



Land Use Change Analysis Using Plugin MOLUSCE in Yogyakarta Urban Agglomeration Area

Dian Hudawan Santoso^{1*}, Puryani², Tissia Ayu Algary³, Moch. Chaeron⁴, Ichlasul Kevin Hilmi⁵
^{1,3,5}Department of Environmental Engineering, Faculty of Technology Mineral and Energy, UPN Veteran Yogyakarta, Indonesia

^{2,4}Department of Industrial Engineering, Faculty of Industrial Engineering, UPN Veteran Yogyakarta, Indonesia

Email: ^{1*}dian.hudawan@upnyk.ac.id, ²puryani@upnyk.ac.id, ³tissiaayu@upnyk.ac.id, ⁴m.chaeron@upnyk.ac.id, ⁵kvnhilmi@gmail.com

Abstract

Rapid and dynamic changes in land use have the potential to impact a variety of environmental and socio-economic factors. This research endeavors to project land use change in the Yogyakarta Urban Agglomeration Region in 2024 and 2026 by leveraging image analysis technology. The proposed methodology involves the implementation of image analysis through the utilization of the MOLUSCE (Modeling Land Use Change) plugin and Artificial Neural Networks (ANN). The MOLUSCE plugin facilitates the modeling and simulation of land use change, informed by historical data and environmental variables. The employment of ANN enhances prediction accuracy by leveraging its sophisticated and non-linear data processing capabilities. The satellite image data from recent years was processed to identify patterns of change and their driving factors. The analysis of land use change between 2024 and 2026 in the study area revealed a substantial increase in built-up land, amounting to 9.03%, indicative of the proliferation of urbanization. Conversely, green open space witnessed a substantial decline of 25.96%, signifying the conversion of green land into built-up land.

Keywords: Land Use, MOLUSCE, Urban, Spatial.

1. INTRODUCTION

The development of urban areas has an impact on changes in the region's surroundings. The most pronounced impact is experienced by areas directly adjacent to it with the city center, both positive and negative impacts. Movement of activities in Yogyakarta urban agglomeration area is very dynamic regarding changes in physical aspects, economic, and social. The urban agglomeration area is a transition zone that occurs in suburban areas. Urban agglomeration brings several changes important, such as changes in land use, water and soil resources, degradation of the environment, and so on (Lee, J., & Kim, K., 2022). Urban agglomeration areas are experiencing rapid development, especially from in terms of infrastructure in line with the city's development (Miller, J. R., & Frazier, P. S; 2018). Growth in numbers. The increasing population has resulted in high levels of development of facilities and infrastructure, including the need for shelter/housing. Jha, M. K., & Bandyopadhyay, S. (2019) explains that the growth of urban areas triggers the loss of agricultural land, so that farmers' livelihoods and provision of food source land for the community decrease. The pace of development also causes land changes vegetated to non-vegetated (Hsu, Y., & Liu, H., 2019).

Urban agglomeration areas are areas that are formed from the existence of various centres of activity grouped in one particular location (Fang et al., 2017). According to the central place theory, various activities in a location tend to merge at the centre of the

region. Examples of agglomeration of settlements, industry, trade and services (Fang et al.,2020). The city of Yogyakarta and its surrounding area is one form of settlement agglomeration due to population growth. According to the Yogyakarta spatial pattern plan, the agglomeration area includes Sleman and Bantul regencies, which are called the Yogyakarta Urban Agglomeration (APY). According to Garcia, L. A., & Suárez, C. (2020), agglomeration is defined as a set or combination of two or more centres of activity that can be grouped in one particular location. Agglomeration itself can be an agglomeration of settlements, industries, trade and services, and others. Which, can grow past an area's administrative boundaries to form a new area that does not have good planning. Agglomeration areas themselves can be formed because various activities that influence each other at a certain location are centred at a certain point, which results in the emergence of savings from locations that are close to each other (Almeida, C., & Silva, R., 2020).

The Yogyakarta Urban Agglomeration Area consists of Kapanewon Depok, Kapanewon Mlati and Kapanewon Gamping are included in the Regency administration Sleman, then Kapanewon Pengasih, Kapanewon Sewon and Kapanewon Banguntapan included in the Bantul Regency administration. The location of the Kapanewon-kapanewon directly adjacent to the city of Yogyakarta. These kapewon include In the Yogyakarta Urban Agglomeration area, there is significant development significant because there is a lot of mixing of activities between urban and rural characteristics, making it vulnerable to the impact of expanding urban activities. Sleman Regency as part of the APY area certainly experienced this significant development of residential areas. This is what attracts people developers and individual communities to build houses on land which is still available. The development of residential areas causes this to happen the increasing intensity of land use, especially the pattern and direction of development settlements and will also ultimately increase the density of motorized vehicles impact on changes in ambient air quality.

The Yogyakarta Agglomeration Area is experiencing regional development caused by several factors that indicate the level of development success. The level of regional development is also caused by factors such as area, distance to the capital, district or city, road width, distance to social, population and economic centres that support the area. (Valent., 2021). The development of urbanisation has occurred spatially in this area, which is caused by the conversion of land from agricultural land to built-up land. Based on (Valen, 2021) there has been a change in the area of settlements in the APY area in Sleman Regency, experiencing an increase of 471.55 Ha or 4.98% of the total 9467.16 Ha of total land use area. This land change is dominated by the Ngemplak sub-district of 79.63 Ha with changes in vacant land to settlements of 48.12 Ha and agricultural land to settlements of 31.76 Ha. Based on the journal, agricultural land use change experienced a significant decrease in land use at 586.59 Ha. This can occur because agricultural land use is converted into built-up land. Thus, the use of built-up land that experienced significant changes was in settlements and service trade, which experienced changes worth 471.52 Ha and 158.24 Ha respectively.

The growth of the Yogyakarta agglomeration area in Yogyakarta Special Region Province continues to increase every year, one of which is also caused by the amount of population growth. According to data from Bappeda (2018), the total population in the Special Region of Yogyakarta reached 3,818,521 people spread across 5 districts/cities. This number increased from the previous year by 1.33%. Based on the journal Nuraeni (2020), the average population increase was 1.25% every year for the last 4 years. Yogyakarta city area has the highest density of 13.448 / km² and is one of the city's built

up areas (Built Up Area) while Yogyakarta City itself is the smallest land with a value of 1.02%.

Landsat imagery was used to analyse the information presented from the maps to determine the problems arising from the development of agglomeration areas. The purpose of this analysis is to find out the basic problems, causes and relationships between different variables to encourage the formation of changes due to urban agglomeration in Yogyakarta. The unmanaged development of agglomeration areas will lead to changes in land use from agricultural to built-up land, which will result in social and economic environmental problems.

2. METHOD

This research was conducted in the Yogyakarta Urban Agglomeration Area which includes parts of Sleman Regency, parts of Bantul Regency and Yogyakarta City. The Yogyakarta urban area was chosen due to the growing population which in turn is predicted to affect land use change in the study area.

The data used in this study are Landsat 8 OLI/TIRS satellite image data of the Yogyakarta agglomeration area in 2018, 2020, 2022, and 2024.

Image data processing using Qgis version 2.8.1. which has the Mollusce plug-in feature. This mollusce plug in can be used to analyze land cover changes from year to year. The stages of the research are shown in Figure 1.

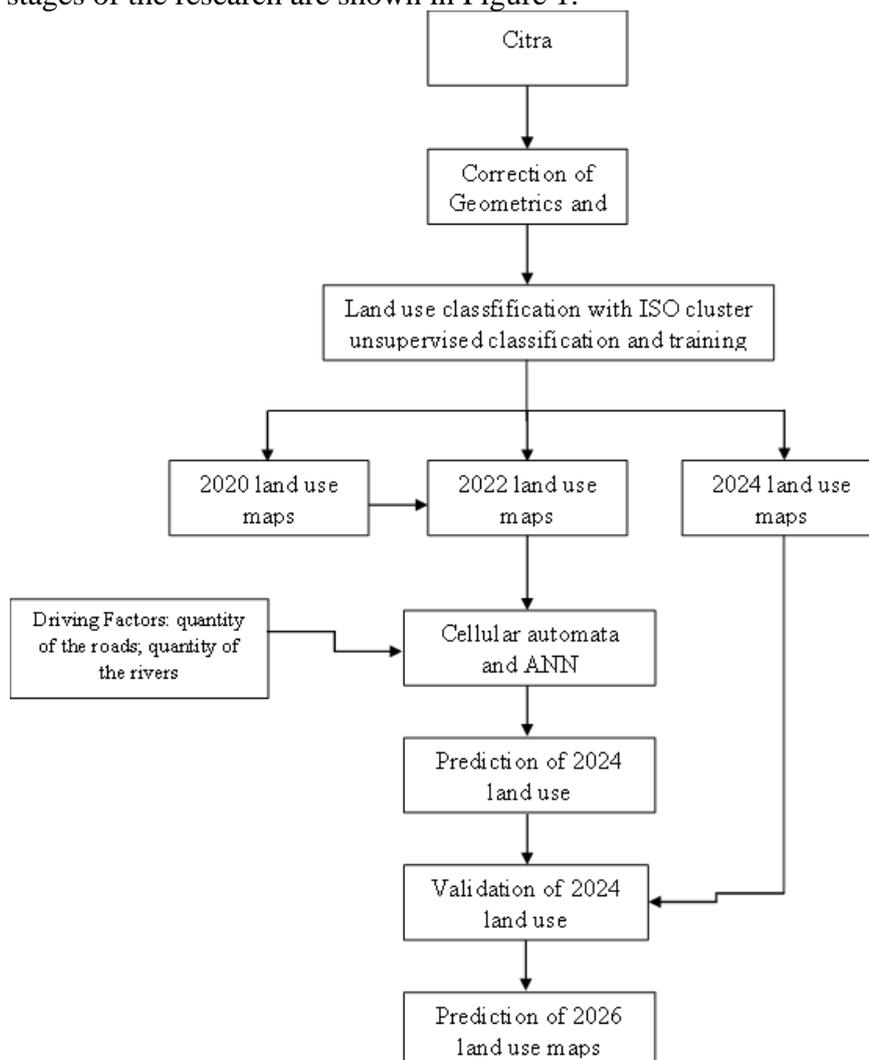


Figure 1. Stages of the research

This land use classification stage uses secondary data in the form of Landsat 8 OLI/TIRS satellite imagery, then image data obtained from USGS is carried out Band Classification on the arctoolbox feature to combine 4-3-2 band satellite imagery which produces false color then defines the band to 3-2-1 to become true color imagery, the results can be seen in Figure 2. After that, the projection is changed, because the satellite still uses a geographic system so it requires changing to 49S which is the zone of Yogyakarta and its surroundings, then the projection results are clipped so that the image is only in the agglomeration area so that it can better understand the land use contained in the map. The result needs to be ISO unsupervised classification and sample training so that it can be converted into land use. Satellite Imagery 2018 Band 3-2-1 is shown in Figure 2.

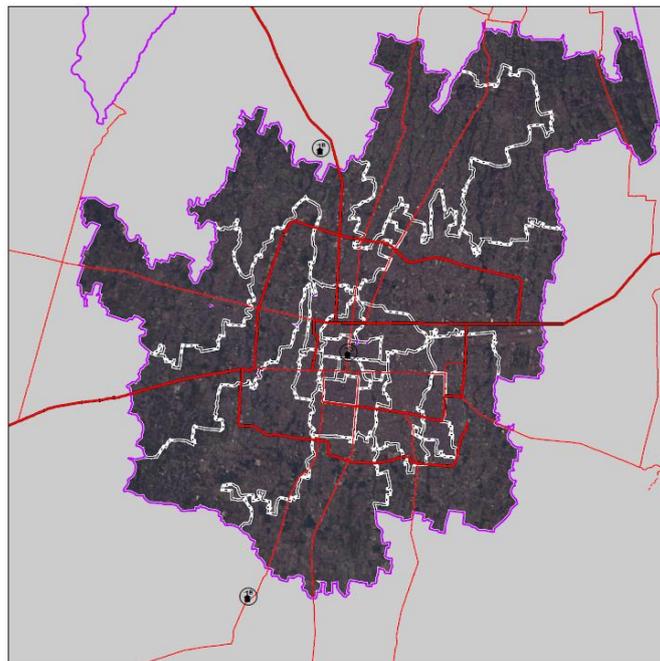


Figure 2. Satellite Imagery 2018 Band 3-2-1

3. RESULTS AND DISCUSSION

Modeling land use change using Cellular Automata with MOLUSCE Plug In Modeling can be done using QGIS 2.18 Software with a Plug In called Modeling of Land Use And Change (MOLUSCE). In using this plug in, a driving factor is required before modeling. The driving factors used in this study are roads and rivers that supply land use needs and facilitate every activity that encourages the development of agglomeration areas.

These roads and rivers need to be made into Tagged Image File Format (TIFF.) data to determine the extent of the value of the number of roads and rivers. This change can be felt from the change in the transition value which, has a range of 0-1, while 0.01 to 0.09 indicates that there is a change in land use, while the value between 0 and 1 does not indicate a significant change. Projections of land use change can be initiated using the MOLUSCE method:

1. Model Input: This process requires the entry of initial and final satellite data, namely in the Initial section which is the year 2020 and Final which is the year 2022.

2. Area Change: At this stage the results of the transition matrix are equalized to show the magnitude of possible land use changes that can occur. The area change is shown in Figure 3.

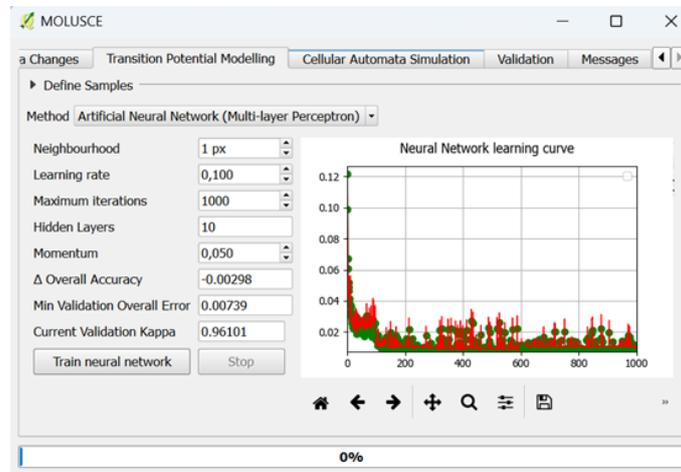


Figure 3. Area Change

3. Transitional Potential Modeling: Regression model generated by the Artificial Neural Network method. This value shows the level of overall accuracy to find out how much accuracy the results of the mollusce process have to detect land use in 2020 and 2022, the result is 0.02 with a kappa coefficient value of 0.96.

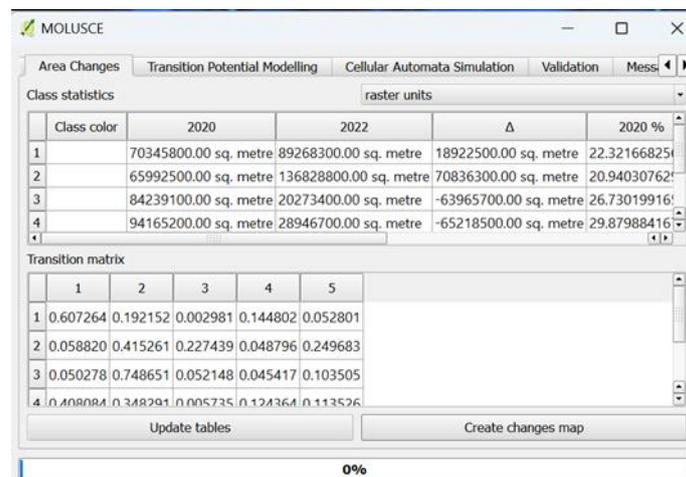


Figure 3. Transitional Potential Modelling

4. Cellular Automata Simulation: This land use modeling is used to find out how far from the estimated land use will be made by setting the number of simulation iterations worth 2 or indicating 2 years of final data.
5. Model validation: Model validation is needed to determine the accuracy of the results of land use projections by comparing them with existing land use images during the year. The results show a kappa value of 0.009 which means the results are still not entirely correct, this can be seen in the percent correctness which is only 35 percent which means that the results cannot be trusted, this can occur due to various things such as errors in driving factors or from Artificial Neural Networks that have not worked properly because this ANN relies on artificial intelligence in projecting to the next few years. The validation is shown in Figure 4.

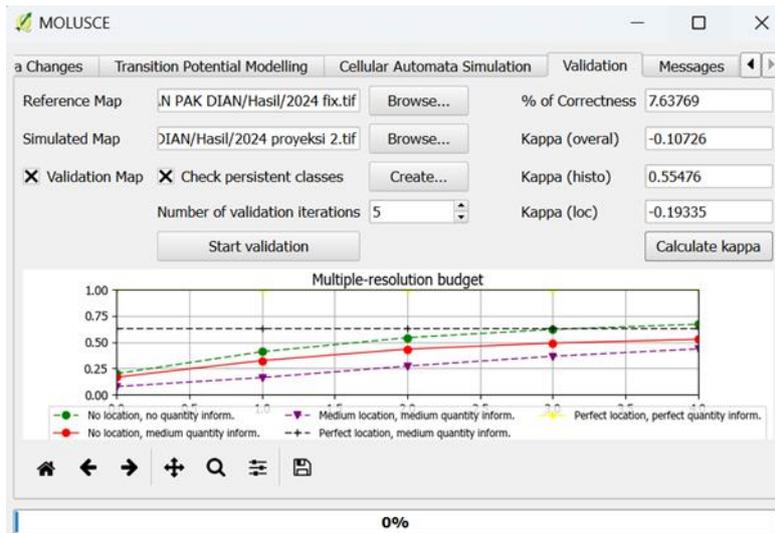


Figure 4. Validation

Rapid and uncontrolled land use change can cause environmental, economic, and social threats. Land cover change can be predicted by image interpretation and remote sensing combined with geographic information systems. The problem of land use change will always arise if it is not mitigated from the beginning, hence the importance of analyzing land use change. The map of land use change 2024 is shown in Figure 5.

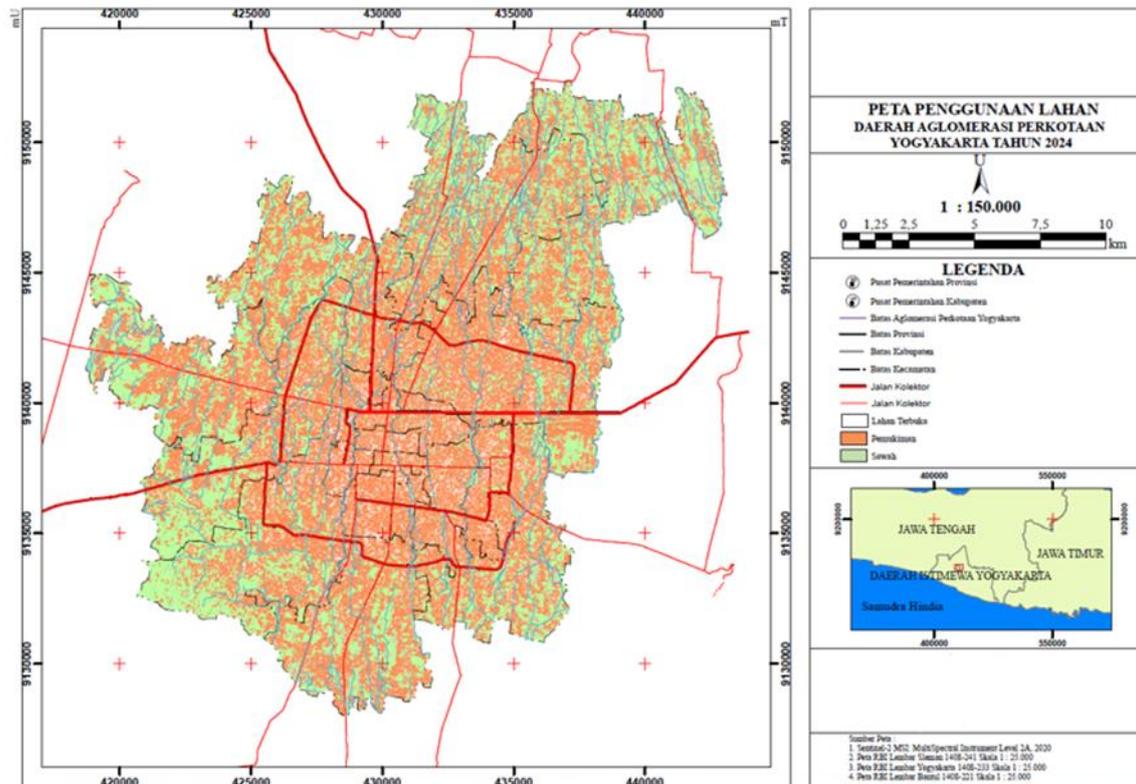


Figure 5. Map of Land Use Change 2024

Making a land use change analysis map using the help of existing satellite imagery LANDSAT 8 OLI/TIRS in the year obtained from the USGS. Satellite images used are from 2018, 2020, 2022, and 2024. Satellite images will be converted into land use maps with the help of the sample training feature in arcGIS, then the first 2 years, namely 2018

and 2020, are used as experimental material and test the accuracy of the plug in land use change analysis, namely MOLUSCE with Qgis 2.18 and then projected and then do the same thing on the 2022 and 2024 maps to project them further into the future. The map of land use change projections 2026 is shown in Figure 6.

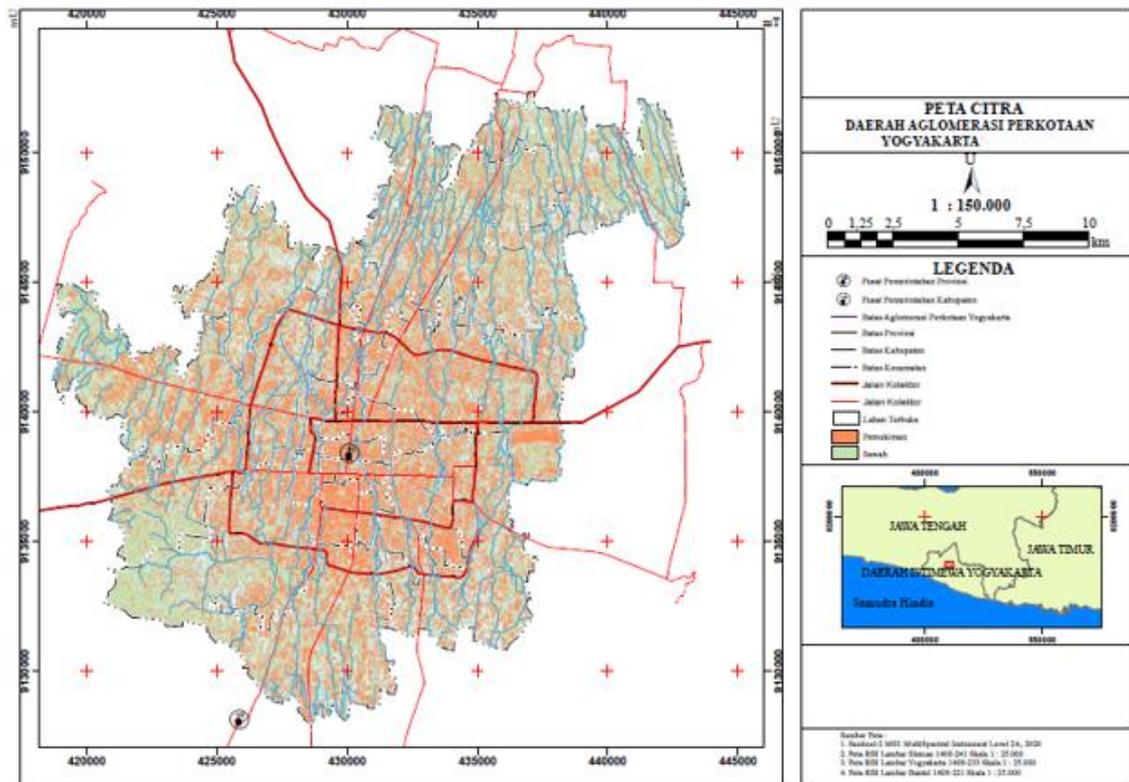


Figure 6. Map of Land Use Change Projections 2026

As shown in Table 1 and Table 2, in the period 2024 to 2026, the area of Built-up Land shows a significant increase. Based on the data, there is an addition of 17,665 ha or around 9.03%. This increase indicates an expansion of development, which could include housing, infrastructure, or commercial areas. This phenomenon generally occurs in urban areas that experience population growth and the need for space for economic activities (Hansen., 2018).

Table 1. Land Use Area in 2024

No.	Land Use Type	Area
1.	Built-up Land	195,691 ha
2.	Green Open Space	135,009 ha
3.	Vacant Land	19,462 ha

Table 2. Projected Land Use Area in 2026

No.	Land Use Type	Area
1.	Built-up Land	213,356 ha
2.	Green Open Space	99,959 ha
3.	Vacant Land	36,847 ha

In contrast, Green Open Space (RTH) experienced a fairly drastic decline during the same period. This decrease of 35,050 ha or about 25.96% could indicate the conversion of green land into built-up land. This trend often occurs in areas experiencing rapid urbanization (Swain, et al., 2017), where green land is sacrificed to support

economic growth (Scott & Smith., 2017). This decline can have an impact on environmental quality, such as reduced water catchment areas (Hewett, et al., 2020) and increased air pollution (Shaddick, et al., 2020).

Meanwhile, Vacant Land experienced a very significant increase of 17,385 ha, or almost 89.33%. This increase could be due to a change in land status from green open space or agricultural land to land that has not been optimized. This vacant land often appears as land that is awaiting a change in status or licensing to be developed into a built-up area in the future.

Overall, the data shows an urbanization trend that leads to an increase in built-up land at the expense of green open space. This reflects the high urbanization pressure in the region. However, the considerable increase in vacant land also indicates that there are potential areas that have not been fully utilized, which could be the focus of future spatial and environmental policies.

In the study of land use change, the quantity of infrastructure-such as roads and rivers-exerts a significant influence on the underlying factors. Roads, for instance, play a pivotal role in enhancing accessibility to specific regions, thereby prompting the conversion of land from green open spaces or agricultural land into built-up areas, encompassing residential and commercial developments. Research indicates that an increase in the number of roads often correlates with rapid urban expansion, where previously inaccessible regions begin to experience substantial development. The presence of rivers, in addition to providing aesthetic value, is crucial as a vital water resource for communities. In this context, the analysis of the impact of these two elements on land use change can be conducted through satellite data modeling to identify emerging transition patterns.

In regard to the thresholds or specific distances employed in models to analyze land use change, this paper observes that transition values are established within a range of 0-1. Values between 0.01 and 0.09 are indicative of significant changes in land use. This parameter reflects the importance of proximity to infrastructure when examining areas undergoing transformation to gain a deeper understanding of urbanization dynamics. The MOLUSCE model, which is employed in this research, utilizes an artificial neural network (ANN) approach to accurately predict potential transitions based on these driving factors. This modeling approach encompasses not only the quantity of infrastructure but also the quality and the distance from infrastructure relative to other strategic locations. As a result, more valid and comprehensive predictions regarding future trends in land use are produced.

The ramifications of alterations in land use are intricate, encompassing substantial environmental, social, and economic repercussions. The expansion of urban areas often results in a decrease in green open spaces, which can have detrimental effects on local ecosystems and biodiversity. The loss of natural habitats can lead to a disruption in ecological balance, contributing to the emergence of phenomena such as urban heat islands, altered water drainage patterns, and diminished air quality. Moreover, as urban areas expand into previously undeveloped land, the risk of habitat fragmentation and loss of wildlife corridors is increased.

The social implications of urban expansion, characterized by the development of built environments, are not monolithic. While increased development may provide more housing options and improve access to services for growing populations, it can also lead to gentrification processes that displace long-standing communities. This displacement can further exacerbate social inequalities, as marginalized groups may find themselves compelled to relocate due to rising property values and living costs associated with urban development.

From an economic perspective, the expansion of built-up areas can potentially stimulate local economies through the creation of jobs and the enhancement of infrastructure. However, this growth may not be sustainable if proper management practices are not in place. The heightened demand for resources, such as water supply, becomes more pronounced with higher population densities resulting from urbanization. Furthermore, the transition from agricultural or green spaces to commercial or residential developments has given rise to concerns regarding food security, as arable land undergoes diminution.

Incorporating a comprehensive discussion on these implications provides a holistic understanding of how changes in land use impact various facets of life within affected regions. It underscores the necessity for sustainable planning approaches that consider environmental preservation alongside economic growth and social equity when addressing future land use changes within the Yogyakarta Urban Agglomeration Area.

4. CONCLUSION

From the analysis of land use change between 2024 and 2026 in the study area, it can be concluded that there was a significant increase in built-up land by 9.03%, reflecting the expansion of urbanization. On the other hand, green open space experienced a drastic decrease of 25.96%, indicating the conversion of green land into built-up land. The 89.33% increase in vacant land indicates the existence of underutilized land, which may be developed in the future. This emphasizes the importance of balanced spatial management to maintain environmental balance and support sustainable development.

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