PREDICTION OF SPATIAL LAND USE LAND COVER CHANGES IN BOVEN DIGOEL, SOUTH PAPUA IN 2031 AND 2041 USING LCM AND CA-MARKOV MODELS

Dewi Novita SARI[1], Muhammad Hafizh Fadhl MUTASHIM[2], Frichelia Varadhita RESTUVICA[2], Kusuma Prayoga Basuki PUTRA[3], Aziz Akbar MUKASYAF[4], Nirma Lila ANGGANI[4], Ayodya Rido NUGRAGA[2]

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ABSTRACT

Boven Digoel Regency, located in South Papua Province, is one of the eastern regions of Indonesia targeted by the government for the development of a food estate project. However, massive land use and land cover (LULC) change require careful prediction over the coming decades to balance development with environmental sustainability. This study integrates advanced spatial modeling techniques to analyze recent trends and predict future LULC changes for 2031 and 2041. The objectives of this study are (1) to analyze the trend of forest to non-forest land use change in Boven Digoel Regency in 2024 using Land Change Modeler (LCM) and (2) to analyze the prediction of forest to non-forest land use change in 2031 and 2041 using Cellular Automata Markov (CA-Markov). The data used in this study include the administrative boundary of Boven Digoel, SPOT 6/7 imagery from 2016 and 2021, Digital Elevation Model (DEM), road network, government centers, river network, and settlements. The methods used in this study are a deep learning approach based on the LCM and a CA-Markov model, which combines CA-Markov land cover prediction methods. Results show that forest areas increased by 27.58% from 2016 to 2021 but are predicted to decline by 18.73% in 2031 and 51.49% in 2041, mainly due to ongoing plantation expansion in southern and northern Boven Digoel. This plantation expansion is predicted to spread from the southern and northern parts of Boven Digoel. Future studies should incorporate updated boundary information and integrate socio-economic, policy, and environmental drivers, such as soil and rainfall, to improve spatial accuracy and enhance the relevance of land use and land cover analysis.

Key-words: *LULC change, Multi-Criteria, LCM, CA-Markov, GIS.*

1. INTRODUCTION

South Papua is distinguished by its characteristic tropical rainforest climate and biodiversity, which is distinct from other regions of eastern Indonesia. Boven Digoel is one of the districts in South Papua that still faces significant challenges related to land use and land cover change. The Boven Digoel Forest is part of the lowland tropical rainforest landscape in Boven Digoel, Southern Papua, characterized by unique ecological features and relatively minimal large-scale anthropogenic disturbances. In the classification of natural forest ecosystems, this area is dominated by lowland tropical rainforest with high humidity, annual rainfall exceeding 2,500 mm, and extremely high biodiversity in terms of both flora and fauna. The dominant vegetation consists of tall, closed-canopy tree species such as *Pometia pinnata*, *Intsia bijuga*, *Palaquium* spp., as well as species from the *Dipterocarpaceae* family, which are found only in the Indo-Malayan and Papuan regions (Barri et al., 2019).

[1]*Department of Geographic Information Science, Faculty Geography Universitas Muhammadiyah Surakarta. Corresponding author* (DNS) dns104@ums.ac.id*

[2]*Laboratory of Remote Sensing and GIS, Faculty Geography Universitas Muhammadiyah Surakarta. (MHFM) hafizhfadhl39@gmail.com , (FVR) varadhitapcd@gmail.com , (ARN) ayodya.rido@gmail.com*

[3]*Department of Disaster Management, Faculty of Mineral Technology, Universitas Pembangunan Nasional "Veteran" Yogyakarta. (KPBP) gisprayoga@gmail.com*

[4]*Department of Geography, Faculty Geography Universitas Muhammadiyah Surakarta. (AAM) aam617@ums.ac.id , (NLA) nla624@ums.ac.id*

The stratified forest structure and dense canopy make this forest a highly effective natural carbon sink, with substantial stand biomass and a high rate of carbon accumulation (Hendri et al., 2022). Beyond its vegetation cover, the Boven Digoel Forest also holds crucial macro-ecological functions. The region forms part of the broader regional hydrological system, sustaining the stability of major river flows in Papua, such as the Digul River and its tributaries. In forestry science, the role of forests as catchment areas is vital for regulating water systems, preventing seasonal floods, and facilitating groundwater recharge (Wambrauw, 2015). In addition, the swamp and peat forest areas in the southern part of Boven Digoel serve as significant soil carbon stocks, with quantities reaching hundreds of tons per hectare. However, this potential also carries high vulnerability (Dommain et al., 2016). When swamp and peat forest areas are drained or cleared for food estate projects or large-scale plantations, the carbon stored over thousands of years can be released in a short period, triggering greenhouse gas emissions far greater than those caused by conventional land-use conversion (Gandhi, 2013). From a socio-ecological perspective, the forests of Boven Digoel cannot be separated from the presence of indigenous communities who have lived in and with the forest for generations (Putrie et al., 2025). Ethnic groups such as the Awyu, Korowai, Kombai, and others maintain an unwritten yet highly structured system of spatial management. Within the framework of forestry science, the practices of these indigenous communities reflect a form of traditional silvicultural system based on functional zonation (Kristin et al., 2025).

Unfortunately, the ecological and social values of the Boven Digoel forest are now under severe pressure, primarily due to national development policies that have yet to fully incorporate landscape-based approaches and the rights of indigenous peoples. Since the early 2000s, thousands of hectares of forest in this region have been allocated for large-scale plantation concessions, including the establishment of food estate areas (Parsch, 2024). The expansion of food estates as part of the National Strategic Projects (PSN) has further intensified this pressure. Spatial analyses and Land Use Land Cover (LULC) simulations indicate that much of the land being converted lies within primary forests, peatland areas, and customary territories (Putrie et al., 2025). Within the framework of sustainable forest management, such development contradicts the precautionary principle, as it disregards the forest's ecological carrying capacity, its carbon sequestration potential, and its socio-cultural values.

Food Estate is an Indonesian government program to increase national food security through integrated agricultural development (Direktorat Pengukuhan dan Penatagunaan Kawasan Hutan Direktorat Jenderal Planologi Kehutanan dan Tata Lingkungan, 2020). This program is part of the National Strategic Program (PSN) and the National Food Barn Program (LPN) for the period 2020-2024 (Widiastuti et al., 2023). This program is prioritized in several provinces, including North Sumatra, Central Kalimantan, East Nusa Tenggara, and Papua. This is reinforced by Regulation of the Minister of Environment and Forestry Number P.24/Menlhk/Setjen/Kum.1/10/2020 concerning the Provision of Forest Areas for Food Estate Development, referred to as P.24 (Walhi, 2021).

The province of South Papua will be one of the priority areas for the food estate plan in the coming year. The development will require at least 1.3 million hectares of forest land, part of which is in Boven Digoel Regency (Econusa, 2021). Boven Digoel Regency has an area of 2,710,829 ha (BPS, 2025). This area is certainly considered to have potential for converting peatlands into food estates in the future.

According to the initial report on the food estate project, carbon reserves estimated at 2.7 million hectares of forest and peatland in Merauke, Mappi, and Boven Digoel will be converted into food barns by 2024 (Lantipo, 2022). It is estimated that 2.7 million hectares of land in South Papua can absorb around 268 million tons of carbon (Simamora et al., 2021; Widiastuti et al., 2023; Swindles et al., 2024). This is not the first time this project has been carried out. Previously, there have been several stages of development on several islands in Indonesia (Rasman et al., 2023; Neilson & Wright, 2017). Based on data from several NGOs, approximately 200,000 hectares of peatland capable of absorbing ±50 million tons of carbon will be threatened with destruction as a result of this project (Walhi Kalimantan Tengah, 2021). This amount is only a small part of other land cover areas in Papua. This certainly contradicts Indonesia's agreement to the COP 26 international agreement in Glasgow in 2021. Indonesia is being encouraged by the international community to reduce carbon emissions by 26% by 2030 (Redaksi Hijauku, 2021).

A novel methodology is imperative to forecast the long-term ramifications of developmental initiatives in Boven Digoel by using combination GIS (remote sensing) and deep learning). Remote sensing technologies, such as satellite imagery, LiDAR, and radar, enable large-scale and frequent monitoring of forested areas including remote zones thus, allowing accurate detection of land-use and land-cover changes, biomass, canopy structure, and forest health (FAO, 2019). When combined with GIS and advanced machine learning models (e.g., LCM, CA-Markov), these systems support accurate classification, predictive land-cover simulations, and evidence-based forest management (Gadal & Mozgeris, 2025). Moreover, long-term sensors like Landsat ensure continuity for temporal trend analysis. These remote methods are not only cost-effective compared to traditional ground surveys but also pivotal for early alerting, decision-making, and sustainable land governance (Wulder et al., 2019). In addition to land change data, spatial information is required to identify the location, distribution, and extent of forests that will be converted into agricultural land (Fikriyah et al., 2024).

Deep learning is a method that facilitates the expeditious and automated classification of extensive land use, and it can be integrated with spatiotemporal satellite imagery data (Masolele et al., 2021; Benjamin et al., 2020). The sophistication of this approach lies in its ability to classify data quantitatively, effectively, and cost-efficiently (Masolele et al., 2021; Sari et al., 2024). The Land Change Modeler (LCM) is a tool employed for the analysis of land use and land cover changes. It is most commonly used to detect, understand, and predict landscape changes, particularly in the context of environmental management and regional planning. It is integrated into software such as IDRISI TerrSet (Sànchez-Marrè, 2022). The LCM is capable of analyzing change patterns based on satellite imagery, identifying the drivers of change (e.g., human activities or environmental conditions), and predicting future changes using techniques such as Markov Chain and Cellular Automata (Mokarram & Minh, 2022).

The properties of the Markov CA model are contingent on past, present, and future conditions. This model incorporates specific binding rules for future pixel changes (Mokarram & Minh, 2022). Consequently, these models necessitate a high degree of accuracy. One applicable model is the CA-Markov model (Mishra et al., 2014). The software's advanced visualization capabilities and Kappa value model validation ensure the accuracy of the results, which support decision-making related to land use planning and sustainable environmental management.

Research on forest to non-forest land use change using LCM and CA-Markov is still rare, as the majority of studies focus on overall land use change. For instance, Akdeniz, (2022) examined alterations in land use in Belek, Turkey, employing Landsat imagery from 1985, 2000, and 2021, and projected future changes up to the year 2040 using LCM. The findings indicated an augmentation in residential areas, forests, and water bodies, accompanied by a diminution in barren land and agricultural land. The 2040 prediction indicates a 5.46% expansion of residential areas and a 4.21% decrease in agricultural land. Another study by Khan et al., (2021) detected land use changes in Quetta, Pakistan, between 1998 and 2018 and predicted changes up to 2028 using CA-Markov. Their findings include an increase in built-up areas by 6.56 km^2 and a decrease in green areas and open spaces.

Concurrently, Asra et al., (2020) employed the CA-Markov model to forecast land-use alterations in the Bila Sub-Watershed up to the year 2036. The results indicated a substantial decline in primary dryland forests and shrublands, accompanied by an increase in mixed dryland agriculture and secondary dryland forests. The scientific validity of this model is supported by a Kappa value of 0.9. The integration of these two methodologies has been demonstrated to yield precise outcomes for applications in land use forecasting and predictive studies.

Based on this background, the specific objectives of this study are as follows: (1) to analyze trends in the extent of forest to non-forest land use change in Boven Digoel Regency from 2016 to 2021 using LCM and (2) to analyze predictions of the extent of forest to non-forest land use in 2031 and 2041 using CA-Markov. The present study focuses on LULC modeling with driving factors such as distance to roads, government, settlements, rivers, and slope.

2. STUDY AREA

Boven Digoel Regency was formerly part of Merauke Regency in Papua Province and was established as a separate regency in 2002. Prior to the administrative restructuring and provincial changes, in 2000 the Merauke Regency Government allocated 460,000 ha for plantations, mostly forest areas, designated for 12 companies (Andrianto et al., 2014). Boven Digoel Regency is one of four regencies that share a direct border with Papua New Guinea. From an astronomical perspective, the Boven Digoel Regency is situated within the following coordinates: 4°58'-7°00' south latitude and 139°90'-141°00' east longitude. In the formation of the administrative region of Boven Digoel Regency up to 2023, Boven Digoel Regency has 20 districts with a population of 71,997 as of 2024 (Pemerintah Kabupaten boven Digoel, 2023). Boven Digoel exhibits the capacity to expedite the cultivation of food crops in Papua, with a total of 610,990 ha of rice field land designated as S3 land suitability class (Wulanningtyas et al., 2025). Approximately 1,531 ha of agricultural land are utilized by 2,044 indigenous farmers, primarily engaged in hunting, vegetable farming, fruit cultivation, bio-pharmaceuticals, oil palm, cocoa, and rubber. According to BPS data from 2025, over 90% of the indigenous or traditional communities of Boven Digoel reside in rural villages. This district is also one of the areas with the highest stunting rates in South Papua in 2023, at 42%, with a poverty rate of 20%. On the other hand, it has experienced an expansion of oil palm plantations exceeding 23,275.18 ha (Savitri et al., 2023). **Fig. 1.** illustrates the administrative location of the study area.

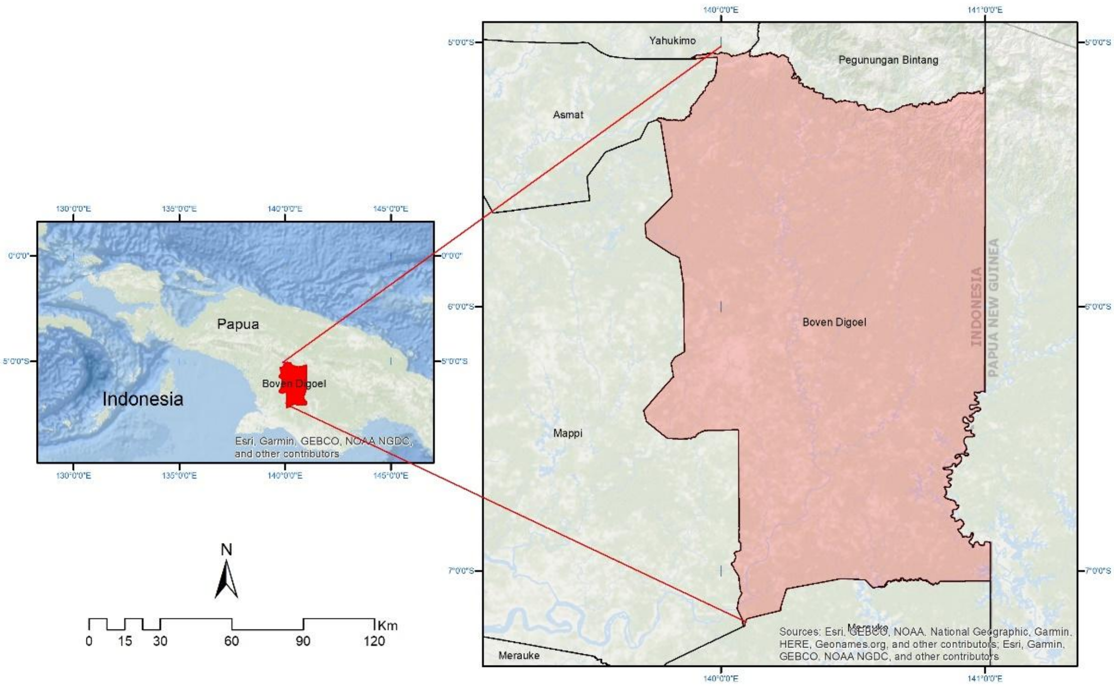

Fig. 1. Location of study in Boven Digoel, West Papua.

3. DATA AND METHODS

3.1. Pre-processing

The research process is divided into six stages: preparation, data processing, data analysis, data validation, and completion. The initial processing stage is comprised of three primary components: satellite image download, layer stacking, and radiometric correction of images. Its primary function is to amalgamate disparate scenes, comprising distinct bands, into a unified entity. Image correction is a process that aims to enhance the visual clarity of images that have been compromised. This phenomenon is attributable to the elevated cloud cover observed around the equator. The correction implemented in this study is radiometric correction. **Table 1** shows the data utilized in this study following a geodatabase model (Nicoară & Haidu, 2011).

Table 1.

Data and sources used in the study.

Nr	Data	Source	Purpose
1	*Shapefile* data on the administrative boundaries of Boven Digoel Regency in 2016	Geospatial Information Agency	Research area boundaries
2	SPOT remote sensing images from 2016 and 2021.	USGS	LULC identification
3	Large-scale land cover classification regulations	Geospatial Information Agency	LULC identification
4	Digital Elevation Model (DEM) with a spatial resolution of 8–30 m.	Geospatial Information Agency (DEMNAS)	Analysis of driving factors slope
5	*Shapefile* data on road networks	Geospatial Information Agency	Analysis of driving factors to accessibility
6	*Shapefile* data on government centers	Geospatial Information Agency	Analysis of driving factors to government centers
7	*Shapefile* data on river networks	Geospatial Information Agency	Analysis of driving factors to rivers
8	*Shapefile* data on settlements	Geospatial Information Agency	Analysis of driving factors to LULC

3.2. Processing

In the digital image processing stage with deep learning, maximum likelihood classification (MCL) is used to identify differences in land use changes, mainly conservation forest land in Boven Digoel. MLC is a statistical-based guided model used to group image pixels into the most likely classes. This method is more complex in calculating probabilities (Malczewski, 1998). Based on the LULC classification of Boven Digoel from Geospatial Information Agency, there are eight land use/land cover types as follows in **Table 2.**

Table 2.

LULC classes Considered in this study.

Nr	LULC	Description
1	Agriculture	Areas utilized for agricultural purposes, with or without water management
2	Forest	Land covered with various types of trees or vegetation that are not managed by humans
3	Openland	Land that is neither cultivated nor inhabited
4	Plantation	Planned cultivation aimed at achieving optimal commodity yields
5	River	A substantial watercourse, typically formed naturally
6	Settlement	Areas specifically used for residential purposes
7	Shrubland	Land dominated by shrubs or low woody vegetation, typically less than 5 meters in height, with sparse or no large trees
8	Wetland	Low-lying land that is flooded and typically contains aquatic vegetation

Source: Geospatial Information Agency (2024).

The land use map generated from the supervised method is still an estimate (tentative). Accuracy testing of land use modeling with actual conditions in the field is required. In machine learning, there is a term called a confusion matrix that can be used for accuracy testing of land use modeling. A confusion matrix is a table that describes errors in land use obtained from the image classification process **(Table 3).** The table contains rows and columns representing the number of correctly and incorrectly classified data points. The classification was based on 30 randomly selected samples generated using the Create Random Points tool in ArcGIS. All 30 samples were validated using Google Earth imagery from the same year as the input data to minimize validation errors. Among the eight-land use/land cover (LULC) classes, forest is the most dominant. Therefore, the sampling process generally yielded the highest number of samples from the forest class compared to other LULC classes. The following is an example of creating a confusion matrix. The matrix calculation consists of the overall proportion of the number of correct pixels (Congalton & Green, 2019). The Kappa coefficient is calculated based on the formula (Stehman, 1997) with interpretation (Landis & Koch, 1977):

$$Overall\ acuracy\ (OA) = \frac{\Sigma_i n_{ii}}{N} \tag{1}$$

$$Producer's\ accuracy\ for\ class\ i\ (PAi) = \frac{n_{ii}}{r_i} \tag{2}$$

$$User's\ accuracy\ for\ class\ i\ (UAi) = \frac{n_{ii}}{C_i} \tag{3}$$

$$Kappa = \frac{n\sum_{i=1}^{q}(nii) - \sum_{i=1}^{q}(riCi)}{n^2 - \sum_{i=1}^{q} riCi} \tag{4}$$

Table 3.

Confusion matrix used to compute OA, PA, and UA.

Validation / Model				Row Total (r_i)
	LCu	LCa	LCw	
LCu	nuu	nua	nuw	ru
LCa	nau	naa	naw	ra
LCw	nwu	nwa	nww	rw
Column total (C_i)	Cu	Ca	Cw	N

where:
nii = Number of correctly classified samples (pixels) in class i (diagonal of the confusion matrix)
N = Total sample for accuracy test
r_i = Total number of reference samples in class i (row total)
c_i = Total number of samples classified as class i (column total)
k = kappa coefficient
q = number of land classes

The accuracy of land use was assessed by calculating the Kappa coefficient, as outlined by Landis & Koch (1977). An acceptable accuracy value (substantial) when using the Kappa method is >0.6 for land use classification mapping. **Table 4.** presents the standard interpretation of Kappa results used in this study.

Table 4.

Interpretive standard for the kappa Index.

Kappa Index	Interpretation
>0.8	Almost Perfect
>0.6	Substantial
>0.4	Moderate
>0.2	Fair
0-0.2	Slight
<0	*Poor*

Source: Landis & Koch (1977).

3.3. Post-Processing

This study employed TerrSet LiberaGIS (version 20.0.2), utilizing the Land Change Modeler module. The mandatory stages were changing analysis and transition potential. In the first stage, the LCM Session Parameters were set using land cover data from two different years along with road and slope (elevation) data. Change Analysis was then conducted to identify land cover changes between the two years, followed by the creation of Change Maps to specify which land cover classes would be predicted in this case focusing on transitions toward plantation areas.

The Spatial Trend of Change module was applied to examine human-induced patterns of change, particularly the conversion of forest to plantations, using a polynomial trend function to capture dominant directions of change (Kurniawan & Roychansyah, 2023). The Transition Sub-model was then used to identify and model forest-to-plantation transitions, incorporating driving factors such as roads, settlements, government facilities, slope, and rivers. Finally, the Multi-Layer Perceptron (MLP) algorithm was applied to generate a transition potential map (ranging from 0 to 1), where values close to 0 indicate very low likelihood of change, and values close to 1 indicate very high likelihood of change (Clark Labs, 2017).

CA-Markov is a method for projecting land use changes by assuming that future land change patterns will be similar to those that occurred in the past (Deng et al., 2009; Asra et al., 2020). This projection takes into account land use classes in the previous period as well as the influence of surrounding land use (*neighborhood*) (Hadibasyir et al., 2023).

The Markov Chain module generates a transition matrix or probability matrix, which shows the transition of land use from the initial period to the predicted period. Markov equations are constructed by referring to the distribution of land use at the beginning and end of the observation period, which is represented in the form of a vector (single-column matrix), and a transition matrix that describes the probability of change between land classes. The relationship between the three matrices can be illustrated mathematically:

$$\text{MLC.Mt} = \text{Mt+1} \tag{5}$$

$$\begin{vmatrix} LCuu & LCua & LCuw \\ LCau & LCaa & LCaw \\ LCwu & LCwa & LCww \end{vmatrix} \begin{vmatrix} Ut \\ At \\ Wt \end{vmatrix} = \begin{vmatrix} Ut+1 \\ At+1 \\ Wt+1 \end{vmatrix} \tag{6}$$

where:

Ut, At, and Wt represent the proportion (probability) of each land cover class (urban, agriculture, and woodland/water) at time t.

The transition probabilities are denoted by $LCij$, where i is class at time t and j is the class at time $t+1$.

For example, *LCcua* indicates the probability of land cover changing from urban *(u)* at time *t* to agriculture *(a)* at *t+1* (Asra et al., 2020).

The following **Table 5**. directly corresponds to the Markov transition probability matrix presented in Equation 4. The table represent the number of pixels in each land cover class at year *i* that are projected to year *i+n*.

Table 5.

Predicted land use calculations in CA-Markov.

LULC year i	LULC year i+n		
	Pit2	Pit2	Pzt2
Pit1	Xii	……	……
Pit1	……	Xii	……
Pzt1	……	……	Xii

Description:

Mt = Map at time *t*
Mt+1 = Map at time *t+1*
MLC.Mt = Markov Land Cover model applied to map *Mt*
LC = *LULC* changes
u = Urban
a = Agriculture
w = Woodland/water
Pit1 = Pixels of land use type *1* in year *t1*
Pit2 = Pixels in land use type *2* in year *t2*
i = year-1
n = prediction year
z = number of land use types
Xii = probability of pixels remaining in the same classin period *t1-t2*

3.4. Projection using driving factors

Forest land projections for 2031 and 2041 can be made using the CA-Markov algorithm (please see the research methodology in **Fig. 2**).

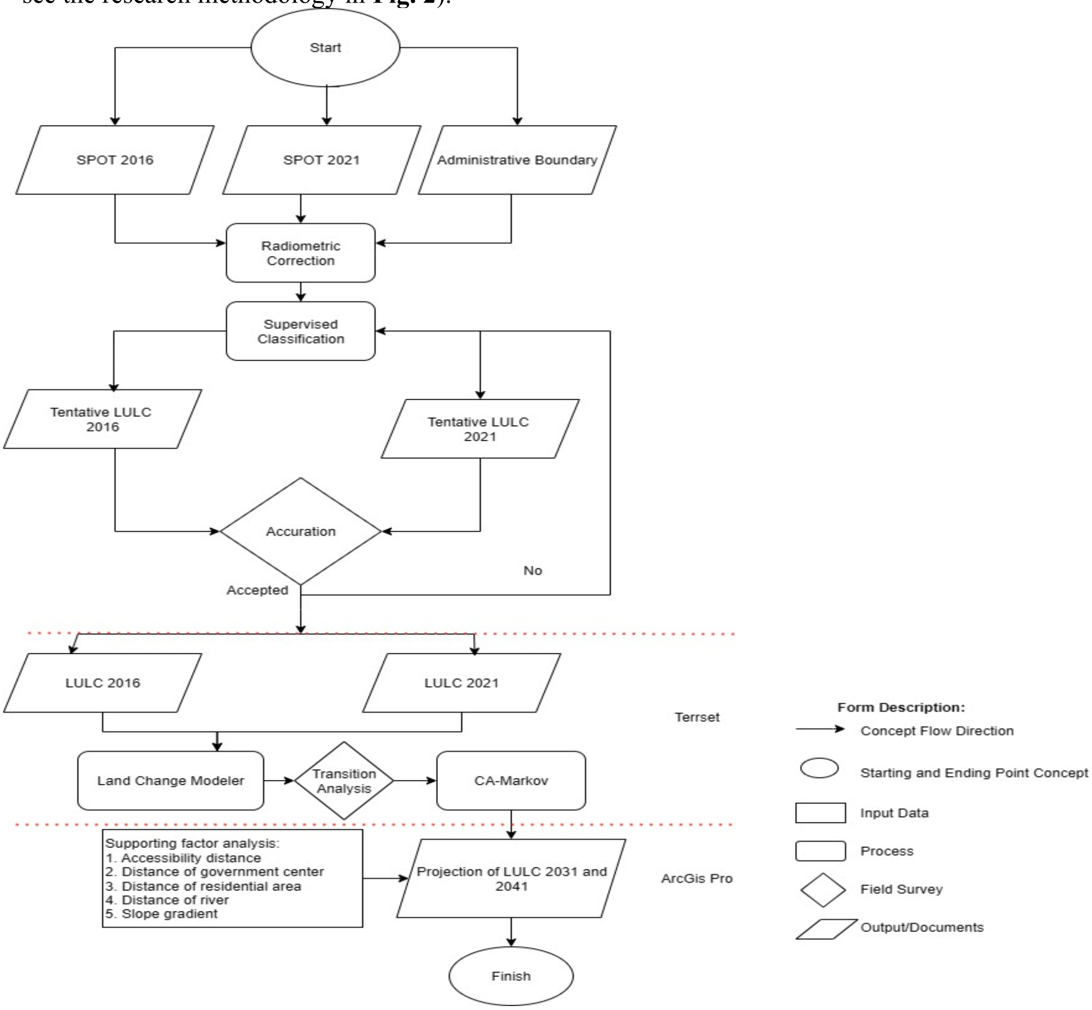

Fig. 2. Flowchart of research methodology.

The predictions are made using transition analysis with the most recent year being 2021. The selection of driving factors was based on observed land cover changes over the two-year period, reflecting human activities in the study area. Distance to roads represents accessibility and the influence of transportation networks on land development, while distance to government centers indicates concentrations of human activity, such as sub-district offices. Distance to settlements reflects population expansion, and proximity to rivers shows human utilization of water resources. Slope affects land use suitability, with steep areas generally avoided for settlements or other human activities, whereas flat areas are more likely to be developed.

The satellite data used are SPOT-6/7 (*Satellite Pour l'Observation de la Terre*) with spectral bands of Panchromatic (1.5 m), Blue (450–520 nm, 6 m), Green (530–590 nm, 6 m), Red (625–695 nm, 6 m), and NIR (760–890 nm, 6 m). The spatial resolution is 1.5 m (pan-sharpened) and 6 m (multispectral), with a temporal revisit of 1–3 days when both satellites operate in constellation (European Space Agency (ESA), 2024). The acquisition time was 2016 and 2021. These images can record appearances better than medium-resolution images, especially for areas around the equator with high cloud cover. The method used to create LULC maps is maximum likelihood classification. This method allows for maximum classification of land use based on criteria that have been exemplified at the time of classification (Mosleh, 2025). These datasets were processed and analyzed to generate land use/land cover maps, which were then used as inputs for the Land Change Modeler to project future scenarios. The results will be in the form of algorithm values from software that can distinguish land cover from predicted to unpredictable. Furthermore, the results can be analyzed using several supporting factors such as accessibility, distance from government centers, residential areas, river flows, and slope gradients. An example of prediction using driving factors was also conducted by Sow et al., (2016), who used satellite data from the Global Solar Atlas (GSA) and the Global Wind Atlas (GWA) to assess the potential of green hydrogen derived from two renewable energy sources, solar and wind.

4. RESULTS

4.1. Past LULC Classification and Classification Accuracy

Based on the results of LULC changes from 2016 to 2021 **(Fig. 3**), a confusion matrix was created to determine the overall accuracy and kappa index.

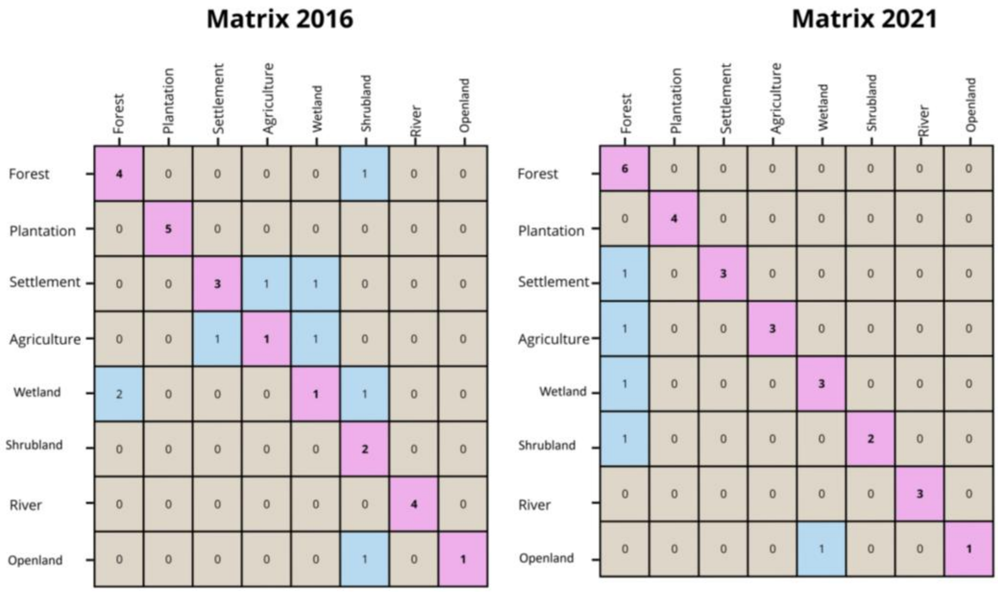

Fig. 3. Confussion matrix 2016 and 2021.

This became the basis for validating the prediction model to ensure its suitability for use (Congalton & Green, 2019). Based on the LULC modeling results, the matrix in 2016 had 21 correct values out of a total of 30 samples. The overall accuracy was 70% with a kappa index value indicating substantial agreement (0.652). Meanwhile, the matrix in 2021 had 25 correct values out of a total of 30 samples. The overall accuracy was 83.33%, with a kappa index indicating high agreement (0.804) between the classification and reference data. The confusion matrix results were then used to develop models for the years 2031 and 2041 using the TerrSet software.

4.2. Mapping and projection of LULC in Boven Digoel

Based on land cover change data from 2016 to 2021 (**Fig. 4** and **Table 6**), the most striking change occurred in the forest category, which increased by 329,765.53 ha (13.07%), from 1,992,569.58 ha (79.19%) to 2,322,335.11 ha (92.26%). This increase is a strong indication of rehabilitation or reforestation efforts, as well as the possibility of shrub or swamp land being reclassified as forest. This is reinforced by data showing that shrubland decreased dramatically by 148,426.51 ha (-5.90%) and swamp land decreased by 107,297.52 ha (-4.27%). Additionally, open land has significantly decreased by 17,222.55 ha (-0.68%), indicating substantial land conversion over the past five years. On the other hand, agricultural land has declined sharply to almost disappear, from 56,794.47 ha to only 149.82 ha (-2.25%), most likely due to conversion into forests, plantations, or other forms of land use. Conversely, plantation land increased by 6,279.56 ha (0.25%), indicating an expansion of areas for the cultivation of perennial crops. These changes reflect intensive land use dynamics, with a dominant conversion to forest and plantations, although further study is needed to determine whether the increase in forest cover is natural, the result of rehabilitation, or merely a change in classification.

According to data from the Indigenous Territory Registration Agency (BRWA) in 2024, Papua has approximately 13.4 million hectares of indigenous territory, with 92% of it, or 12.35 million hectares, having the potential to become indigenous forests (World Resource Institute (WRI) Indonesia, 2025). The indigenous community in Boven Digoel has a spatial management system based on "customary rights" (Ungirwalu et al., 2025), where customary areas are used communally and with full local wisdom. Traditional activities such as hunting, farming, fishing, and non-timber forest product collection are carried out without damaging the ecological structure of the forest. Therefore, the 2016-2021 LULC change showing an increase in forest area may reflect the sustainability of indigenous peoples' management practices or changes in land cover classification due to natural vegetation recovery in indigenous territories.

However, it cannot be ignored that during the same period there was a large-scale conversion of swamp and agricultural land to other forms of land cover (Savitri et al., 2023). This indicates external pressures, such as plantation expansion or development interventions, that have the potential to marginalize indigenous peoples' management systems. In some cases (Amin et al., 2025) (Wulanningtyas et al., 2006), land conflicts arise due to overlaps between large-scale concessions and customary territories that have not been legally recognized.

Predictions of LULC changes for 2031 and 2041 (**Fig. 4**) indicate relatively moderate but consistent shifts, particularly between the two primary categories of forest and plantation. Forests, although still dominating land cover (more than 90% of the total area), are expected to undergo a gradual decline: by 20,020.36 ha (-0.75%) between 2021 and 2031, and by 16,481.52 ha (-0.66%) between 2031 and 2041. This decline suggests that pressure on forest areas persists, albeit not to the same extent as in previous periods. This phenomenon may be attributed to various factors, including plantation expansion and infrastructure development, which have led to a gradual shift in the boundaries of natural forests.

Conversely, the area dedicated to plantations is projected to rise steadily, from 68,963.04 ha in 2021 to 104,469.12 ha in 2041, representing an increase of 35,506.08 ha (1.42%) over the span of two decades.

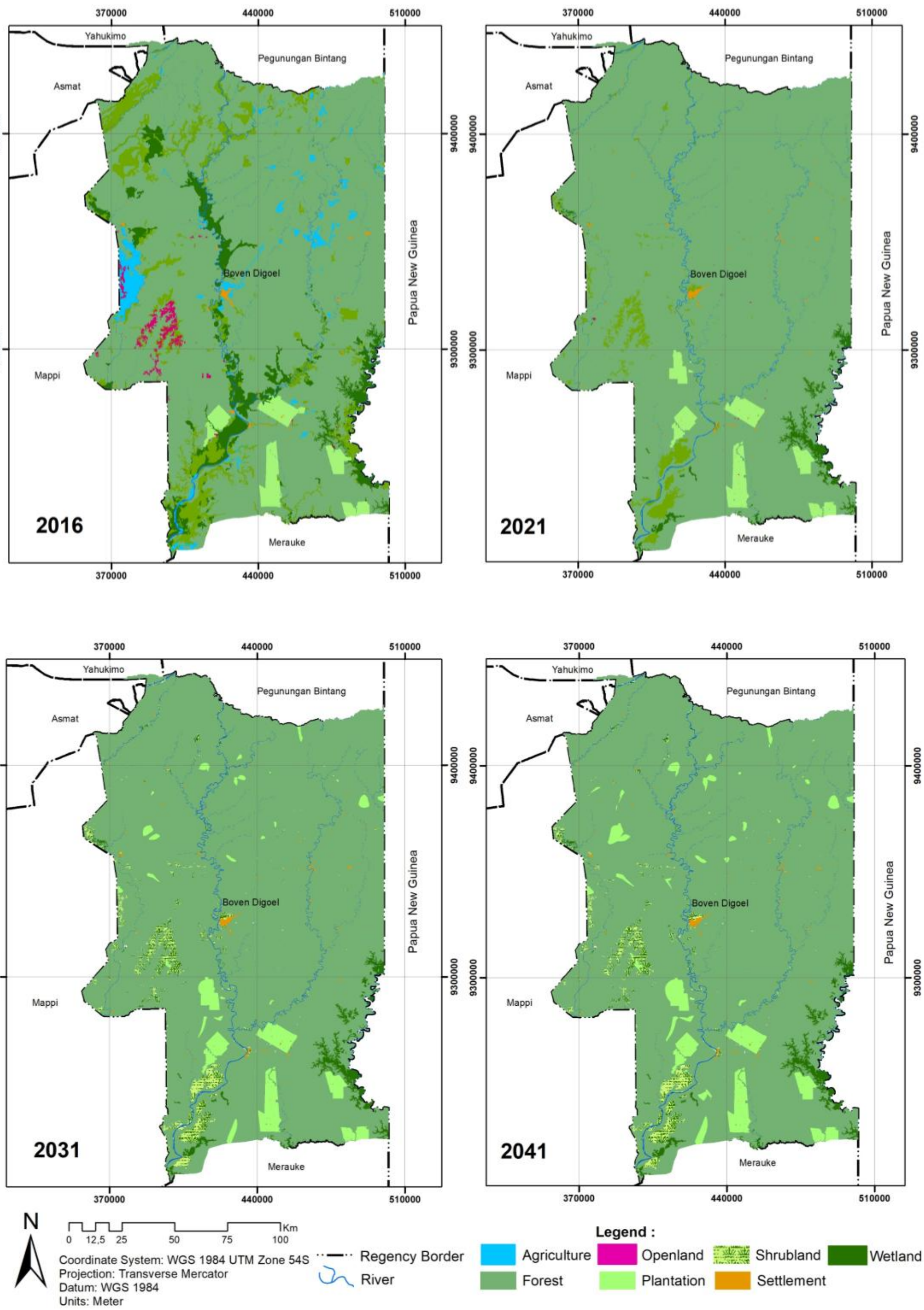

Fig. 4. Projection of LULC changes in Boven Digoel from 2016, 2021, 2031, and 2041.

Table 6.

Calculation of predicted LULC areas in 2016, 2021, 2031, and 2041.

LULC	Area 2016 (ha)	(%)	Area 2021 (ha)	(%)	LULC changes from 2016 to 2021 (ha)	(%)	Area 2031 (ha)	(%)	LULC Prediction 2021 to 2031 (ha)	(%)	Area 2041 (ha)	(%)	LULC Prediction 2031 to 2041 (ha)	(%)
Forest	1,992,569.58	79.19	2,322,335.11	92.26	329,765.53	13.07	2,302,314.75	91.51	-20,020.36	-0,75	2,285,833.23	90.86	-16,481.52	-0.66
Plantation	62,683.48	2.49	68,963.04	2.74	6,279.56	0.25	87,987.60	3.50	19,024.56	0.76	104,469.12	4.15	16,481.52	0.66
Settlement	7,560.84	0.30	6,477.69	0.26	-1,083.15	-0.04	6,472.53	0.26	-5.16	0.001	6,472.53	0.26	0	0
Agriculture	56,794.47	2.26	149.82	0.01	-56,644.65	-2.25	150.12	0.01	0.30	0.001	150.12	0.01	0	0
Wetland	143,388.09	5.70	36,090.57	1.43	-107,297.52	-4.27	36,072.18	1.43	-18.39	0.001	36,072.18	1.43	0	0
Shrubland	205,753.63	8.18	57,327.12	2.28	-148,426.51	-5.90	57,208.32	2.27	-118.80	0.004	57,208.32	2.27	0	0
River	29,672.07	1.18	25,352.07	1.01	-4,320.01	-0.17	25,246.44	1.00	-105.63	0.004	25,246.4	1.00	0	0
Openland	17,680.88	0.70	458.33	0.02	-17,222.55	-0.68	460.71	0.02	2.38	0.001	460.71	0.02	0	0
Total	2,516,103.04	100	2,517,153.75	100			2,515,912.65	100			2,515,912.65	100		

Source: Analysis, 2025.

This phenomenon signifies a shift toward the intensification of commodity-based economic activities, such as oil palm plantations (Obidzinski et al., 2025), which is often the main driver of land use change in Papua. This growth is likely to take space from natural forests or other land that is not intensively utilized. Meanwhile, other categories such as settlements, swamps, scrubland, and open land show a stagnant trend with no significant change. This may reflect physical space constraints, protection of specific ecosystems, or land-use policies that restrict the expansion of such land types. However, this stability could also indicate that future pressure will be more focused on forests as a reserve space for economic expansion.

4.3. Driving factors for LULC changes

Driving factors in LULC prediction modeling serve to determine the impact of land use changes and directly influence the accuracy and success of predictions (Congalton & Green, 2019). In this study, the main focus is on the conversion of forest land to plantations in the next 20 and 30 years. Driving factors can be derived from the causes of land conversion, such as distance from roads, distance from government offices, distance from settlements, distance from rivers, and slope (**Fig. 5**).

Road availability is one of the most influential factors affecting land change (Chen et al., 2022). Land proximate to major road networks is more susceptible to conversion, particularly to plantations and settlements. The high accessibility of these regions has been demonstrated to encourage investment and accelerate the mobilization of heavy equipment and construction logistics. The augmentation in plantation area from 2016 to the 2041 forecast is expected to be concentrated in areas proximate to major roads or recently constructed roads, suggesting a pattern of linear deforestation following transportation networks.

Areas in close proximity to government centers have been observed to experience heightened intensity in land cover changes (Allan et al., 2022). This phenomenon can be attributed to several factors, including heightened development activity, streamlined access to bureaucratic processes, and the strategic utilization of space for infrastructure, public services, or economic zones. Land use in Boven Digoel such as settlements, plantations, and open land is more likely to undergo changes in function in these zones, due to the attractiveness for investment and concentration of human activities. Conversely, land far from government centers tends to exhibit greater stability, particularly if it lacks adequate accessibility.

It has been demonstrated that areas adjacent to settlements are subject to elevated pressures with regard to land change (Allan et al., 2022), This phenomenon is especially evident in the transformation of scrubland, open land, or swamps into urban areas or plantations. Community activities in Boven Digoel, including the expansion of cultivated land and the construction of residential and public facilities, have contributed to these changes. Conversely, land situated in remote areas, distant from major population centers, exhibits greater stability. These areas frequently persist as natural forests or scrubland due to their inaccessibility to the day-to-day activities of the community.

Rivers function as customary activity corridors for indigenous communities and natural transportation routes in Boven Digoel. Consequently, land adjacent to rivers is subject to alterations in use, including traditional agriculture, water resource extraction, and the construction of basic facilities. However, these areas are also vulnerable to conversion into plantations, especially if companies utilize rivers as logistics routes. Nevertheless, in certain instances (Andrianto et al., 2014)(Wulanningtyas et al., 2025), the land around the river remains protected due to its status as a flood-prone area or conservation zone. Boven Digoel is characterized by the presence of several major rivers that extend in a uniform pattern from north to south.

The topography is also an important factor (Plateau et al., 2023). Land with low to moderate slopes (0‑15%) is more accessible and cultivable, rendering it more vulnerable to changes such as conversion to plantations, agriculture, or settlements. Conversely, regions characterized by precipitous slopes (>25%) are often preserved as woodlands, a practice influenced by factors including challenging accessibility, the potential for erosion, and their elevated ecological value. This phenomenon elucidates the predominance of forest fragmentation in hilly regions and steep slopes, while changes are more prevalent in relatively flat lowlands. Boven Digoel, as observed through the

DEM, exhibits low to moderate slope gradients across the majority of the region. A limited number of regions in the northern area are characterized by high slope gradients that border the Papua Mountains.

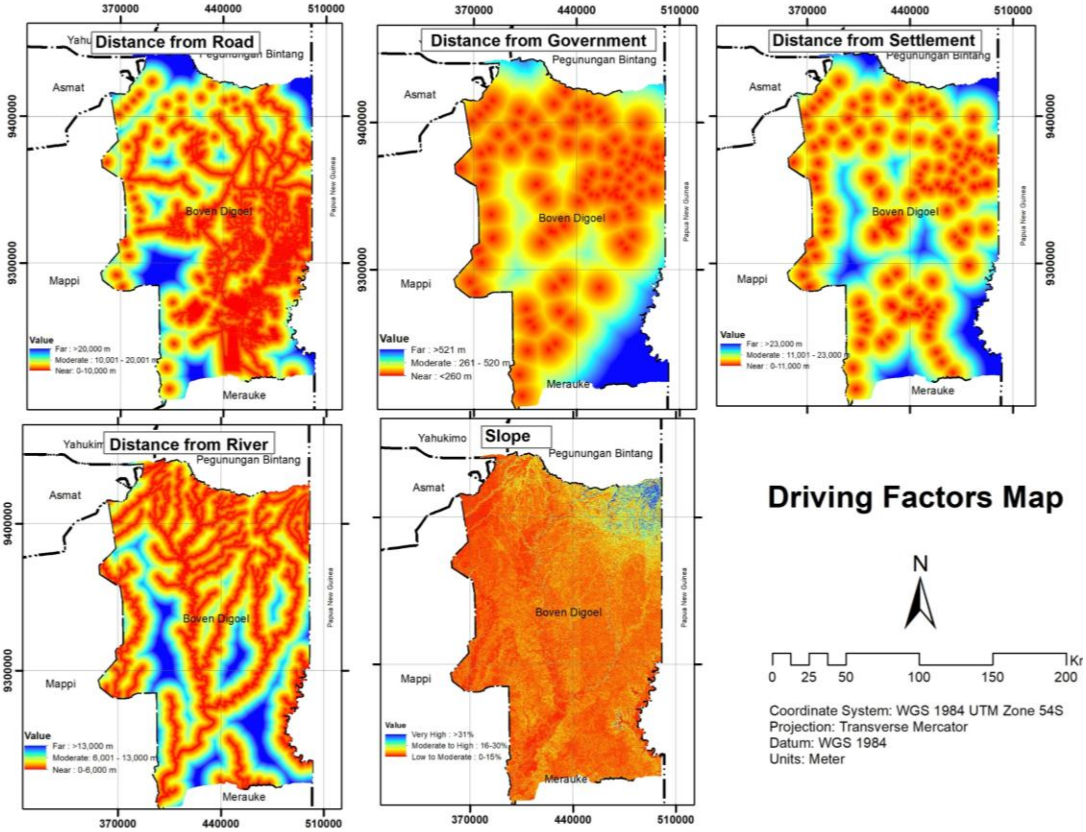

Fig. 5. Predictors of LULC include distance from roads, distance from government, distance from settlements, distance from rivers, and slope.

4.4. Model Validation

Model validation is used to test the results of our modeling. Model validation for 2031 and 2041 (**Fig. 6)** explains the statistical test results for the CA-Markov model, which can be seen in the Terrset software.

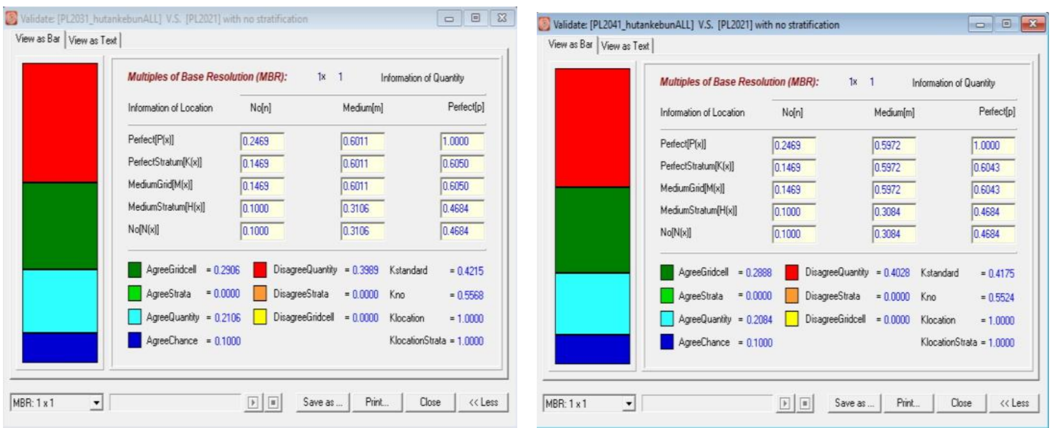

Fig. 6. Validation model results for 2031 (left) and 2041 (right).

The results of spatial validation between land cover predictions for 2031 and 2041 (**Fig. 6**) and actual conditions show varying levels of agreement in terms of location and quantity. The standard Kappa index (Kstandard) for 2031 is 0.4215, higher than that for 2041 at 0.4175, indicating moderate accuracy. The AgreeGridcell values for both years are nearly identical, approximately 0.29, indicating that only about 29% of the total pixels are spatially consistent. Meanwhile, the Klocation and Klocation Strata values are both 1, indicating that the prediction model has very high location accuracy, even perfect, both overall and based on stratification.

On the other hand, Kno values for 2031 and 2041 of 0.5568 and 0.5524 indicate that the agreement in terms of quantity is still moderate, so more attention needs to be paid to the distribution of predicted land use classes. The agreement proportion at the grid cell level (Agree Grid cell) is 0.29806 and 0.2888, and the agreement based on quantity (Agree Quantity) is 0.2106 and 0.2084, supporting these results. Conversely, the quantitative mismatch is quite high, at 0.3999 and 0.4028. These results indicate that although the prediction of land change locations is fairly accurate, the model still has limitations in balancing the distribution of area between land use classes precisely.

5. DISCUSSION

Based on the results of this study, the integration of LCM and CA-Markov can be used to predict spatial expansion of agricultural land while evaluating its potential environmental impacts, such as carbon stock calculations. Advanced spatial modeling can be used for the implementation of REDD+ (Reducing Emissions from Deforestation and Forest Degradation) schemes. By analyzing the dynamics of land cover changes over time and projecting future change patterns, spatial estimates of forest cover loss and land conversion with potential carbon emissions can be made. By integrating carbon stock data per land cover class, TerrSet can be used to calculate carbon stock changes and identify areas with high emissions risk due to deforestation.

From a forestry perspective, the conversion of forest land into non-forest uses, particularly plantations as projected to occur in Boven Digoel Regency until 2041 carries complex ecological and social implications. Deforestation not only reduces above and below ground carbon stocks but also disrupts critical functions of tropical forest ecosystems, such as hydrological cycle regulation, soil conservation, and habitat provision for Papua’s endemic biodiversity (Simamora et al., 2021; Swindles et al., 2024). The significant forest loss of 36,501 ha from 2016–2041 is a clear indicator of land-use pressures that are inconsistent with the principles of sustainable forest management. Within the framework of the Forest Landscape Integrity Index (FLII), the decline of primary forest without clear silvicultural systems can diminish landscape integrity and trigger further degradation, even when such changes appear spatially small (Potapov et al., 2017).

In general, predictions from the CA-Markov model demonstrate a consistent expansion of plantations in lowland areas that were once natural forests. In forestry science, this illustrates the edge effect, where forest fragmentation creates transitional zones that are highly vulnerable to disturbances. These zones may eventually become the starting points of structural and functional degradation, reducing the forest’s ability to store carbon and sustain biodiversity. From a management perspective, such trends must be mitigated through landscape-based forest governance, which integrates spatial predictions with adaptive forest zoning policies. For example, the implementation of protected functions in areas with the highest predicted change (deforestation hotspots) should be prioritized through social forestry schemes or the recognition of customary forests (Ungirwalu et al., 2025; World Resource Institute (WRI) Indonesia, 2025). This aligns with the principle of Free, Prior and Informed Consent (FPIC) in equitable tropical forestry (Giupponi, 2018).

The spatial estimations such as those presented in this study, the value of carbon stock loss and emissions can be mapped precisely and serve as the basis for conservation-based incentive schemes for indigenous peoples or carbon credit offset mechanisms (Swindles et al., 2024; Mokarram & Minh, 2022). In the context of food estate development, a land-sparing forestry approach preserving primary forest zones while intensifying agriculture on degraded lands should be prioritized to avoid trade-offs between food security and environmental conservation (Neilson & Wright, 2017). This approach is more consistent with Indonesia's commitments to the SDGs (particularly SDG 13: Climate Action and SDG 15: Life on Land) as well as the 2015 Paris Agreement.

This study has some limitations related to data accuracy and the scope of LULC modeling. The availability of high-resolution, update boundary spatial data remains a challenge, which may affect the precision of LULC classification and change detection. We acknowledge that additional parameters could improve the model's accuracy in future studies. Studying LULC changes requires more complex parameters beyond distance to government centers, roads, settlements, rivers, and slope. Other driving factors, such as soil type and rainfall, can also influence LULC changes (Entahabu et al., 2023). For example, soil type provides information on mineral content, which can serve as a basis for land transformation. Rainfall affects not only soil strength but also water absorption capacity. Population size or density can also drive LULC changes, particularly in urban or semi-urban areas. However, in large areas with low population density, the effect of population as a driving factor may be insignificant, resulting in a lower impact on land use change.

The increase in plantation areas, as shown in **Fig. 4.** and **Table 6.** indicates intensified agricultural activity and human-induced land conversion in Boven Digoel. In contrast, settlement areas remain relatively stagnant, which may be attributed to low population growth, limited suitable land for new settlements, and local development policies that constrain residential expansion. The population growth rate in Boven Digoel Regency is relatively low, approximately 1.9% per year based on the latest data from the Central Statistics Agency, 2025. Total Fertility Rate (TFR) since 2020 is constant at 2.1 according to the population projection of 2015-2045 Intercensal Population Survey (SUPAS) (BPS, 2025). This contrast suggests that while agricultural expansion is actively transforming the landscape, urban or residential growth is more restricted, highlighting the different dynamics and drivers affecting land use change in the region. Therefore, the massive land changes occurring in this region are not driven by natural population growth but are instead structured and managed by government policies and industrial activities.

6. CONCLUSIONS

The results obtained indicate a significant increase in forest cover from 2016 to 2021, followed by a gradual decline until 2041, resulting in a total loss of 36,501 hectares. Conversely, the plantation area exhibited a consistent increase, rising from 2.49% to 4.15% of the total area, suggesting an expansion of cultivated land that has the potential to supplant natural cover. The categories of swamp, scrub, and open land underwent a precipitous decline, suggesting a transition to more intensive land use. Settlements and agriculture exhibited a marked tendency toward stagnation, with minimal to no observable change. The transition from forest to plantation is evident in the southern to northern expansion of Boven Digoel.

The application of LCM and Markov CA to model LULC change yielded an overall accuracy of 70% with a kappa index of 0.652 in 2016 and an overall accuracy of 83.33% with a kappa index of 0.804 for 2021. Consequently, the model for 2031 and 2041 is deemed acceptable, contingent upon the five driving factors that influence the model, namely distance to roads, government, settlements, rivers, and slope. The present study centered on the investigation of changes in land use and land cover (LULC) from forest land to plantations. The observed decrease in forest area is primarily associated with the expansion of plantation land, which increased from 68,963.04 ha, or 27.58% (2016–2021), to 87,987.60 ha, or 18.73% (2021–2031), and 104,469.12 ha, or 51.49% (2031–2041). This finding suggests that forest conversion to non-forest (primarily plantations) is the dominant trend, with potential impacts on carbon stocks, biodiversity, and ecosystem stability.

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