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Analysis of Prediction of Land Availability in Residential Areas Using the Cellular Automata Method in Batangan District

Rizka Nurhaimi Ayuningtias[1*], Ayomi Dita Rarasati[2]
[1,2]Universitas Indonesia, Depok, West Java, Indonesia
Email: rizkaayunungtias@gmail.com[1*], ayomi@eng.ui.ac.id[2]

ABSTRACT
The land cover change will be impacted by population growth and its activities. This research aims to predict land cover change in the Batangan sub-district from 2013 to 2033. The method used is quantitative, based on satellite image data, followed by cellular automata modeling using the MOLUSCE plugin on QGIS software. The land cover themes used are open areas, built-up areas, forests, water bodies, agriculture and livestock, and transportation. Spatial variables that are considered to influence the prediction results are road networks, built-up areas, agricultural land, and water bodies. The predicted land area that can be used for settlements in 2033 is 272.81 hectares, while the land required for settlements based on population projections with additional labor due to the existence of industrial allotment areas is 840.74 hectares. This results in a shortage of land for the development of residential areas of 567.93 hectares, which should be a concern for the local government in making policies for residential areas in the Batangan sub-district. The implications of this land cover change also need to be considered in the environmental and social contexts.
Keywords: Land Cover, Prediction, Settlements.

INTRODUCTION

Land functions to meet human needs and their activities. Human activities are growing rapidly and diversely, which is not balanced by the limited availability of land, resulting in the convention of undeveloped land becoming built land Land use change refers to human activities carried out to meet socio-economic needs such as settlements and infrastructure (Kumar et al., 2023; Monsaputra, 2023). Land Use Land Cover (LULC) management plays an important role in overcoming environmental problems in line with the global population growth of 9.7 billion people by 2050 (United Nations, 2022).

The increase in population encourages changes in land use and land cover leading to the expansion of built-up areas and cultivation areas by reducing the area of forest areas (Obiahu et al., 2021; Wang et al., 2021). Land use change and land cover are the result of a complex interaction between socioeconomic, environmental and institutional factors (Blissag et al., 2024). In addition to population growth, industrial development can lead to a reduction in agricultural land and an increase in built-up land. This land conversion will affect the land cover pattern which changes the spatial pattern around the industrial area (Muslim et al., 2023; Naikoo et al., 2020).

Approaches to the method of modelling land cover change include MCE (multi-criteria evaluation), MLP (multi-layer perceptron), SLEUTH (slope, land use, exclusion, urban extent, transportation, and hillshade), LR (logistic regression), ANN (artificial neural network), and GWR (geographic weighted regression). The ANN method is one of the transition potential models contained in MOLUSCE (Modules for Land Use Change Simulations) developed for QGIS (Penfound & Vaz, 2024). ANN is a technique used in predicting land cover/land use change maps. Land cover maps were obtained based on the cellular-automata (CA) method approach which will be validated by the kappa correction test (Atef et al., 2023; Sankarrao et al., 2021). The advantages of the CA model are that it can be simple, flexible, intuitive, and can combine variable data spatially and temporally (Blissag et al., 2024).

Previous research was conducted by Hapsary; Subiyanto; and Firdaus (2021) to predict land change using the artificial neural network (ANN) approach contained in the MOLUSCE plugins in QGIS software. In this study, using the ANN method produced a kappa accuracy value greater than the logistic regression method (Nhu et al., 2020). So the research conducted by the author uses the ANN method to predict land cover in Batangan District for the next 10 years, namely 2033 (Hapsary et al., 2021).

Currently, the company PT Hwa Seung Indonesia has been built there with a workforce need of 26,602 workers. The growth of industrial companies and immigrant labour, will affect the need for land for residential areas but is limited to other land functions, especially agricultural and aquatic functions (DPMPTSP Pati, 2023; Hossain & Huggins, 2021) Therefore, this study aims to determine the land cover in 2033 and the availability of land that can be used for residential areas.

RESEARCH METHODS

Study Location

Batangan District is one of the sub-districts in Pati Regency located in the eastern coastal area. The north is bordered by the Java Sea, the east is bordered by Rembang Regency, the south is bordered by Jaken and Jakenan Districts, and the west is bordered by Juwana District. This sub-district is one of the largest salt production centres in Indonesia spread across several villages such as Pecangaan Village, Mangunlegi Village, Lengkong Village, Jembangan Village, Bumimulyo Village, Ketitangwetan Village, and Raci Village (Ulfa et al., 2021).

The method in this study is quantitative with a spatial approach. This approach uses MOLUSCE which is one of the plugins in QGIS software. The steps in land cover prediction are (1) input of land cover data in 2013 and 2018 as well as spatial variable data, (2) evaluating correlations using Pearson's correlation method, (3) transition potential modelling, (4) cellular automata simulations, and (5) validation (Lukas et al., 2023).These stages are carried out to obtain a land cover prediction map in 2033.

Pearson's correlation can be calculated using Equation 1. Where rxy is Pearson's correlation coefficient, ∑xy is the sum of the multiplication of the variables x and y, n is the number of samples, and S is the standard deviation. The coefficient value has a range between -1 to 1. The correlative value of -1 is negative between the two variables, the value of 0 has no correlation, and the value of 1 has a positive correlation (Leni et al., 2023)

Kappa accuracy test to measure the accuracy of prediction of land cover change assisted by confusion matrix (Muhammad et al., 2016).The kappa test formula in equations 2 to 3. The interpretation of the value of the kappa coefficient can be seen in Table 1.

Kappa = ... 2

Kappa Loc = ... 3

Kappa Histo = ... 4

Table 1. Kappa Test

Coefficient value	Interpretation
< 20	Poor
2,21 – 0,40	Fair
0,41 – 0,60	Moderate
0,61 – 0,80	Good
> 0.81	Very Good

Population Projections

The analysis determines the population projection in the next 10 years by using an exponential method that has a higher level of accuracy for assuming continuous population growth. The following is the exponential projection formula in equation 5:(Rahmi , 2017)

$Pn = P_{0ern}$ or P_t = P0ert 5

Information:

Pn or P_t = total population in year n or t

P0 = total population in the first year
r = population growth rate
n or t = time period in years
e = 2.7182818 (the prime number of the natural algorithm system)

Data

The data used is a land cover map that has been processed from a SPOT6/7 image map to a raster type map. There are 6 types of land cover at the study site, namely open areas, fasum building areas (public facilities), forest areas, aquatic areas, agricultural and livestock areas, and transportation areas. The development of land cover area can be seen in table 1. from 2013, 208 and 2023.

Table 2. Land cover area of Batangan District in 2013, 2018, and 2023

Land Cover	2013 (ha)	2018 (ha)	2023 (ha)
Open Area	919,67	975,90	975,90
Fasum Building	262,85	270,95	270,95
Forest	31,71	31,72	31,72
Waters	2067,94	2057,68	2057,68
Agriculture and Livestock	2430,94	2376,10	2376,10
Transportation	38,68	39,43	39,43

Source: SPOT image mosaic data 6/7, 2024

The land cover depicted from 2013, 2018, and 2023 can be seen in figure 2. As illustrated that in the north of the study location is a water area that has an area of almost 36%. Meanwhile, the area of agriculture and livestock is 41% in the central to southern part. Land cover changes were not very visible spatially in 2018 and 2023.

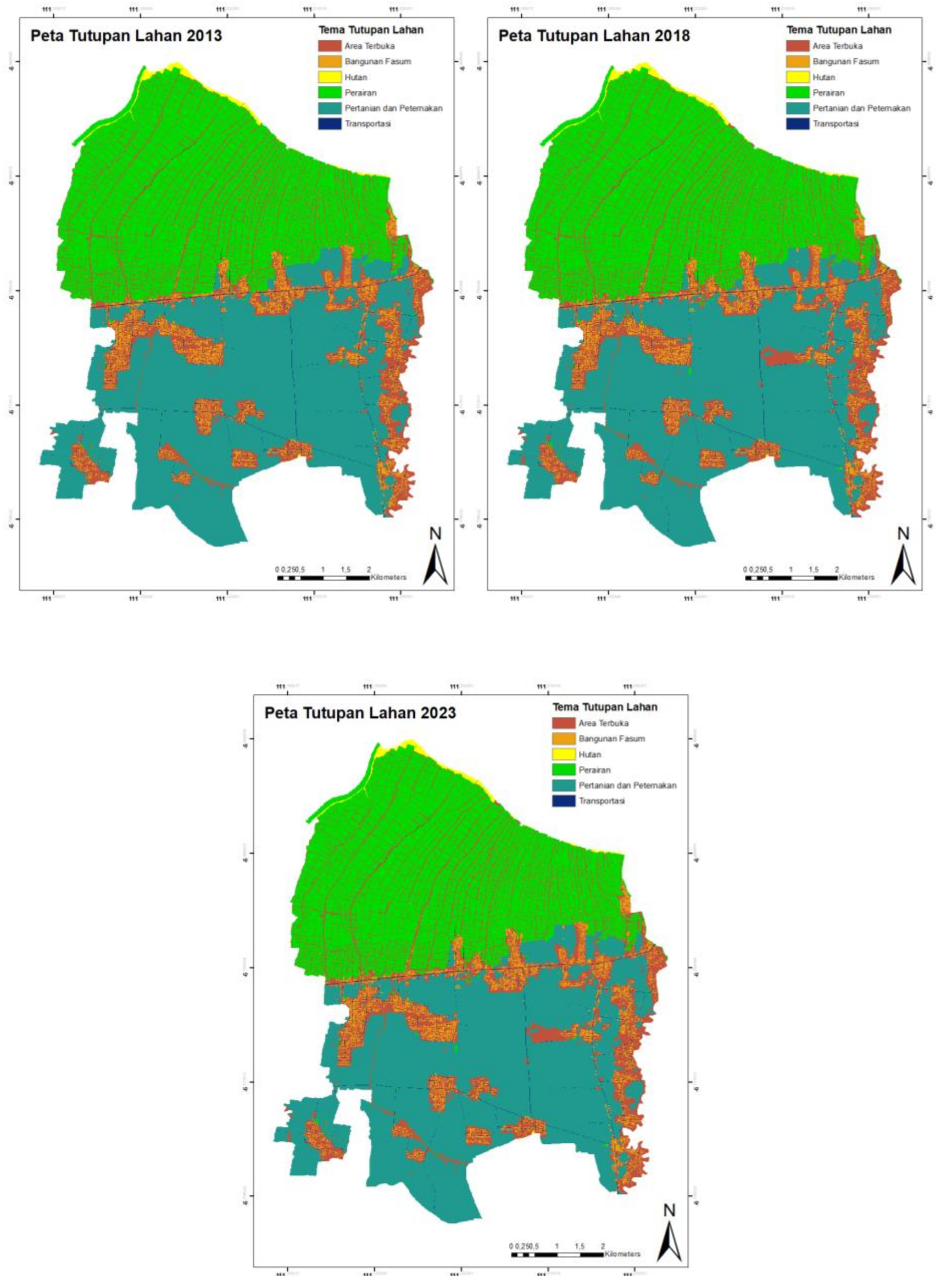


Figure 1. Land cover map of Batangan District

Source: SPOT image mosaic data 6/7, 2024

Discussion

The spatial variables used need to be processed in ArcGIS software using the Euclidean distance method with an output cell size of 5 because the map used is a 1:5,000 detail scale map as shown in Figure 4. Euclidean distance is used to calculate the distance from each cell at its nearest source. This tool is used on each spatial variable in this study. The result is a raster map in Figure 5. As basic data used for the land cover prediction process. Each of the spatial variable maps after analysis produced 5 distance criteria. The results of the Euclidean distance analysis can be seen in the chart Table 2.

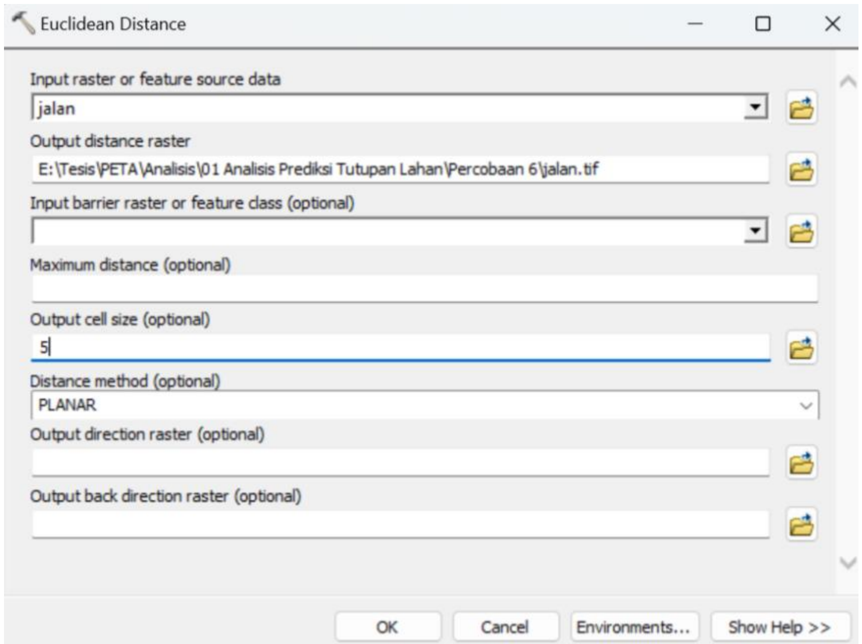
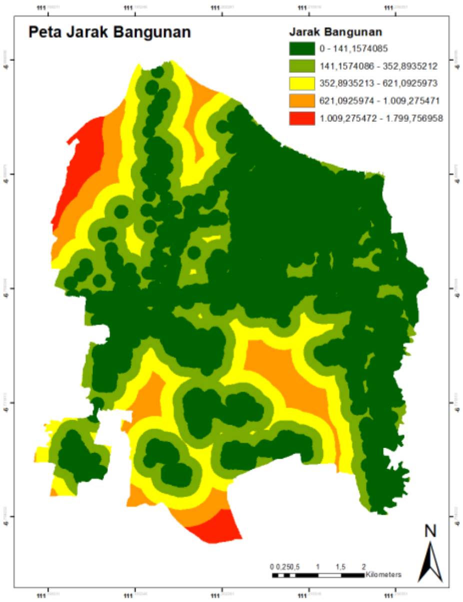


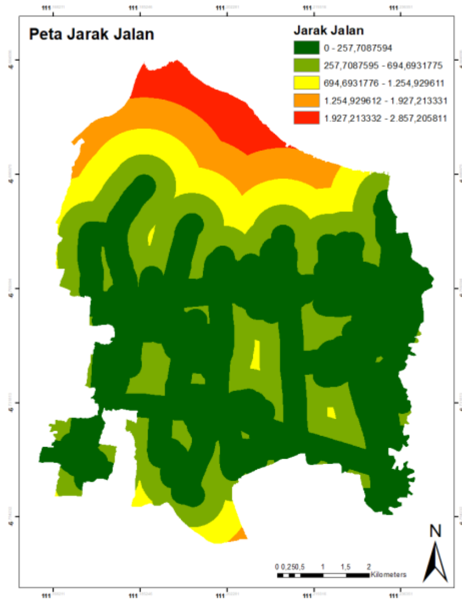
Figure 2. Euclidean Distance in ArcGIS

Source: author, 2024

Table 3. Euclidean Distance Results

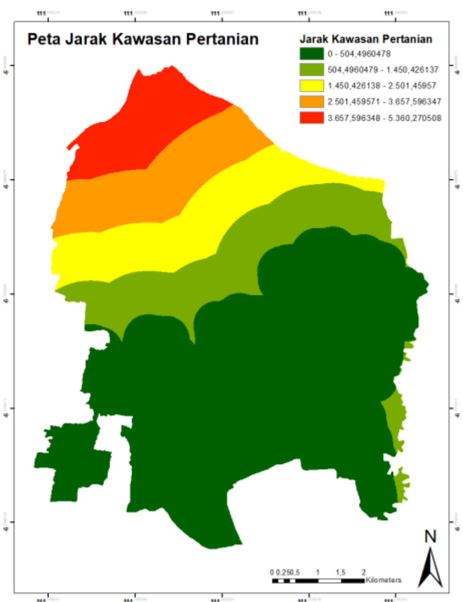
The results of the building distance map show that in the northern left and south ends where there are few buildings so there is a red color.	On the road distance map, it can be seen that the northern part has a red color which means that there are no roads compared to other areas at the study site.

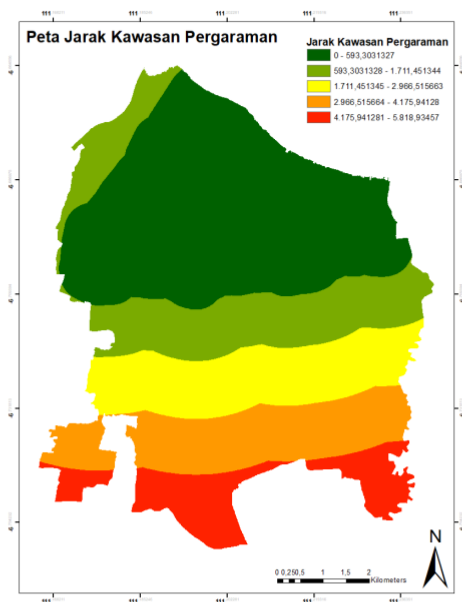




The further north it goes, the redder the color which indicates that the agricultural area only exists from the central part to the south.

The salt area is concentrated in the central to northern part so that the central part to the south and the northern part on the left do not have these areas.





Source: author, 2024

The results of Pearson's correlation (table 4.) in the modeling for the variables of salt areas with roads and salt areas with agricultural areas have negative values, which means that between the two variables there is a negative correlation. The salt area and the road have a negative correlation because there is no road network in the salt area so that the two variables do not correlate with each other. Agricultural areas and salt areas also have a negative correlation because they are located in two separate areas, the salt area is in the north area while the agricultural area is in the southern area.

Table 4. Pearson Correlation Results

Spatial Variables	Road	Salt Areas	Building	Agricultural Area
Road	..	-0,35	0,29	0,75
Salt Areas		..	0,22	-0,57
Building			..	0,24
Agricultural Area				..

Source: author, 2024

The change in area (table 5.) that occurred in the land cover in 2013 and 2018 from this modelling showed a change in the decrease in the land cover of the built-up area of buildings and public facilities by -0.96%. The area of aquatic land cover also decreased by -0.17%. The land cover that has increased in area is the open area land cover of 0.97%.

Table 5. Area changes on the 2013 and 2018 maps

Land Cover Theme	2013 (sq. meter)	2018 (sq. meter)	Δ (sq. meter)	2013 %	2018 %	Δ %
Open Area	9159925,00	9716375,00	556450,00	15,93	16,89	0,97
Fasum Building	24290300,00	23740350,00	-549950,00	42,23	41,27	-0,96
Forest	317025,00	317025,00	0,00	0,55	0,55	0,00
Waters	20637825,00	20538000,00	-99825,00	35,88	35,71	-0,17
Agriculture and Livestock	425775,00	433925,00	8150,00	0,74	0,75	0,01
Transportation	2688050,00	2773225,00	85175,00	4,67	4,82	0,15

Source: author, 2024

In the transition potential modeling stage, the method used is an artificial neural network (multi-layer perception). The neighbourhood used is 1 pixel, learning rate 0.100, maximum iterations 1000, hidden layers 10, and momentum 0.050. The validation result of kappa is 0.91 so that this model can be used for the automata cellular simulation model to predict land cover maps in 2033 (Iskandar et al., 2024).

Table 6. Transition Potential Modelling

Neighbourhood	1 px
Learning rate	0,100
Maximum Iterations	1000
Hidden layers	10
Momentum	0,050
Δ Overall accuracy	-0,00693
Min. validation overall error	0,01745
Current validation kappa	0,91297

Source: author, 2024

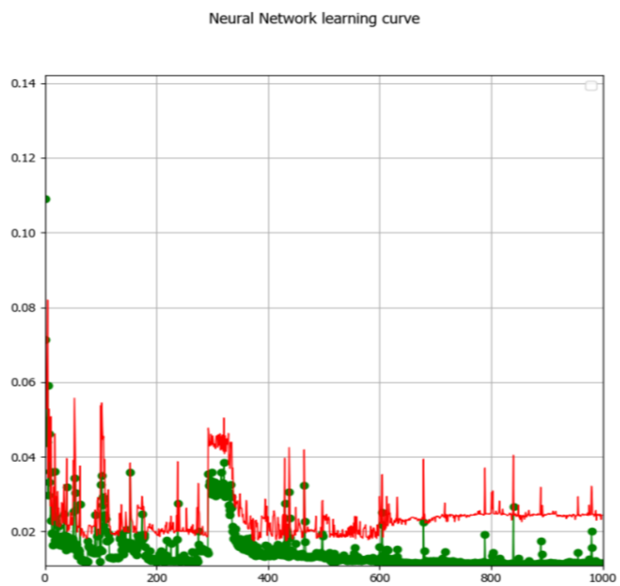


Figure 3. Spatial Variables

Source: author, 2024

The result of the Kappa correction test in prediction modeling is 1 with a percentage of 100% (table 7.). The results interpret that the map modeling carried out has a very good correction rate. So that it is well-validated and can be used for modeling simulations.

Table 7. Area changes on the 2013 and 2018 maps

% of correctness	100
Kappa (overal)	1
Kappa (histo)	1

Kappa (filter)	1

Source: author, 2024

Changes in the land cover area of the modeling process can be seen in the table above in the land cover of buildings, public facilities, and aquatic land. The open area has increased by 60.71 hectares. The types of open areas at the study site are sports fields, cemeteries, grasslands, yards, hardened surfaces/fields, shrubs, vacant land, and mixed plants. The land cover that experienced the largest decrease in area was agriculture and livestock covering an area of 54.84 hectares as shown in Table 8. and shown in figure 6.

Table 8. Changes in land cover area on the 2013 and 2018 maps

Land Cover	Area (hectares)		Gap 2013-2023
	2013	2033	
Open Area	919,67	980,38	60,71
Fasum Building	262,85	272,81	9,96
Forest	31,71	30,01	-1,71
Waters	2067,94	2053,27	-14,67
Agriculture and Livestock	2430,94	2376,10	-54,84
Transportation	38,68	39,22	0,53

Source: author's analysis, 2024

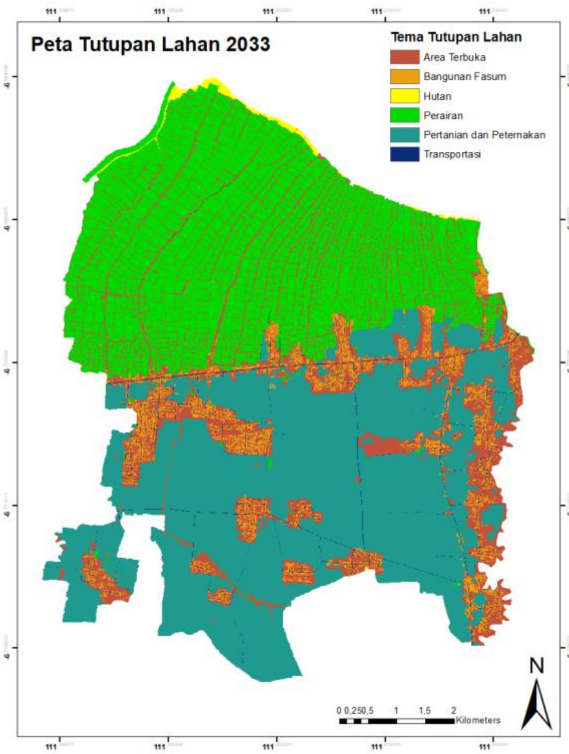


Figure 4. Spatial Variables
Source: author, 2024

CONCLUSION

The land area based on the prediction results of cellular automata that can be used as a residential area is 272.81 hectares. Meanwhile, the area of land needs in residential areas is according to the projected population with an increase in labor of 840.74 hectares. The lack of land availability for residential areas of 567.93 hectares needs attention from the local government to provide a policy for residential areas in Batangan District in the form of vertical residential areas by considering economic and social conditions that need to be studied more deeply in the next study.

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