Evaluating the Impact of Ibu Kota Nusantara (IKN) Development on Land Cover Using Machine Learning-Based Sentinel-2A Satellite Image Classification

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Abstract. The development of Ibu Kota Nusantara (IKN) in East Kalimantan as Indonesia's new capital city has the potential to cause significant changes to land cover patterns, especially in tropical rainforest areas. This study aims to evaluate the impact of IKN development on land cover using Sentinel-2A satellite image data and a machine learning approach. The study area is focused on the IKN Core Urban Area by comparing land cover conditions in 2022 before development and 2024 after development. Three classification methods were used including Random Forest, Support Vector Machines, and Classification and Regression Trees. The results showed that the RF model had the best accuracy with an overall accuracy value above 93% in both time periods. Spatial analysis showed a decrease in vegetation area and an increase in open land as an indication of intensive land clearing activities. These findings emphasize the importance of continuous land cover monitoring to support IKN's vision as a green city and achieve sustainable development targets (SDGs 11 and 15). This research is expected to serve as a reference for the formulation of adaptive and environmentally friendly spatial policies.

Keyword: Ibu Kota Nusantara (IKN), Land Cover Classification, Machine Learning, Sentinel-2A

1. Introduction

The development of Ibu Kota Nusantara (IKN) is one of the Government of Indonesia's ambitious projects. According to Law Number 3 of 2022 concerning about IKN, the main purpose of developing IKN is to become one of sustainable city in the world, as a key driver of Indonesia's future economy, and as a national symbol [1]. East Kalimantan has been chosen as the main location for the new Indonesian Capital City and is one of the largest tropical rainforest areas in the world, so the potential damage caused by this project is a serious concern among global academics [2]. One of the major concerns is the potential degradation of ecosystem quality in East Kalimantan due to land use changes driven by urban development. This could result in deforestation and exert significant pressure on the ecological environment [3]. In addition, Geleta and Laekemariam stated that uncontrolled land use change could result in the degradation of soil quality [4]. Thus, in the context of IKN development, land use must be carefully monitored to reduce its impact on the environme

Land use monitoring is crucial for policymakers and regional planners to organize urban areas, develop mitigation measures, and restore natural ecosystems [5], [6], [7]. The development of the new government center area in East Kalimantan can have an impact on land use change. This large-scale infrastructure development will certainly affect ecosystem function and species distribution, especially endangered species [8]. In addition, the reconstruction of areas dominated by tropical rainforests can also significantly change the land use pattern around the IKN area, from natural forests to built-up areas. Monitoring the inclusive development of IKN is carried out to ensure environmental sustainability with a minimum of 75% green area (forest city) and in line with the objectives of Sustainable Development Goals (SDGs) indicator 11 on "Sustainable Cities and Settlements" [1]. In addition, SDGs number 15 on "Terrestrial Ecosystems" which highlights the conservation of terrestrial ecosystems and mitigation of environmental damage impacts is also a target that must be achieved in the transition of green land into modern capitals.

In the context of land use change in IKN, the application of satellite technology is an effective way to obtain land cover or land use classification in an area. Land cover classification involves the process of separating different types of land cover using various classification methods developed in satellite image studies [9]. Various relevant approaches have been applied for this classification purpose. For example, research conducted by Cavur et al. focused on predicting the land cover and land use class of St. Petersburg urban area using Support Vector Machines method and Sentinel-2A satellite imagery which had an accuracy value of 83.64% [10]. Another study conducted by Abdi compared several land cover and land use (LCLU) classification methods between 2017 and 2018 with four time points in an area of 10 km 12 km in the Uppsala region, Sweden [11]. The comparison used four algorithms, namely Support Vector Machine, Random Forest, Extreme Gradient Boosting, and Deep Learning by utilizing Sentinel-2 satellite images. This research shows that the application of the SVM method with a dataset using Sentinel-2 satellite imagery produces a higher overall accuracy (OA) value compared to other classification methods, which is 75.8%, followed by XGB at 75.1%, RF at 73.9%, and DL at 73.3%. We suggest further research to compare mono-temporal, multi-temporal data, and the effectiveness of red edge banding on different vegetation classes.

There have been many studies that examine land cover classification using satellite imagery, but a research that specifically analyzes the direct impact of IKN development based on LCLU classification using machine learning method has never been done before. Based on this research gap, this study aims to compare the accuracy of land cover classification methods using Support Vector Machine (SVM), Random Forest (RF), and Classification and Regression Trees (CART) approaches to determine the best method in mapping accurate land cover patterns through Sentinel-2A satellite image data obtained from Google Earth Engine. In addition, this research also aims to analyze land cover changes in the IKN area by comparing land cover patterns before the ratification of Law Number 3 of 2022 concerning the National Capital City and in 2024 so that the impact of IKN development on land cover changes in the region can be known.

The main contribution of this research is its approach to monitoring land cover changes in the IKN using Sentinel-2A imagery and systematically comparing three machine learning algorithms (Random Forest, SVM, and CART) over two important periods, before and after IKN development after two years, thereby revealing actual changes in the core area of national development and producing applicable thematic maps to support sustainable development policies. This study differs from other studies that generally only highlight land cover classification across broader Indonesian regions and lack a specific focus on IKN, such as the study from Habibi et al. that combines Sentinel-2 and ESA World Cover for land cover mapping [12]. Furthermore, previous research often limited itself to evaluating machine learning algorithms without directly linking their findings to new capital city development policies, as seen in comparative studies in West Sumatra and Jambi [13], [14]. This study is distinctive because it produces spatial data-based policy recommendations supporting the realization of Sustainable Development Goals (SDGs) 11 and 15, grounded in empirical analysis of the IKN development case.

Beyond contributing to methodological advancements, this research provides in-depth knowledge for other researchers seeking to identify the best methods for mapping land cover patterns specific to the IKN area. It serves as an important reference for IKN authorities in formulating policies and improving spatial management related to environmental changes. By identifying the most effective land cover classification method, relevant authorities can plan environmental impact mitigation programs more effectively. Additionally, this research benefits the community by fostering a better environment in the long term. The study encourages synergy among government, researchers, and community stakeholders to protect the environment and promote sustainable development in the IKN area, thereby helping to achieve SDGs 11 (Sustainable Cities and Settlements), which prioritizes environmentally friendly urban strategies to maintain ecological balance, and SDGs 15 (Terrestrial Ecosystems), which focuses on the protection of terrestrial environments.

2. Research Methods

This research uses Sentinel-2A satellite image data as the main data source. Google Earth Engine (GEE) is used as a medium for processing satellite images so that the resulting images can be used for the analysis process. **Figure 1** below shows the flow chart used in this research.

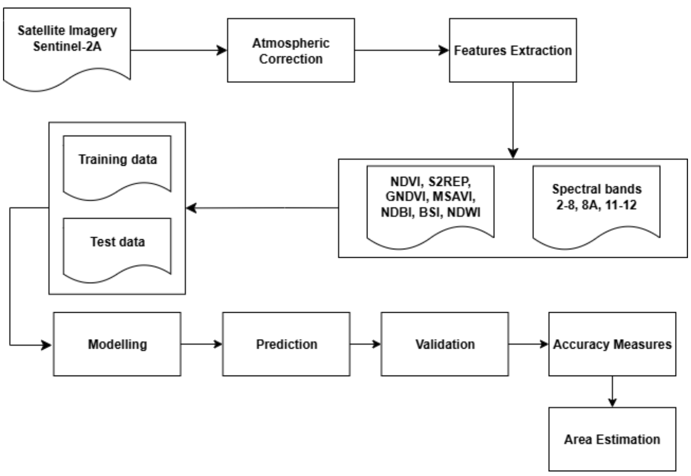


Figure 1. Flowchart of Land Cover Classification Research Using Sentinel-2A

2.1. *Study area*

The study area in this research is the Core Urban Area of IKN which is one of the Government Areas in IKN consisting of six Government Areas as shown in **Figure 2** namely Central, West, South, East, East 2, and North. The delineation of this area is located at 116°44'45.240" East and 0°53'8.520" N-S with an area of 56.180.796 Ha.

Figure 2. IKN Land Cover Classification Research Study.

2.2. *Data source*

The data used in this study is satellite image data derived from Sentinel-2A. The Sentinel-2 Multispectral Instrument (MSI) consists of two satellites, namely Sentinel-2A and Sentinel-2B, which observe the earth's surface at a spatial resolution of 10 m, 20 m, and 60 m [15]. The data used in this study is satellite image data derived from Sentinel-2A. The Sentinel-2 Multispectral Instrument (MSI) consists of two satellites, namely Sentinel-2A and Sentinel-2B, which observe the earth's surface at a spatial resolution of 10 m, 20 m, and 60 m [16]. Another unique aspect of Sentinel-2 data is the presence of three edge bands, which are capable of capturing strong vegetation reflectance in the near infrared part of the electromagnetic spectrum [11]. In the process of building a land cover classification model, the bands used from Sentinel-2A imagery are bands 2 to 8a, followed by bands 11 and 12. This study uses two image data from two different median values of time periods to capture land cover and use before and after the development of IKN. **Table 1** are details of the satellite imagery used in modeling the land cover classification for the IKN area.

Table 1. Satellite Imagery Used

Period	Time	Satellite Imagery	Band
Before IKN Construction	January 1st–June 30th, 2022	Sentinel-2A	2–8a, 11–12
After IKN Construction	January 1st–June 30th, 2024		

The same period, from January 1st to June 30th, was selected for both the pre- and post-IKN construction analysis to ensure consistency in seasonal and climatic conditions that substantially affect satellite-derived vegetation indices and land cover characteristics. By synchronizing the time windows for both years, the study minimizes confounding factors caused by differences in rainfall, temperature, and phenological changes, which could lead to bias in the detection of land cover change. This methodological choice enhances the reliability and scientific validity of the comparative analysis, ensuring that any observed changes in land cover are primarily due to IKN development activities rather than natural seasonal variations, thereby supporting robust interpretation of the results.

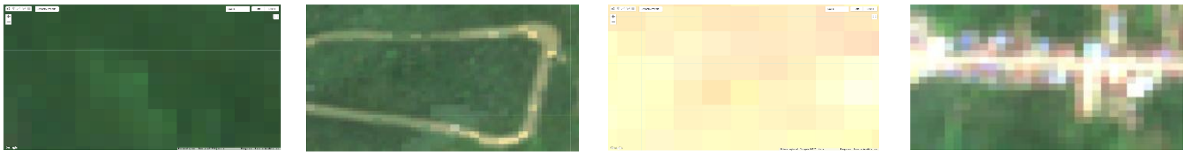
This study also utilized various indices that were calculated based on the values of each band on the sentinel 2A satellite image. The indices represent the intensity of each land cover class such as vegetation, water bodies, open land, and built-up land. Table 2 shows the satellite image indices used.

Table 2. Satellite Image Indices Used

Label	Satellite Image Index	Description	Sources
NDVI	*Normalized Difference Vegetation Index*	NDVI is used to measure the presence and health of vegetation.	[11], [17], [18], [19]
S2REP	*Sentinel-2 Red-Edge Position Index*	S2REP is used to detect vegetation stress and biomass.	[20]
MSAVI	*Modified Soil Adjusted Vegetation Index*	MSAVI is used to detect vegetation in areas with sparse.	[17], [20]
BI	*Bare Soil Index*	BI is used to identify areas of bare soil.	[20]
NDBI	*Normalized Difference Built-up Index*	NDBI used to identify development areas.	[11], [21]
NDWI	*Normalized Difference Water Index*	NDWI used to identify water bodies.	[17], [18], [21]

2.3. *Data Preparation*

Data used in this research in order to train the classifier is a random point sample spread in the area and it is necessary to label the land cover class to be predicted. The labeling process was performed manually for each random sample points based on the imagery from Sentinel-2A. In large-area land cover classification using satellite imagery, point-based sampling for training machine learning models is widely adopted to balance efficiency and accuracy. Although the entire area like IKN has almost unlimited satellite data points, labeling every pixel is impractical and resource-intensive. Instead, selecting representative and stratified point samples that capture the diversity of land cover types enables robust model training and effective classification of the entire area. Studies have demonstrated that well-distributed point-based samples can deliver high-accuracy classification results. For example, Tsutsumida and Kato used a point-based visual interpretation scheme via Google Earth Engine where 44 investigators collected stratified reference samples across four land cover classes to train random forest classifiers, achieving over 92% overall accuracy [22]. This approach mitigates investigator bias and uncertainty while making labeling scalable and manageable. Thus, point-based sampling is a validated practical solution for large-scale land cover mapping with machine learning. **Figure 3** shows the land cover classes that were labelled in the image data, including vegetation, water body, open land, and built-up land.



(a) (b) (c) (d)

Figure 3. Land Cover and Land Use Classes: (a) Vegetation, (b) Water Bodies, (c) Open Land, and (d) Built-up Land

2.4. *Classification methods*

The machine learning method used in this research is the supervised learning method where this method relies on previously labeled data to be used as learning material to classify land cover. The supervised learning methods used in this research are Random Forest (RF), Support Vector Machines (SVM), and Classification and Regression Trees (CART). These methods are often used in modeling land cover and land use classification as in the research conducted by Amin et al. with a case study of land cover and land use classification of Pakistan's mountainous areas [23].

The RF method is an extension of the bagging technique, where many decision trees are built from random data samples (bootstrap) and random feature selection at each branching with the best model from a set of individual models will be selected by involving voting methods [24]. This classification model has strong robustness and performs quickly against noisy data. RF models can reduce overfitting, are able to determine feature importance, improve accuracy, have few hyperparameters, and high training speed [25]. Due to its ability to handle complex data, reduce overfitting, and explain the influence of features, RF is very suitable for use in land cover classification involving various types of data and multi-dimensional input variables such as spectral, texture, or other spatial data [26].

SVM is a supervised classification algorithm that searches for an optimal hyperplane to separate data into two classes [27]. This hyperplane is chosen to have the widest margin over the closest points of each class, called support vectors. For data that cannot be linearly separated, SVM uses a kernel trick to map the data to a higher dimensional space so that it can be linearly separated [27]. In some studies related to land cover and land use classification such as research by Dabija et al. which shows that the SVM model has the best accuracy on testing data in cases of classification in several regions such as Brailia, Catalonia, and Warsaw [28].

The CART method utilizes recursive binary division to divide data into more homogeneous groups based on certain predictor variables, resulting in a decision tree that functions iteratively for both classification and prediction. Although this method has a tendency to result in overfitting, pruning is often applied to improve generalization. The speed, ease of interpretation, and accuracy make CART a widely relied upon method in land cover classification, especially in satellite image analysis and land cover change mapping [29], [30]. Its wide application is proven in various remote sensing studies that emphasize the practicality and performance of CART in the spatial data ecosystem.

2.5. Evaluation Methods

In this study, the method used to evaluate the classification results of the model is to build a confusion matrix from the comparison of actual classes to predicted classes. According to Sari et al., the confusion matrix is used to review the accuracy of the classification results which can be obtained by the overall accuracy [31].

Confusion matrix describes the contingency table between the original class of the dataset and the predicted class based on the classification model. Based on the confusion matrix, several measures of model goodness can be derived such as accuracy, Kappa coefficient, and Macro F1.

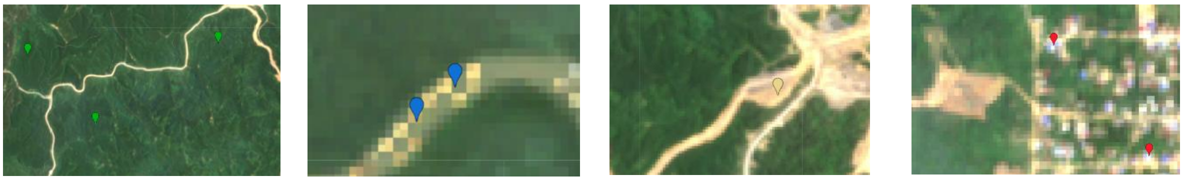
3. Results and Discussion

Figure 4 displays the map of the research area derived from Sentinel-2A satellite imagery, showing conditions before (January 1st–June 30th, 2022) and after (January 1st–June 30th, 2024) the development of IKN. These images are the result of several preprocessing stages designed to ensure data quality and reliability for land cover classification. The Sentinel-2A images were filtered to include only acquisitions within the specified time windows to maintain seasonality consistency. Specific spectral bands (B2, B3, B4, B5, B6, B7, B8, B8A, B11, B12) crucial for distinguishing land cover classes were selected. Cloud masking was conducted based on the Sentinel-2 Scene Classification Layer (SCL) to exclude pixels affected by clouds, cirrus, and snow/ice, thereby removing potential noise. Reflectance values of the bands were normalized to a 0–1 range for standardization. Data with more than 50% cloud coverage were discarded. A median composite was created for each period to minimize residual noise and temporal anomalies, and the imagery was clipped to the IKN study area boundary. This thorough preprocessing workflow provided high-quality input data for subsequent machine learning classification and subsequent analysis, making the maps in Figure 4 a valid visual basis for land cover class labeling and comparative evaluation of land cover changes during IKN development.

(a) (b)

Figure 4. Map of the research area from sentinel-2A satellite imagery (a) before the development of IKN (January 1st–June 30th, 2022) and (b) after the development of IKN (January 1st–June 30th, 2024).

The land cover classes in this study are divided into four main categories, namely vegetation, water bodies, open land, and built-up land with each identified based on the visual characteristics in the image shown in **Figure 3**, after class determination, the classification process continues with the selection of sample points that representatively depict each land cover class. As an illustration, **Figure 5** shows that sample points for the vegetation class are placed in areas that clearly show vegetation characteristics and so on for the other classes.



(a) (b) (c) (d)

Figure 5. Example of objects: (a) vegetation, (b) water body, (c) open land, and (d) built-up land.

Based on the results of the labeling process for classification purposes, the frequency and distribution of sample points for all land cover classes are equal for both the pre-development and post-development periods of IKN, with a total of 800 points for vegetation, 401 points for water bodies, 416 points for open land, and 424 points for built-up land. These points constitute the dataset used to build the classification model, with 80% of the data allocated for training and the remaining 20% reserved for testing.

3.1. *Land cover and land use classification results*

To review the classification results of each model used at different time points, **Table 3** shows the accuracy metric values used to select the best model from RF, CART, and SVM based on the predictions in the testing data.

Table 3. Accuracy metrics of classification models

Period	Method	*Overall Accuracy*	*Kappa Coefficient*	*Macro F1*
Before Development of IKN	**RF**	**94.49%**	**0.92**	**0.94**
	CART	89.72%	0.86	0.88
	SVM	86.72%	0.82	0.85
After Development of IKN	**RF**	**93.92%**	**0.92**	**0.93**
	CART	91.48%	0.88	0.85
	SVM	87.10%	0.82	0.90

Based on the measures of accuracy and classification model goodness in **Table 3**, it can be seen that the RF classification model is the best model at each time point used. The RF model has a very good performance in predicting land cover and land use classes when viewed based on its accuracy value. In addition, the high values of Kappa coefficient and Macro F1 indicate that the model has performed well in distinguishing between the predicted classes and providing excellent quality of agreement between labels. This is in line with research conducted by Pokhariya et al. which shows that the RF model has the best performance in performing land cover classification when compared to other models such as SVM, Decision Tree, and CART [32]. The following is the confusion matrix of the RF model.

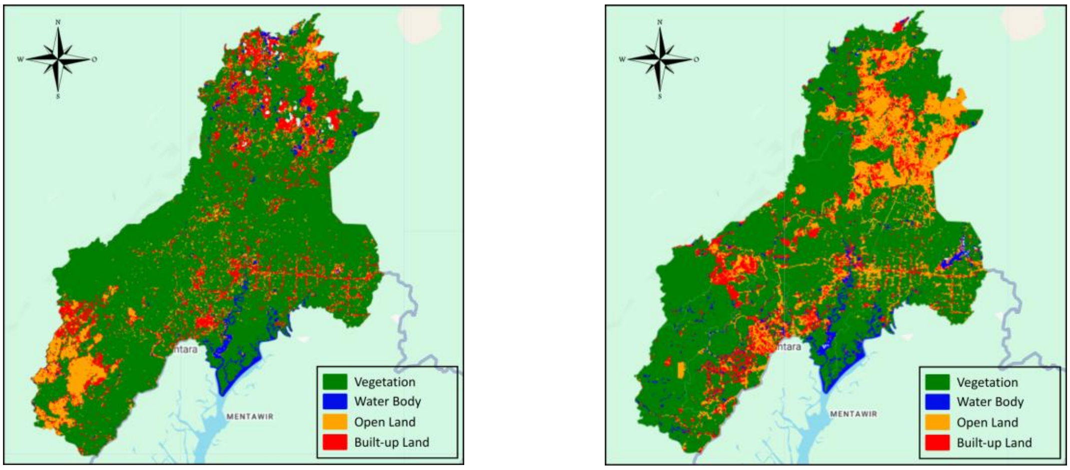
Table 4. Confusion matrix of prediction results of land cover and land use classes of IKN

Time Period	**Sample**		**Prediction**				**Total**
			Vegetation	**Water Body**	**Open Land**	**Built-up Land**	
Before Development	Class	Vegetation	**145**	0	0	1	146
		Water Body	0	**84**	0	1	85
		Open Land	0	0	**66**	15	81
		Built-up Land	2	0	3	**82**	87
	Total		147	84	69	99	**399**
After Development	Class	Vegetation	**163**	0	0	0	163
		Water Body	4	**74**	0	1	79
		Open Land	3	0	**75**	7	85
		Built-up Land	0	0	10	**74**	84
	Total		170	74	85	82	**411**

Based on the confusion matrix in **Table 4**, the classification model used demonstrates a high level of reliability and accuracy for mapping land cover in the IKN area during both time periods, excelling particularly at identifying Vegetation and Water Body classes. It should be noted that the number of points in Table 4 only represents the predicted samples used for evaluating the model's performance, not the actual spatial extent or area of each land cover class. Although the accuracy values for open land and built-up land classes remain satisfactory, there is scope for model improvement to enhance the accuracy of these classes and the overall classification. Therefore, the confusion matrix points are a subset for validation purposes, and the actual land cover areas are derived from full spatial prediction results across the entire study region. This distinction is important to clarify to avoid misinterpretation of the sample counts as indicative of land cover extent.

3.2. *Mapping of land cover and land use area of IKN region*

The land cover and land use areas of the IKN region were mapped using the RF method because it has the best performance in predicting land cover and land use classes. The mapping was conducted in two time categories, namely before the construction of IKN (January 1st–June 30th, 2022) and after the construction of IKN (January 1st–June 30th, 2024), as a tool to compare the changes in land cover and land use areas.



(a) (b)

Figure 6. Land cover classification map using Random Forest (a) before the development of IKN (January 1, 2022 – June 30th, 2024) and (b) after the development of IKN (January 1, 2024 – June 30th, 2024).

Figure 6 shows the classification of land cover and land use areas divided into four categories with their respective category colors. Based on the figure, there is an area category that appears to have changed significantly, namely the open land category. The area of this category has widened within two years. In addition, it can also be seen that the vegetation and built-up land categories tend to decrease. The complete area characteristics are listed in **Table 5**.

Table 5. Land cover and land use of IKN area

Period	Land Cover and Use Class	Area (km^2)
Before Development of IKN	Vegetation	426.68
	Water Body	10.27
	Open Land	52.58
	Built-up Land	68.10
After Development of IKN	Vegetation	400.03
	Water Body	17.29
	Open Land	86.24
	Built-up Land	56.95

Before the development of IKN, the area of vegetation was 426.68 km^2, including the agricultural land, forests, and other green areas. This category represents important ecosystems that function in air quality control, biodiversity conservation, and fulfillment of community needs. However, the development of IKN caused a decrease in vegetation area in 2024 to 400.03 km^2, illustrating land use changes, deforestation, or transformation to other uses, such as agriculture, urban development, or commercial activities [8]. This is supported by **Figure 6**, which shows the transformation of some vegetation areas into open land and built-up land areas. This phenomenon aligns with the significant increase in open land, from 52.58 km^2 to 86.24 km^2, reflecting a deforestation for land clearing and indicating the early stages of the urban development process. Meanwhile, built-up land, that consists of residential and other buildings, decreased from 68.10 km^2 to 56.95 km^2. This decline could be due to the revitalization process or the demolition of old built-up areas. Spatially, built-up land tends to shift to other areas and be replaced by vegetation, as shown in **Figure 6**, which shows the change of open land and built-up land into vegetation areas. This indicates a revegetation process, in line with the vision of developing IKN as a 'forest city' [33], which is expected to have a positive impact on the environment by reducing the earth's surface temperature [34]. In addition, the area of water bodies increased from 10.27 km^2 to 17.29 km^2 in 2024, indicating an integrated and sustainable water supply effort in reduce drought in IKN as stated in the Net Zero Strategy. However, it should be noted that the total land cover area before and after development is not exactly the same due to limitations during data processing, particularly cloud masking. Some areas were masked out due to cloud cover, resulting in loss of data pixels in certain locations, which causes minor discrepancies in total area estimations. Therefore, while these figures provide valuable insight into land cover changes, direct ground observations would be necessary to fully confirm and refine these spatial changes using satellite imagery.

4. Conclusion

This study concluded that the Random Forest (RF) method proved to be the most accurate for land cover classification, achieving an overall accuracy of 94.81% for the pre-development period and 93.92% for the post-development period. The findings indicate that the development of IKN resulted in a decrease in vegetation area from 422.59 km^2 to 400.03 km^2 and an increase in open land from 52.71 km^2 to 86.24 km^2 over two years, signaling initial deforestation due to land clearing. This supports the importance of a forest city strategy and highlights the need for continuous spatial monitoring using remote sensing and machine learning to meet SDGs 11 and 15 targets and ensure the sustainability of Kalimantan's tropical forest ecosystems during IKN development. However, this study has limitations, notably the inability to conduct extensive ground checking or field validation of the classification results due to logistical and temporal constraints. As a result, while the classification accuracy is high based on statistical metrics, on-the-ground verification was restricted, which may affect the certainty of some mapped land cover classes. Future research should include systematic field surveys to validate and refine the remote sensing classification outputs, enhancing the robustness and reliability of the land cover maps.

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