Vol. 12(2): 242-257, May 2024

DOI: https://doi.org/10.23960/jsl.v12i2.865

Jurnal Sylva Lestari

P-ISSN: 2339-0913
E-ISSN: 2549-5747

Journal homepage: https://sylvalestari.fp.unila.ac.id

Full Length Research Article

Modeling Land Cover Change Using MOLUSCE in Kahayan Tengah Forest Management Unit, Kalimantan Tengah

Beni Iskandar[1,*], Saidah[1], Adib Ahmad Kurnia[2], Ahmad Jauhari[3], Fathul Zannah[4]

[1] Department of Forestry, Faculty of Agriculture and Forestry, Universitas Muhammadiyah Palangkaraya, Palangka Raya, Indonesia
[2] Department of Geography, Faculty of Mathematics and Natural Sciences, University of Indonesia, Depok, Indonesia
[3] Department of Forestry, Faculty of Forestry, Universitas Lambung Mangkurat, Banjarbaru, Indonesia
[4] Department of Basic Education, Faculty of Teacher Training and Education, Universitas Muhammadiyah Palangkaraya, Palangka Raya, Indonesia
[*] Corresponding Author. E-mail address: beniiskandar@umpr.ac.id

ARTICLE HISTORY:

Received: 9 December 2023
Peer review completed: 9 January 2024
Received in revised form: 22 January 2024
Accepted: 19 February 2024

KEYWORDS:

Forest management unit
Kahayan Tengah
Land cover change
Land cover prediction
MOLUSCE

ABSTRACT

A management unit-based land cover change analysis was examined in Kahayan Tengah Forest Management Unit (FMU) to understand past, present, and future land cover to assist forest management planning in Kahayan Tengah FMU. This study aims to model land cover change in 2011 and 2016, predict 2021, and simulate land cover in 2026 in Kahayan Tengah FMU. Modeling land cover prediction and simulation using MOLUSCE from the QGIS plugin. The results revealed that agricultural land experienced significant increase in total area during 2011–2016. Modeling potential land cover transitions in 2011 and 2016 with the Artificial Neural Network method showed a Kappa coefficient of 0.701 in the good category, and simulation of land cover in 2021 with the Cellular Automata method showed a Kappa coefficient of 0.672 in the good category. By 2026, the agricultural land will continue to increase while forest land tends to remain stable in its total area. This study managed to predict land cover in 2021 and simulated 2026 with good accuracy. Thus, this data and information can support forest management planning in Kahayan Tengah FMU.

1. Introduction

Land cover change causes land degradation, climate change, and the destruction of biodiversity and ecosystem services (Angerer et al. 2023; Elmhagen et al. 2015; Kim et al. 2019). Land cover change has multiple impacts on the present and future balance of ecosystems (Dilnesa 2018; Yifru et al. 2021). Land cover change is caused by the high demand for land for plantations, agriculture, timber companies for economic development activities, and forest fire (Alisjahbana and Busch 2017; Juniyanti and Situmorang 2023; Ramadhan et al. 2023). Land cover is dynamic, requiring continuous assessment, analysis, and monitoring using environmental and anthropogenic variables to obtain integrated and accurate results. Temporal land cover data helps identify environmental changes, a database for future regional development management, and a parameter for sustainable forest management assessment (Duan et al. 2023; Hossain et al. 2023; Larbi 2023).

The Indonesian government has issued policies to improve the forestry sector, one of which is by establishing "*Kesatuan Pengelolaan Hutan*" or Forest Management Unit (FMU) as the smallest forest management unit following its principal and designation that is managed efficiently and sustainably (Drasospolino et al. 2023). Strengthening FMU is a national priority between 2010 and 2020 to reduce deforestation and forest degradation (Massiri 2023). Kahayan Tengah FMU is located in Kalimantan Tengah Province, Indonesia. This FMU is dominated by swamp forests, the most carbon sink and biodiverse forest ecosystem in the world, and swamp forests have received much attention for their essential contribution to global climate change mitigation strategies (Astiani et al. 2017; Hergoualc'h et al. 2023; Igu 2016; Ledheng et al. 2022; Miettinen et al. 2016; Novita et al. 2021). However, this land cover has been degraded and deforested due to agricultural expansion and forest fires (Afitah and Isra 2021; Boakye et al. 2020; Irwani and Kartodihardjo 2022; Marwanto and Pangestu 2021; Scriven et al. 2015), therefore, it is important to identify land cover changes and their projected changes to achieve sustainable forest management in the Kahayan Tengah FMU.

The early detection of land cover changes and projection of land cover to assess sustainable forest management in FMU is mandatory to inform future forest management. However, previous land cover change assessments in relevant decades only measured past and current land cover change (Hussain and Karuppannan 2023; Wahyuni et al. 2021). This constraint is a very important thing to discuss because by knowing future events, we can develop a risk mitigation plan. Currently, modeling algorithms can understand past, present, and future land cover (Ramadan and Hidayati 2022). Modeling land cover change is essential to identify future changes and mitigate possible risks (Beroho et al. 2023). The Modules for Land Use Change Simulation (MOLUSCE) plugin in Quantum GIS provides several algorithms for future land cover prediction and change probability matrices (Boakye et al. 2020). Artificial Neural Network (ANN) and Cellular Automata (CA) algorithms are the two popular algorithms for land cover prediction and simulation (Alshari and Gawali 2022; Osman et al. 2023). The application of this combination has successfully modeled future land cover change (Lukas et al. 2023; Saputra and Lee 2019).

This study focused on the Kahayan Tengah FMU, Kalimantan Tengah, Indonesia, covered by swamp forests. Swamp forests contribute the most carbon sequestration and have the highest biodiversity in the world. Moreover, research on land cover change modeling in FMU is still limited. Therefore, implementing MOLUSCE with a combination of ANN and CA algorithms is appropriate for analyzing past, current, and future land cover conditions with environmental and anthropogenic variables as inputs. This study can thus provide important information on land cover dynamics and future land cover projections in FMU as basic information for developing sustainable forest management plans. This study aims to model land cover change in 2011 and 2016, predict land cover in 2021, and simulate land cover in 2026 in the Kahayan Tengah FMU.

2. Materials and Methods

2.1. Study Area

The current research was conducted in Kahayan Tengah FMU, Central Kalimantan Province, Indonesia. Kahayan Tengah FMU which are divided into Unit III, Unit XIII, and Unit XVIII with a total area of 376,010 ha, geographically situated 113° 30' 0"–114° 30' 0" E and 2° 30' 0"–1° 30' 0" S (**Fig. 1**). The flowchart of the research is provided in **Fig. 2**.

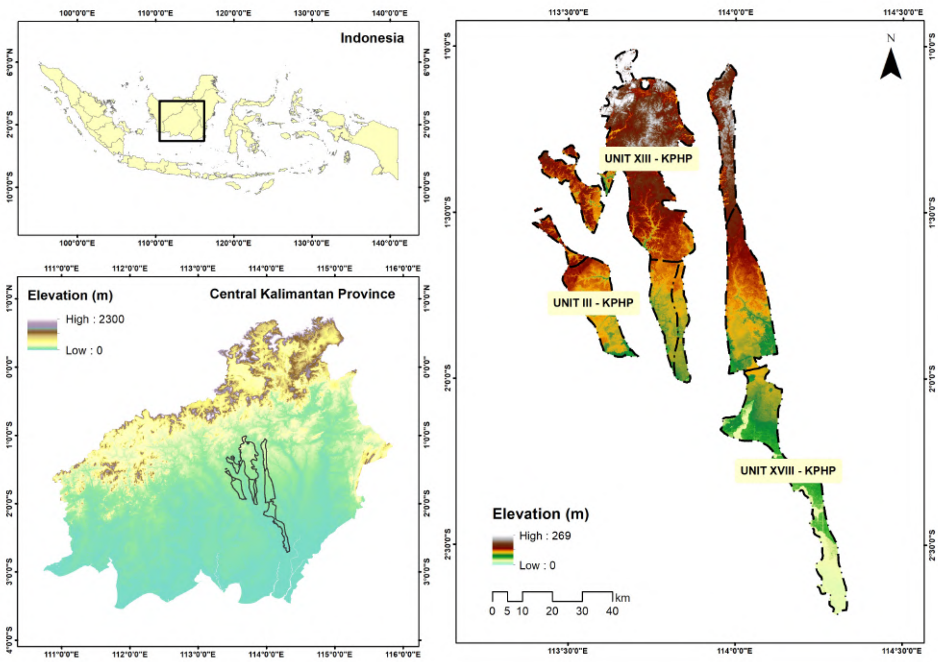


Fig. 1. Study area.

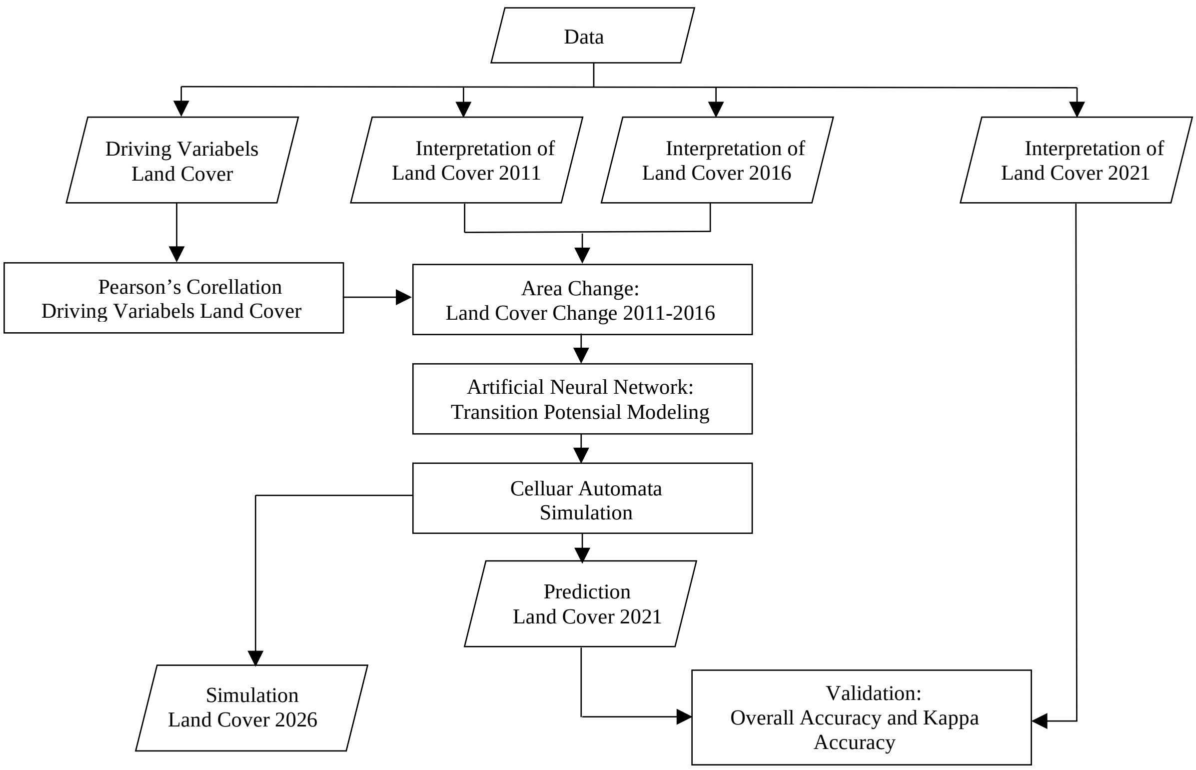


Fig. 2. Study flowchart.

2.2. Data Collection

The data used are land cover, digital elevation model (DEM), settlements, roads, and rivers. The data sources of this study are provided in (**Table 1**). Predicting land cover change requires the variables responsible for land cover change (Li and Li 2019). Human activity variables are distance from settlements, rivers, and roads as drivers of land cover change, and the variables of natural factors are elevation and slope as drivers of land cover change. Some of the land cover change variables selected in this study refer to previous studies with some modifications (**Table 1**) (Alshari and Gawali 2022; El-Tantawi et al. 2019; Ramadan and Hidayati 2022).

Table 1. Variables of land cover change

Variables	Data Model	Methode	Value Extraction	Sources
Elevation	Raster	Reclassify analysis	Digital number	https://earthexplorer.usgs.gov/
Slope	Raster	Slope analysis	Digital number	https://earthexplorer.usgs.gov/
Distance from settlements	Vector to raster conversion	Multiring buffer	Variable distances in Kahayan Tengah FMU	https://tanahair.indonesia.go.id/
Distance from road		Multiring buffer		https://tanahair.indonesia.go.id/
Distance from river		Multiring buffer		https://tanahair.indonesia.go.id/
Distance from forest		Multiring buffer		Indonesian Ministry of Environment and Forestry

2.3. Land Cover Classification

We used land cover from the Indonesian Ministry of Environment and Forestry (MoEF). MoEF uses a visual interpretation method to identify land cover on Landsat imagery. MoEF uses a visual interpretation method to identify land cover on Landsat imagery. We used land cover in 2011, 2016, and 2021. This classification results from an equalization modification (Letsoin et al. 2020; Lukas et al. 2023). The land cover classifications used were natural forest, shrubs, agriculture, and bare land. Land cover descriptions are presented in (**Table 2**). The accuracy of MoEF land cover is above 0.90 (Margono et al. 2014; Purwanto et al. 2015); thus, we believe that the land cover map matches the facts on the ground.

Table 2. The land cover classification scheme

Classes	Descriptions
Natural forest	All land types of forest cover, such as dryland forests and swamp forests
Shrubs	Low-level vegetation in the form of shrubs and swamp shrubs
Agriculture	Dryland farming or dryland farming mixed with shrubs
Bare land	All types of bare land or land affected by humans

2.4. Evaluating Correlation Variables

The MULSCE QGIS plugin offers several techniques for evaluating the correlation of variables, such as Pearson’s correlation and Cramer Coefficient, to measure the correlation of data driving factors of land use change (Hakim et al. 2021). This technique accurately measures the correlation between two variables, illustrating the correlation level between two variables (Zhi et al. 2017). This research uses variables with interval and ratio scale types so that these variables can be measured for correlation. Variables that are tested in the research are in **Table 1**. The value of the correlation coefficient that tends towards 0 is the weaker the level of correlation (Hakim et al. 2019; Li et al. 2015; Pandey 2020). Variables with correlation coefficients above 0.7 should not be selected as variables driving land cover change (Muhammad et al. 2022).

2.5. Area Change and Transition Matrix

The plugin MOLUSCE estimates land cover change and quantifies the land cover change transition matrix (Muhammad et al. 2022; Padma et al. 2022). The land cover change analysis describes the change between the first year's land cover and the second year (Hakim et al. 2019). Land cover in 2011 was used as the first year, and land cover in 2016 was the second year. The transition matrix calculates the probability of area change and transition using land cover data and variables that drive land cover change.

2.6. Transitional Potential and Cellular Automata (CA) Simulation

The MOLUSCE (https://plugins.qgis.org/plugins/molusce/) plugin proposes four transition modeling methods, namely Artificial Neural Network (ANN), Weight of Evidence (WoE), Logistic Regression (LR), and Multi-Criteria Evaluation (MCE) to produce potential transition maps. Elevation, slope, distance from the settlement, distance from the road, distance from the river, and distance from the forest are considered in this research as potential transition determinants of future land cover change. ANN modeling is a reliable technique in many studies for land cover change (Lukas et al. 2023; Rahman and Esha 2022; Saputra and Lee 2019). The ANN algorithm was run with a neighborhood rule of 1 px, learning rate of 0.001, maximum iterations of 1000, 10 hidden layers, and momentum of 0.050 (Khan and Sudheer 2022; Li et al. 2017; Muhammad et al. 2022; Perović et al. 2018). ANN modeling with a Kappa coefficient value of 0.60–0.80 showed good accuracy so that we could analyze land cover prediction and simulation (Foody 2020). In the next step, analyze the CA algorithm to produce a prediction or simulation map of land cover obtained from the results of the potential transition step. We predicted land cover in 2021, and we simulated land cover in 2026. ANN-CA combination has been widely used in land cover prediction and simulation research since this approach is more effective than linear regression and efficient in land cover change analysis and is suitable for assessing land cover change and simulating future scenarios (El-Tantawi et al. 2019; Folharini et al. 2023; Muhammad et al. 2022).

2.7. Validation

Validation was conducted by comparing the actual land cover in 2021 with the predicted land cover in 2021. This validation uses the Kappa coefficient calculation technique. The Kappa coefficient in remote sensing is popularly used to assess land cover accuracy (Foody 2020). The Kappa coefficient was calculated using Equation 1 (Petropoulos et al. 2015).

$$Kappa\ coefficient = \frac{\sum_{i=1}^{r} X_{ii} - \sum_{i=1}^{r} X_{i+} X_{+i}}{N^2 - \sum_{i=1}^{r} X_{i+} X_{+i}} \quad (1)$$

where Xii is the diagonal value of the *i-th* row and *i-th* column, $X{+}I$ is the total area (ha), $X{+}I$ and $Xi{+}$, and N is the total area (ha).

3. Results and Discussion

3.1. Evaluating Correlation Variables

Based on the results of the Pearson's Correlation test between variables, it does not have a strong relationship, or the variables are free from autocorrelation (**Table 3**). The correlation coefficient between two variables has a strong relationship with a coefficient value ≥ 7 (positive or negative) (Muhammad et al. 2022). Distance from the forest, elevation, distance from roads, and distance from settlements are variables with the highest correlation coefficient values. Thus, the variables are used in the analysis of land cover change. The variables driving land cover are shown in (**Fig. 3**).

Table 3. Pearson's correlation value of variables

	Slope	Elevation	Distance from road	Distance from settlements	Distance from river	Distance from forest
Slope		0.37	-0.24	-0.17	-0.17	-0.17
Elevation			-0.17	-0.04	0.21	-0.53
Distance from road				0.58	0.20	0.11
Distance from settlements					0.25	0.22
Distance from river						-0.23
Distance from forest						

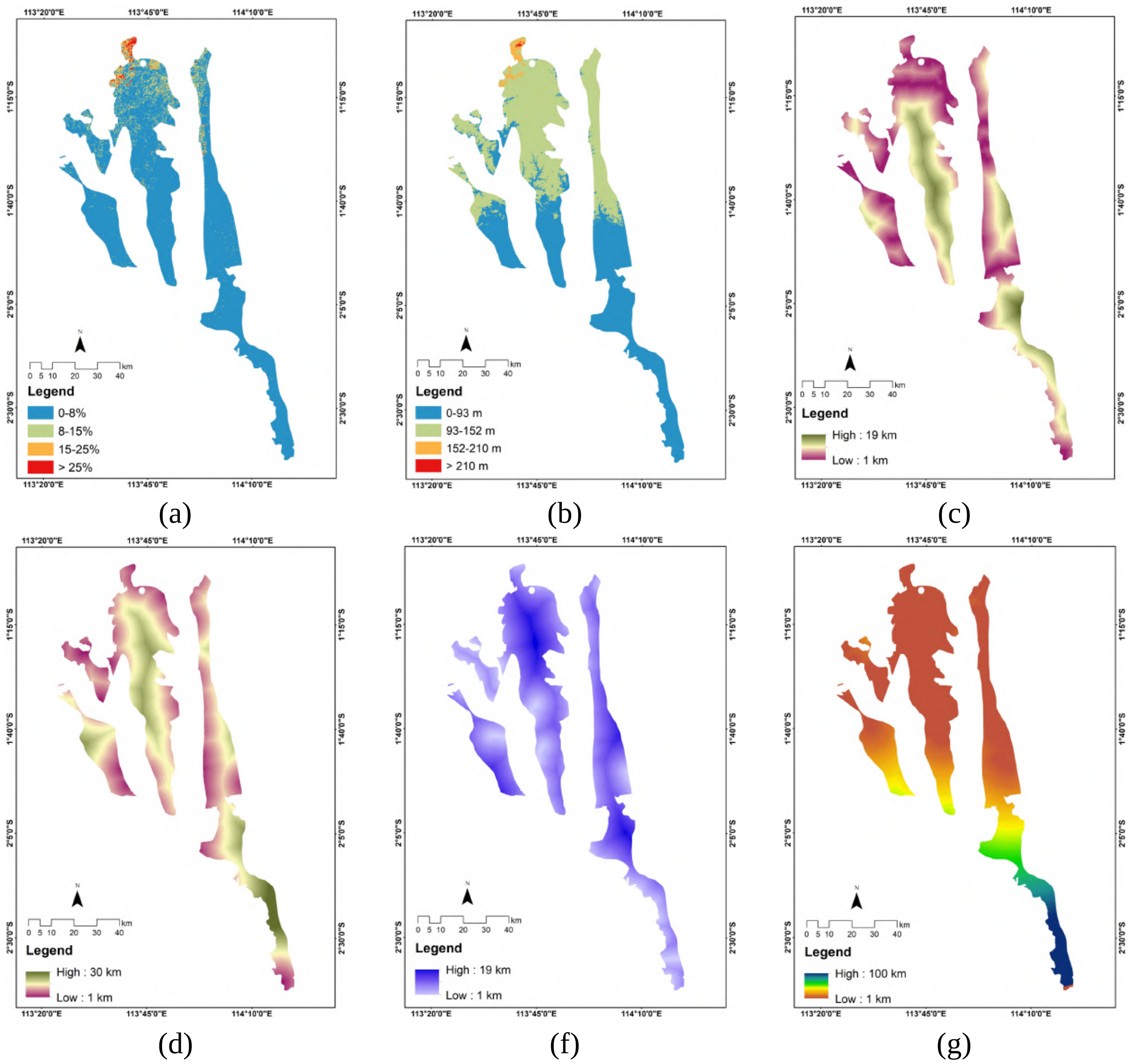
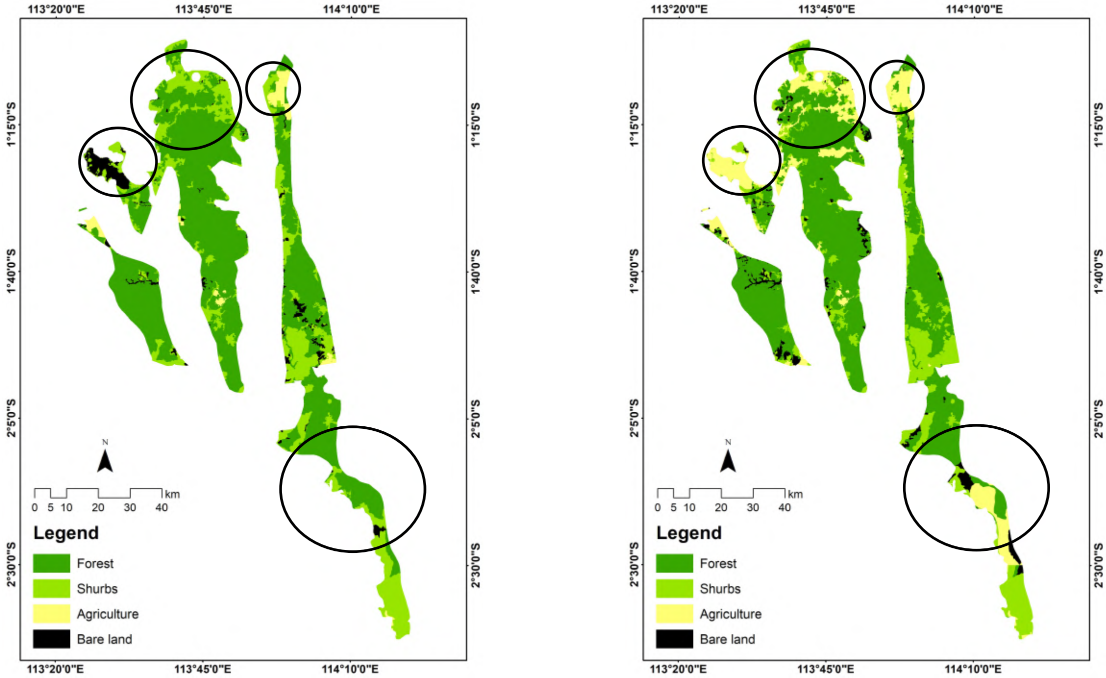


Fig. 3. (a) Slope, (b) elevation, (c) distance from road, (d) distance from settlements, (e) distance from the river, and (f) distance from the forest.

3.2. Area Change and Transition Matrix

Land cover conditions in Kahayan Tengah FMU changed during the period 2011–2016 (**Fig. 4**). We circle the areas that have changed and we identified the change from bare land to agricultural conversion, shrubs to agricultural conversion, and forest to agricultural conversion (**Fig. 4**). Topographic conditions, community access in the form of roads, rivers, and the presence of settlements are variables driving land cover change. The land cover change tended to occur in low topography, near roads, rivers, and settlements. This variable reflects human activities that continually expand agricultural and bare land. In line with other research results, human activity is the primary driver of land cover change (Saputra and Lee 2019; Song et al. 2018).



(a) (b)

Fig. 4. (a) 2011 land cover and (b) 2016 land cover.

Forest cover was dominant in 2011 and 2016, with 257.212 ha (68%) and 235.121 ha (62.5%), respectively. Agricultural land cover increased sharply by about 43.328 ha, but other land cover (forest, shrubs, and bare land) decreased by -22.091 ha, -20.686 ha, and -0.369 ha, respectively (**Table 4**). The trend is for bare land cover and shrubs to convert into agricultural land (**Fig. 4**). Unit XVIII Kahayan Tengah FMU has a large part of its area included in the food estate project and the One Million Hectare Peatland Development Project in Kalimantan Tengah Province in 1995. This project aims to develop an integrated food estate into a national food barn (Marwanto and Pangestu 2021; Ramadhani et al. 2021). In addition, the demand for land for agriculture or plantations is very high in Kalimantan (Scriven et al. 2015).

Table 4. Area changes for the period 2011–2016

Classification	Area 2011 (ha)	2011 Year (%)	Area 2016 (ha)	2016 Year (%)	Area Change 2011–2016 (ha)
Forest	257.21	68.00	235.12	62.50	-22.09
Shrubs	94.32	25.00	73.45	19.50	-20.68
Agriculture	9.52	2.50	52.84	14.00	+43.32
Bare land	14.95	3.90	14.58	3.80	-0.36
Total	376.01	100.00	376.01	100.00	

The transition matrix describes the pixel ratio that changes from one land cover class to another (Muhammad et al. 2022). The transition matrix presents the probability value of land cover change at any given time (Xiao et al. 2022). The diagonal values represent a measure of class stabilization, and each off-diagonal value represents a transition from one class to a different class (Muhammad et al. 2022). The transition matrix values are in the interval 0 to 1. The results of this study showed the most stable probabilities in forest cover (0.90) and agriculture (0.86) (**Table 5**) from 2011 to 2016. The most dynamic classes were shrubs and bare land. Shrubs showed a high probability of changing to agriculture (0.30) and bare land showed a high probability of changing to agriculture (0.51) and shrubs (0.32) (**Table 5**). Therefore, forest and agricultural cover is the most stable, while shrubs and bare land will experience rapid fragmentation in the future. Based on (**Table 5**), a land cover change transition map can be created (**Fig. 5)**. This figure illustrates areas with high (15) to low (1) transition potential in Kahayan Tengah FMU.

Table 5. Transition matrix of land cover

	Forest	Shrubs	Agriculture	Bare land
Forest	0.90	0.02	0.03	0.03
Shrubs	0.01	0.65	0.30	0.02
Agriculture	0.00	0.13	0.86	0.00
Bare land	0.02	0.32	0.51	0.14

3.3. Transitional Potential Modeling and Cellular Automata (CA) Simulation

We used the ANN algorithm to model potential transitions and the CA algorithm for the 2021 prediction and 2026 land cover simulation. The ANN algorithm obtained a Kappa coefficient value of 0.701, and then we used the CA algorithm to predict 2021 land cover and simulation of 2026 land cover (**Fig. 6**). Kappa coefficient values above 0.6 were categorized as good or strong agreement (Foody 2020). According to Ramadan and Hidayati (2022), the ANN algorithm's Kappa coefficient value is influenced by neighborhood, learning rate, maximum iterations, hidden layers, and momentum. Factor input values cause differences in Kappa coefficient values (Khan and Sudheer 2022; Muhammad et al. 2022; Perović et al. 2018; Ramadan and Hidayati 2022). The larger the factor value, the more generalized the computational results in the ANN algorithm process, and the larger the maximum number of iterations will affect the Kappa coefficient results and the longer the computation process (Ramadan and Hidayati 2022).

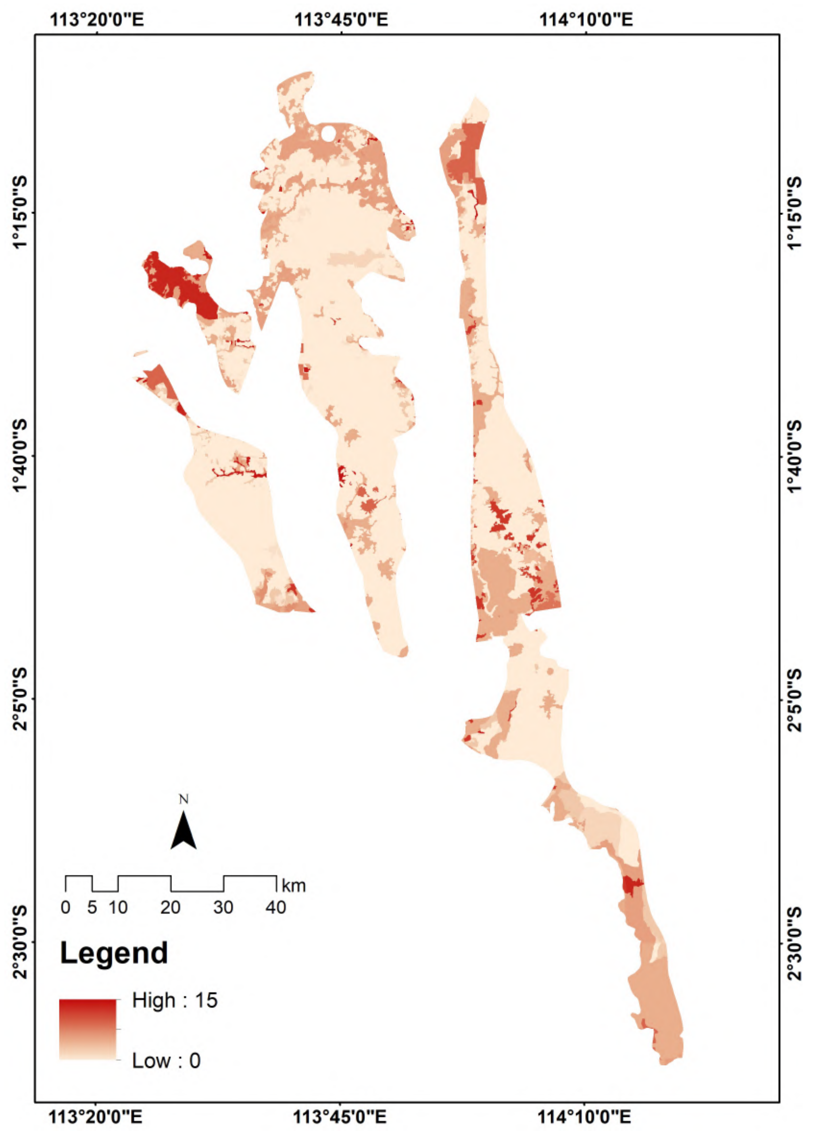


Fig. 5. Map of land cover transition.

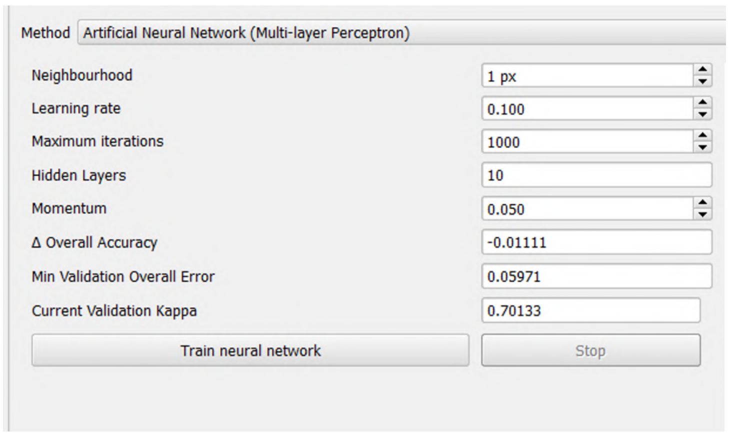
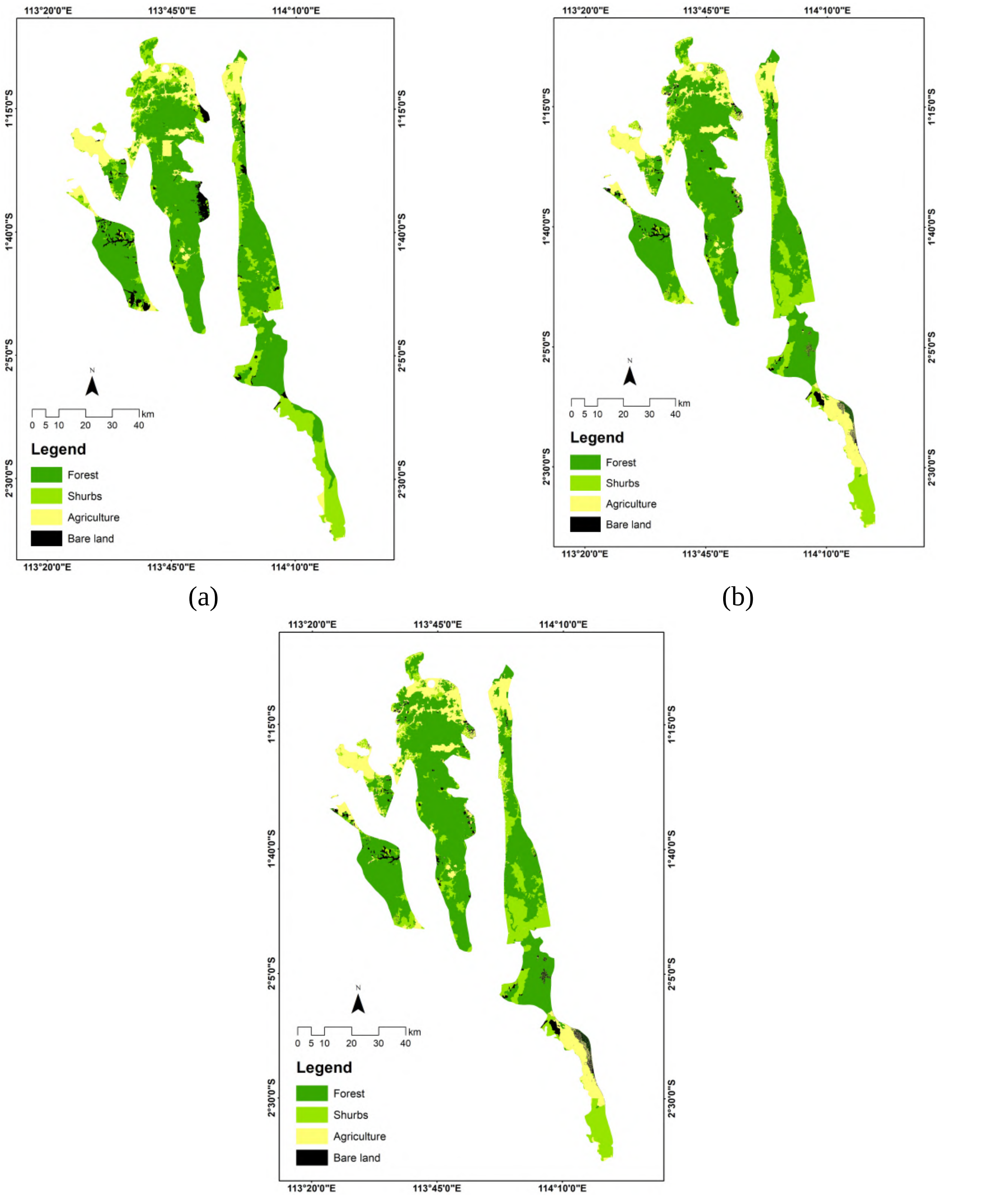


Fig. 6. ANN algorithm transition potential model.

The results of this study show an average area difference of 1.89 ha between actual land cover in 2021 and predicted land cover in 2021, so the coverage of prediction land cover is close to actual land cover (**Tabel 6**).

Table 6. Prediction and simulation of land cover year 2021 and 2026

Classification	2021 Actual (ha)	2021 Actual (%)	2021 Predictions (ha)	2021 Predictions (%)	2026 Simulation (ha)	2026 Simulation (%)
Forest	231.90	61.60	230.47	61.30	229.83	61.10
Shrubs	81.58	21.60	72.21	19.20	71.68	19.10
Agriculture	49.57	12.30	63.75	17.30	64.03	17.00
Bare land	12.94	3.50	9.56	2.50	10.45	2.78
Total	376.01		376.01		376.01	



(a) (b)

(c)

Fig. 7. (a) Actual land cover 2021, (b) predicted land cover 2021, and (c) land cover simulation 2026.

In 2026, based on our research, forest cover will decrease by 229.83 ha, while other land covers will increase by 71.68 ha, 64.03 ha, and 10.45 ha, respectively (**Table 6**). Thus, agricultural and bare land cover are on a trend to increase. The land cover map is presented in **Fig. 7**. Kahayan Tengah FMU must implement strategies to prevent deforestation or degradation of swamp forests. Kahayan Tengah FMU can conduct community-based forest management through social forestry programs and partnership schemes. This program is to realize the community's welfare around the forest and forest sustainability. In addition, the FMU must educate the community to increase agricultural land productivity so that there is no expansion of agricultural land in the future. It can broadly impact and align with the national forest community empowerment issues (Golar et al. 2021). According to Suwarno et al. (2018), predictive modeling and simulation of land cover are important factors for formulating scenarios for forest planning in FMU.

3.4. Validation

The results of this study found that the procedure's accuracy and user's accuracy of bare land were very low, while other land covers showed high procedure accuracy and user's accuracy (**Table 7**). Remote sensing experts will conclude the accuracy of land cover using the Kappa coefficient value (Lechner et al. 2020). The results of this study have a Kappa coefficient of 0.672 (**Table 7**). This value is considered a good value in land cover change analysis and land cover prediction modeling (Alam et al. 2021; Perović et al. 2018). According to Foody (2020), this value ranks from good accuracy to excellent accuracy. The results of this study successfully predicted land cover in 2021 well; therefore, the results can be used to support sustainable forest management planning in Kahayan Tengah FMU.

Table 7. Contingency matric

2021 Actual	2021 Simulation				Total (ha)	Producer's accuracy (%)
	Forest	Shrubs	Agriculture	Bare land		
Forest	211.48	13.76	5.05	1.60	231.90	91.19
Shrubs	9.86	51.83	16.16	3.71	81.58	63.53
Agriculture	4.32	3.81	40.91	0.52	49.57	82.52
Bare land	4.80	2.80	1.61	3.72	12.94	28.75
Total (ha)	230.47	72.21	63.75	9.56	376.01	61.29
User's Accuracy (%)	91.76	71.77	64.17	38.91	Kappa coefficient	0.672

4. Conclusions

Land cover in Kahayan Tengah FMU in 2011 and 2016 experienced dynamics, but the largest change occurred in the land cover class of agriculture. Modeling the potential transition of land cover change for 2011–2016 with ANN and CA algorithms showed a Kappa coefficient of 0.701 in the good category. In 2026, the trend of agricultural land cover increased, but other land cover showed a decrease in area. Validation between prediction and actual land cover in 2021 has a Kappa coefficient of 0.672 in the good category. The results of this study successfully predict and simulate land cover in 2021 and 2026. Therefore, this study is one of the types of information that can support future forest management planning in Kahayan Tengah FMU. Future research needs to analyze how much each variable contributes to driving land cover change.

Acknowledgments

The authors thank the Research and Development Council of Muhammadiyah Central Board for providing the research grant, the Institute for Research and Community Service of the Universitas Muhammadiyah Palangkaraya, which supported the research reporting and evaluation process, and the Faculty of Agriculture and Forestry, Universitas Muhammadiyah Palangkaraya.

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