Green infrastructure development challenges: The case of Yogyakarta International Airport

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Abstract

Infrastructure development, such as airports, often impacts the surrounding economic growth. On the one hand, the airport's economic growth is a desirable logical consequence. However, economic growth often occurs due to increased mining, industrial, plantation, trading, service, and other economic activities, causing changes in land use that do not follow the Spatial Planning and Regional Plans. Therefore, it may have implications for environmental damage. This paper proves a change in land use around Yogyakarta International Airport. Changes are observed through differences in land use in 2015, before the airport plan was built, and 2021, after the airport was operational. The random forest algorithm method is used to classify land use data sets. Furthermore, using the Multilayer Perceptron Neural Network Marcov Chain/ MLP NN-MC algorithm, it is predicted that the conversion of rice fields and plantations around the front side of the airport for housing and business will become even greater in 2030. Thus, the airport's construction has increased land use for business and residential purposes, while the green surface has been dramatically reduced. It was identified that there was a misuse of land use. Without good management, changes in land use can have an impact on decreasing environmental quality.

Keywords: green infrastructure, land use change, land use prediction
JEL Classification: Q57; R14; O44.

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1. Introduction

Regulating and controlling land/space use is a very important part of realising sustainable development/green infrastructure (de-Sousa et al., 2021; Dong et al., 2025). Green infrastructure is a policy to realise natural and semi-natural spaces/networks to improve ecosystem services to mitigate disasters, reduce pollution, reduce urban heat, and function as a shared space/recreation (Lopes et al., 2025). Green infrastructure policy is not only for the sake of environmental sustainability, but also as a solution to realize healthier cities, livable cities, and a better quality of life (Azadgar et al., 2025). However, massive infrastructure development, especially in developing countries, is often less than optimal in terms of environmental sustainability (Agudelo-Hz et al., 2023). Massive land conversion from green areas to built-up areas without being balanced with efforts to create adequate replacement green spaces has an impact on increasing environmental damage, increasing various disasters, and increasing global warming (Elsharkawy et al., 2022; Gençay and Durkaya, 2023; Sati, 2014). In addition, limited data/information related to how the presence of a development impacts land use now and in the future is also one of the problems of low mitigation efforts (Hamad et al., 2018).

This research is novel in two main aspects. Firstly, the integration of the random forest algorithm for land use classification with the Multilayer Perceptron Neural Network-Markov Chain (MLP-NN-MC) algorithm for spatial prediction, which has not been widely applied in the context of airport development in Indonesia. Secondly, this research also emphasises the importance of green infrastructure with a spatial approach that considers ecological and socio-economic aspects, as a basis for formulating sustainable spatial policies. Infrastructure development often does not integrate the policies implemented with spatial and environmental factors. Policies that are less integrated and do not include modelling of future predictions also result in less than optimal targets and even failure of implementation in the field. In addition, policies that are not spatially based result in the distribution between infrastructure development and the provision of green areas that do not pay attention to the balance between environmental aspects and socio-economic factors (Azadgar et al., 2025). To support environmentally sound development policies, land use prediction modelling is needed to determine future land use patterns and as a basis for formulating land management policies. Land use prediction modelling can be done based on past land use maps, accompanied by driving variables that affect land use (Utami et al., 2024). Land use prediction modelling can be easier to do and can produce accurate data when utilising Artificial Intelligence (AI) technology. The ability of AI in spatial modelling can simplify data complexity, extract data, extrapolate complex data, simplify mathematical calculations, and analyse probabilities simultaneously to produce accurate future spatial modelling (Chandan et al., 2020; Lin et al., 2023). Modelling done manually without using AI technology would require a long time, a very complicated process, complex mathematical calculations, and less accurate results (Mahmoudzadeh and Abedini, 2022; Mirsanjari et al., 2021)Modelling done manually without using AI also has the disadvantage that it is difficult to integrate with other data and to carry out further analysis.

In recent decades, the development of AI technology for land use modelling has been very rapid and diverse, with each algorithm offered having advantages and disadvantages (Henríquez et al., 2022; Jatayu et al., 2022). Several researchers continue to develop modelling techniques to produce more accurate modeling data, one of which is a hybrid modelling algorithm. This algorithm has the advantage of being able to dynamically improve the process and improve the quality of very complex land use predictions (Alam et al., 2021; Utami et al., 2024). Some hybrid algorithms for land use modelling include Multilayer Neural Network (MLP-NN) - Marcov Chain (MC); Cellular Automata (CA) - Marcov Chain (MC); Random Forest Algorithm (RFA) & Cellular Automata (CA). By analysing land use prediction models through AI (Multilayer Perceptron Neural Network), it is hoped that future land use information produced will be more accurate, so that it can be used as material for formulating spatial planning policies and sustainable land management. Currently, the development and implementation of AI in land management science plays a very important role because the policies formulated are more effective and efficient and can guide the development of urban and rural areas optimally and sustainably (Hamad et al., 2018; Tarawally et al., 2019; Nyamushosho et al., 2022).

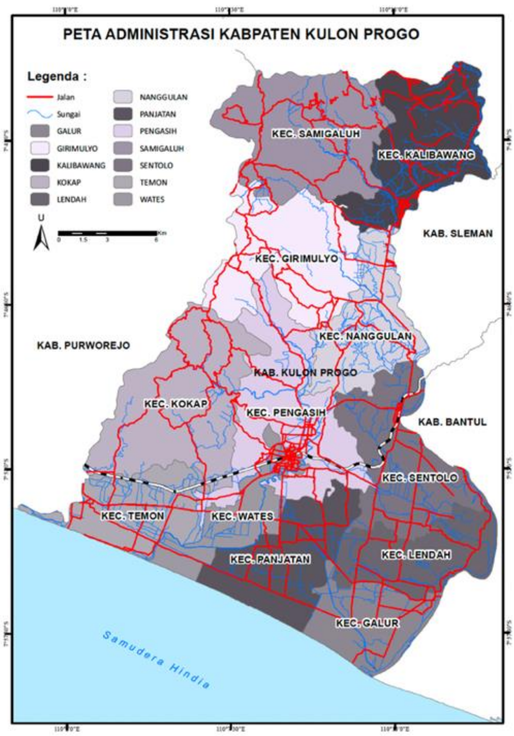
Land use prediction modelling can also determine agglomeration patterns and urban sprawl development in an area (Mosammam et al., 2017; Malarvizhi et al., 2022). With AI technology capable of predicting future land use, land use planning can be formulated in advance to ensure that each land function is interrelated and mutually supportive. AI-based land use prediction can also provide an overview and identify related regional development patterns (whether following axis theory/sector theory/concentric theory/location theory), identify early centres of growth and economic activity, so that policy makers can prepare more optimal land use designation plans. Predictive modelling of land use is also the basis for calculating the area of lost green space and planning the area of replacement green space, so that the environmental balance can be planned. Against this background, the research questions to be answered in this paper are: 1) How does land use change around Yogyakarta International Airport (YIA) before and after airport development?; 2). What are the drivers of land use change? 3) What is the projection of future land use based on artificial intelligence modelling using Multilayer Perceptron Neural Network-Markov Chain algorithm? This paper is prepared to answer the problems in implementing green infrastructure. This paper is structured as follows: the first session describes the development of the methodology for land use prediction based on AI technology; the second session provides an overview of the research object and the data used, followed by the third session describing the methodology based on Artificial Intelligence. The fourth section describes the results of the analysis, and the fifth section concludes.

2. Methodology

This research was conducted in Kulon Progo Regency, which is one of the developing regions. This region is a research priority because the area around the construction of Yogyakarta International Airport (YIA) has a very varied morphology, namely the northern side is an area of denuded/eroded volcanic hills with steep slopes and moderate rainfall intensity (119 mm/month) so that some areas are prone to landslides. In contrast, the southern side has gentle slopes prone to flooding. In addition, the southern side borders the Indian Ocean as a subduction zone of the Indo-Australian plate, which is prone to tsunamis.

The Kulon Progo regency is dominated by fertile agricultural land, and the people who depend on it are farmers, fishermen, aquaculturists, agricultural labourers, and breeders. The massive infrastructure development in the YIA airport area has the potential to accelerate economic growth. Still, it can also harm the social, economic, and cultural life of the community, as well as cause environmental damage. This development's positive and negative impacts certainly need to be mitigated, one of which is through land use prediction modelling to formulate sustainable regional planning. The state of the study area is shown in Figure 1.

Figure 1.
Research Location Land Use Prediction Modelling



Source: Earth Map of Indonesia (2021)

Administratively, Kulon Progo Regency consists of 12 sub-districts with an area of 586.28 km^2. This research uses several variables and data sources, which are described in Table 1.

Table 1. Variable, Data, and Source

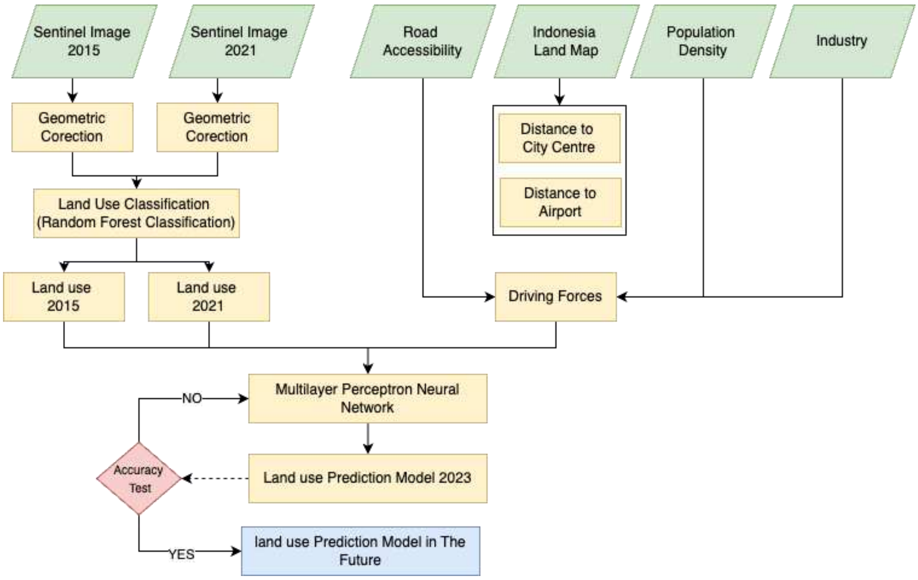
No	Variable	Data	Source
1	Land use map 2015	Sentinel Imagery 2015	*United States Geological Survey (USGS)*
2	Land use map 2021	Sentinel Imagery 2021	*United States Geological Survey (USGS)*
3	Road accessibility	Road network map	Public Works Department
4	Earth map of Indonesia	distance to city centre, distance to airport	Geospatial Information Agency
5	Population density data	Population density	Central Statistics Agency

The multitemporal land use map used includes a 2015 map that represents the condition of the study area before airport development, while the 2021 map represents the condition of land use after airport development. Some software used to analyse spatial data include: 1) ArcGIS, to perform interpolation, spatial data analysis, and visualise spatial data; 2). ENVI 4.8 for processing Sentinel satellite images in 2015 and 2020; 3). Q-GIS with random forest algorithm to interpret/classify land use; 4). Idrisi Terr-Set (Land Change Modeler using Multi-layer Perceptron Neural Network/MLP-NN method) to develop a land use prediction model.

Secondary data variables in this study include: road accessibility, distance to city centre, distance to airport, number of industries, and land use map. Meanwhile, primary data was used to obtain field samples to calculate the accuracy of land use. In this research, land use data were obtained from the interpretation of Sentinel-2 imagery in 2015 and 2021. Sentinel-2 imagery was chosen because it has a spatial resolution of 10m, which is much better than Landsat imagery (Inderaja Catalogue, 2023). Land use classification analysis was conducted through Google Earth Engine (GEE) using a random forest algorithm. In this research, the land use classification is divided into 5 (five) classes, namely: a). vegetation; b). water body; c). built-up land; d). rice field; and e). sand/sand dunes.

The implementation of Artificial Intelligence in this research includes two aspects: the use of a random forest algorithm for land use classification and a Multilayer Perceptron-Neural Network (MLP-NN) Markov Chain algorithm for land use prediction modelling. The MLP-NN Markov Chain algorithm was chosen because it is very effective in developing models and can produce more accurate modelling data. (Raj and Sharma, 2022). The neural network analysis algorithm, as an artificial neural network, can generalise land use transitions through a supervised backpropagation algorithm as a basis for predicting future land use (Mirsanjari et al., 2021)This approach can also operate on data with a very large capacity and multi-time data, making it very reliable in analysing and modelling land use transition patterns. In addition to using machine learning technology, the data analysis process is also carried out spatially by utilising Geographic Information System applications through query analysis and map overlay to obtain a multitemporal land-use change map. The flowchart of this research is described in Figure 2.

Figure 2. Flowchart of Land Use Prediction Modelling Research



Source: Processed by Author

In this research, remote sensing technology, geographic information systems and the use of Artificial Intelligence (AI) through algorithms (random forest and multilayer perceptron neural network) can solve various cognitive problems, especially related to land use patterns to optimise the use of natural resources. This ability of Artificial Intelligence has been applied in various fields of interest, including industrial development, business, health, social media, navigation, browsers, banking, etc. *(Li et al., 2023; Tao et al., 2024)*Various studies show that Artificial Intelligence is proven to extract data, classify data in statistical codes, understand data better, and recognise patterns as a basis for compiling predictive modelling in the future. The robustness of Artificial Intelligence, the availability of various applications, and the availability of various data in this big data system are opportunities that should continue to be developed, especially for realising green infrastructure development.

Multilayer Perceptron Neural Network Markov Chain is a deep learning method, a branch of machine learning, enabling algorithms to solve problems in the machine learning domain. MLP-NN is also a hybrid machine learning development in the Idrisi Terr-Set software. With this development, this algorithm is often used in various studies, especially for modelling. Some previous literature shows that this algorithm can produce more accurate usage prediction data compared to other methods (Mishra & Rai, 2016; Girma et al., 2022). Multilayer perceptron is one of the algorithms that can analyse more than two layers, so it is very compatible with analysing data with large capacity. On the other hand, if only a single layer of data is used, a simpler neural network algorithm is sufficient.

The neural network algorithm implements the concept of regressing a simple linear function:

$$f\ (x) = 3x + 2 \quad (1)$$

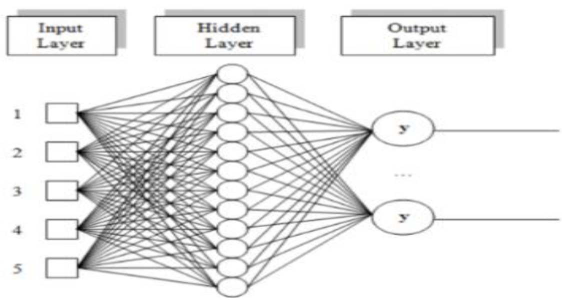
This regression requires only two layers, the input layer and the output layer. The logic concept used in neural networks refers to the system of neurons in the human brain when it is working, where each neuron is interconnected, and information continues to flow. The working system in this neuron has a point and a weight, which add up to a weighted sum (medium.com). The Marcov chain method, on the other hand, is a data processing chain that can account for the characteristic transitions between events with a higher degree of accuracy (Man et al., 2019). In addition, the Marcov chain approach is also able to simplify mathematical calculations, so this application is widely used by researchers in land use prediction (Hazani et al., 2021; Tariq et al., 2022).

The layers required in land use prediction analysis are more complex, so non-linear regression analysis is required. This multilayer perceptron algorithm uses a fully connected layer and an activation function on all neurons in the hidden layer. The non-linear regression function can be done with the following equation:

$$f\ (x) = \sqrt{2x^2 + 1} \quad (2)$$

In this research, researchers attempt to process spatial and textual data in a multitemporal manner for further analysis using AI (Multilayer Perceptron Neural Network) to model future land use predictions. Spatial data with very large capacity, including multi-temporal land use maps (2015 and 2021), maps / spatial data of factors affecting land use change (road network, distance to city, distance to airport, industry, and population density), is very complex. Human capacity cannot perform calculations, analysis, or coding manually with such complex data. However, with the development of machine learning in the form of deep learning through multilayer perceptron neural network, Markov chain, large, complex data with various patterns, point value, weight, and weighted sum can be used as an activation function as the output of the neuron system. Figure 3 is the working system in the multilayer perceptron neural network algorithm.

Figure 3. Multilayer Perceptron Neural Network Algorithm Architecture



Source: Modified from Muliantara & Widiartha, (2011) The random forest algorithm is one of the machine learning techniques that can be used to classify data sets into very large data units (Liao et al., 2023). This approach has been widely applied in various fields, including economic, social, environmental, and disaster analysis (Liu et al., 2022). This algorithm is one of the reliable algorithms in land use classification. The working system of the random forest algorithm is carried out by combining trees as decision trees and providing training data sets. In the random forest classification system, several decision trees are constructed and combined to obtain stable and accurate data predictions (Billah et al., 2023).

The use of this random forest algorithm will be used to classify land use in Sentinel imagery in 2015 and 2021. This algorithm system is performed in a supervised manner to obtain land use classification within a study area. In this algorithm, a training area is required (land use samples, namely: built-up land, vegetation, water bodies, rice fields and sand), so that these samples can then be used as a basis for processing satellite imagery data with high capacity, and finally produce a land use classification according to the given training area.

The Random Forest algorithm is one of the approaches often used for land use classification because it is a collection of decision trees trained using the bagging method (the correct algorithm to reduce data noise and the best method for datasets with numerical attribute data) *(*Dubertret et al., 2022*)*. Several studies on supervised classification have shown that this algorithm can produce land use classifications with higher accuracy compared to the use of the Support Vector Machine (SVM) algorithm or the Minimum Distance algorithm (Sianturi, 2022; Siska et al., 2022). Google Earth Engine as a platform that contains various machine learning including random forests can facilitate researchers in obtaining diverse spatial data, can facilitate researchers in analysing spatial data in large amounts of data, and with several existing features can provide convenience in obtaining data from interpretation and spatial analysis (Nghia et al., 2022).

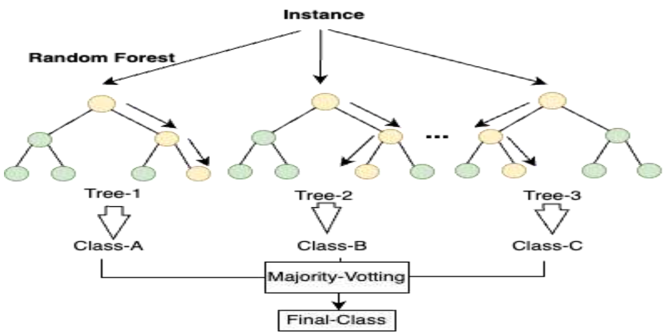
3. Results and Discussion

This paper aims to produce a land use map and a future land use prediction modelling map based on road network variables, distance to the city centre, distance to the airport, and the number of industries. This database is needed to determine how much land conversion occurs in each period and each land use class classification. This change can undoubtedly be the basis for predicting the area of agricultural land, the area of industrial and commercial areas, the area of residential areas, and the area of forest/protected areas in the future. The preparation of land use predictions based on various aspects and the addition of other spatial data analysis can be used to formulate a map of land capability and suitability, so that it can produce priorities and directions for land use according to its designation. Land use prediction data on the economic aspect can also be a basis for stakeholders to choose strategic and appropriate locations for business development so that the invested capital can generate optimal profits.

3.1 Land use maps in 2015 and 2021

The preparation of land use maps carried out in this research uses the random forest algorithm. This algorithm is one of the machine learning algorithms capable of producing land use maps quickly, easily, and with accurate results. The advantage of this random forest method is that it can produce many trees, which can be used as a basis for majority voting analysis/determining classes in the output of data/image analysis. Random forest has the advantage of effectively dealing with overfitting problems caused by random classification (Zulfajri et al., 2021). The simple concept of the random forest method workflow to produce data/land use classification can be explained as shown in Figure 4 below:

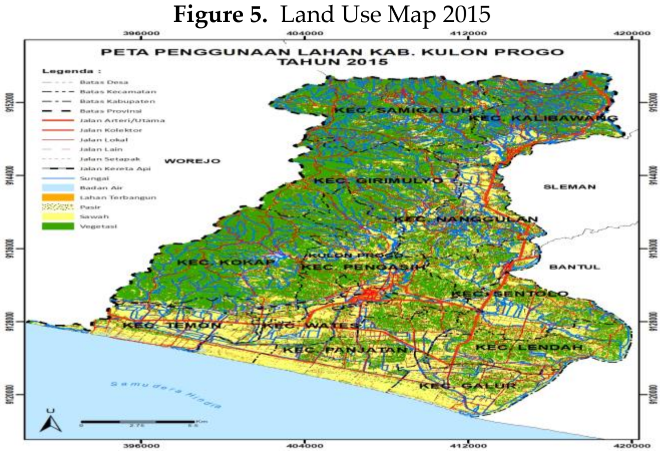
Figure 4. Simple Concept of Random Forest Algorithm



Source: Adapted from Koehrsen, W. (2018). Random Forest: Simple Explanation. [Medium.]

The land use map used in 2015 provides an overview of land use conditions before the airport was built and the condition of Kulon Progo Regency, which is relatively more dominated by agricultural and forest land. The results of sentinel image interpretation in 2015 produced a land use map as shown in Figure 5.

Figure 5. Land Use Map 2015



Source: Interpretation of Sentinel imagery in 2021 through a random forest algorithm

Figure 5 shows that land use on the south and east sides of Temon, Panjatan, Galur, Lendah, and Sentolo sub-districts is mostly in paddy fields. In 2015, the area of vegetation (forest/mixed plantation) in Kulon Progo Regency reached 52.11%, and the area of paddy fields reached 32.33%, while the area of built-up land was only around 3.88%. However, along with the construction of various infrastructures, the increase in population and the growth of various economic growth centres correlate with increased land use change. The land use map in Kulon Progo Regency in 2021 can be presented as Figure 6.

Figure 6. Land Use Map 2021

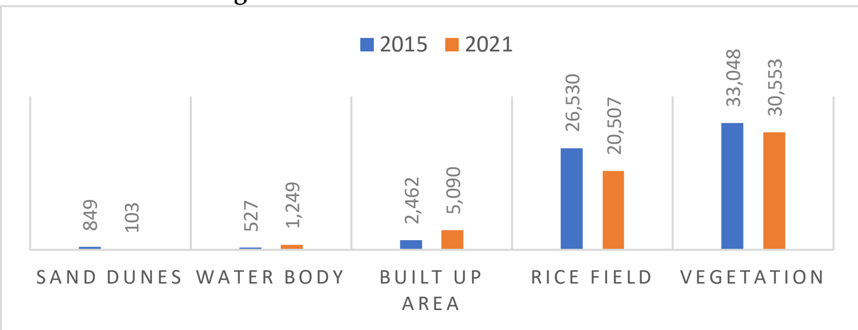
Source: Interpretation of Sentinel imagery in 2021 through a random forest algorithm

Figure 6 shows that the construction of various infrastructures and the increasing growth of economic centres have implications for increasing built-up land and suppressing the existence of rice fields and vegetation (forests and mixed gardens). The construction of the YIA airport in the Temon sub-district has converted mixed gardens and agricultural land into massively built-up land. Data related to the extent of land use in Kulon Progo Regency for the 2015 and 2021 periods are presented in Appendix 1.

a. Map of Land Use Change from 2015 to 2021

The random forest algorithm utilised in this research can efficiently produce land use classification. Furthermore, data analysis through overlaying land use maps in 2015 and 2021 reveals significant changes in paddy fields, where a decrease of 6,022.6 hectares has been documented for just six years. Concurrently, the area designated for vegetation land cover (comprising forests and mixed gardens) has undergone a substantial contraction, amounting to 2,495 hectares. Conversely, built-up land has shown an increase, reaching 103 hectares. The extent of land use change in Kulon Progo Regency can be presented as Figure 7.

Figure 7. Land Use Area in 2015 and 2021



Source: Processed by Author

In this study, the spatial distribution of land use changes that occurred from 2015 to 2021 can be presented in Figure 8

Figure 8. Land Use Change Map 2015 to 2021

Source: Processed by Author

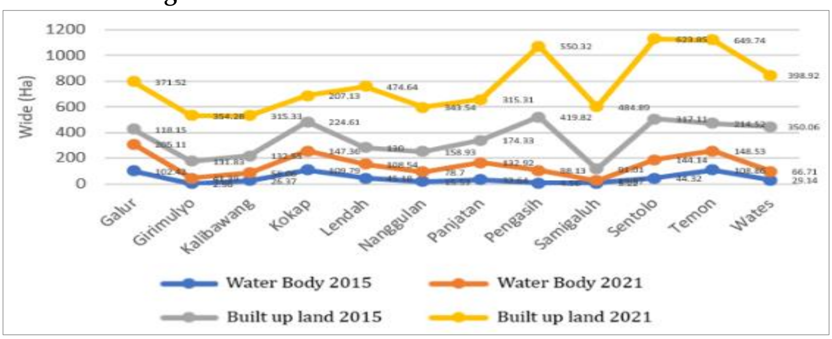
Figure 8 shows the spatial distribution of massive land use change at the YIA airport construction site and surrounding areas located in Temon Sub-district and several regions in Sentolo, Lendah, Pengasih, and Galur Sub-districts. Some areas that experienced massive land use change were areas on the southern side of Kulon Progo Regency with relatively flat morphological conditions/slopes. Meanwhile, on the northern side of Kulon Progo Regency, the level of land use change that occurred was relatively lower. Physical/morphological factors influence the change in highland use, such as the south side having relatively flat slopes, being passed by national/provincial road access, and being relatively close to the city centre. In contrast, the north side has slopes ranging from undulating to steep hilly conditions and a high landslide vulnerability. Data on the extent of land use change between 2015 and 2021 in detail is presented in Table 2.

Table 2. Area of Land Use Change 2015-2021

No	Land Use 2015	Land Use 2021	Land Use Change	Area (Ha)
1	Vegetation	Vegetation	Unchange	26,358.90
2	Vegetation	Water Body	Change	291.33
3	Vegetation	Built Up Area	Change	1,604.66
4	Vegetation	Rice Field	Change	4,786.01
5	Vegetation	Sand Dune	Change	7.79
6	Water Body	Vegetation	Change	63.11
7	Water Body	Water Body	Unchange	279.10
8	Water Body	Built Up Area	Change	70.46
9	Water Body	Rice Field	Change	97.83
10	Water Body	Sand Dune	Change	16.54
11	Built Up Area	Vegetasi	Change	633.63
12	Built Up Area	Water Body	Change	81.99
13	Built Up Area	Built Up Area	Unchange	888.53
14	Built Up Area	Sand Dune	Change	15.90
15	Rice Field	Vegetation	Change	3,496.92
16	Rice Field	Water Body	Change	588.96
17	Rice Field	Built Up Area	Change	2,510.08
18	Rice Field	Rice Field	Unchange	14,757.12
19	Rice Field	Sand Dune	Change	55.46
20	Sand Dune	Vegetation	Change	0.87
21	Sand Dune	Water Body	Change	8.09
22	Sand Dune	Built Up Area	Change	15.74
23	Sand Dune	Rice Field	Change	23.85
24	Sand Dune	Sand Dune	Unchange	7.62

Source: Processed by Author

Figure 9. Land use has increased from 2015 to 2021



Source: Processed by Author

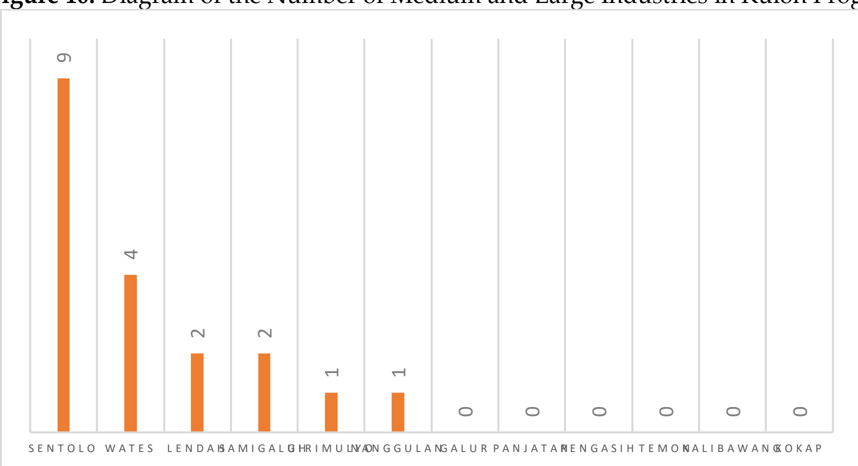
Within 6 years, the highest increase in land use occurred in built-up land. Data on the increase in land area in each sub-district is presented in Figure 9. The findings of this study indicate that the massive infrastructure development that occurred, one of which was for the construction of the Yogyakarta International Airport / YIA airport as well as the increase in built-up land for trade, services and settlements, resulted in a very massive impact on the decline in vegetation cover, which was reduced by 2,495 Ha and reduced rice fields by 1,572 Ha. The findings of this study corroborate previous research conducted by Suwanlee et al., (2023).

That infrastructure development in rural areas reduces agricultural land as a source of community livelihood. On the one hand, the massive land conversion in both types of land use can encourage regional economic growth, facilitate air transportation facilities, and open various business/investment opportunities. However, on the other hand, the reduction of agricultural land impacts the reduction of agricultural production, which correlates with a decrease in farmers' income. In addition, reducing vegetation cover also impacts ecosystem imbalance and decreases environmental quality. This research shows that the higher the land value, the higher the importance of land. The findings of this study are in line with the research of Schneider et al., (2020). Land use change is strongly influenced by the role of actors and socio-economic policies on land.

3.2 Driving Factors of Land Use Change

In this research to produce land use prediction modelling, data input is needed in the form of multitemporal land use and driving factors of land use change. Some driving factors used to develop land use modelling include economic, social, physical, and location aspects. The following variables drive land use change in the study area: 1) Industry; 2) Population density; 4) Road accessibility; 5) Distance to City Centre; 6) Distance to Airport.

Figure 10. Diagram of the Number of Medium and Large Industries in Kulon Progo



Source: Department of Industry and Trade of Kulon Progo Regency (2021)

Data on population density in Kulon Progo Regency is presented in Table 3 below:

Table 3. Population Density in Kulon Progo Regency

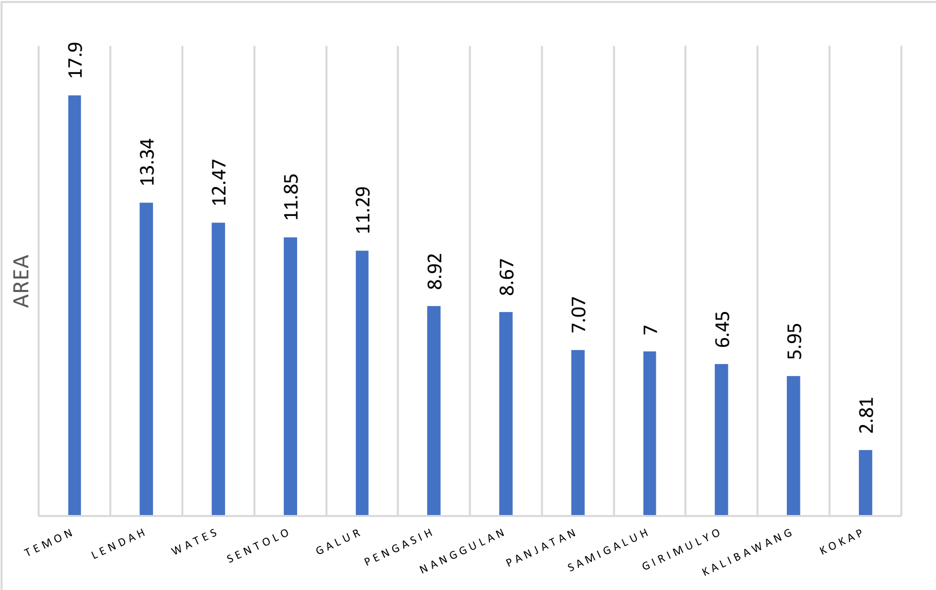
No	District	Population	Area	Population Density
1	Wates	48,948	3,200.24	15.30
2	Lendah	41,108	3,559.19	11.55
3	Galur	32,749	3,291.23	9.95
4	Panjatan	38,784	4,459.23	8.7
5	Pengasih	52,529	6,166.46	8.52
6	Temon	29,125	3,629.89	8.02
7	Nanggulan	30,883	3,960.67	7.8
8	Sentolo	36,115	5,265.34	6.86
9	Kalibawang	29,877	5,296.36	5.64
10	Kokap	36,115	7,379.95	4.89
11	Samigaluh	28,093	6,929.31	4.05
12	Girimulyo	24,621	5,490.42	4.48

Source: Kulon Progo District Central Statistics Agency (2021)

Wates district, as the centre of government and economic centre, is the most densely populated, followed by Kecamatan Lendah and Galur. Meanwhile, the three sub-districts with the lowest population density are Girimulyo, Kokap, and Kalibawang. Morphologically, these three sub-districts have a hilly morphology and are dominated by forests and moorland. In this research, researchers also analysed the building density of each sub-district, which is presented in Figure 11. Based on Table 3 and Figure 11, it can be seen that sub-districts with high population density correlate with the level of building density. However, this condition is an exception for the Temon sub-district, because the YIA airport development influences the high density of built-up land.

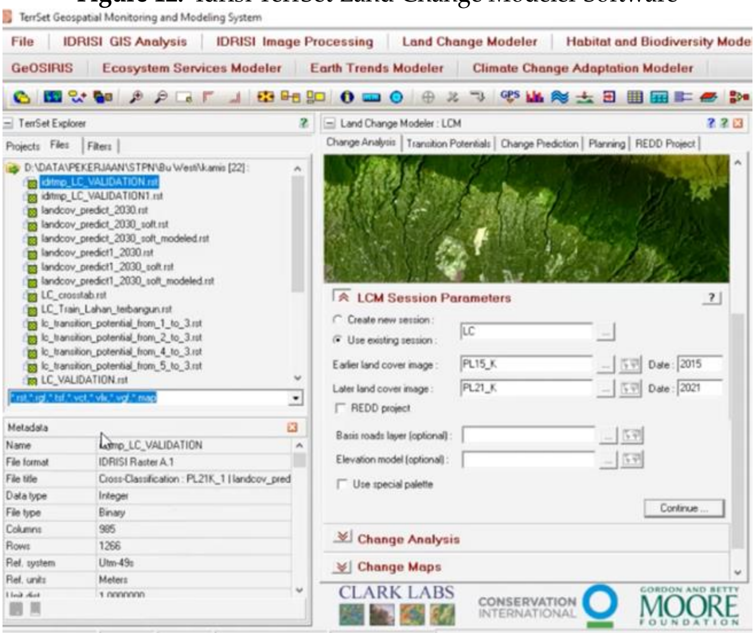
The rapid technological capabilities of Artificial Intelligence can be implemented to produce future land use prediction modelling (2030) in the study area. This research shows that AI through the Multilayer Perceptron Neural Network - Marcov Chain algorithm can produce land use prediction modelling in 2030 with land use classes in the form of five classes: built-up land, rice fields, water bodies, vegetation, and sand. The MLPNN-Markov Chain algorithm can quickly process very complex data, data with huge capacity, multitemporal data, and variables, with a more straightforward process and accurate results. MLPNN-MC, in this research, can calculate the future land use probability based on land use maps in 2015 and land use in 2021, as well as variables driving land use change. Figure 12 below shows the data input stage in modelling land use prediction.

Figure 11. Building Density Level per Sub-district in Kulon Progo Regency



Source: Processed by Author

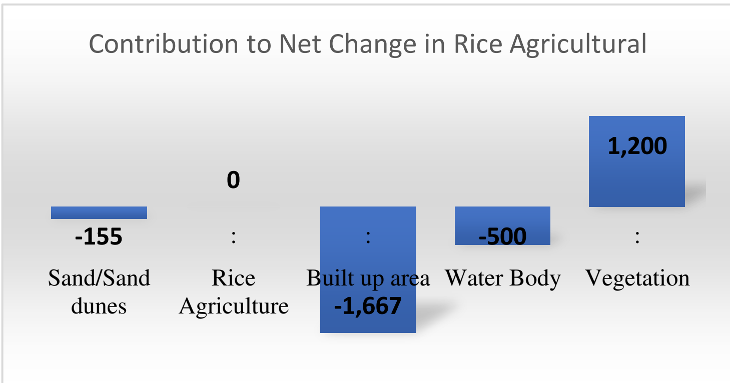
Figure 12. Idrisi TerrSet Land Change Modeler Software



Source: Processed by Author

Figure 12 shows that various forms of modelling analysis can be carried out through TerrSet software, including modelling for climate change adaptation patterns, modelling to assess ecosystem services, biodiversity modelling, and others that can be optimised for natural resource management. In this research, the primary data input used in compiling the modelling is multitemporal land use for at least two periods, in this research using the 2015 and 2021 periods. In the Land Change modeler in Idrisi TerrSet, the data is in raster format, namely in the form of "rst". Some things that need to be considered in building a modelling database include that the data format must be the same, and the input data must have the same reference system, which in this research uses the UTM-49S system. One of the advantages of this software is that it can easily represent the value of land use change through the analysis of gains and losses. The following is an example of calculating profits and losses contained in the land change model to analyze changes in the use of rice fields to other uses (vegetation, built-up land, water, and sand).

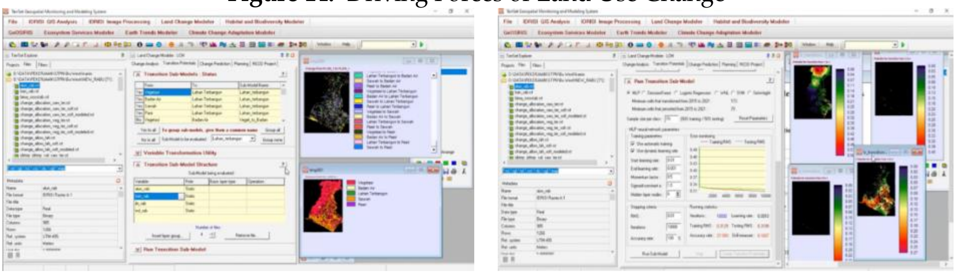
Figure 13.
Calculation of Gain and Losses in Land Change Modeler



Source: Processed by Author

The land use change analysis data generated in this study are the basis for predicting future land use change. Furthermore, in the Land change modeller, what is relied upon is the transition potential, which contains the process for conversion from one land class to another, for example, paddy fields turning into sand, built-up land, vegetation, or water bodies. The conversion process in this stage is carried out for all other types of uses, namely water bodies, built-up land, vegetation, and sand, changing to different uses. At this stage, the transitional potential process is quite complex, as each land use can be converted quickly and accurately. In addition to using inputs in the form of multitemporal land use as the basis for compiling the transition potential, the modelling also requires the driving factors of land use change. This research uses several driving factors in the form of road networks, government centres, airports, industries, and population density as input data formatted as raster data. The following are the drivers used in land use prediction modelling.

Figure 14. Driving Forces of Land Use Change



Source: Processed by Author

Data-driven input in modelling is integral to formulating predictions of future land use. The selection of driven data is adjusted to the region's conditions and based on several previous literature reviews. The road network is one of the driving factors that often affects the increase in land use change. The study area shows that the accessibility of roads, especially some national roads / provincial roads/district roads, is a factor that encourages land use change. In addition, the industry, which is primarily centred in the Sentolo Sub-district, is also very influential in increasing land use change. The medium-scale and large-scale industrial centres in Sentolo Sub-district trigger the growth of several settlements, shops, services, and other supporting facilities, so the development of built-up land is increasing in this area. Likewise, the government centre in Pengasih Sub-district also triggers the growth of various public facilities and supporting infrastructure, a magnet for people to live and settle around these locations.

In addition to the factors mentioned above, a strong driving factor in Kulon Progo Regency is the construction of an airport and various other supporting facilities that have caused this area to become a new growth centre for developing multiple economic activities. The construction of hotels, road extensions, shopping complexes, services, warehousing, and land conversion continues to occur massively. The promising economic value, the availability of various facilities, and the increasing number of workers around the airport will trigger the growth of settlements and their supporting facilities, undoubtedly increasing the need for land.

In the next stage, the input data of land use change and the driving data are processed for transition potential through the back propagation (BP) learning algorithm through a Multilayer Perceptron Neural Network. In this process, the MLP artificial neural network performs analysis with several layers, including input layers, hidden layers, and output layers. In the next stage, researchers use the Markov chain algorithm, which makes probability transitions. In this research, the probability in the Markov chain will provide an overview of the possibility of land use change in the future. The technique used in the Markov chain to analyse future events is done mathematically (Rizanti and Soehardjoepri, 2017; Shen et al., 2020). The concept used in the Markov chain is to plan changes in variables that occur in the future based on changes in variables that occurred in the past, and by analysing the state-to-state movement affected by variables in a specified period (Andry, 2015).

In land use change research, marcov chain analysis is one of the most frequently used methods (Girma et al., 2022; Alemneh & Biazen Molla, 2022). Modelling land use change through marcov chains in this research uses the following formula:

$$P = Pij = \begin{bmatrix} P_{11} & P_{12} & \cdots & P_{1n} \\ P_{21} & P_{22} & \cdots & P_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ P_{n1} & P_{n2} & \cdots & P_{nn} \end{bmatrix} .(0 \leq P_{ij} \leq 1). \quad (3)$$

Where:
P = transition probability matrix
Pij = probability of land use I changing to land use j over the years from the starting point to the target point
N = number of land use classes

Land use predictions can be conducted more rapidly and accurately using the aforementioned equation, particularly when supported by compatible computing systems. The Markov Chain algorithm is among the preferred methods adopted by many researchers. For instance, Man et al. (2019) emphasized that the Markov Chain method effectively accounts for transitional characteristics between events and achieves higher accuracy compared to other algorithms.

Following the outlined stages and procedures, a spatial land use prediction model for 2030 was generated. The prediction results indicate a significant increase in built-up land, especially surrounding Yogyakarta International Airport (YIA) and the industrial zones in Sentolo District. The study also analyzed land use conversions from non-built-up land (such as rice fields, water bodies, vegetation, and sand) to built-up areas within Kulon Progo Regency.

The model reveals that the most extensive changes occur in paddy fields and vegetated areas. The spatial pattern of land use transformation tends to be concentrated around the airport and major transportation corridors, such as the national and southern crossroads. This trend suggests that infrastructure development and industrial expansion are key drivers of land conversion in the region. The quantitative data on the predicted land use areas are summarized in a corresponding table.

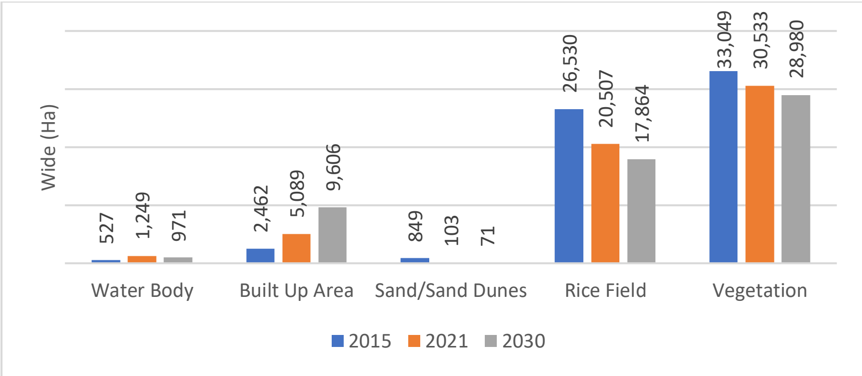
Table 4. Predicted Land Use in 2030

No	Land Use	Wide (Ha)
1	Bulit Up Area	9,606.42
2	Water Body	971.62
3	Sand Dunes	71.74
4	Rice Field	17,863.88
5	Vegetation	28,980.45

Source: Processed by Author

Meanwhile, the following graph shows the periodic pattern of land use change from 2015 to 2021 and predictions for 2030.

Figure 18. Land Use Data 2015, 2021, and 2030 Prediction



Source: Processed by Author

The results of land use prediction modelling, as shown in Figures 17 and 18, are essential for policymakers/government in formulating land stewardship regulations and for consideration in planning and developing the region. This prediction data can also determine the correct location for people or investors to invest. Choosing a strategic and suitable location to build and grow a business is one of the keys to obtaining optimal economic benefits. Land use change and prediction data can also be used to monitor land use and utilisation, map the level of suitability and unsuitability of land use, and evaluate land management. The land use prediction modelling produced in this research can be integrated with regional spatial plan data so that it can be used to predict future land unsuitability. This data is an integral part of formulating how mitigation needs to be done to reduce land conversion, plan and protect sustainable food agricultural land, maintain the sustainability of protected areas, and forest areas.

The database used to build land use prediction modelling can also be integrated with other spatial data so that it can be used to conduct further analysis, including determining the level of carbon emissions, determining agricultural productivity, determining damage to ecosystems, etc. The ability of artificial intelligence in machine learning and deep learning in this research can provide a predictive picture of land use, so that the optimisation of land use to encourage economic growth while still paying attention to environmental aspects can be realised. With this mechanism, the concept of land stewardship, where land has a vital role in the development of economic growth, and land, which also plays a crucial role in environmental sustainability, becomes inseparable, where both have a powerful reciprocal relationship. Both interests can be answered through artificial intelligence, where various complex data, data with large capacity, and multitemporal data can be accurately analysed, elaborated, and modelled as a basis for formulating land and natural resource management policies.

The land use prediction modelling findings in this study indicate that future green infrastructure development faces various challenges. The increasing demand for land is influenced by socio-economic policies, increasing population, the level of land suitability, and people's preferences for land resulting in high pressure on vegetated land and agricultural land as studied by Susilo, (2017); Utami et al., (2023). The concept of green infrastructure by integrating social, economic, and environmental sustainability is fundamental, as studied by (Huang et al., 2025). However, realising this requires many challenges because land has economic value, which is often still the main priority for development.

4. Conclusion

Land use change is influenced by very complex and dynamic drivers. Land use changes are influenced not only by location factors such as proximity to airports/industrial areas/city centres/road access, social (population) and economic factors, but also by policies and the roles of actors with interests in the land. Land use prediction modelling in this study is one of the mechanisms to provide information on the extent, pattern, spatial distribution, and form of future land use. The land use projections produced in this study show that massive infrastructure development and economic growth in the study area are increasingly suppressing the existence of vegetated land (mixed gardens, forests, greenbelts) and agricultural land.

The reduction in vegetation cover from 2015 to 2021, which covers an area of 2,495 ha and is predicted to decrease further by 1,572 ha in 2030, has implications for ecosystem changes and threatens environmental sustainability. Reducing vegetation cover, which has not been offset by efforts to create proportionate green space, is a challenge to achieving development. The prediction results show that 2030 there will be massive land use in the form of built-up areas, especially around the YIA airport and the industrial area in the Sentolo district. This prediction map can determine the correct location for the community or investors to invest, as choosing a strategic and appropriate location is one of the keys to achieving optimal economic benefits.

In addition, land use predictions can be used to monitor land use and utilisation, map the level of suitability and unsuitability of land use, and evaluate land management. The predictive map of future land use is also essential to formulating mitigation policies in suppressing land conversion, planning and protecting sustainable food agricultural land, maintaining the sustainability of protected areas/natural habitats, and preserving the environment. This research still has limitations, so future research needs to analyse how the land use prediction scheme can integrate the balance and optimisation between socio-economic aspects and environmental sustainability.

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Appendix 1.

Land Use in Kulon Progo Regency in 2015 and 2021 (Ha)

No	District	Water body (Ha)			Built Up Area (Ha)			Sand dunes (Ha)			Rice Field (Ha)			Vegetation (Ha)		
		2021	2015	Δ	2021	2015	Δ	2021	2015	Δ	2021	2015	Δ	2021	2015	Δ
1	Galur	205.11	102.42	102.68	371.52	118.15	253.36	28.04	20.08	7.96	1,952.07	2,243.91	-291.85	590.24	662.41	-72.16
2	Girimulyo	41.39	2.96	38.44	354.28	131.83	222.45	0.09	0.27	-0.18	771.40	843.19	-71.79	4,455.96	4,644.88	-188.92
3	Kalibawang	58.06	26.37	31.68	315.33	132.55	182.78	3.30	0.87	2.43	794.73	1,107.03	-312.29	4,115.62	4,020.22	95.40
4	Kokap	147.36	109.79	37.58	207.13	224.61	-17.48	1.15	792.96	-791.81	839.66	5,914.71	-5,075.06	5,846.77	5,914.71	-67.94
5	Lendah	108.54	45.18	63.36	474.64	130.00	344.64	3.44	0.85	2.59	1,329.01	1,743.25	-414.24	1,793.68	1,790.03	3.65
6	Nanggulan	78.70	15.59	63.12	343.54	158.93	184.61	0.58	0.97	-0.39	2,314.41	1,966.06	348.35	1,265.85	1,861.54	-595.69
7	Panjatan	132.92	32.64	100.28	315.31	174.33	140.98	18.31	5.01	13.30	2,698.79	2,754.91	-56.12	1,224.73	1,423.18	-198.45
8	Pengasih	98.13	4.56	93.57	550.32	419.82	130.50	2.51	0.74	1.77	2,465.19	2,262.58	202.61	3,223.71	3,652.15	-428.45
9	Samigaluh	19.87	5.22	14.65	484.89	91.01	393.88	0.27	0.09	0.18	399.37	780.63	-381.26	5,608.63	5,636.08	-27.44
10	Sentolo	144.14	44.32	99.82	623.85	317.11	306.74	6.77	2.57	4.21	2,793.77	2,552.89	240.88	1,524.11	2,175.75	-651.64
11	Temon	148.53	108.86	39.67	649.74	214.52	435.22	24.65	6.85	17.80	2,208.08	2,473.13	-265.04	620.37	848.02	-227.65
12	Wates	66.71	29.14	37.58	398.92	350.06	48.87	14.19	17.87	-3.68	1,941.21	1,888.00	53.21	283.76	419.73	-135.97
Total		1,249.45	527.03	722.42	5,089.47	2,462.93	2,626.54	103.30	849.13	-745.83	20,507.70	26,530.29	-6,022.60	30,553.44	33,048.69	-2,495.25

Source: Land Use Map Analysis 2015 and 2021