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RESEARCH ARTICLE

Prediction and Simulation of Land Use and Land Cover Changes Using Open Source QGIS. A Case Study of Purwokerto, Central Java, Indonesia

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Abstract Population size multiplies along with the increasing need for residential space. As often occurs in developing cities like Purwokerto, population growth is associated with land use/land cover (LULC) change to accommodate housing demand both in the present and future. Therefore, this study was intended to map LULC changes in three different years: 2008, 2013, and 2018, and predict the change in 2023. For LULC data extraction, a pixel-based digital classification with a maximum likelihood algorithm was applied to Landsat images. In addition, the LULC change prediction was modeled with Modules for Land Use Change Simulations (MOLUSCE) from the QGIS plugins. It used two algorithms: artificial neural network (ANN) with a multilayer perceptron (MLP) and cellular automata (CA). The LULC classifications for 2008, 2013, and 2018 were 88%, 86%, and 88% accurate, while the prediction was 75.26% accurate, with a kappa of 0.634. Predictions and simulations indicate fluctuations in LULC change in the City of Purwokerto periodically, especially for built-up land, showing growth that continues to increase significantly.

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1. Introduction

Land use and land cover change (LULC) change is one of the indicators for urbanization process. The influence of human activities on landscape is the main driving factor for the LULC change process in an urban area (Liu et al., 2020). LULC change is related to environmental change and ecological shift, the expansion of built-up land will encourage the loss of green space, loss of agricultural land, and affect the local urban climate to increase the regional economy (Muhammad et al., 2022).

The simulation model helps to know the transition of changes in the past to the present, to find out the transition patterns and generate predictions in the future from the detected transition patterns. Several simulation models of change and spatial distribution that are successful in predicting the direction of change in LULC are Markov-chain, cellular automata, cellular automata-artificial neural network, and artificial neural network-Markov chain (Kaswanto et al., 2021; Muhammad et al., 2022). MOLUSCE is able to perform LULC change prediction can be modeled with the artificial neural network (ANN), specifically multilayer perceptron (ANN-MLP), and cellular automata algorithms.

Purwokerto is developing through the trade and service sector. The development was triggered by the regional identity as the best educational area and its history as a trade transit center between the eastern and western parts of Java. A study by Munggiarti and Buchori (2018) found that the existence of a public campus at the Universitas Jendral Sudirman in Purwokerto also increased the change in LULC by 81.2% in a radius of 1 Km. The spatial structure of Purwokerto gives rise to a corridor area along the road that expands the function of urban land. Through the Regional Medium-Term Development Plan, every five-year period a development policy is established to achieve long-term development. In this study, detection of changes in LULC was carried out according to the RPJMD period, namely 2008 to 2013 and 2013 to 2018 to determine the transition process.

The spatial-temporal approach produces geographical patterns and temporal patterns caused by several driving factors. Pattern identification requires time series data containing information on the spatial distribution of landscape changes. Remote sensing data capturing landscape changes in particular pixels because each pixel captures responses to geographical features of the electromagnetic spectrum (Jensen, 2015). Remote sensing satellites have captured the earth's surface for decades and produce huge data sets that are real time and time series. Integrating remote sensing with GIS is applied in this study using open source QGIS. The application of MOLUSCE still needs to be explored, so it helps to develop the proper use of the open-source MOLUSCE method widely.

Modeling in MOLUSCE uses two sets of data: LULC and driving factors its change. These factors include the distance from the city center, distance from the river, distance from the main road, slope, and elevation. The selection of driving factors is considered from the spatial structure of the Purwokerto city area and the influence of terrain conditions which are mountainous landscapes. Mapping of LULC changes in the city of Purwokerto can be used as a recommendation in the city development as the proposed new autonomous region. For this reason, the study aimed to map the LULC condition in 2008, 2013, and 2018 and predict LULC changes that would potentially occur in 2023 in PNAR Purwokerto.

2. Methods

Study Area

The research location is proposed new autonomous region (PNAR) Purwokerto (Figure 1), part of the regional expansion plan of the Banyumas Regency (Radar Banyumas, 2020). It consists of nine districts: Purwokerto Timur (the proposed capital district), Purwokerto Utara, Purwokerto Barat, Purwokerto Selatan, Kembaran, Sumbang, Baturraden, Karanglewas, and Kedungbanteng. Adminsitratively, PNAR Purwokerto belongs to the Province of Jawa Tengah, Indonesia. PNAR Purwokerto is 256.17 km^2 in area, with the largest district, Kedungbanteng, covering 60.22 km^2, the city lies about 0 to 3,100 meters above sea level (masl) and is topographically characterized by flat to very steep slopes (BPS Kabupaten Banyumas, 2019).

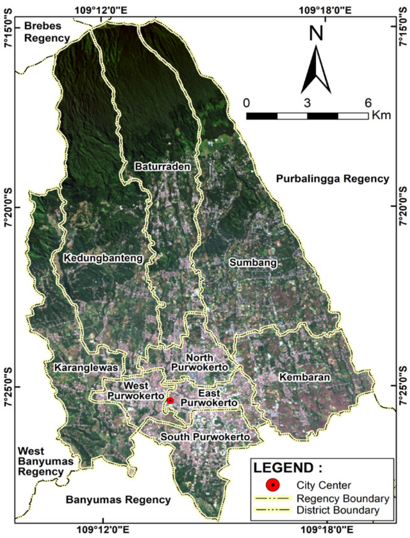


Figure 1. Study Area

Data Collection

The LULC conditions in three different years were determined from Landsat 5 Thematic Mapper (TM) image data recorded in 2008 and Landsat 8 Operational Land Imager (OLI) image data in 2013 and 2018 available at the U.S. Geological Survey (USGS) (Table 1). In addition, the Shuttle Radar Topography Mission (SRTM) Digital Elevation Model (DEM) with a spatial resolution of 30 meters (Table 2) was used to determine the elevation and slopes in the study area. In addition, shapefile data from the Geospatial Information Agency (BIG) is also needed such as the RBI Map of Banyumas Regency data. The image data used had been geometrically and radiometrically corrected. The use of the corrected image data is to obtain a good image quality with the appropriate pixel values and geographic positions of the pixels.

Classification

In this research, the LULC classification refers to the 2014 SNI (Indonesian National Standard) of the National Standardization Agency (BSN) for mapping LULC on a 1:100,000 scale with some modifications. The use of the 2014 SNI BSN is based on the image data used with a spatial resolution of 30 meters which is classified in the medium resolution category so that it is suitable for use at an optimal scale of 1:100,000 (SNI BSN, 2014). The LULC classes are built-up land, open land, agricultural land, water body, and vegetation (Table 3).

The Landsat 5 TM in 2008 and Landsat 8 OLI in 2013 and 2018 were used in the LULC classification. Maximum likelihood algorithm is use for pixel-based classification. Maximum likelihood classification is used because it can consider the average value between bands and also the diversity between one class and another to minimize errors in LULC classification. Then, a majority filter with a moving window size of 3x3 was applied to the classification to obtain homogenous pixels and remove isolated pixels (Danoedoro, 2012). Confusion matrix is used for determining the accuracy of the result classification, by spreading stratified random points. The field data were obtained from interviews, observations of a collection of Google Earth images, and direct observations in the field. Because the Covid-19 pandemic management-initiated population movement control and, thus, restricted measurements directly in the field, the research samples were tested through Google Earth imagery. Ramadhani & Susilo (2016) stated that Google Earth has the smallest object extraction capability of 0.67 meters so it can be used for sample testing using medium-resolution images such as Landsat.

Table 1. Research Data and Data Sources

Data	Acquired Information	Providers	Sources
Landsat 5 TM Image in 2008	LULC in 2008	USGS	https://earthexplorer. usgs.gov/
Landsat 8 OLI Images in 2013 and 2018	LULC in 2013 and 2018		
Google Earth image of PNAR Purwokerto in 2008, 2013, and 2018	LULC in 2008, 2013, and 2018	Google Maps	https://www.google .com/maps
Shuttle Radar Topography Mission (SRTM) Digital Elevation Model (DEM), 30m resolution	Topography	NASA Earthdata	https://dwtkns.com /srtm30m/
RBI Map of Banyumas Regency, Scale 1:25.000	Geospatial data (in shapefile)	BIG	https://tanahair.indo nesia.go.id/ portal-web

Source: (U. S. Geological Survey, 2019)

Table 2. Satellite Image Properties

Satellites	Sensors	Time of Acquisition	Resolution (m)	Bands
SRTM	Radars	February 2000	30	C, X, L
Landsat 5	TM	July 28, 2008	30	1, 2, 3, 4, 5, 6, 7
Landsat 8	OLI	June 24, 2013	30	1, 2, 3, 4, 5, 6, 7
Landsat 8	OLI	May 5, 2018	30	1, 2, 3, 4, 5, 6, 7

Source: (U. S. Geological Survey, 2019)

Table 3. Land Use/Land Cover Classes

Classes	Descriptions
Built-up Land	Buildings made for residential and/or non-residential purposes, e.g., settlements, multi-story buildings, and factories
Open Space Land	Open or vacant land without buildings or other vegetation covers
Agriculture Land	Land used to produce crops, e.g., irrigated rice fields, rainfed rice fields, and dry fields
Water Body	All bodies of water, e.g., rivers, lakes, and reservoirs
Vegetation	All existing vegetation, except for agricultural plants

Source: (SNI BSN, 2014) with modifications

Table 4. Driving Factors of Land Use/Land Cover Change

Factors	Sources	Classifying Method
Elevation	SRTM DEM (30m resolution)	Ranked
Distance from the main road	Main road data (from BIG, .shp)	Euclidean Distance
Distance from the river	River (from BIG, .shp)	Euclidean Distance
Distance from the city center	Wibowo (2014)	Euclidean Distance
Slope	SRTM DEM (30m resolution)	Ranked

Prediction and Simulation

LULC classification in the three years observed and the driving factors of LULC changes are the two data required for predicting LULC in the coming years. The factors include elevation, slope, and distances from the main road, the river, and the city center. Differences in elevation and slope affect LULC, for example, the elevation in the city is around 0 - 400 meters with flat topographic conditions dominated by built-up land and elevations of more than 700 meters with steep slopes dominated by vegetation. The factor of distance from the main road and the city center also affects LULC, the dominant main road in the city center, and the farther the city center the main road decreases. The main road is dominated by built-up land and the further the built-up land decreases. The distance from the river affects the LULC, many rivers are found in upstream with LULC of vegetation and rivers located at lower elevations, the LULC varies from agriculture, open space, and built-up.

The prediction uses the MOLUSCE plugin of the QGIS software. This plugin can measure the area of change and can predict future LULC with Artificial Neural Network (ANN) methods of Cellular Automata (CA) and Multi-Layer Perceptron (MLP). There are six stages of processing: data input, evaluation of correlations, calculation of area changes, transition potential modeling (TPM), cellular automata (CA) simulation, and validation.

In prediction and simulation, the first stage was to input all relevant data and make sure that the appropriate geometry size. The MOLUSCE plugin will check the inputted data, if the data does not match then it cannot be continued. Second, the driving factors of LULC change were analyzed based on their Pearson correlation coefficients to determine whether or not and to what extent they influence changes. Pearson correlation was chosen because it has clear boundaries in expressing the relationship and is suitable for ratio and interval data types. Third, calculate the change in LULC area and the probability of the transition that occurs. The calculation is obtained from the LULC classification in two different years. Fourth, perform TPM to determine the potential for transition changes that occur using the ANN algorithm, namely MLP. Fifth, LULC change was simulated by inputting data in 2008 and 2013 to the CA algorithm to predict LULC in 2018. The use of CA can model the dynamics of changes between cells that are orderly and interact with each other, where these cells are LULC (Manson, 2001). Sixth, the simulation results of the LULC predictions for 2018 were validated with the 2018 LULC classified using the maximum likelihood. Validation was carried out on the MOLUSCE plugin to determine the accuracy of the LULC prediction data model. According to (Hakim et al., 2019) if the results of the validation of the LULC prediction modeling with an accuracy of more than 75%, it can be continued. Furthermore, simulations were carried out for 2x iterations on the 2013 LULC data with 5-year intervals to produce LULC in 2023 (Al-Rubkhi, 2017). The details of procedure explained in Figure 2.

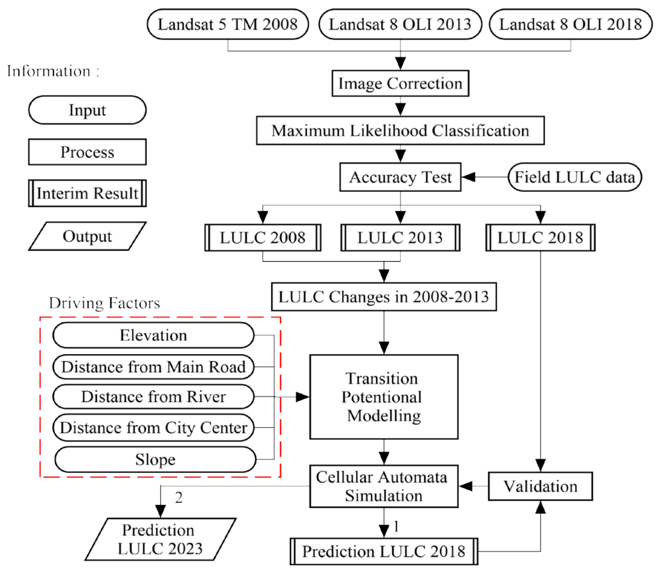


Figure 2. Research Flowchart

3. Result and Discussion

LULC Classification

The LULC classification scheme is based on the 2014 SNI of the National Standardization Agency for 1:100,000 mapping with several modifications totaling five classes, namely agriculture, open space, water body, built up and vegetation classes. The use of the 2014 SNI BSN classification scheme is adjusted by medium resolution image data such as Landsat with a spatial resolution of 30 meters so that it has an optimal scale of 1:100,000 (Saputra, 2020). In the current study, this technique employed the maximum likelihood algorithm, producing five LULC classes for 2008, 2013, and 2018 data with 88%, 86%, and 88% accuracy. With these rates, the classification results meet the minimum requirement for accuracy, 85 % (Anderson, 1971). An accuracy of 85% is considered to have a maximum error rate between the results of the LULC classification and the reference data so an accuracy of more than 85% is still acceptable.

Multitemporal LULC Changes

The LULC conditions in PNAR Purwokerto were constantly changing from one year of observation to the next (2008, 2013, and 2018), as seen in the spatial information visualized in Figure 3. This map shows that vegetation was mainly scattered in the north, particularly on the flanks of Slamet Volcano, where there are only a few influences from human activities. Human activities of course depend on the existing topographical conditions, for example the condition of steep slopes is rare and even there is no human activity, while on flat to gentle slopes many human activities occur. Meanwhile, the built-up land formed a clustered pattern mostly in areas with flat to gently sloping topography, and agricultural land was located on the city outskirts with flat to gently sloping topography. The open space land was found in the east and north, while the water body was not much visible in any of the observation years because it had the least number of pixels among the LULC classes identified in the research.

In line with the multitemporal and spatial dynamics indicated by Figure 3, the information provided in Tables 6 and 7 show that each LULC class in PNAR Purwokerto had a different area in 2008, 2013, and 2018. The condition of the built-up class for 3-year periods continues to expand and spread in all directions. This happened because the City of Purwokerto became a Regional Activity Center (PKW) and the population grew by 8.01% from the period 2008 to 2013 and increased by 6.75% in the period from 2013 to 2018 (Regional Infrastructure Development Agency, 2017; BPS Kabupaten Banyumas, 2019). The increasing population requires space for housing such as settlements and the existence of PKW affects economic activities so that urban growth occurs. Further, several objects identified and classified as open land were agricultural fields that suffered drought impacts, were drained, or had little to no paddy, while some others were building roofs that might have a spectral reflectance value similar to that of open space land. The class of water bodies in the 3 years continues to decline. The decrease was due to the acquisition of image data in May, June, and July, which coincided with the dry season so that the number of existing water bodies could be reduced. Besides, only a few had a surface area of more than 30 m^2, the minimum object size detectable by Landsat 5 and 8. Meanwhile, the vegetation area increased from 109,812,600 m^2 in 2008 to 117,840,600 m^2 in 2013 then decreased to 115,629,300 m^2 in 2018. The increase and decrease in the area of vegetation classes can be caused by misinterpretations such as agricultural land which can be in the form of vegetation. Agricultural land with the conditions such as green mature paddy fields and corn can produce spectral reflectance similar to vegetation. The ripe crop canopy has covered the ground base, it can produce a pure pixel crop canopy without mixed reflectance from soil or water (Hoffer, 1984).

Prediction and Simulation

Evaluating the Correlation between Land Use/Land Cover Change Variables

Changes in existing LULC conditions depend on driving factors. The driving factors are evaluated and the correlation are calculated to determine the relationship between changes LULC transition in 2008-2013 to produce LULC predictions in 2018. Pearson Correlation technique is used because it has clear boundaries and suitable for ratio and interval data types. These driving factors are presented in a map visualization in Figure 4.

Table 8 shows the correlation factor distance from the river has a negative value than other factors. The distance from the main road factor has the highest correlation value,

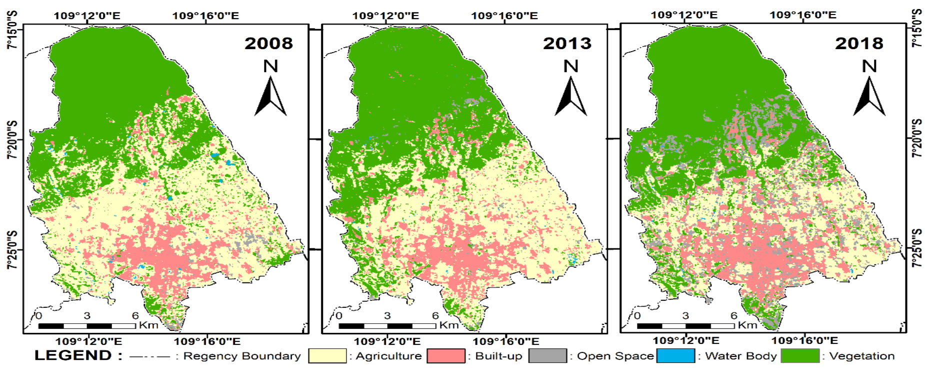


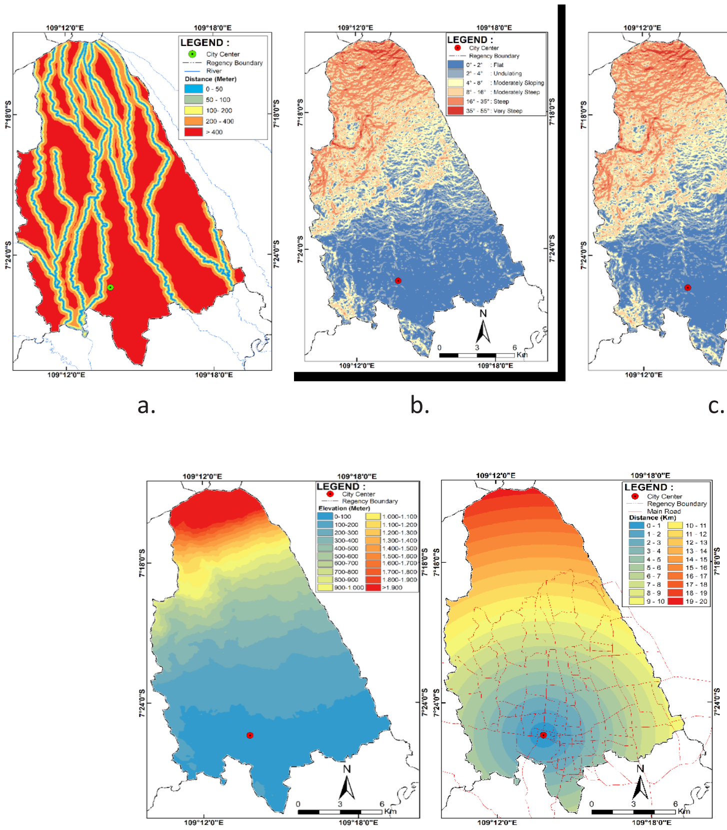
Figure 3. Maps Showing the Multitemporal Land Use/Land Cover Conditions in PNAR Purwokerto

Table 5. Total Area of Each Land Use/Land Cover Class in Square Meters

Classes	Total Areas (m^2)			Temporal Area Changes (m^2)	
	2008	2013	2018	2008–2013	2013–2018
Agricultural Land	110,212,200	99,257,400	66,035,700	-10,954,800	-33,221,700
Built-up Land	34,016,400	37,312,200	42,813,000	+3,295,800	+5,500,800
Open Space Land	4,389,300	4,743,000	34,732,800	+353,700	+29,989,800
Water Body	1,207,800	485,100	427,500	-722,700	-57,600
Vegetation	109,812,600	117,840,600	115,629,300	+8,028,000	-2,211,300
Total	259,638,300	259,638,300	259,638,300	0	0

Table 6. Total Area of Each Land Use/Land Cover Class in Percentage

Classes	Total Areas (%)			Temporal Area Changes (%)	
	2008	2013	2018	2008–2013	2013–2018
Agricultural Land	42.45	38.23	25.43	-4.22	-12.80
Built-up Land	13.10	14.37	16.49	+1.27	+2.12
Open Space Land	1.69	1.83	13.38	+0.14	+11.55
Water Body	0.47	0.19	0.16	-0.28	-0.02
Vegetation	42.29	45.39	44.53	+3.09	-0.85
Total	100.00	100.00	100.00	0.00	0.00



a. b. c. d. e.

Figure 4. Driving Factors: (a) Distance from the River, (b) Distance from the Main Road, (c) Slope, (d) Elevation, and (e) Distance from the City Center

Table 7. Pearson Correlation Coefficient of the Driving Factors of Land Use/Land Cover Change

Pearson Correlation		Distance from			Slope	Elevation
		River	Main Road	City Center		
Distance from	River	-	-0,2132	-0,2477	-0,3393	-0,2928
	Main Road		-	0,6968	0,7602	0,9316
	City Center			-	0,7317	0,7750
Slope					-	0,8845
Elevation						-

namely the correlation between the road variable and the elevation of 0.9316. This value is obtained because the majority of the main roads are at low elevations. The lower the elevation, the more main roads there are. Topographical conditions affect the main road so that changes in LULC can be affected such as the increase in built-up land around the main road in the City.

Area Changes

Calculation of changes in LULC in the period 2013 and 2018 is used to calculate the probability of the transition that occurs. The transition probability is obtained from the calculation of the total area of the current LULC area (T1) which will change to another LULC or not change at the next LULC (T2). The existence of a transition probability value can be used to model the possibility of changes in LULC in the future. Based on Table 9. the largest transition probability value in the vegetation class is 0.8863. This value means that the probability of transition from vegetation class to permanent vegetation is 0.8863. The greater the value of the transition probability, the more likely it is to change and contrariwise.

Table 8. Transition Matrix of Land Use/Land Cover Changes

Transition Matrix	Agriculture Land	Built-up Land	Open Land	Water Body	Vegetation
Agricultural Land	0.7433	0.0581	0.0240	0.0027	0.1719
Built-up Land	0.0976	0.8703	0.0096	0.0001	0.0224
Open Land	0.6260	0.1419	0.1331	0.0010	0.0980
Water Body	0.5060	0.1088	0.0320	0.0410	0.3122
Vegetation	0.0971	0.0050	0.0104	0.0012	0.8863

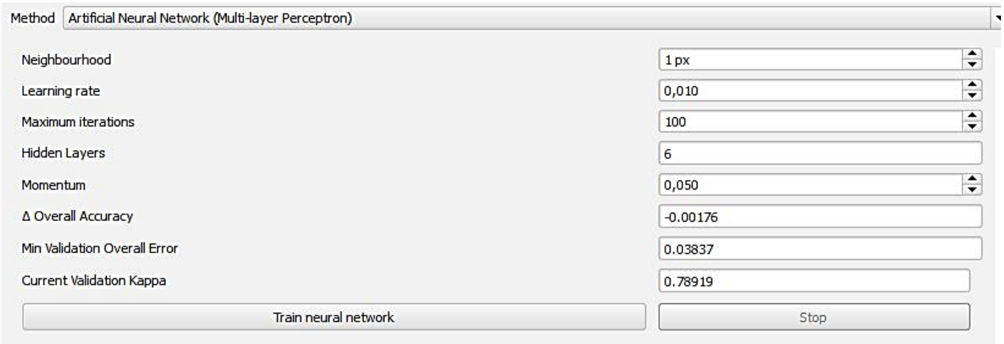


Figure 5. The Result of Transition Potentional Modelling

Table 9. Comparison of the Prediction and Pixel-based Classification Results for 2018

Classes	Areas (m²)		Area Changes (m²)	Area Changes (%)
	Prediction	Maximum Likelihood		
Agricultural Land	96,602,400	66,035,700	30,566,700	11.773
Built-up Land	44,114,400	42,813,000	1,301,400	0.501
Open Space Land	1,967,400	34,732,800	32,765,400	12.620
Water Body	228,600	427,500	198,900	0.077
Vegetation	116,725,500	115,629,300	1,096,200	0.422
Total	259,638,300	259,638,300	0	0

Transition Potentional Modelling

Transition potential modeling (TPM) was used to generate LULC predictions for 2018 with the ANN-MLP algorithm on MOLUSCE. The inputted data were LULC conditions in 2008 and 2013 and the driving factors after the correlation analysis. The results of the MLP modeling in Figure 5 obtained a kappa validation value of 0.789 with an overall minimum error of 0.03837. According to (Cohen, 1960) this value can be used, because it has a kappa value with a strong level of agreement, which is in the range of 0.60 to 0.80. This value is influenced by several factors, such as momentum, hidden layers, maximum iterations, learning rate, and the neighborhood. The value of kappa validation in modeling will be smaller if the momentum, hidden layers, learning rate, and neighborhood factors have greater values because the greater the factor value used, the more generalized the results of the computational value in the MLP process. The maximum iterations factor with more iterations will make the modeling better, but it takes a longer time to compute the process.

Land Use/Land Cover Prediction for 2018 and Model Validation

The TPM modeling with one-time cellular automata iteration resulted in LULC predictions for 2018. The predicted LULC data and the LULC data obtained from the pixel-based classification with maximum likelihood had different areas, as presented in Table 10. The former was validated with the latter, and the results showed that the predicted data had 75.26% accuracy, with a kappa of 0.634. The strong value of kappa indicates that the model can be used to predict LULC conditions in 2023 (Cohen, 1960; Hakim, 2019). The map of the predicted LULC for 2018 is visualized in Figure 6.

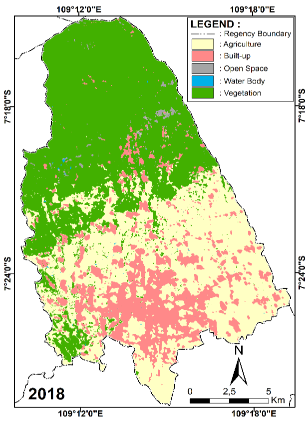


Figure 6. Land Use/Land Cover Prediction Model for 2018

Land Use/Land Cover Prediction for 2023

The CA modeling with two-time iterations resulted in LULC predictions for 2023. Based on Figure 7 (the map visualization of the predicted data) and Table 11 (changes in LULC area from 2018 to 2023), there are substantial differences in the LULC conditions in 2018 and 2023. Agricultural land, built-up land, and vegetation were predicted to have larger areal shares in 2023, whereas open land and water body would decrease in area.

Table 10. Land Use/Land Cover Change in 2018–2023

Classes	Areas (m²)		Area Changes (m²)	Area Changes (%)
	2018	2023		
Agriculture Land	66,035,700	90,845,100	+24,809,400	+9.56
Built-up Land	42,813,000	50,187,600	+7,374,600	+2.84
Open Space	34,732,800	1,939,500	-32,793,300	-12.63
Water Body	427,500	216,900	-210,600	-0.08
Vegetation	115,629,300	116,449,200	+819,900	+0.32
Total	259,638,300	259,638,300	0	0

LULC changes are influenced by the size of the LULC transition matrix value. The open space class for the period 2018 to 2023 is the highest change. This is because the value of the transition matrix for the open space class to agriculture is 0.626 so this value has a large enough probability of change to become agriculture. Meanwhile, the water body class has the lowest change due to the transition matrix value from water body to agriculture of 0.5060 and becoming vegetation of 0.3122.

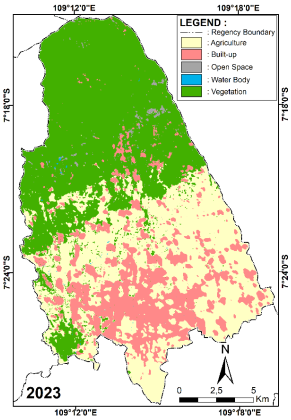


Figure 7. Land Use/Land Cover Prediction Model for 2023

4. Conclusion

The land use/land cover (LULC) in the PNAR of Purwokerto City for 3 periods in 2008, 2013, and 2018 had fluctuating changes, but the biggest change occurred in the agricultural land class. LULC classification have an accuracy of 88% in 2008, 86% in 2013, and 88% in 2018. The accuracy value of the classification results has met the minimum criteria of 85% that have been determined so that it can be accepted and continued. Meanwhile, the results of LULC prediction modeling in 2023 have an accuracy rate of 75.26% with a kappa value of 0.634. The prediction results of LULC 2023 can be accepted because it has a strong kappa value. Changes in LULC that will occur in 2023 are that the class of agricultural land, built-up land and vegetation will increase in area and the class of open land and water bodies will decrease. The increasing and decreasing changes are caused by the size of the LULC transition matrix value that occurs.

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