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Built-Up Development Prediction Based on Cellular Automata Modelling Around New Yogyakarta International Airport

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ABSTRACT

New Yogyakarta International Airport (NYIA) in Kulon Progo Regency was developed with the primary objective of fostering economic growth. The initiation of operations at NYIA in March 2020 triggered substantial urban development in the surrounding area. This research aimed to monitor the changes in land cover and predict the development of urban areas. The research methodology comprised the use of Random Forest, Classification, and Regression Tree machine learning algorithms to create land cover maps. It also incorporated Cellular Automata (CA), which was used to make prediction related to land development. The results showed that the land cover map had an overall accuracy level of above 0.80. Furthermore, it was observed from the results of the time series land cover analysis that there was a rapid growth in built-up lands. Between 2013 and 2017, these lands expanded by 572.38 hectares and further increased by 268.97 hectares from 2017 to 2023, leading to the conversion of 571.64 hectares of agricultural lands. On the basis of these findings, it was projected that by 2033, there would be an expansion of 386.08 hectares in built-up lands, with approximately 356.82 hectares converted from agricultural areas. The accuracy assessment of the 2023 land cover prediction map showed a high level of correctness, with a 97% accuracy rate. On the basis of these results, it was concluded that land conversion is essential to prevent environmental degradation, and further research can be carried out with the aim of assessing environmental quality indices.

Keywords: built-up, cellular automata, New Yogyakarta International Airport

INTRODUCTION

The enhancement of the local economy within a region is often associated with development and implementation of various public infrastructures [Gibson et al., 2019; Thacker et al., 2019]. As rightly observed in a previous investigation, development of public infrastructure significantly influenced several aspects of the lives of residents in a community. This type of development was observed to result in an escalation of consumption value, subsequently leading to a significant rise in both employment opportunities and labor productivity. Accordingly, an increase in these aspects have been observed to have a substantial and positive impact on the economy as well as welfare of communities [Suminar et al., 2016]. Infrastructure includes the facilities developed by public agencies for various purposes. These facilities include transportation, water supply, electric power, waste disposal and other services established to foster various social and economic objectives [Thacker et al., 2019; Devitama et al., 2020; Syalianda and Kusumastuti, 2021]. Development initiatives can have both favorable and adverse effects on the lives of individuals, particularly when it occurs in suburban or rural areas that are not traditionally economic centers. For instance, the construction of New Yogyakarta International Airport (NYIA) in Kulon Progo Regency, situated on the outskirts of the Temon subdistrict, had both positive and adverse effects on the community in which it was built [Rachmawati et al., 2019; Rahmayanti et al., 2019]. This airport was developed with the sole purpose of spurring economic growth and enhancing the local economic well-being of the community where it is located. Furthermore, its development aimed to maximize international tourist arrivals, which have previously been underused, with the goal of boosting the regional income from the tourism sector [Kadarisman, 2019; Utami et al., 2021].

The construction of NYIA began with land acquisition and was completed in March 2018. This process triggered several controversies, with certain impacted residents, who were affiliated with Wahana Tri Tunggal (WTT), expressing their opposition to the development in Glagah Village and Palihan Village. The main concern of these individuals was that the construction of the airport would eventually displace lands, and these lands had been their source of livelihood. However, some residents supported the construction of NYIA and this was primarily because of the substantial compensation made available. The construction of this airport substantially affected the residents in five villages, including Glagah, Kebonharjo, Palihan, Sindutan, and Jangkaran. This impact was substantial, affecting 19 hamlets and approximately 2,700 families, as well as leading to the conversion of 4,400 plots of land. It is important to acknowledge that after NYIA began operating in March 2020, a significant increase in urban development was observed in its vicinity, including the construction of hotels, shops, and other public infrastructure. Currently, three hotel buildings stand in front of NYIA exit. As rightly stated in previous research, this rapid urbanization has the potential to engender environmental issues. This is evidenced by the fact that uncontrolled changes in land cover can impact environmental quality by influencing such factors as microclimate, land subsidence, and flood disasters, among other environmental concerns [Yang and Zeng, 2018; Majidi et al., 2019; Zamroni et al., 2021]. Therefore, it is essential to monitor the changes in land cover resulting from the impact of NYIA development as a means of regulating and ensuring environmental quality. In this research, the data reflecting these land cover alterations were subsequently used to forecast the future land cover development in the area, using remote sensing technology and raster-based modeling. This predictive data played an important role in the formulation or adjustment of Regional Spatial Plans.

Land cover change analysis and built-up lands development predictions were conducted using the remote sensing technology. In this regard, Landsat 8 time series image data was leveraged to detect the changes in land cover, especially in built-up areas [Karra et al., 2021]. The prediction regarding the expansion of the built-up lands were made through the application of Cellular Automata (CA) modeling [Yeh et al., 2021; Agustina et al., 2022]. This form of modeling refers to the use of a dynamic model that simulates the local interactions between cells within a grid. In this context, each cell represented a specific land use, and the changes were highly influenced by rules that take into account the land use of neighboring cells [George et al., 2021; Grattarola et al., 2021]. As rightly established by previous examinations, the CA model relies on its main components, which include state cells, rules or change functions (transition rules or transition functions), and the consideration of neighboring cells [Bobkov et al., 2021]. The aim of this research was to analyze the shifts in the usage of land cover in the vicinity of NYIA, with a particular emphasis on seven sub-districts that were expected to be impacted by the presence of the airport. Additionally, the research was carried out to forecast the future trends in the development of urban land in the area. This exploration is particularly urgent as its primary goal is centered on the continuous monitoring of the growth of built-up lands in the research area. This monitoring allows for effective control over development processes and ensures that these processes are not solely economically driven but also consider the environmental conditions of the region.

METHODOLOGY

This research was conducted in the immediate vicinity of Temon Sub-district, which is presently home to NYIA. This area comprises Temon, Kokap, Panjatan, Pengasih, and Wates sub-districts within Kulon Progo Regency, as well as Bagelen and Purwodadi sub-districts in Purworejo Regency. A visual representation of the research sites is shown in Figure 1.

Land cover map processing

Data collection and analysis for generating land cover time series in the research area were conducted using the Google Earth Engine (GEE) platform via the code.earthengine.google.com webpage. For this analysis, the satellite image data used for land preparation were obtained from Landsat 8, captured in 2013, 2017, and 2023, and sourced from the United States Geological Survey (USGS) with Reflectance Tier 1 data level. Furthermore, the selection of image recording times was determined based on recording intervals. In accordance with previous investigations, GEE incorporated cloud removal and median algorithms and ensured that the satellite images used were cloud-free and accurate representatives of the conditions during the chosen periods [Fariz and Nurhidayati, 2020]. The Landsat 8 USGS Surface Reflectance Tier 1 images used were readily usable. This was primarily because the images were orthorectified and their reflectance was calibrated. Specifically, the input leveraged in this research consisted of bands 1, 2, 3, 4, 5, 6, and 7. These bands were used primarily because of their observed superior accuracy when compared to using other bands (excluding panchromatic and cirrus) in Landsat 8 imagery [Yu et al., 2019: Fariz and Nurhidayati, 2020].

The process of mapping land cover time series relied solely on machine learning-based supervised classification. As established in a previous study, one of the key strengths of machine learning is its ability to manage high-dimensional data, such as remote sensing data, and its potential to effectively categorize data-points into multiple classes with intricate characteristics [Maxwell et al., 2018]. The machine learning algorithms from GEE leveraged in this exploration include RF (Random Forest) and CART (Classification and Regression Tree). It is important to acknowledge that these algorithms had quite good accuracy for land cover mapping compared to others, such as SVM [Wahap and Shafri, 2020; Kulithalai Shiyam Sundar and Deka, 2022; Abubakar et al., 2023].

Research sample

In this research, the land cover map was simplified into four primary classes, namely built-up land, mixed forests and gardens, open land, and agricultural land (as detailed in Table 1). This classification was necessitated by the constraints of selecting homogeneous Regions of Interest (ROIs) from Landsat images with a spatial resolution of 30 meters. Accordingly, it is crucial to establish that the process of multispectral classification through machine learning requires an adequate number of training samples (ROIs). In this case, 50 sample points (pixels) were collected for each land cover class, taking into account that the

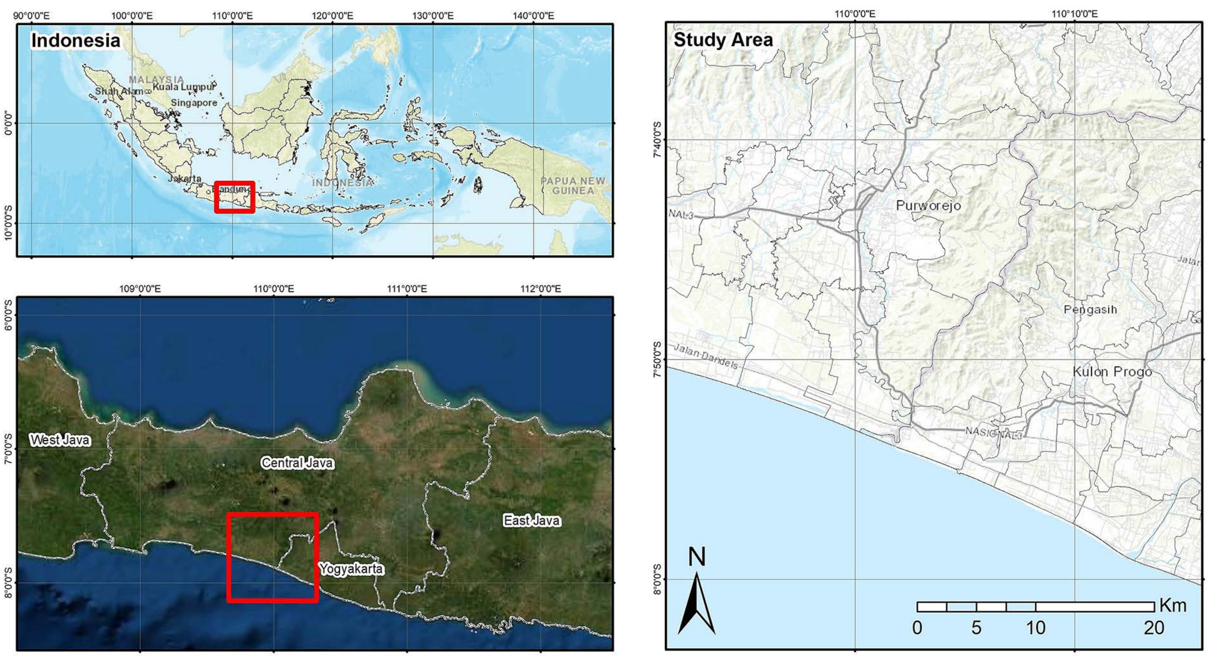

Fig. 1. Research sites

total number of land cover classes being mapped was fewer than 12 [Lillesand et al., 2004]. In addition to the training samples, test samples were also gathered to evaluate the accuracy of the classification results using the kappa index. This research incorporated a total of 170 test sample points (pixels) consisting of high-resolution satellite imagery. These images served as the reference or test reference in this research, acting as a base map within GEE. Some of these data points were obtained from field surveys, and in the cases where differences in appearances arose due to variations in recording times, the Landsat 8 imagery was used as the reference.

Driving factors

Driving factors are crucial variables in constructing a transition probability model. In this exploration, the driving factors considered were pre-existing variables that contributed to the expansion of built-up lands. It is important to acknowledge that each region may possess unique geographical conditions, resulting in variations in the driving factors for built-up land development. However, there are generally recognized driving factors that exert a significant influence on land change in Indonesia, including proximity to roads, distance from existing built-up areas, topography, and distance from essential facilities. These factors have been found to play a substantial role in shaping land development patterns [Nurhidayati et al., 2017; Susilo, 2017; Saputra and Lee, 2019; Yogi et al., 2022]. As previously mentioned, this research was conducted in specific areas within the Kulon Progo Regency and Purworejo Regency. In these regions, a very significant phenomenon of rising land prices, particularly in the vicinity of Jalan Lingkar Selatan (JLS) and NYIA has been observed in previous investigations [Edy et al., 2021]. Accordingly, in the research related to the prediction of changes in land cover, the driving factors considered include proximity to roads, existing built-up areas, markets, airports, and population density [Hendrayana et al., 2023]. This present exploration, on the other hand, did not include topographic factors, even though topography can indeed have a significant influence on the development in the region [Pravitasari et al., 2021].

In this research, the driving factors considered comprised distance from roads, proximity to facilities and airports, and distance from existing built-up land. The topographic factors were analyzed through cost distance analysis, setting this research apart from the method taken in the study by Sukri et al. [2023] and Hendrayana et al. [2023] which was solely centered on the use of Euclidean distance. Cost Distance is a valuable feature that has been leveraged in the computing of distance to the nearest source for each cell while taking into account specified costs from a cost surface. This method has been found to be superior to Euclidean distance, because it accurately reflects complex land cover considerations, particularly topographic factors [Xia et al., 2019; Pazúr et al., 2020].

Land cover prediction

Prediction of land cover was obtained for both 2023 and 2033. Specifically, for the 2023 prediction, the results were compared with the classification outcomes of the existing land cover map. For this prediction process conducted through Cellular Automata (CA), QGIS software was utilized, which incorporated the MOLUSCE plug-in. The prediction process comprised several stages, beginning with the input data, which included land cover maps and multiple driving factors. These variables have been observed to be instrumental in constructing transition probability models. In MOLUSCE, transition probability models can be created using various methods, such as Artificial Neural Network (ANN), Logistic Regression

Table 1. Land cover class used in research sites

Land cover	Operational limitations
Built-up	The land cover consists of buildings with clay roofs, including residential areas, trade and service buildings, government infrastructure, and other built-up land
Forests and mixed gardens	Woody vegetation land cover such as dry land forests, community forests, and mixed gardens
Open field	Land cover consists of open soil such as sand and embankment
Agricultural land	Non-woody vegetation land cover such as moorland, and rice fields

(LR), and Weight of Evidence (WoE). Typically, the WoE method is determined through expert justification, while the ANN and LR rely solely on computational methods. For this exploration, the ANN method was adopted because several studies show its effectiveness in predicting land cover changes [Xu et al., 2019; Wayan Gede Krisna Arimjaya and Dimyati, 2022]. A flow diagram of the research is shown in Figure 2.

RESULT AND DISCUSSION

Land cover map accuracy test

The land cover map, which was generated through classification in the research area, was assessed for accuracy before being used for subsequent analyses. This accuracy test was conducted using two methods, namely Overall Accuracy (OA) and Kappa Accuracy (KA). Accordingly, the results of the accuracy tests performed on the land cover time series showed that the land cover map with the highest accuracy was achieved using the Random Forest machine learning algorithm, both for mapping in 2017 and 2023 (as presented in Table 2). Following the observations of previous investigations, random Forest stands out as the most effective machine learning method due to its consistency, non-linearity, and capacity to produce the classification results that are resilient to noise [Pelletier et al., 2015]. The results of time series land cover mapping accuracy tests using machine learning are presented in Table 2.

In general, all machine learning methods tested had an accuracy exceeding 0.80. However, upon closer examination, some misclassifications were observed, particularly between open and built-up lands. This phenomenon occurred primarily because a significant portion of built-up land in the research area consisted of village settlements, comprising houses with yards or mixed gardens (as shown in Figure 3).

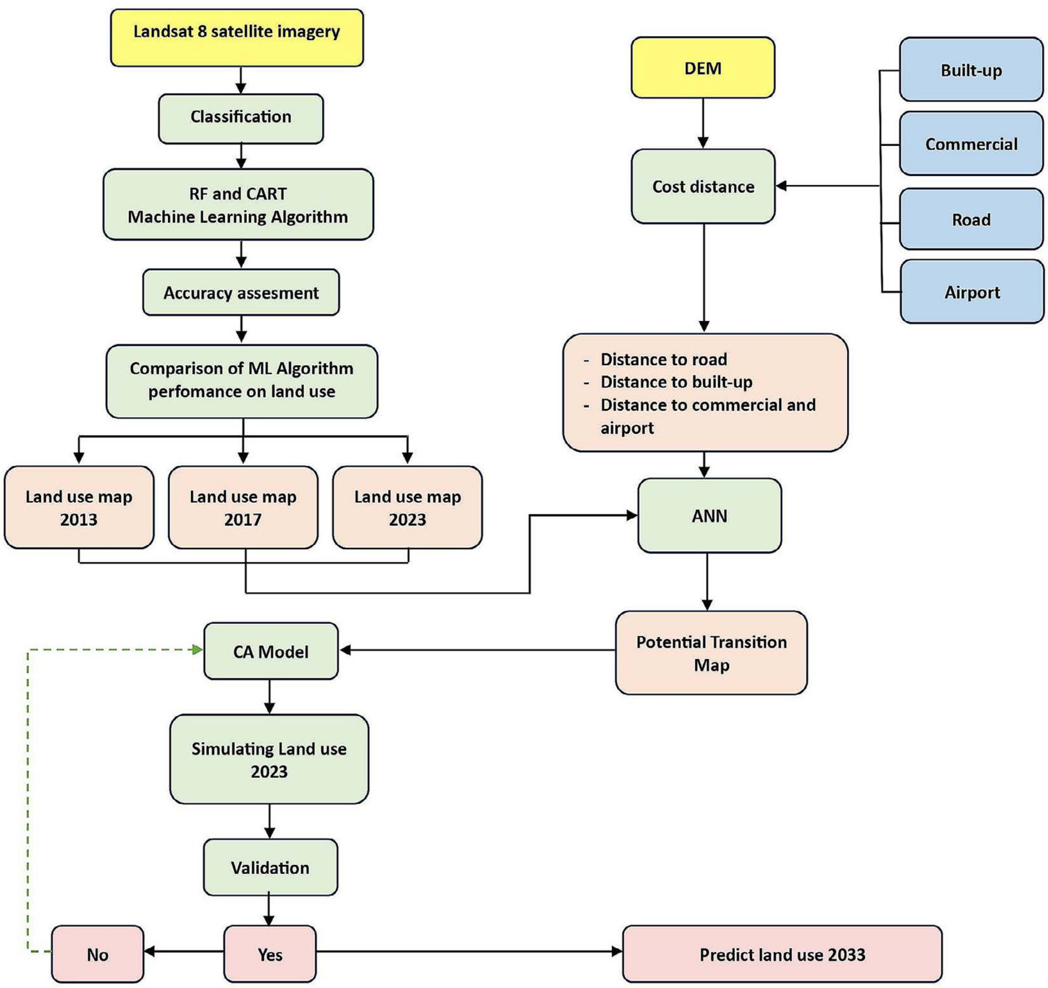

Fig. 2. Research flow chart

Table 2. Land cover mapping accuracy test results using machine learning

Machine learning	2013		2017		2023	
	OA	Kappa	OA	Kappa	OA	Kappa
CART	0.86	0.80	0.84	0.77	0.82	0.74
RF	0.81	0.72	0.86	0.80	0.91	0.86

Note: processing results, 2023.

The presence of these heterogeneous features led to a blend of spectral responses, making it challenging to distinguish between built-up lands, vegetation, and vacant lands. Consequently, these mixed pixels contributed to the misclassifications observed [He et al., 2010], and presented a significant limitation and challenge in the mapping research of built lands in Indonesia [Nur Hidayati et al., 2019]. Fig. 3 presents a comparison of the appearance of village settlements on the Landsat 8 and Maxar images. The choice of training samples is a critical factor in ensuring the accuracy of mapping results. In this context, these samples should accurately represent each land cover class and be devoid of mixed pixels. If classification results are still unsatisfactory, particularly in the cases such as the confusion between vegetations and built-up lands, the solution is to resort to visual interpretation. However, it is important to consider the fact that visual interpretation is less efficient in terms of processing time but can often lead to more precise and reliable results when dealing with complex or ambiguous land cover scenarios [Nur Hidayati et al., 2018].

Land cover change

The land cover classification in the research area consisted of four primary classes namely built-up lands, mixed forests and gardens, open lands, and agricultural lands. According to the classification results, the land coverage in 2023 at the research location was predominantly composed of mixed forests and gardens, spanning an area of approximately 19,336.55 hectares (54.01%). Furthermore, a significant portion of this land coverage was distributed in Kokap District and Bagelen District with an area of 5,800.71 and 4,660.63 hectares respectively. Built-up lands, on the other hand, showed highly dynamic development, and by the end of 2023, they were projected to occupy an approximate area of 1,417.49 hectares (3.96%). The largest spatial distribution of built-up lands was observed in Temon and Purwodadi Districts, with an area of 426.80 and 372.69 hectares, respectively. Accordingly, the expansion of built-up lands in Temon district can be attributed to the presence of NYIA, among other factors. Information on changes in land cover at the research location is presented in Table 2 and Figure 4.

The analysis of changes in land cover at the research location, based on Landsat 8 image classifications from 2013, 2017, and 2023, aimed to identify the impact of the establishment of NYIA in the Temon sub-district area. The results of this analysis showed that built-up lands have experienced the most rapid development in the research location. Between 2013 and 2017, an increase of approximately 572.38 hectares was observed, with the largest expansion occurring in the Purwodadi district, which amounted to approximately 235.47 hectares. This was followed by Temon district, which accounted for an increase of approximately 179.19 hectares. This trend was found to progressively continue in the period

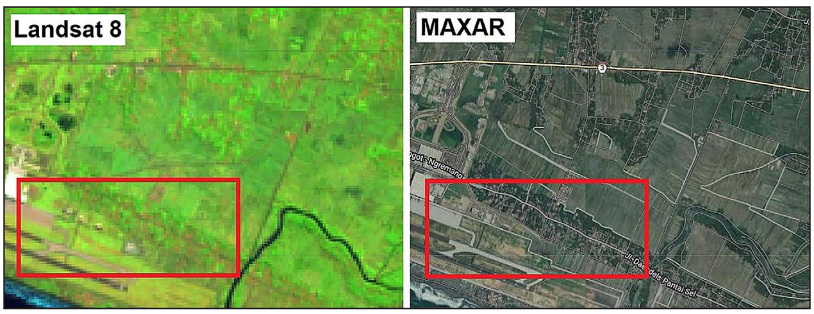

Fig. 3. Appearance comparison of village settlements

Table 3. Land cover time series of research locations

No	Land cover	2013		2017		2023	
		Area (ha)	%	Area (ha)	%	Area (ha)	%
1	Built-up	576.14	1.61	1148.52	3.21	1417.49	3.96
2	Forests and mixed gardens	19571.71	54.67	19433.89	54.29	19336.55	54.01
3	Open field	965.98	2.70	949.49	2.65	931.43	2.60
4	Agricultural land	14685.65	41.02	14267.58	39.85	14114.01	39.43
	Total	35799.48	100	35799.48	100	35799.48	100

Note: Landsat 8 image processing.

from 2017 to 2023, with built-up lands expanding by 268.97 hectares, and the majority of this increase was observed in Wates sub-district, totaling an increase of approximately 150.98 hectares. As a result, it can be seen that the total growth in built-up land area at the research location from 2013 to 2023 was approximately 841.35 hectares. The expansion of these lands in Purwodadi Sub-district between 2013 and 2017 was primarily influenced by the development of the Jalan Lingkar Selatan (JLS), which led to the urbanization of agricultural lands to built-up areas along the JLS. Meanwhile, Temon sub-district was found to experience the most substantial increase in built-up lands, and this was largely attributed to development of NYIA. This is evident from the concentration of the new built-up lands around the airport, which primarily comprised trade and service structures and infrastructure, such as hotels, shops, restaurants, and various other buildings. A comprehensive overview of development and appearance of built-up land cover around the research location is presented in Table 4.

The rapid development of built-up lands in an area inevitably leads to the conversion of other land cover types, and if left uncontrolled, can result in a decline in environmental quality [Sanjoto et al., 2020]. This phenomenon is evident in the research location, where the level of urbanization around NYIA has led to rapid land conversion. Accordingly, the most affected land cover in this area corresponded to agricultural lands, which witnessed a reduction of approximately 418.07 hectares from 2013 to 2017 and a subsequent decrease of around 153.37 hectares from 2017 to 2023. More lands have also been urbanized from mixed forests and gardens, causing a decrease in area of approximately 235.16 hectares from 2013 to 2023. It is important to acknowledge that the decline in agricultural land areas was most pronounced in three sub-districts, namely Purwodadi (242.21 hectares), Temon (163.37 hectares), and Wates (63.26 hectares). These changes in the use of agricultural lands have been observed to adversely impact the agricultural productivity in the region, particularly in the three sub-districts that possess productive agricultural lands with irrigated rice fields capable of yielding two harvests per year. Table 4 presents the information on the changes observed with regard to land use at the research location.

Land cover prediction

Prediction of land cover changes at the research location was carried out using the CA method. This method includes the use of a transition probability model constructed by leveraging artificial neural network (ANN). ANN creates a transition probability model by leveraging the function and non-linear weighting of each driving factor within a network, thereby enabling the accurate forecasting of land cover changes [Gharaibeh et al., 2020]. Furthermore, the network in ANN imitates human brain tissue by the use of interconnected artificial neurons. This method operates through a process of learning and recall, repeatedly analyzing a phenomenon until it achieves a pattern with high accuracy and low root mean square error (RMSE) [Li et al., 2013]. In this regard, the results of land cover prediction for 2023, which were generated using ANN, were subjected to accuracy testing against the land cover maps produced through machine learning-based supervised classification. The accuracy test showed that prediction results had an accuracy rate of 97%. Through the contingency table calculation, it was also observed that the predicted results included a total of 181.25 hectares of both misses and false alarms. In terms of land cover prediction for 2033, prediction was made that the coverage of built-up lands will increase by 386.08

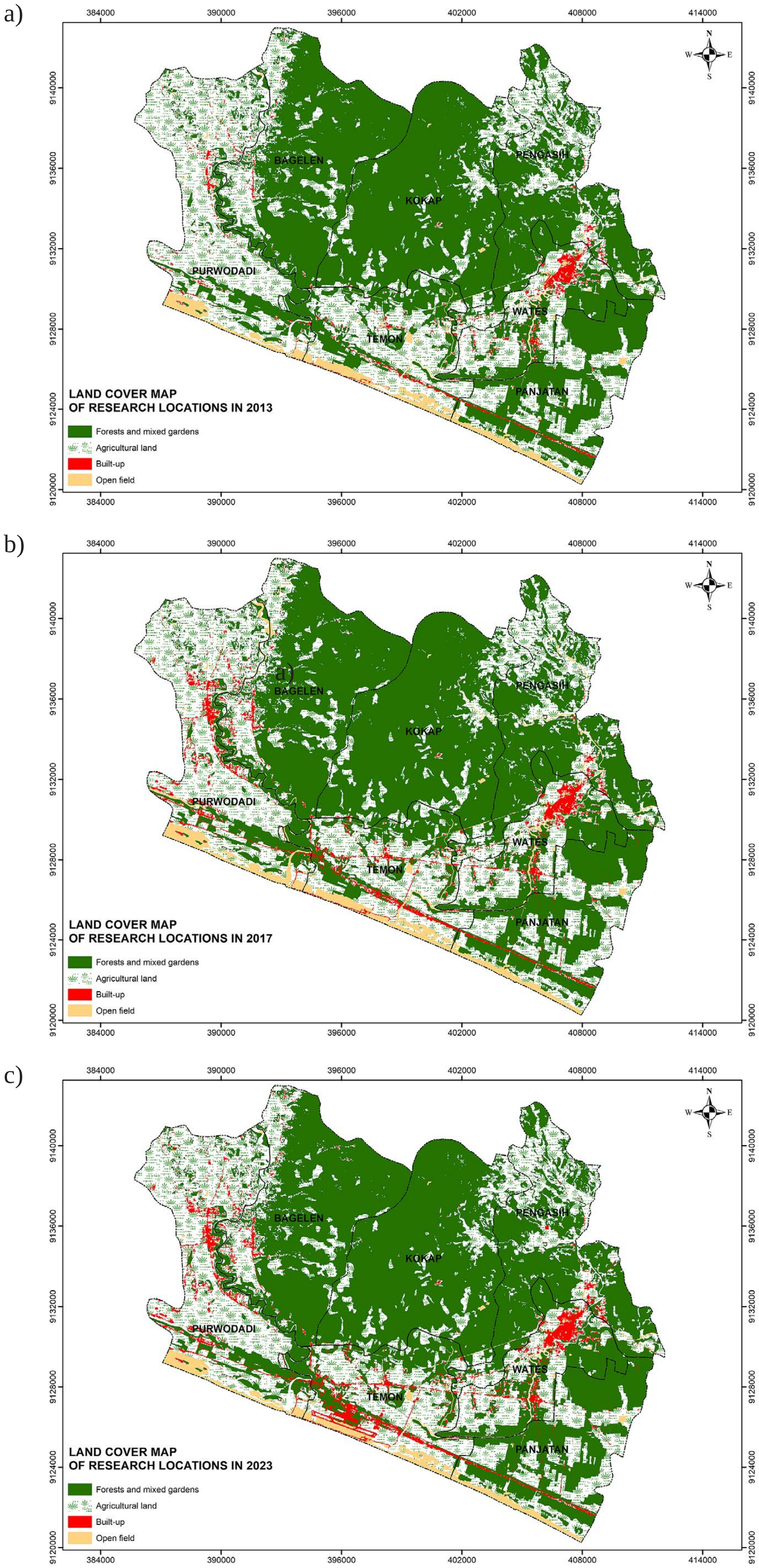

Fig. 4. Land cover time series 2013 (a), 2017 (b) and 2023 (c)

Table 4. Land cover changes data for each district in the research sites

Kokap sub-district	Years/area (hectar)		
Land cover	2013	2017	2023
Built-up	4.81	8.95	10.26
Forests and mixed gardens	5803.34	5801.26	5800.71
Open field	15.43	24.87	15.04
Agricultural land	1107.77	1105.73	1104.92
Wates sub-district			
Land cover	2013	2017	2023
Built-up	230.15	284.19	338.05
Forests and mixed gardens	1192.07	1174.33	1154.65
Open field	67.78	95.23	58.78
Agricultural land	1380.45	1350.29	1317.19
Temon sub-district			
Land cover	2013	2017	2023
Built-up	96.63	275.82	426.8
Forests and mixed gardens	1233.35	1152.81	1092.08
Open field	353.81	403.24	328.03
Agricultural land	2356.33	2266.26	2192.96
Pengasih sub-district			
Land cover	2013	2017	2023
Built-up	47.04	63.50	86.09
Forests and mixed gardens	3258.19	3252.99	3243.85
Open field	20.72	76.13	19.59
Agricultural land	2008.63	1997.86	1984.45
Panjatan sub-district			
Land cover	2013	2017	2023
Built-up	57.72	83.84	86.71
Forests and mixed gardens	2417.97	2401.16	2398.5
Open field	217.12	228.81	216.56
Agricultural land	1731.07	1722.09	1721.77
Purwodadi sub-district			
Land cover	2013	2017	2023
Built-up	113.10	348.57	372.69
Forests and mixed gardens	1002.31	990.27	986.11
Open field	287.26	456.56	281.63
Agricultural land	4570.33	4347.92	4328.12
Bagelen sub-district			
Land cover	2013	2017	2023
Built-up	26.66	83.63	98.87
Forests and mixed gardens	4664.45	4661.05	4660.63
Open field	3.91	66.06	0.34
Agricultural land	1531.04	1477.40	1464.56

Note: source – Landsat 8 time series image processing.

Table 5. Land cover prediction data 2023 and 2033

No	Land cover	2023 (eksisting)		2023 (prediction)		2033 (prediction)	
		Area (ha)	%	Area (ha)	%	Area (ha)	%
1	Built-up	1417.49	3.96	2655.46	5.04	2655.46	7.42
2	Forests and mixed gardens	19336.55	54.01	19301.95	53.92	19904.31	53.34
3	Open field	931.43	2.60	915.95	2.62	915.95	2.56
4	Agricultural land	14114.01	39.43	13133.76	38.43	13133.76	36.69
	Total	35799.48	100	35799.48	100	35799.48	100

Note: source – processing results, 2023.

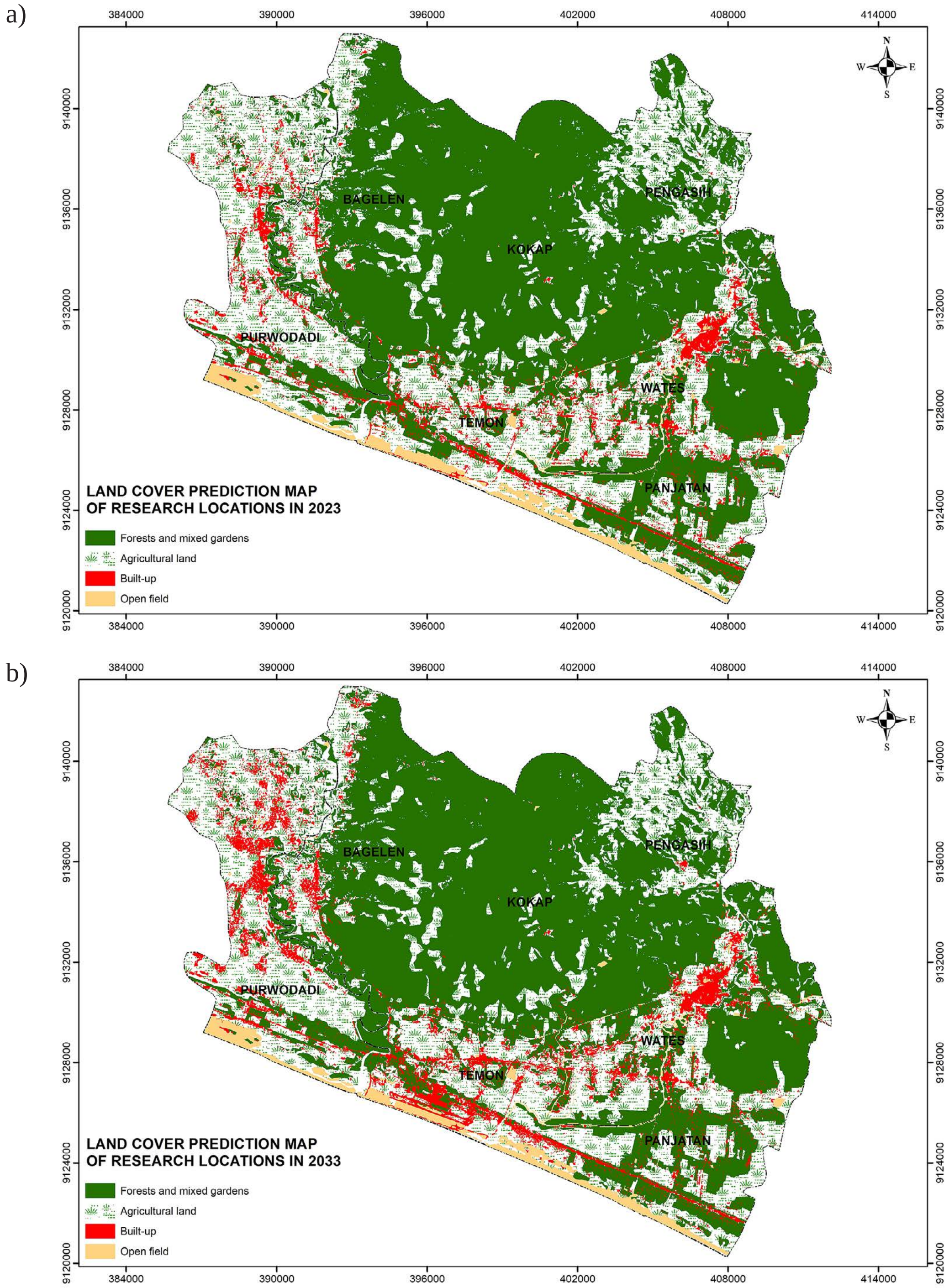

Fig. 5. Land cover prediction map 2023 (5a) and 2033 (5b)

hectares. The primary land cover converted during this period was agricultural lands, with an area of approximately 356.82 hectares. Table 5 and Figure 5 present the information on the land cover prediction at the research location.

CONCLUSIONS

On the basis of the obtained research results, several key conclusions were drawn. The rapid development of built-up lands was a prominent trend in the research location. Between 2013 and 2017, it expanded by 572.38 hectares, and from 2017 to 2023, it increased by approximately 268.97 hectares. Furthermore, it was found that the majority of this expansion occurred in the Temon and Purwodadi sub-districts. The most significant land cover conversion observed during this development was the urbanization of agricultural lands, totaling 571.64 hectares. The land cover prediction for 2033, generated using CA, showed an increase of approximately 386.08 hectares of built-up land. Prediction emphasized that the primary land cover that would be converted during this period includes agricultural lands, with an area of approximately 356.82 hectares. Moreover, the accuracy test results showed that prediction accuracy for the 2023 land cover map was 97%. Lastly, the research results can be further developed into an index for assessing the current environmental quality. This index can serve as a foundation for ongoing monitoring of the environmental conditions in the vicinity of NYIA.

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