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Comparison of Land Cover Change Prediction Models: A Case Study in Kedungkandang District, Malang City

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Abstract

The infrastructure of Malang City is currently being directed towards the eastern and southeastern parts, Kedungkandang District. Infrastructure plays an important role in the aspect of land cover change, which raises the complexity of the emergence of urban forms and dynamics. This study compares three models, Artificial Neural Network (ANN), Logistic Regression (LR), and Multi-Criteria Evaluation (MCE), to predict changes in land cover in the Kedungkandang District using the Cellular Automata (CA) approach. The prediction results indicate that the ANN and MCE models have the highest overall Kappa values (prediction accuracy), while the ANN and LR models have the highest location-specific Kappa values. However, overall, the ANN model demonstrates the highest accuracy and performance among the other two models. This research makes a significant contribution to urban planning by highlighting the importance of using machine learning-based technology to predict land cover changes in Malang City, particularly in the Kedungkandang District. Stakeholders can leverage this technology to design more effective and sustainable infrastructure policies and implement preventive measures to mitigate the negative impacts of uncontrolled urban growth.

1. Introduction

Cellular Automata (CA) is a land cover change modeling approach that explicitly calculates urban drivers and influences from the surrounding environment (Campos et al., 2018; Wahyudi & Liu, 2016). Historically, CA has long been used to capture the complex dynamics of land cover change processes created by John von Neumann (1903–1957) during the 1950s. CA is considered the simplest type of dynamic spatial model (Sfa et al., 2020; White & Engelen, 2000) and is a grid-based modeling approach where each cell is in a specific state, in this case, specific land use or cover. Five important components prepared and determined in the CA process, including cell space, cell state, neighborhood, transition rules, and iteration time (Feng et al., 2019). Time runs in discrete time steps. At each time step, all cells update their state simultaneously based on the previous cell state, environment, and transition rules (Qian et al., 2020; van Delden et al., 2011). The core of the CA-based model is the transition rule, where the appropriate transition rule is the main determinant for the ability of a good predictive model (Xing et al., 2020). This transition rule requires several spatial factors of land change to model the transition potential.

Many techniques are used to model transition potential and map transition potential (Dewa et al., 2022; Roodposhti et al., 2019; Sfa et al., 2020), including Weight of Evidence (Campos et al., 2018), Logistic Regression (Campos et al., 2018; Cao et al., 2020; Mustafa et al., 2018; Wang et al., 2019), Multi Criteria Evaluation (Campos et al., 2018; Fu et al., 2018; Gharaibeh et al., 2020; Mohamed & Worku, 2020; Sipahioğlu & Çağdaş, 2023),

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Artificial Neural Network (Campos et al., 2018; Gharaibeh et al., 2020; Li & Yeh, 2001). Support Vector Machine (Campos et al., 2018), and other techniques. Each of these analytical techniques uses structurally different formulations, which will affect the accuracy of the results of modeling land cover changes in CA (Roodposhti et al., 2019). This study tries to compare the predictions of land cover change in Kedungkandang District, Malang City and use three transition potential model techniques, including Artificial Neural Network (ANN), Logistic Regression (LR), and Multi-Criteria Evaluation (MCE).

ANN is considered the best model that relies on artificial intelligence (Gharaibeh et al., 2020) and has a large enough capacity to recognize and classify patterns through the training or learning process (Yeh & Li, 2002). Non-linear relationship between land change factors and the process of understanding complex patterns such as urban growth can be captured by the ANN model very well (Gharaibeh et al., 2020). ANN can be designed to estimate the likelihood of land change and development in each iteration of the simulation in CA based on past trends (Yeh & Li, 2002). However, ANN has major drawbacks, one of which is that it is difficult to understand its internal computation process (Park et al., 2011; Shafizadeh-Moghadam et al., 2017).

In contrast to ANN, the use of LR is quite popular because of its ability to analyze the relationship between land cover changes and the factors that occur quantitatively. In addition, the LR model can also identify the extent to which these factors influence land cover change, thereby enabling researchers to clearly understand the role of various land change factors in the future (Cao et al., 2020). The ANN and LR models in this study are specifically based on machine learning, where there is no researcher intervention in the modeling process. To compare the results between the model generated by machine learning and the model with human intervention, the researchers also considered using MCE. This MCE model substantially relies on expert knowledge and judgment in making the weighting of its spatial factors (Yeh & Li, 2002). Based on this, it can be understood that MCE integrates spatial conditions and human decisions, thereby demonstrating a great ability to measure the comprehensive effects of various factors of resulting land cover change (Yao et al., 2022; Zadbagher et al., 2018)

As a sub-district that has developed rapidly over the last ten years and supported by various infrastructure developments, the changes in the spatial dynamics of Kedungkandang District in the future need to be identified. It is in line with the statement (Shafizadeh-Moghadam et al., 2017), that in carrying out efficient monitoring and management of land cover, knowledge of previous land dynamics, current trends, and predictions of future developments are required. Three techniques in modeling the transition potential in this study are utilized to formulate the best model that can capture the dynamics of change in Kedungkandang District in the future

2. Data and Methods

2.1. Study Area

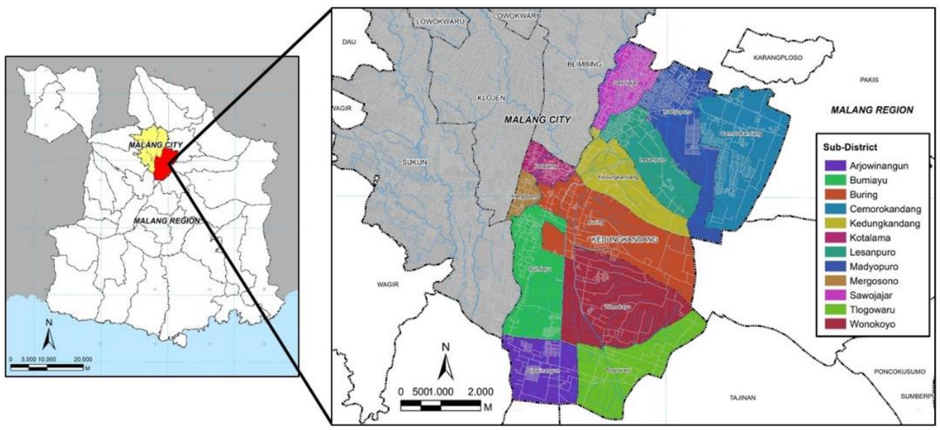
Malang City, as the second-largest city in East Java Province, continues to experience very rapid urban development, in terms of population and land development, as well as the growth of primary and regional activities. This caused settlement development to be pushed towards the outskirts of the city due to the saturation that occurs in the city center (Adrianto et al., 2017). One of the potential areas for settlement development is Kedungkandang District, where the area of non-developed land is the highest in Malang City currently (55% of the total area of undeveloped land). In line with this, historically, Kedungkandang District has also experienced the conversion of non-built land into the highest built-up land in Malang City from 2009 to 2019 (Table 1). It can be indicated that the conversion of non-built land into built-up land in Kedungkandang District has the potential to occur again in the future.

Administratively, Kedungkandang District has 12 sub-districts (Fig. 1), most of them adjacent to Malang Regency. Previous research Rofii (2021) showed an urban sprawl phenomenon in Malang City in 2014 with a type of land spread, ribbon development that leads to outside Malang City, one of which is around the city limits in Kedungkandang District. Based on these conditions, the researcher considers the Kedungkandang District area to have a high urgency to be modelled the dynamics and patterns of land cover changes, so that the Regional Government can take the right policy.

Table 1. Land Cover Change of Non-Built Land to Built-up Land per District in Malang City

District	2009 Land Cover (hectares)			2019 Land Cover (hectares)			Land Cover Change (ha)
	Wet Land Paddy	Non-Wet Land Paddy	Non-Agricultural Land	Wet Land Paddy	Non-Wet Land Paddy	Non-Agricultural Land	
Kedungkandang	619	1,505.31	1,864.69	511	1,207	2,271	406.31
Sukun	322	396.80	1,378.20	181	452	1,464	85.80
Klojen	0	0	883	0	1	882	0
Blimbing	142	7	1,628	75	10	1,692	64
Lowokwaru	311.62	102.44	1,944.10	247	78	1,935	40.18

Source: Malang City Central Bureau of Statistics 2010 and 2020



Source: Author, 2022

Figure 1. Location of Study

2.2. Data Source and Research Framework

Initially, land cover data for three different years were collected to enable analysis of changes over time. Additionally, several spatial factors identified as drivers of land cover changes in Kedungkandang District were also included in the analysis. These factors may include distances from key infrastructure such as main roads or existing urban facilities. The data were gathered from various available open-source platforms and then processed using GIS (Geographic Information System) software, specifically QGIS, to prepare them for further analysis. An innovative aspect of data collecting in this research is the utilization of web scraping or data scrapping technique to retrieve Point of Interest (POI) data from the Google Maps platform. All collected and processed data will be utilized in the simulation process to predict future land cover changes. Detailed explanations regarding the data sources and collection techniques can be found in Table 3.

There are three scopes in the research framework presented in Figure 3. The first scope is land cover map using Landsat 7 and Landsat 8 data. This map is to identify the dynamics of previous land change in Kedungkandang District, namely in 2012, 2016 and 2020. The second scope is to conduct an evaluation with correlations among various spatial factors used to determine only a few spatial factors with the highest relationships. The third scope is the transition potential model from three techniques or models, including ANN, LR and MCE. The last scope is the simulation of prediction of future land cover changes, which is until 2036.

This study will use MOLUSCE (Modules for Land Use Change Evaluation) and LanduseSim as CA-based modeling tools. MOLUSCE is used in the prediction simulation process using the ANN and LR techniques. The prediction simulation process using the MCE technique is using the LanduseSim software. It is due to the limitations and difficulties in using MOLUSCE for the MCE model simulation process. Modeling with the MCE technique used in this study only uses the weights generated from previous studies. So, MOLUSCE is harder to run because it must include a pairwise comparison matrix. Then, by using the MCE model, MOLUSCE can only represent the transition from one class in one simulation process, while LanduseSim makes it easier for researchers to perform simulations by representing all transition classes. The following are the steps for processing CA in this study:

1. Preparation of Land Cover Maps

The study area is divided into cells as the basis of analysis in modeling. Landsat image was generated using the USGS Earth Explorer with a resolution of 30 meters. Pansharpening process is carried out to get a smaller image resolution of 15 meters. It is because the study area only covers the administration of the sub-districts. The land cover map in this study was produced through a land cover classification process based on the appearance of Landsat image using the supervised classification technique. The Semi-Automatic Classification Plugin (SCP), which is an open source plugin in QGIS, is used in the supervised classification process. Land classification uses the five land cover categories described in Table 2. Furthermore, the classification results need to be validated and tested for accuracy, where the validation of the land cover classification is processed with the THRASE plugin with references to GoogleEarth images in 2012, 2016, and 2020. Then, test the classification accuracy of land cover is done using the AcATAMa (Accuracy Assessment of Thematic Maps) plugin, so it can generate Kappa values.

Table 2. Land Cover Categories

No.	Land Classification	Description
1	Built-up areas	Areas undergoing changes or conversions from natural or semi-natural land cover to impermeable and permanent land cover such as buildings, roads, and other pavements
2	Vegetation	Areas that are not cultivated for agricultural activities are generally dry land overgrown with natural vegetation such as forests, shrubs, grass, reeds, and others.
3	Agricultural Areas	Areas that are cultivated for agricultural activities
4	Water body	All water features such as rivers, swamps and others
5	Bare land	Areas that are not covered are either artificial, natural or semi-natural

Source: Author, 2022

2. Modelling the Transition Potential

In creating the transition potential model, various spatial factors of land cover change are required. The spatial factors used in this study include, (1) distance to road networks; (2) proximity to highways; (3) proximity to toll roads; (4) distance to parks/green areas; (5) distance to existing settlements; (6) availability of telecommunication networks; (7) availability of electricity networks; (8) proximity to transportation facilities; (9) distance to educational facilities; (10) distance to healthcare facilities; (11) distance to trade and service facilities; (12) distance to industrial areas; (13) distance to office facilities; (14) distance to city centers; (15) slope; (16) water bodies; (17) boundaries; (18) cultural heritage sites; (19) wetlands; and (20) disaster-prone areas. Furthermore, Pearson correlation was used to measure the relationship between one spatial factor and another (i.e., existing settlement factors with other spatial factors). The correlation evaluation results of various spatial factors of land cover change in Kedungkandang District showed that there are 4 spatial factors that have a strong and positive correlation with the development of existing settlements in Kedungkandang District, (1) distance to electricity networks with a correlation value of 0.66; (2) distance to educational facilities with a correlation value of 0.67; (3) distance to commercial facilities with a correlation value of 0.72; and (4) distance to road networks with a correlation value of 0.66. The correlation values of these four spatial factors in this study are positive, indicating that land cover changes around existing settlements may potentially occur if the distance to these four strongly correlated spatial factors is closer.

The spatial factors of land cover changes used in the simulation process must be converted into raster units based on proximity measurements. Proximity is a measurement based on the distance between two objects as points in geographic space. Two of the most commonly used proximity metrics are Euclidean Distance and Manhattan Distance (Nkweteyim, 2018). Measurement of proximity in this study was carried out using the Euclidean distance. Euclidean distance is a commonly used technique, it can recognize distances and calculate the proximity of each factor to land cover changes based on the distance (Liang et al., 2018). The Euclidean distance in this research is processed in QGIS using the Proximity tool and is measured based on the grid/cell distance that is per 15 meters. Figure 2 shows various spatial factors of land cover change in Kedungkandang District that

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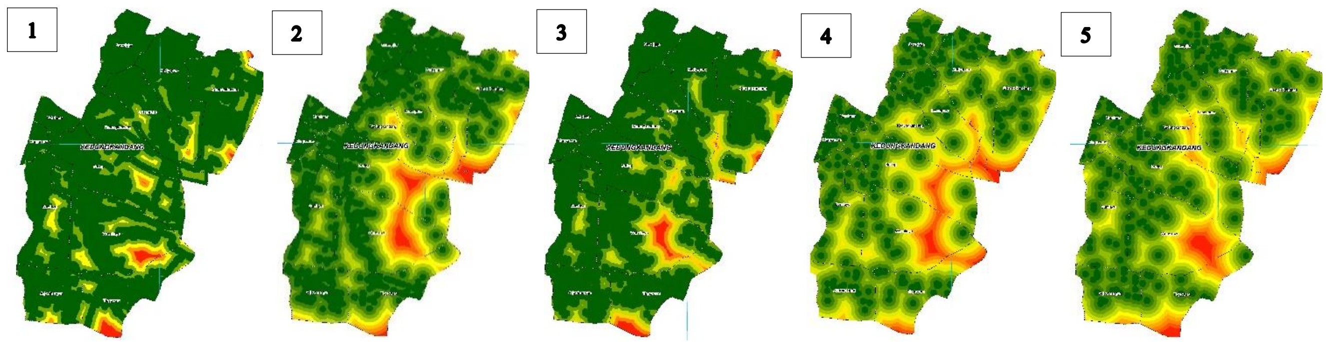
have gone through the Euclidean distance process. Then, the transition area along with the driving and limiting factors that have been in the euclidean distance, was analyzed in the MOLUSCE plugin with several techniques (ANN, LR and MCE) to produce a potential model for land cover change transitions.



Distance to Road | Distance to Commercial Facilities | Distance to Existing Settlement | Distance to Educational Facilities | Distance to Electricity Network

Source: Author, 2022

Figure 2. Euclidean Distance Map of Spatial Factors of Land Cover Change

3. Simulation of Land Cover Change Prediction

The simulation of land cover change uses the Cellular Automata approach, based on the transition potential model implemented in the previous stage. This study performs five iterations of the simulation starting from 2016 to 2036. The simulation results, the generated predictions, need to be validated to test the accuracy of the results. One of the most frequently used techniques to test simulation results is Kappa statistics. The CA process in the MOLUSCE plugin also provides tools to validate simulation results, especially with Kappa statistics. The Kappa statistical process is to compare the simulated map with the actual map in the same year, in order to evaluate the accuracy of the model using the % truth and the Kappa validation coefficient (Mienmany, 2018).

Table 3. List of the used Datasets in this Study

No.	Variabel	Metadata	Processing	Source
1	**Land Cover**			
1.1	2012 land cover map	▪ Satellite portrait dated 04-28-2012 ▪ Cloud <10% ▪ Resolusi of 30m	Pansharpening process to a resolution of 15m	Landsat 7 image
1.2	2016 land cover map	▪ Satellite portrait dated 05-08-2016 ▪ Cloud <10% ▪ Resolution of 30m	Pansharpening process to a resolution of 15m	Landsat 8 image
1.3	2020 land cover map	▪ Satellite portrait dated 22-12-2020 ▪ Cloud <10% ▪ Resolution of 30m	Pansharpening process to a resolution of 15m	Landsat 8 image
2	**Spatial Factors of Land Cover Change**			
2.1	Distance to road	Malang city road base map	Rasterized with a pixel size of 15x15 meters	▪ OpenStreetMap ▪ The Spatial Planning of Malang City for the period of 2020-2030
2.2	Distance to existing settlement	2020 land cover map	Rasterized with a pixel size of 15x15 meters	Citra Landsat 8
2.3	Distance to electricity network	POI of electrical substation	Rasterized with a pixel size of 15x15 meters	PT. PLN (State Electricity Company)
2.4	Distance to educational facilities	POI of school building	Rasterized with a pixel size of 15x15 meters	Data Scrapping
2.5	Distance to commercial facilities	POI of trade and service buildings	Rasterized with a pixel size of 15x15 meters	Data Scrapping

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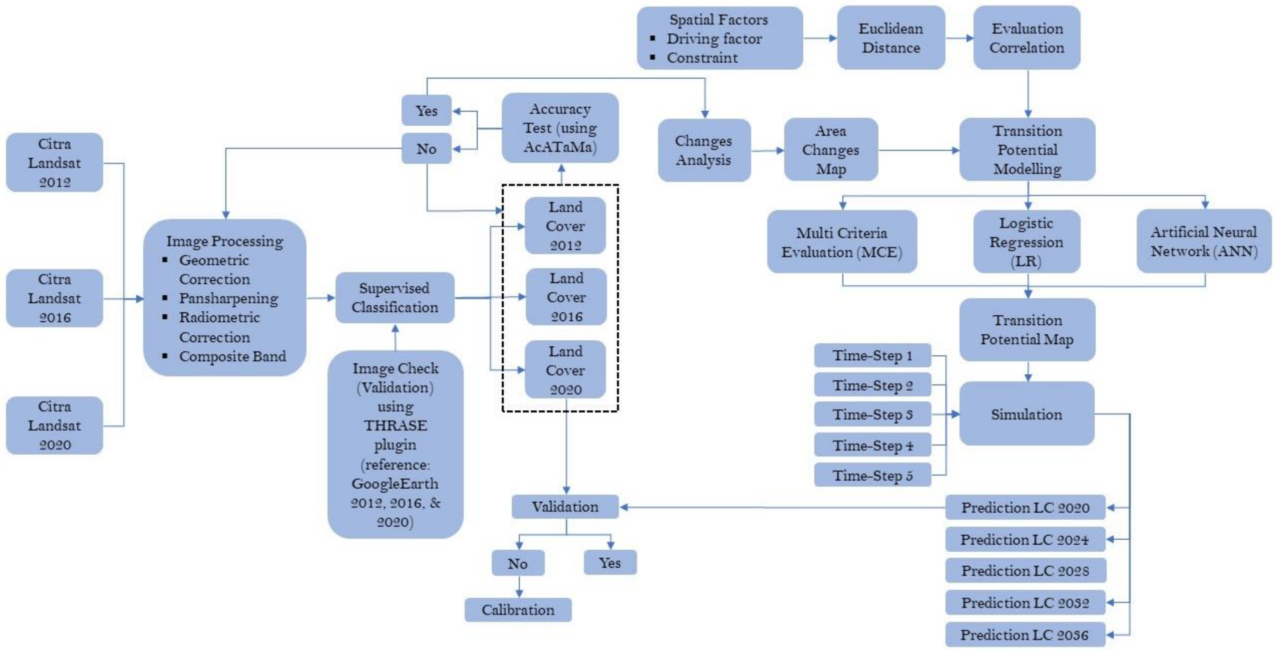


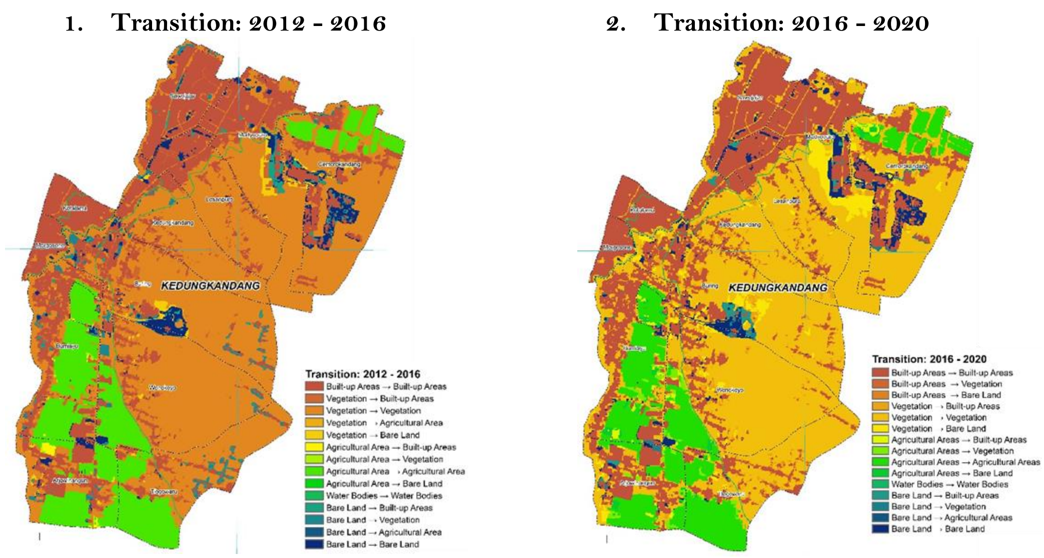
Source: Author, 2022

Figure 3. Research Framework

3. Results and Discussion

3.1. Land Cover Change

Land cover change is calculated through the MOLUSCE plugin as a power input, especially in 2012 – 2016 and 2016 – 2020, resulting in a land cover change transition map (Figure 4) and a land cover change transition matrix (Table 4). The largest change in land cover from 2012 to 2020 in Kedungkandang District occurred due to the addition of 335.53 hectares of built-up land and a reduction of 297.90 hectares of vegetation. Agricultural areas have decreased, but not as significant as vegetation. In line with the built-up land, bare land also experienced an increase, indicated by the initiation of new development, resulting in the opening and preparation of open land.



Source: Analysis, 2022

Figure 4. Land Cover Change Transition Map

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Table 2. Land Cover Change Transition Matrix

Land Classification	Areas (Hectares)			Land Cover Change (Hectares)
	2012	2016	2020	
Built-up Areas	955.03	1,117.53	1,290.56	335.53
Vegetation	2,244.17	2,150.13	1,946.27	-297.90
Agricultural Areas	553.61	544.07	470.30	-83.31
Water Bodies	26.10	26.10	26.10	0.00
Bare Land	211.81	152.89	257.49	45.68

Source: Analysis, 2022

3.2. Transition Potential Model

The transition potential model of land cover change in Kedungkandang District will use Artificial Neural Network, Logistic Regression and Multi Criteria Evaluation analysis techniques. When running the ANN model, a learning process is needed using the ANN model parameters (Table 5). This study utilizes a Moore 3x3 neighborhood version (1 px). The neural network learning process requires 1,000 random samples to model the transition potential with ANN. With a learning rate of 0.08, a maximum of 100 iterations, 5 hidden layers, and momentum of 0.05, the best accuracy is obtained from these neural network learning parameters. The minimum validation error is 0.023, with a Kappa value reaching 90%, allowing for the simulation of land cover change prediction.

Table 3. Parameters of Artificial Neural Network Learning Process Model

Parameter	Value
Neighbourhood	1px
Sampel	1000
Learning rate	0,08
Maximum iteration	100
Hidden layer	5
Momentum	0,05

Source: Analysis, 2022

Similar to the ANN transition potential model, the LR transition potential model also needs to define several parameters as described in Table 6. The maximum considered iteration number is 100, and the pixel neighborhood size is 1 px, which means 9 cells (3x3 cells) as well as 1,000 random samples. With these parameters, a pseudo r-square value of 99.1% is generated, which indicates that the logistic regression model is good.

Table 4. Parameter Model Logistic Regression

Parameter	Value
Neighbourhood	1px
Sampel	1000
Maximum iteration	100

Source: Analysis, 2022

The third transition potential model is MCE. The MCE in the transition potential model of land cover change requires the weight of each land change factor. The weights in this study use the results of previous research by Rofii (2021) generated through the AHP process. The study resulted in five spatial factors in land cover change in Malang City, where the four spatial factors were the same as the spatial factors used in this study. The weight of the spatial factors in this study is described in Table 7.

Table 5. Spatial Factor Weighting Land Cover Change for MCE Model

Spatial Factor	Weight
Existing built-up areas	0,404
Roads	0,263
Education facilities	0,125
Commercial facilities	0,121
Electricity network	0,087

Source: (Rofii, 2021)*, processed 2022*

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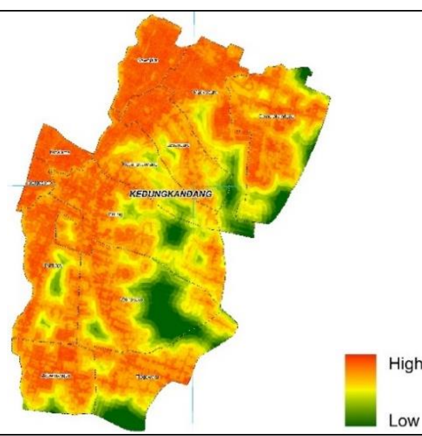
The three models also produce a transition probability map (Table 8) to be further used in the simulation process for predicting land cover changes. The transition potential map represents the possibility of land change with a potential value range of 0 to 100. A value of 0 indicates a low potential for transitional change, while a value of 100 indicates a high transition potential. As the intensity of red color increases, it indicates higher potential transition to other land cover types.

Table 6. Transition Potential Model Map

Model	**Transition Potential Model Map**		
	Vegetation → Built-up Areas	Agricultural Areas → Built-up Areas	Bare Land → Built-up Areas
ANN			
	Vegetation → Built-up Areas	Agricultural Areas → Built-up Areas	Bare Land → Built-up Areas
LR			
MCE			

Source: Analysis, 2022

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3.3. Land Cover Change Prediction Simulation

By utilizing the ANN transition potential model, the prediction of land cover change in Kedungkandang District was generated as described in Figure 5. The prediction results indicate a growth of built-up areas by 146.78 hectares from 2016 to 2036. The most significant changes occurred in vegetation cover, which converted by 90.12 hectares, followed by open land with a conversion of 56.05 hectares.

Source: Analysis, 2022

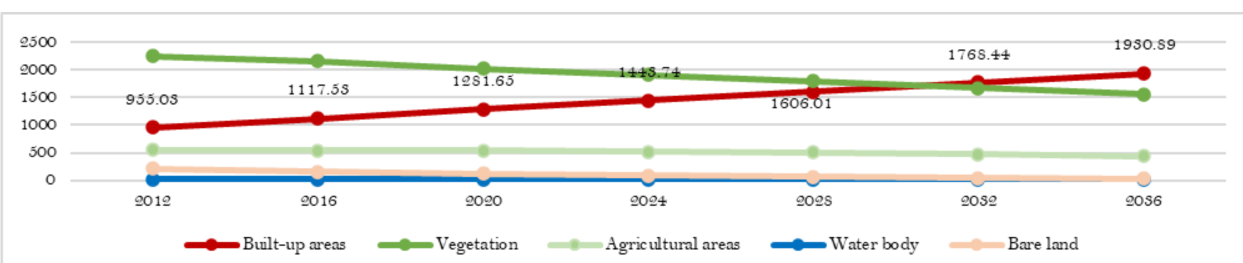
Figure 5. Land Cover Change Prediction with ANN Model

Then, using the LR transition potential model, the predicted land cover changes in Kedungkandang District are described in Figure 6. The prediction results indicate a built-up land growth of 93.16 hectares from 2016 to 2036. This increase in built-up areas tends to be smaller compared to the prediction results obtained using the ANN model. The largest conversion of land cover classes into other land cover classes with the LR model is vegetation, totalling 80.65 hectares.

Source: Analysis, 2022

Figure 6. Land Cover Change Prediction with LR Model

The prediction results in Figure 7. from the MCE model indicate a built-up land growth of 975.85 hectares from 2016 to 2036. This area represents the largest increase in built-up land among the three models. The largest conversion of land cover classes into other land cover classes in the MCE model is vegetation, totalling 687.73 hectares.



Source: Analysis, 2022

Figure 7. Land Cover Change Prediction with MCE Model

The land cover changes per period are shown in Table 9. It can be observed that generally, across all three

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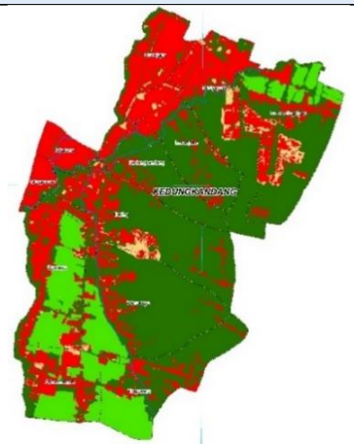
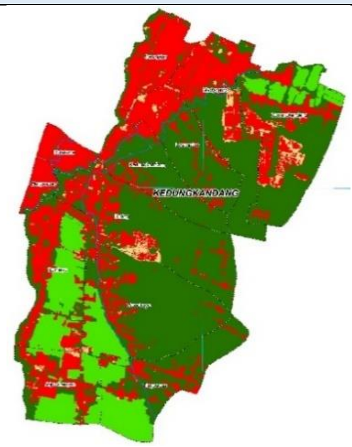
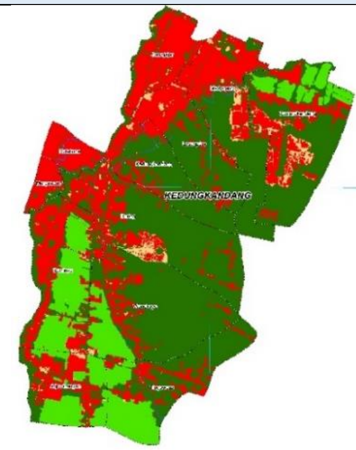
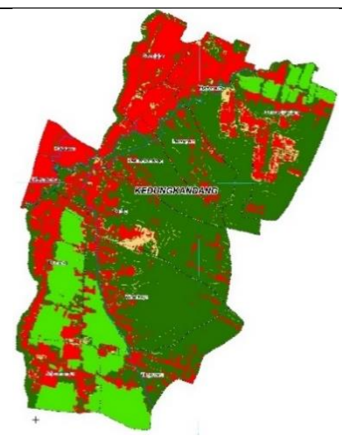
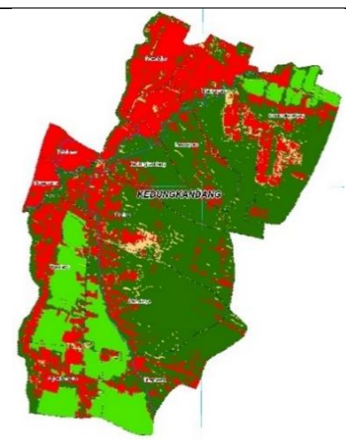
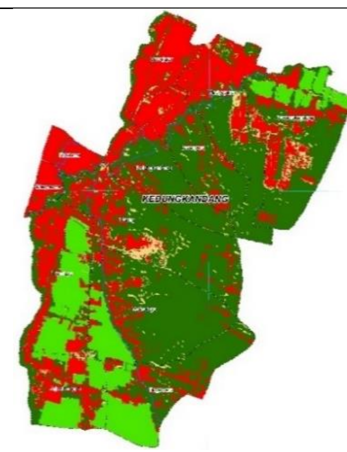
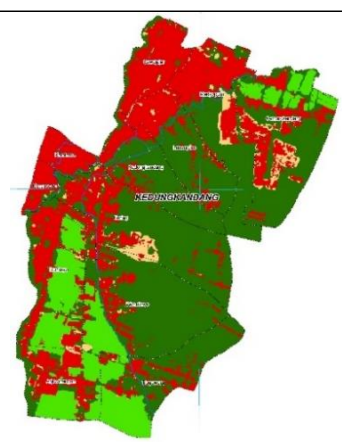
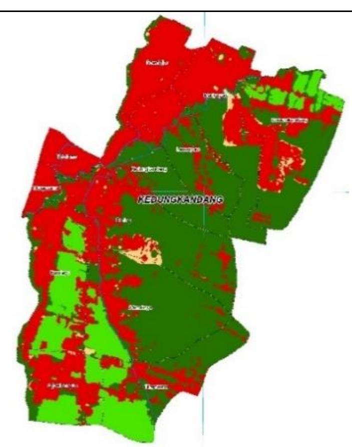
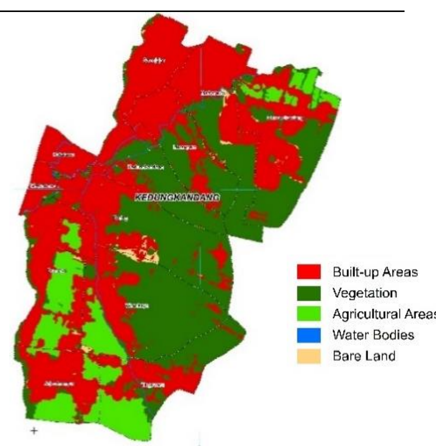
models, the largest growth in land occurs in the neighbourhoods of Buring and Cemorokandang. This is attributed to the development of the Kedungkandang square around these neighbourhoods, as well as their proximity to main road networks such as arterial roads connecting Malang City area with the city centre, the Malang Regency, and the exit toll gate of Malang City. Consequently, this directly contributes to a significant increase in the construction of new formal housing.

Table 7. Prediction Map of Land Cover Change and Direction of Development of Built-up Land

Model	Prediction Map		
	Y2020	**Y2028**	**Y2036**
ANN			
LR			
MCE			

Source: Analysis, 2022

The simulation of prediction of land cover change results that the MCE model predicts a very high increase in built-up land according to the development of built-up land in actual conditions, while ANN and MCE predict a development of built-up land, but not too significantly. The MCE model is the only model that can predict the development of large built-up land around the Malang – Pasuruan toll gate, especially in 2020 which is in line with developments in the existing conditions in 2020.

To validate the prediction results, a comparison is made between the actual 2020 land cover map and the 2020 land cover prediction simulation map. Kappa statistics are used in the validation process with the results in the form of Kappa Histogram, Kappa Location and Kappa Overall (Table 10). Judging from the overall value of Kappa, the highest model accuracy is generated by the ANN and MCE models. Then the highest Kappa location value is generated by the ANN and LR models. It indicates that the ANN and LR models have the simulation ability to determine the location of the development of built-up land very well compared to the MCE model. Based on the validation results, it is known that ANN is the best predictive model of land cover change in Kedungkandang District, because it has the highest Kappa overall and Kappa location values.

Table 8. Validation of Land Cover Prediction Simulation Results from Three Types of Models

Model	% of *Correctness*	Kappa (Overall)	Kappa (Histo)	Kappa (Loc)
ANN	90.77%	0.85	0.91	0.93
LR	90.10%	0.84	0.91	0.93
MCE	90.33%	0.85	0.94	0.90

Source: Analysis, 2022

3.4. Discussion

Previously, Nugroho et al. (2018) conducted a study using ANN models to predict land cover changes in Malang City, achieving a Kappa accuracy rate of 86% for each district in the area. However, the Kappa coefficient varied among different districts, with certain districts like Lowokwaru, Blimbing, and Kedungkandang showing coefficients above 0.6, indicating substantial prediction levels. This study employs a similar approach, utilizing the MOLUSCE plugin in the QGIS application but with the evaluation of 20 spatial factors. Pearson correlation analysis is employed to explore the relationships among these spatial factors more deeply. Positive correlation results indicate that the closer existing settlements are to the studied spatial factors, the greater the likelihood of land cover changes in the surrounding areas. This underscores the significant influence of these spatial factors on urban development, with the Pearson correlation approach aiding in a more comprehensive understanding of this dynamic. In contrast to previous research that did not involve prior evaluations of the spatial factors used, this study achieves a district-level accuracy of 0.85 or 85% using ANN models.

The statement by Shafizadeh-Moghadam et al. (2017) regarding the weakness of MCE, indicating that the transition potential model may undergo linear changes and produce predictions with a linear trend, can be reinforced by the findings of this study. Predictions of land cover changes using the MCE model show a tendency towards a linear trend, possibly resulting from researchers' intervention in the transition potential modeling process. In contrast, the ANN and LR models in this study are entirely managed by machine learning, thus eliminating subjective interference from researchers in setting boundaries or assessments. Furthermore, the Kappa Location results of the MCE model show the lowest Kappa value compared to other models in this study, although the Overall Kappa of the MCE model reaches the highest value equivalent to the ANN model. This suggests that, despite having good overall accuracy, the MCE model may be less suitable for depicting more complex spatial variations in land cover changes. In the end, this research confirms the viewpoint of Gharaibeh et al. (2020) that ANN is considered the optimal model relying on artificial intelligence.

The strength of this research lies in its utilization of advanced modeling approaches to address the challenges of predicting land cover changes in rapidly developing urban areas. Additionally, this study introduces an integrated approach using a combination of Big Data and the CA modeling approach with various transition potential techniques to generate more accurate predictions. Without conducting time-consuming primary surveys, this research effectively gathered data using renewable technologies such as remote sensing and Big Data mining. Validation and accuracy testing were performed using various machine learning-based efficient techniques.

4. Conclusion

This study proposes a modelling approach using Cellular Automata (CA) to predict land cover changes in the Kedungkandang District, Malang City. This approach has been the focus of previous research in modelling the dynamics of land cover changes due to its ability to capture complex spatial and temporal dynamics. Various transition potential modelling techniques, such as Artificial Neural Network (ANN), Logistic Regression (LR), and Multi-Criteria Evaluation (MCE), have been used to model the potential land cover changes. This study makes a significant contribution by comparing these three techniques in the context of the Kedungkandang District. Overall, the ANN transition potential model emerged as the best model for predicting land cover changes in the Kedungkandang District. Based on this, it can be concluded that machine learning models are more accurate, especially in predicting land growth in the Kedungkandang District, compared to models with human intervention.

Overall, this study provides a significant contribution to understanding the dynamics of land cover changes in the urban area of the Kedungkandang District and highlights the importance of using integrated and advanced approaches in land growth modelling. The results can also provide valuable insights for decision-makers in future urban management planning. Furthermore, these prediction results can serve as crucial input for the government in formulating spatial planning, particularly zoning spatial patterns in the Kedungkandang District as a basis for future control. However, some weaknesses need to be considered. For example, this study focuses on using CA to observe the behaviour (local or spatial rules) underlying the emergence of development patterns within land areas. Future research suggestions include modelling land cover change processes based on agents, thereby gaining an understanding of human actions in decision-making processes regarding future land cover changes. Additionally, this study predicts land cover changes based on previous land cover change trends, thus requiring similar target-based research (according to population projections and other objects). This study also does not incorporate future government development plans for the Kedungkandang District. Suggestions for future research could include incorporating these factors to understand the impact of government development plans on future land cover changes.

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