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RESEARCH ARTICLE

Effect of Transportation Infrastructure on Built-up Area Using Prediction of Land Use/Cover Change: Case Study of Yogyakarta International Airport, Indonesia

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Abstract. The development of transportation infrastructure increases the pressure on natural resources, one of which is the increase in the built-up area. The changes do not only happen during the construction of transportation infrastructure but also after its completion. Therefore, this study aims to identify and simulate land use/cover changes in Kulon Progo Regency, Indonesia, to predict the effect of the construction of Yogyakarta International Airport (YIA). A quantitative descriptive method was used with the main data of multitemporal Landsat remote sensing images. Furthermore, the integration of Cellular Automata and Artificial Neural Networks (CA-ANN) was applied to simulate land use/cover change predictions (2035). The results of image classification using the supervised maximum likelihood classification showed an overall accuracy of 85.33% and 86.67% for 2011, and 2015 with 2019 using Landsat 7 and 8 images, respectively. Meanwhile, there was an increase in paddy fields of 1,210.1 ha (2.11%) and built-up area by 2,708.6 ha (4.72%) during 2011 – 2019. Conversely, shrubs and dryland agriculture decreased by 1,594.1 ha (2.78%) and 2,174.1 ha (3.79%). The simulation results indicate that the development of transportation infrastructure further triggers the increase in built-up area, especially around the YIA. Therefore, policymakers and development implementers should adopt and implement appropriate and effective planning for sustainable land use.

1. Introduction

Land cover is a land resource that occupies the earth's surface, while land use is a form of human use of land resources (Giri, 2012). The demand for land use is increasing and divers, land use/cover change (LUCC), causing land resources to become increasingly scarce which leads to land use conflicts (Jiang et al., 2020). LUCC is a spatial phenomenon with a complex and extensive system (Sfa & Nemiche, 2019). This phenomenon can be measured and represented due to the location of occurrence and space occupancy (Bello & Rilwani, 2016). Many factors influence LUCC including nature (Adebayo et al., 2019), socioeconomic conditions of the population, industry, trade, technology use, development policies (Harini et al., 2018), population growth, accessibility, facilities and infrastructure (Williyantoro, 2016), urbanization (Dangulla et al., 2020), and transportation infrastructure (Otuoze et al., 2020).

Furthermore, development is one of the main causes of land use and cover changes (Y. Liu, 2018). The use of land for transportation, commercial industry, and settlements are various forms of development (Wu et al., 2020). Besides being a major cause of land use and cover changes, rapid development also brings benefits as well as social challenges. It causes problems such as the expansion of built-up area, sharp depreciation of agricultural land resources, and environmental damage (J. Liu et al., 2020).

Kulon Progo (research area) is one of the regencies in Yogyakarta Province which has experienced massive development in the last ten years. This location has witnessed many projects, such as the construction of the Yogyakarta International Airport (YIA) and the Southern Cross Road (Jalur Jalan Lingkar Selatan or JJLS) which began in 2017 and 2018 respectively. The infrastructure development, especially the airport, aims to support tourism activities (Rijanta et al., 2019). Furthermore, the development certainly takes up quite a large area, especially for the construction of YIA, and this has led to significant land use changes in this regency. The changes do not only happen during the construction of transportation infrastructure but also after the completion. The existence of transportation infrastructure promotes the agglomeration of life and trade activities (T. Y. Liu & Su, 2021) and triggers the expansion of the built-up area.

This study aims to identify land use/cover (LUC) and perform prediction simulations for changes that will occur (2035) in Kulon Progo Regency to predict the effect of the construction of YIA. Most of the research conducted in the area was about the impacts of the construction of YIA that have already occurred, while future impacts are still limited. Besides mapping the existing land area, the studies on land use predict changes in the future are notable (Giri, 2012) for realizing efficient planning (S. Yang et al., 2020).

LUCC shows a clear spatial-temporal dependence, therefore it is crucial to understand the pattern and precisely model the process (Xing et al., 2020). Recently, advances in geographic information systems (GIS) have provided opportunities and convenience to detect land use changes on a wider spatial and temporal scale (Dangulla et al., 2020) such as remote sensing. This approach is very suitable for the identification of land cover changes (Giri, 2012). Furthermore, GIS technology can also be used to create simulation models for predicting land use/cover changes, the most popular of which is Cellular Automata (Elliot et al., 2020). This model is simple, flexible, and has a strong ability to study LUCC spatial-temporal processes (Qian et al., 2020).

The integration of two or more methods such as CA and ANN improves the reliability of LUCC simulations (Xing et al., 2020). The CA model has the advantage of being simple and flexible to integrate with others. Meanwhile, the ANN can capture non-linear relationships between factors and handle complex patterns of land use changes with high efficiency (Gharaibeh et al., 2020). It presents the best approach for modeling, simulating, and predicting time series systems (Ullah et al., 2019).

Many studies on CA and ANN integration to improve the reliability of predictive modeling of land use changes have been conducted. Qian et al. (2020) applying ANN-CA to simulate the LUC process, ANN was constructed to form a conversion probability map of the environmental factors driving LUC. Meanwhile, Rahmah et al., (2019) was used CA for predicting land use in Semarang City with an accuracy value of 95%, which means the prediction model is very good. The same result was reported by Gharaibeh et al. (2020) that the ANN-CA integration had a better accuracy of 90.04% than the Cellular Automata Markov Chain (CA-MC) with 86.29% accuracy.

In this study, CA and ANN were combined, while the airport construction was used as the main driving factor in predicting LUC changes. We applied two predictive simulations using different time points. It aims to predict the effect of airport construction on LUC change. This is useful for understanding the impact of infrastructure planning and development policies (Guzman et al., 2020) . According to Guo et al., (2020) policymakers should adopt and implement

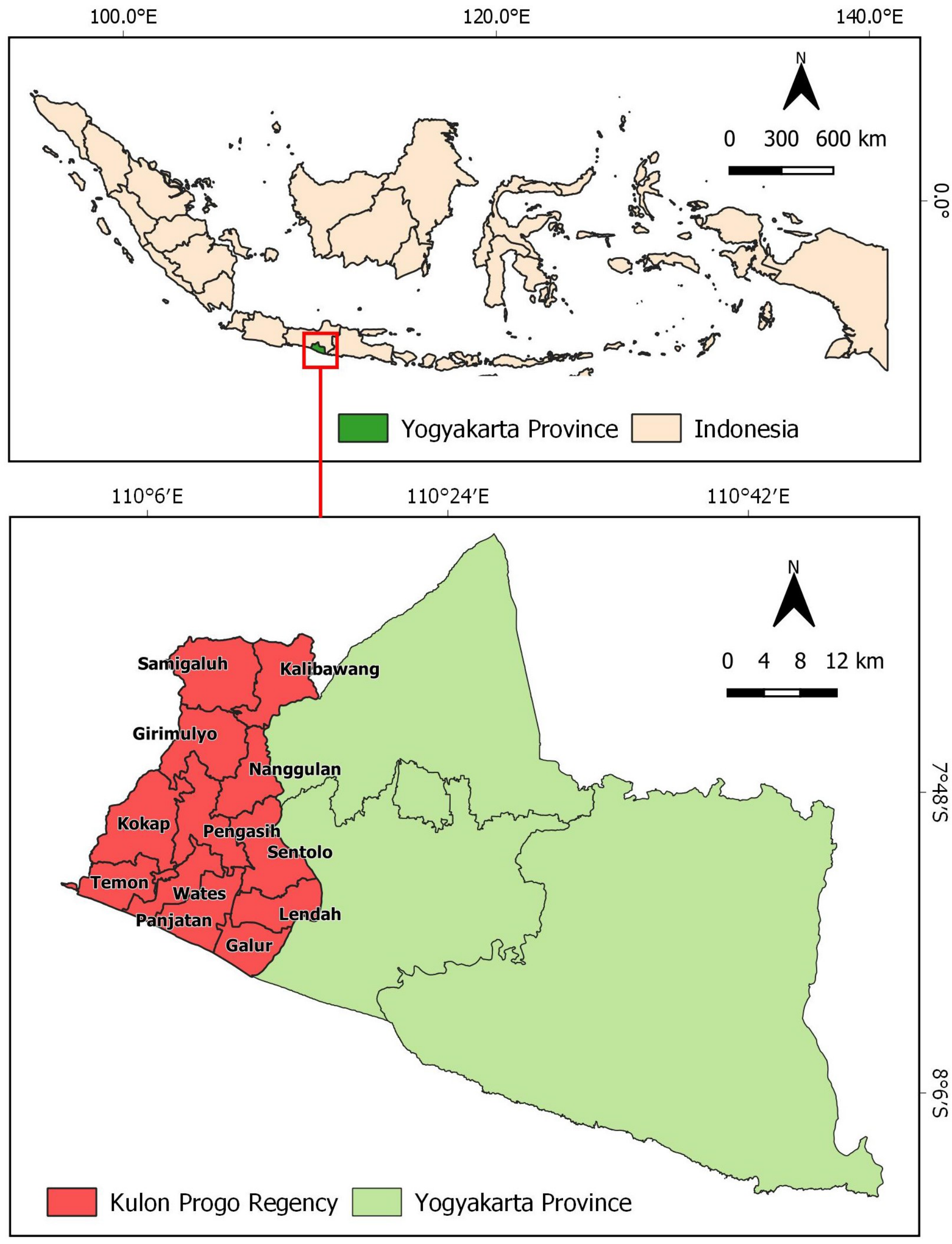

Figure 1. The study area in Kulon Progo, Special Region Yogyakarta, Indonesia

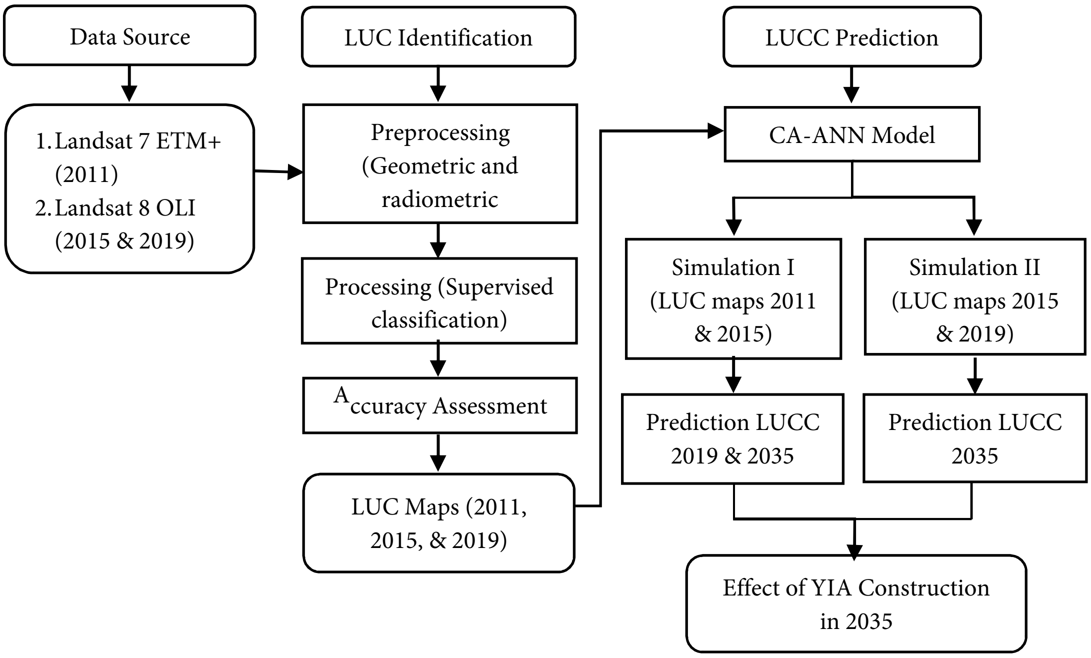

Figure 2. Methodological Flow Chart

appropriate and effective planning for sustainable land management. Moreover, the process of optimizing land resources should be according to the goals and directions of regional development (Liang et al., 2020).

2. Methods

Study area

The study area, namely Kulon Progo Regency (Figure 1) is located west of the Special Region of Yogyakarta, Indonesia. This district is a southern coastal area of the island of Java. This area has a variety of topography, namely the northern part is a highland (> 500 meter above sea level), the middle part is a hilly area (100 - 500 masl), while the southern part is a lowland in the form of a coastal area (> 100 masl). The population in the study area has continued to increase in the last decade. In 2010 the population of this Regency was recorded at 388.869 people, while in 2019 it was recorded at 447.246 people (Badan Pusat Statistik, 2020). The data shows that in the last 10 years the population of this district has increased by 58.377 people. This population growth is due to the high rate of population migration that occurred in 2018–2019. One of the triggers is the construction of Yogyakarta International Airport (YIA).

Method

Data

This study used a quantitative descriptive method with the main data of remote sensing images of Landsat obtained through the Earth Explorer website. A total of 3 data sets were used to map land use/cover, namely 2011, 2015, and 2019. Furthermore, the image with the least clouds from Landsat 7 and 8 was acquired in February 2011, January 2015, and June 2019. A study on land use changes detection was carried out by comparing minimum of 2 land use/cover maps (Reba & Seto, 2020). This study applied maps before and after the YIA construction. The methodological flow chart depicts in Figure 2.

LUC Identification

Land use/cover information was obtained from remote sensing imagery. Four steps in performing land use/cover identification. First, preprocessing stage was classified as multispectral of satellite imagery (Danoedoro et al., 2020) which was corrected geometrically and radiometrically (Wang et al., 2019). Second, in the processing step, the application of supervised classification uses the maximum likelihood method by selecting the desired information category and the training area for each LUC class (Setiady & Danodero, 2016). The LUC classification was based on that of the Indonesian Ministry of Environment and Forestry (KLHK), using 5 different classes, namely paddy fields, built-up area, dryland agriculture, water bodies, and shrubs.

Finally, in accuracy steps, the land use map was tested for accuracy to determine the level of truth. This was done by covering pre-field, field survey, and post-field. The pre-field stage involves determining the sample using stratified random sampling to distinguish each class, in which 75 points are used. Sample points were randomly determined in each land class and evenly distributed in the study area. This sample point is different from the training area in the soil classification to make the accuracy acceptable (Wulansari, 2017). The field survey was conducted to obtain direct information from the field regarding the predetermined sample points and to collect information on land use changes between the maps used and the conditions during the survey. Furthermore, this survey was conducted in 2021, and information on land use conditions in 2011, 2015, and 2019 was obtained by interviewing residents at the observation location. Post-field, namely, calculating accuracy using the accuracy assessment equation as follows:

$$\text{TA (\%)} = \frac{\text{Suitable number of samples } (D)}{\text{Total number of samples (N)}} \; x \; 100\%$$

Sumber: (Khoi & Munthali, 2012)

LUCC Prediction

In this study, the land use maps for 2011, 2015, and 2019 were used to predict LUC change in 2035. Meanwhile, the determination of the predicted land use year followed the system of the software used in the modeling, namely QGIS with the MOLUSCE tools. The analysis used the integration of Cellular Automata and Artificial Neural Network (CA-ANN) methods.

Six steps in performing the prediction of land use/cover change in this study. The first step was to input data, raster, that we have matched for cell size, location, and coordinates. Prediction of land use/cover changes is conducted through simulation with a series of scenarios to experiment strategically (Y. Yang et al., 2020). In this study, the prediction was conducted through two simulations, where the first simulation used data that do not involve the year of airport construction, namely 2011 and 2015. The second simulation used data involving the years of airport construction, namely 2015 and 2019. Furthermore, a prediction was also made for the next 16 years (2035). There were two assumptions considered in the prediction simulation conducted, namely: 1) Development of socio-economic infrastructure will increasingly trigger land use changes in the next 16 years because it will boost the development of settlements, shops, trade, hotels, and so on; 2) Land use changes will be influenced by the regional spatial plan (RTRW), when an area is a green zone then the next 16 years it is unlikely to change. In contrast, when the RTRW is allowed to change land use, then the next 16 years will most likely change.

The second stage, evaluation correlation, calculates the relationship between spatial variables using a person correlation. We used spatial variables including the distance from the road, the built-up area, the market, and the airport, as well as population density. The distance was calculated using Euclidean analysis. Spatial variables used in the simulation were considered to make the predictions more accurate (Gharaibeh et al., 2020). The third stage was to create a change area to discover the LUC change. The fourth stage was produced the transition potential modeling. This indicated that the LUC class was changing to another class. We applied ANN, the neighborhood value of 3 x 3 pixels, and 1000 iterations. The fifth stage was applied cellular automata simulation. The final stage was validation, carried out by comparing the simulated map with the actual map.

Prediction of the Effect of Transportation Infrastructure

The analysis of the effect of YIA construction used comparative data identification and prediction of LUC. Data identification were three maps for 2011, 2015, and 2019. The data prediction is mapped for 2035. The analysis was carried out using spatial and temporal analysis. Land systems are dynamic and operate across spatial and temporal scales (Esgalhado et al., 2020). Spatial analysis was based on land area and spatial patterns of changes that occur. Meanwhile, temporal analysis of the changes that occur in the past, present, and future.

3. Result and Discussion

Land Use/Cover (LUC) Maps

The identification of LUC in Kulon Progo Regency resulted in maps of the years 2011, 2015, and 2019 (Figure 3). Based on the results of the image classification, the area of each land use for 2011, 2015, and 2019 is obtained as presented in Table 1.

Table 1 shows the identification of land use/cover in the Kulon Progo Regency for the years 2011, 2015, and 2019. In 2011, the land use in Kulon Progo Regency was dominated by dryland agriculture with an area of 35,455.33 ha (61.82%). Other areas of use were rice fields 12,369.62 ha (21.57%), built land 5,283 ha (9.21%), shrubs 2,701.60 ha (4.71%), and water bodies 1,542.79 ha (2.69%). In 2015, land use from the largest in a row was dry land agriculture 35,345.23 ha (61.63%), rice fields 13,117.17 ha (22.87%), built-up area 6,072.79 ha (10.59%), water bodies 1,806.62 ha (3.15%), and shrubs 1,010.54 ha (1.76%). In 2019, the land use from the largest in a row was dry land agriculture 33,281.28 ha (58.03%), rice fields 13,579.67 ha (23.68%), built land 7,991.61 ha (13.93%), water bodies 1,392.33 ha (2.43%), and shrubs 1,107.46 ha (1.93%).

Based on the crosscheck in the field, the classification results for 2011, 2015, and 2019 showed an average accuracy value of greater than 81%. Furthermore, the highest overall accuracy was found on maps in 2015 and 2019 at 86.67%, while the lowest was found on the map in 2011 at 85.33%. Generally, the average accuracy was above 81%, indicating that the classification map is in a good category, and can be used for LUCC prediction simulations.

Land Use/Cover Change

The LUC maps indicate that the percentage of dryland agriculture decreased from 61.82 to 58.03%, shrubs from 4.71 to 1.93%, and water body from 2.69 to 2.43% between 2011 and 2019, while rice fields increased from 21.57 to 23.68% and built-up area from 9.21 to 13.93% (Figure 3). The use of paddy fields and built-up area during the period 2011–2019 has always increased. The development of the built-up land puts pressure on agricultural land, as happened in Suzhou, China, the rapid development of built-up area was followed by a gradual decline in agricultural land (Liang et al., 2020). Similarly, in Kano, Nigeria, a significant increase in transportation and built-up

Table 1. Land Use/Cover in Kulon Progo Regency 2011, 2015, and 2019

Land Use/Cover	The year 2011		The year 2015		The year 2019	
	Large (ha)	%	Large (ha)	%	Large (ha)	%
Rice Field	12,369.62	21.57	13,117.17	22.87	13,579.67	23.68
Built-up Area	5,283.01	9.21	6,072.79	10.59	7,991.61	13.93
Dryland Agriculture	35,455.33	61.82	35,345.23	61.63	33,281.28	58.03
Shrubs	2,701.60	4.71	1,010.54	1.76	1,107.46	1.93
Water Body	1,542.79	2.69	1,806.62	3.15	1,392.33	2.43
Total	57,352.35	100.00	57,352.35	100.00	57,352.35	100.00

Source: Data analysis, 2021

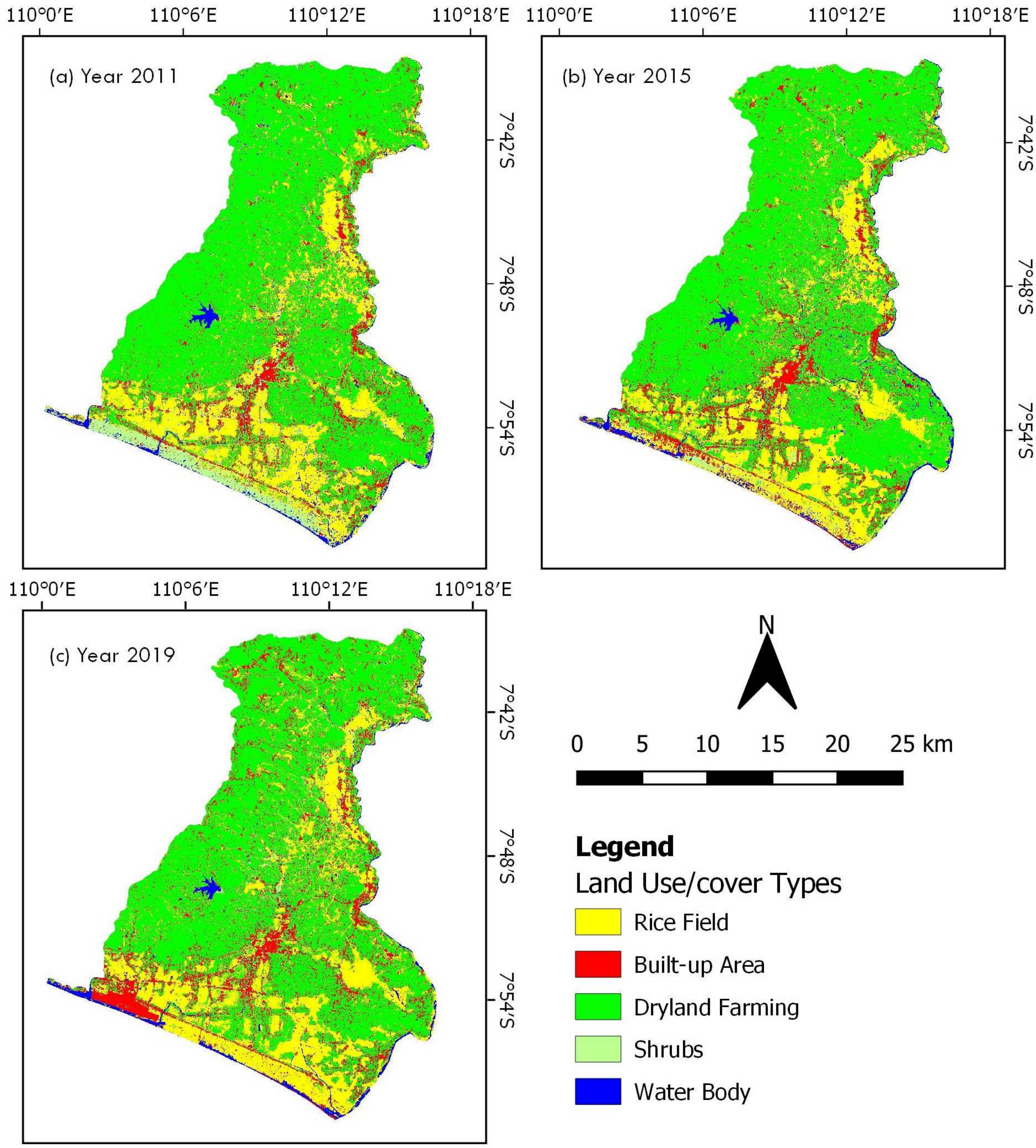

Figure 3. LUC maps of the study area were estimated from Landsat data for years 2011, 2015, and 2019.

areas has caused agricultural land to shrink (Otuoze et al., 2020). Development and urbanization inevitably contribute to the loss of agricultural land and forests converted to other uses (Kurowska et al., 2020). However, what happened in the research area showed something different, even though rice fields were converted to built-up area (airport), the large of rice fields did not decrease. Based on data from the Kulon Progo Agriculture Service, the area of paddy fields in Kulon Progo Regency in 2011, 2015, and 2019 was 10,304 ha, 10,354 ha, and 11,047 ha, respectively. This shows that the paddy fields in study area are increasing in large. The addition of paddy fields is carried out through the printing of new paddy fields, which are part of the Sustainable food and agriculture land or LP2B program in Indonesia (Sukri et al., 2022).

In the research area in 2011–2015, the addition of paddy fields was dominantly carried out by converting shrubs. Similarly, in Horqin Sandy Land, there is an expansion of agricultural land, while grasslands and shrubs experienced a reduction (Zhu et al., 2020). Furthermore, in 2015–2019, the addition of paddy fields was dominantly conducted by converting dryland agriculture in the Wates, Panjatan, Temon, and Sentolo subdistricts. These sub-districts are located in the lowlands with alluvial plain morphology and are suitable and supportive for the extension of paddy fields.

In the built-up area, 6 sub-districts experienced an increase in high including the Temon, Samigaluh, Girimulyo, Sentolo, Kokap, and Pengasih subdistricts. The increase in built-up area is caused by three factors, namely predisposing environmental factors, underlying forces, and proximate causes (Pham et al., 2015). In Temon, the increase was more influenced by the closest causal factor. This includes the YIA airport construction with an area of 600 ha. Meanwhile, in Sentolo, Kokap, and Pengasih sub-districts, the increase was due to the strength of population growth. In 2011–2019, the 3 sub-districts experienced the highest population growth by 6,536, 5,364, and 5,310 people in Pengasih, Kokap, and

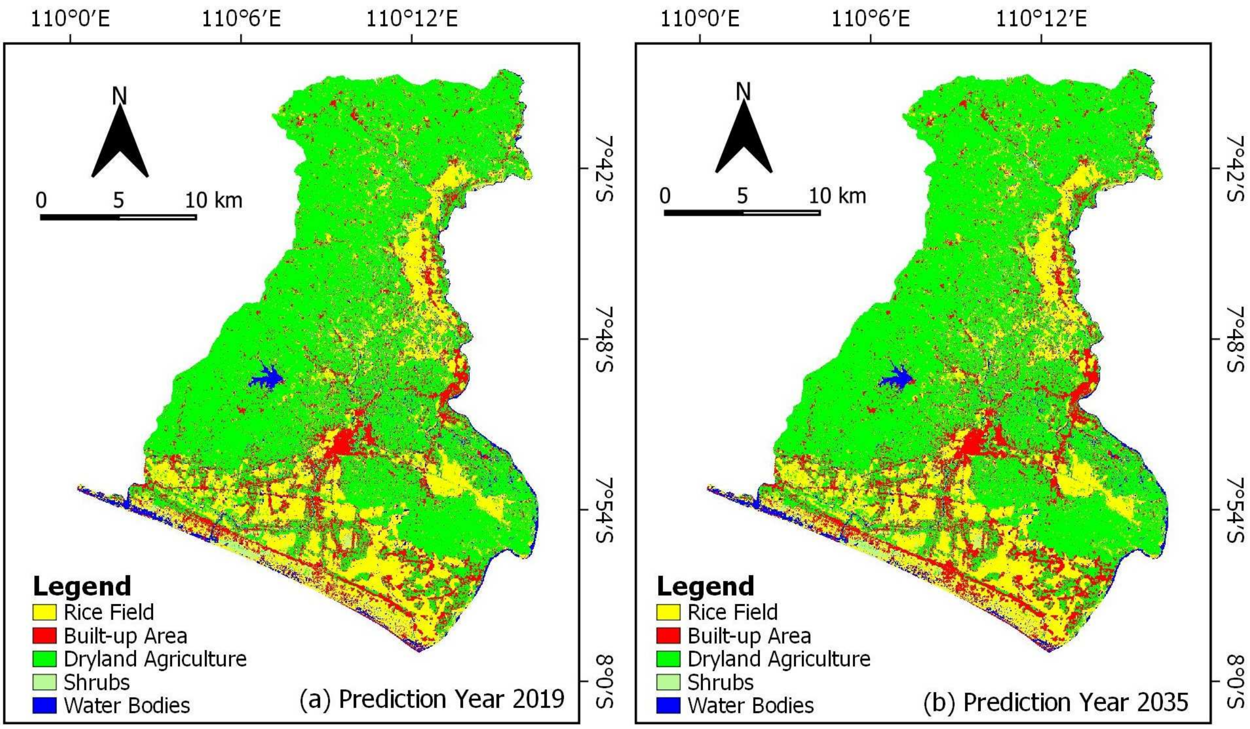

Figure 4. Simulation I prediction of LUC change in Kulon Progo Regency. (a) Prediction for 2019; (b) Prediction for 2035. (Data processed, 2021)

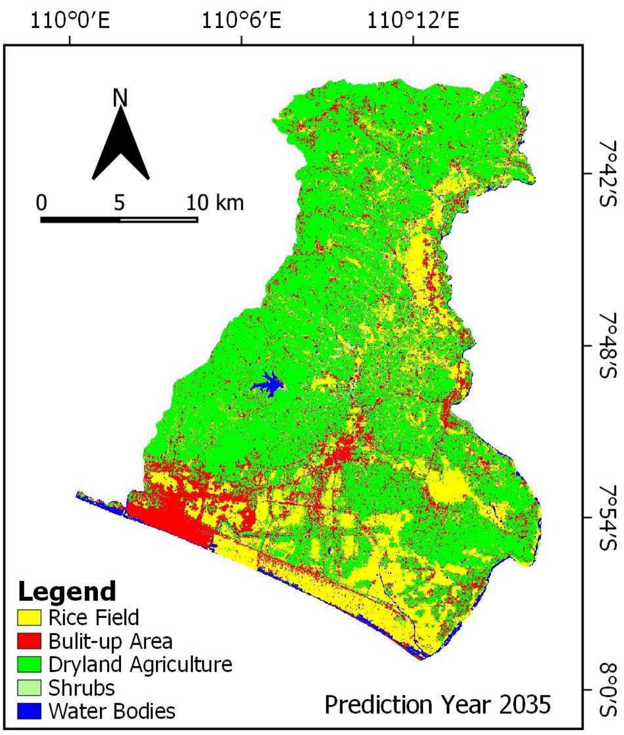

Figure 5. Simulation II prediction of LUC change in Kulon Progo for 2035. (Data Processed, 2021)

Sentolo respectively (Badan Pusat Statistik, 2012; 2020). The population growth causes changes in land use into built-up area because everyone needs a place to live and socio-economic facilities (Dewi et al., 2020). Samigaluh and Girimulyo sub-districts experienced an increase in built-up area due to the strength of economic activities, including nature tourism and coffee shops.

Prediction of Land Use/Cover Change

Two simulations were conducted to predict land use/cover changes in the Kulon Progo Regency in the future (2035). Simulation I used LUC maps 2011 and 2015, meanwhile simulation II used LUC maps 2015 and 2019. The driving factors used for simulation I included roads, population density, existing built-up area, and markets. The driving factors for simulation II included YIA airport, roads, population density, existing built-up area, and markets. Based on the accuracy assessment in simulation I, the Kappa value was 70%, which means that the prediction model is in a good category (substantial agreement). The results of the simulation I are presented in Figure 4, while the result of the simulation II is shown in Figure 5.

Spatially, the image classification showed that the addition of built-up area during the period 2011–2015 dominantly occurred in Pengasih sub-district located in the middle area. The next sub-districts to experience a lot of additional built-up areas were Temon (southern) and Samigaluh (north). Furthermore, the results of simulation I predictions of LUC changes in Kulon Progo Regency for 2019 and 2035 as shown in Figure 4. In the 2015–2019 period, the addition of built-up area is predicted to be significant in the south to the southeast, including Galur, Panjatan, and Sentolo sub-districts. Meanwhile, in 2019–2035, it is predicted to still be significant in the south to the southeast, namely in Sentolo, Panjatan, and Galur sub-districts. This means that simulation I prediction on the addition of built-up area in the research area shows the south to the southeast.

Figure 5 shows the simulation II of LUCC prediction in the Kulon Progo Regency for 2035 based on the 2015 and 2019 maps. Furthermore, the addition of built-up area in 2015–2019 was dominant in Temon and Samigaluh sub-districts. This is the same as what happened in 2011–2015. Based on the prediction results for 2035, changes in built-up area are predicted to be significant in the southern part, namely in the Temon (southwest) and Panjatan (southeast) sub-districts. This means that the YIA airport construction in Temon triggers the area development. Meanwhile, the development of built-up area in Panjatan was triggered by the JJLS construction. The identification and simulation of land use/cover change predictions showed that the dominant built-up area happened in the southern part of the study area. According to (Rijanta et al., 2020) this happened to compensate for regional developments on the north coast of Java Island. Furthermore, the development of transportation infrastructure in the southern region of Java Island (including the Kulon Progo Regency) is the national agenda of the Indonesian government.

Prediction of the Effect of YIA Construction

The prediction of the effect of YIA construction on the built-up area change in the Kulon Progo Regency was used LUCC prediction. The analysis was carried out based on increasing the built-up area and the location of the area from YIA. The result of the analysis is presented in Figure 6.

Figure 6 shows that the changes in built-up area in simulation II increased very significantly compared to simulation I. This is because the addition in 2018 was quite large due to YIA construction, which further triggered the increase in built-up area, especially areas adjacent to the airport, namely Temon and Kokap sub-districts (Figure 5). It is similar to the simulation of land use changes conducted by (Guzman et al., 2020) in Bogota Colombia, where the construction of new transportation infrastructure has an impact on regional development and causes negative effects related to the arrival of residents and industry.

The direction of built-up area development was predicted to be dominant in the southern part. Furthermore, simulation I lead to the southeast, namely, the Sentolo sub-district passed by the national road, as well as Galur and Panjatan sub-districts passed by JJLS, while simulation II leads to the southwest. The development of transportation infrastructure promotes regional economic growth. Additionally, the land use/cover structure will continue to change in line with economic development (Zhu et al., 2020). According to Wang et al. (2019), the development of transportation infrastructure is at risk of causing land degradation and interfering with sustainable development. Therefore, comprehensive planning, integrated policies, and the right layout are required (T. Y. Liu & Su, 2021). Because of this, the paper makes a compelling call for more systematic research on sustainable development and emphasizes the challenges for further research on land use planning not only in Kulon Progo but also in other areas.

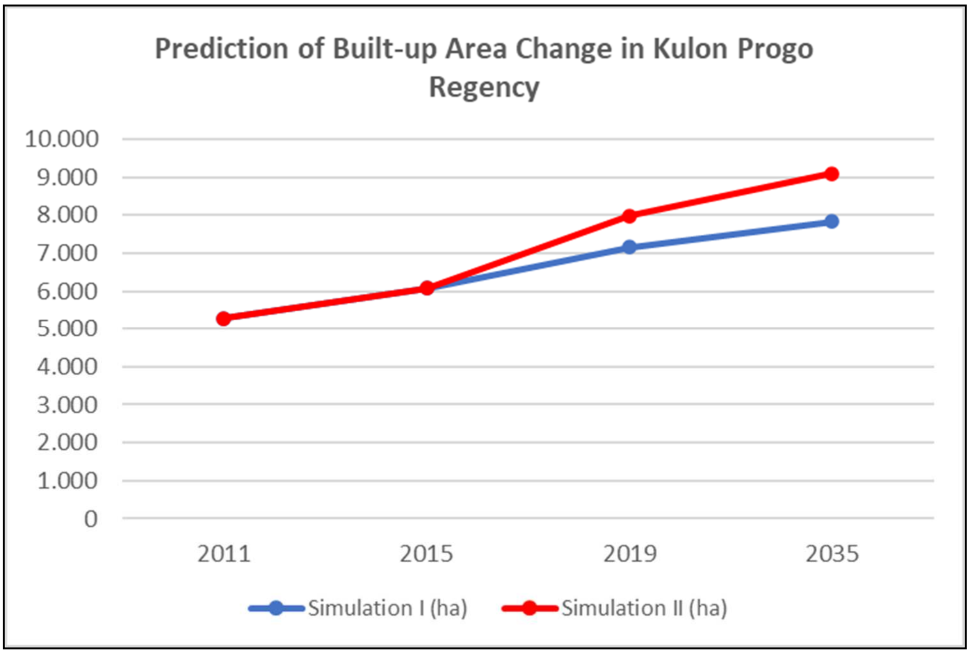

Figure 6. Predicted increase in built-up area from simulations I and II

Conclusion

Land use/cover changes in Kulon Progo Regency in 2011, 2015, and 2019 show that there is an increase in the use of paddy fields by 1,210,05 ha (2.11%) to 13,279.67 ha and built-up area by 2,708.60 ha (4.72%) to 7,991.61 ha. This is due to the conversion of shrubs (2011–2015) and dryland agriculture (2015–2019). Furthermore, most of the addition of paddy fields occurred in the Wates sub-district, while the most built-up area occurred in Temon. The increase in built-up areas is triggered by the development of transportation infrastructure and population growth. This will continue to occur, especially in the southern part, namely Temon (triggered by the airport construction) and Panjatan (triggered by JJLS construction) sub-districts. The limitation of this study is related to the driving factors used in the simulation. Data related to the RTRW of the area should be included in the modeling, even though it is currently readjusted by the local government. However, the driving factors used are sufficient and capable of predicting LUC changes. Further study is recommended to examine the control and supervision of land use following the RTRW. In addition, a strategy to balance the use of agricultural and built-up area to support sustainable development programs should be formulated.

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