040), and Open Land which decreased drastically to 13,126 ha in 2040. This decline in open land is most likely caused by the transition of the land into shrubs through a natural regeneration process or converted into permanent plantation areas. The predictions for 2028 and 2040 confirm that Palangka Raya City is heading towards a transition phase where open land expansion is starting to decrease, but peat swamp forests continue to experience slow degradation. The massive addition of shrub areas demands more intensive sustainable forest management and peat restoration strategies. This data provides an important information base to prioritize controlling land cover change, if not balanced with controlling space utilization, this condition has the potential to increase the risk of flooding, peatland fires, and deterioration of environmental quality around the city

4. CONCLUSION

This study shows that Palangka Raya City experienced significant land cover changes in the 2016–2020 period, characterized by a decrease in forest area and an increase in built-up area. Accessibility factors such as distance from roads and rivers are the main drivers of the expansion. Model validation performed using the spatial validation module showed a high level of accuracy with a Correctness value of 85.84% and an Overall Kappa of 0.783. These values indicate a strong level of model agreement, confirming the reliability of the CA-ANN method for spatial projection purposes. The predictions for 2028 and 2040 indicate that without strict spatial control, the degradation of peat swamp forests will continue. This finding is important as the basis for sustainable spatial planning policies in the city of Palangka Raya.

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