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Prediction of Land Use/Land Cover Change in the New Telaga City Plan Area, Gorontalo Province

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ABSTRACT

The development of the Telaga City planning area as a new city in the peri-urban area controls urban expansion while promoting equitable development and economic growth. However, high pressure from population growth, economic growth, and the need for developed land in peri-urban areas risks triggering land use incompatibility and a decline in environmental quality. In anticipation of these threats, this study aims to predict changes in land use/land cover (LU/LC) in the Telaga City planning area as a basis for future spatial planning. This research is experimental in nature, testing the influence of regional dynamics on changes in LU/LC. The novelty of this research lies in the use of high-resolution SPOT 6/7 image interpretation LU/LC maps, which enable more detailed and accurate identification of changes in LU/LC. The methods used include (1) Euclidean distance and data normalization to obtain data ready for use in the prediction process; and (2) Pearson correlation, Artificial Neural Networks (ANN), Cellular Automata (CA), and Kappa Accuracy for the prediction process. The analysis results show that the ANN model is able to capture the nonlinear relationship between driving factors and land transitions well, as indicated by a kappa validation accuracy value of 91.69%. The prediction results for the 2023–2033 period show that the dominance of vegetated areas will continue, but residential/mixed-use land will experience consistent growth, especially in the southern part, indicating strong urban development pressure. Therefore, the results of this study emphasize the need for LU/LC planning and control to minimize land use incompatibility.

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1. INTRODUCTION

The current development of urban areas tends to experience expansion of built-up areas that will continue to move from the city centre to the suburbs (peri-urban areas) as described in the urban growth model theory. This phenomenon is also occurring in Gorontalo Province. The Gorontalo Provincial Government is responding to this expansion through an innovative new city planning initiative called Telaga City in the peri-urban area (Gorontalo Governor's Decree No. 416/1/XI/2021). The Telaga City Planning Area is expected to control expansion and stimulate economic activity to achieve equitable development, given that Gorontalo Province currently ranks sixth in terms of the highest level of regional inequality in Indonesia (BPS, 2025).

The Telaga City Planning Area is part of the administrative area of Gorontalo Regency. In terms of population, from 2020 to 2025, the Telaga City Planning Area will have the highest population growth rate in Gorontalo Regency. Then, from an economic perspective, Gorontalo Regency has the second highest Regional Domestic Product (RDP) growth rate after the Provincial Capital of Gorontalo (BPS, 2025). It is predicted that the Telaga City Planning Area will have a significant contribution to the economic growth rate in Gorontalo Regency. Furthermore, in terms of policy, the 2024-2043 Gorontalo Province Spatial Plan includes plans to develop a road network that will improve accessibility in the Telaga City Planning Area (Putra and Putu, 2018; Rahayu et al, 2015).

However, the establishment of new cities in peri-urban areas presents its own challenges, particularly in terms of land use. The shift of urban functions to peri-urban areas has resulted in changes in land use/land cover (LU/LC) that generally do not take into account the environment and spatial planning regulations, or occur naturally due to pressure in urban areas (Imana et al, 2025). In addition, along with its development plan as a new growth centre, the need for developed land is expected to continue to increase and drive significant changes in LU/LC. This condition can lead to inappropriate land use if there is no proper planning from the outset. Incompatibility between the biophysical characteristics of the land and its use can result in environmental degradation, soil erosion, decreased land productivity, and increased risk of disasters. The impact of incompatible land use requires high restoration costs or may even be irreparable (Sadesmesli et al, 2017). As a precautionary measure, it is necessary to predict PL/TL using a spatial model approach, which is a representation of the real world system relevant to the issue being studied (Munibah, 2008).

Changes in LU/LC in peri-urban areas are influenced by various factors such as population growth, changes in economic structure, increased space requirements, and regional growth acceleration policies (Pravitasari et al, 2021; Mulya et al, 2022). Population growth and changes in economic structure increase the need for space for settlements, facilities, and economic activities. This need for space tends to be directed towards locations with high accessibility, which is spatially represented by distance. Policies to accelerate regional growth, including road infrastructure development and the designation of growth centers, play a direct role in changing spatial patterns by creating new strategic locations. This increases the functional proximity of land to centers of activity and accelerates land use change in surrounding areas. Thus, distance serves as a spatial indicator that represents the influence of demographic, economic, and policy factors on land use/land cover change.

Referring to this statement, this study limits the driving factors of LU/LC to include distance from roads, distance from water bodies, distance from existing settlements, distance from activity centres, and population density. These factors are based on considerations that include: (1) roads are a major factor driving LU/LC intensification in the surrounding area, leading to effective and efficient regional design (Sarker et al, 2019; Lopa et al, 2022); (2) water bodies such as rivers and lakes are a primary source of water, which is essential for life. Adequate water availability has a positive correlation with LU/LC intensification. Areas with abundant water tend to be used as settlements (Maria and Lestiana, 2014; Widyaningsih et al, 2021); (3) Existing settlements and population density reflect the pressure of built-up land needs, which tend to develop spatially in the surrounding area; and (4) Activity centres have a variety of activities that attract LU/LC in the surrounding area. According to Munawir et al (2019), the distance from the district and sub-district capitals, as well as markets, has a significant impact on land conversion, with land closer to centres of activity showing a higher proportion of developed land. Thus, land that is closer to driving factors has greater potential for LU/LC change than land that is far from driving factors.

The interaction between these driving factors is complex and non-linear, requiring analytical methods capable of capturing these relationship patterns in a more adaptive and accurate manner. In this context, the use of Artificial Neural Network (ANN) methods is considered relevant for modelling the non-linear relationship between the driving factors of LU/LC change and land conversion. ANN is capable of learning from historical LU/LC data to empirically generate the weight of each driving factor's influence. Furthermore, the Cellular Automata (CA) approach is used to model the dynamics of LU/LC change spatially by considering the influence of neighbouring cells and transition rules, so that the resulting LU/LC change patterns are more realistic and reflect the regional development process. Therefore, this study applies the integration of ANN and CA methods to predict LU/LC changes in the planning area of Telaga City. This study was conducted in a peri-urban area designated as a potential new city, thus differing from previous studies that generally focused on peri-urban or urban areas. In addition, the land use/land cover map data used was interpreted from Spot 6/7 imagery with an accuracy of ≥90%. This study aims to predict land use changes in the study area using a spatial modeling approach to identify trends and directions of change as a basis for spatial planning and control.

2. METHOD

2.1. Research Location, Tools, and Materials

The research location focused on four subdistricts that are part of the Telaga City WP, as shown in Figure 1.

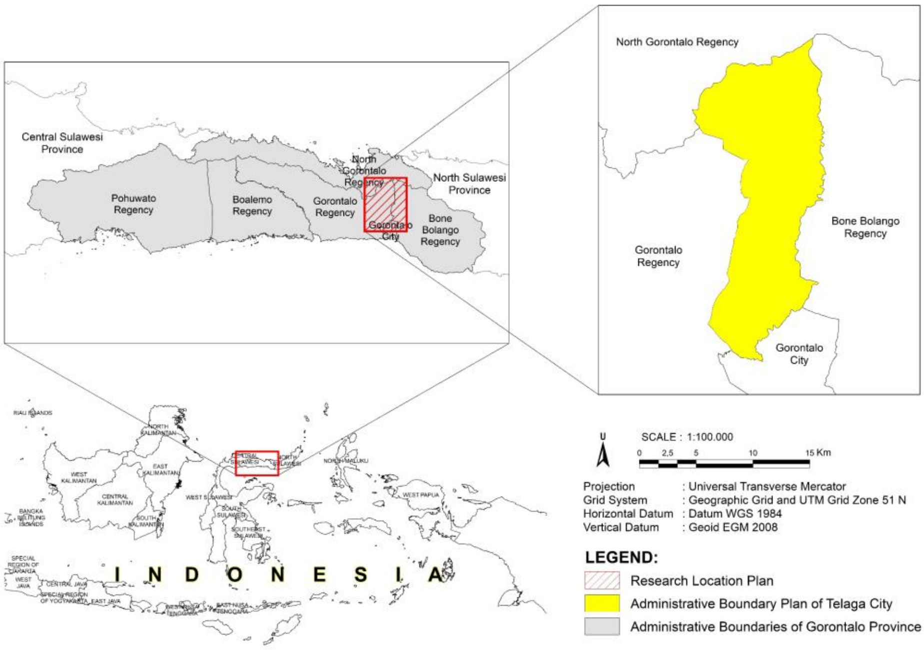


Figure 1. Map of the research location

The tools used were QGIS 3.40.6 software with the moluscе plugin. The materials used included: (1) LU/LC maps of the Telaga City planning area for 2013, 2018, and 2023; (2) Road Network Map; (3) River and Lake Network Map; (4) Settlement/Built-up Area Map; (5) Administrative Map of Limboto District and Gorontalo City as the nearest activity centres; and (6) Population Density Map.

2.2. Data Preparation Stage

The preparatory stage consists of literature review and preliminary data processing. This study utilises machine learning for the LU/LC change prediction process, thus requiring preliminary data processing. The data processed at this stage is data assumed to be a driving factor for LU/LC change. The analysis techniques used are as follows.

Euclidean distance (ED) is a method of classifying the nearest set or neighbourhood by calculating the distance between two objects. This method is used to classify distances for each LU/LC driving factor. The data processed using this technique includes: (1) Existing Road Network Map; (2) River and Lake Network Map; (3) Built-up Land Map; (4) Gorontalo City and Limboto Sub-district Administrative Map as the closest activity centres to the Telaga City planning area. Through this method, data will be obtained that is ready for use in the form of distance from roads, distance from water bodies, distance from built-up land, and distance from activity centres. The ED method calculation formula stated by Juniana et al (2018) is as follows:

$$d_e = \sqrt{\sum_{k=1} m}\left(fd_{i,k} - k_j\right)^2 \tag{1}$$

where: d_e is Euclidean distance; fd_i Training data; k_j is Test data; m is amount of trainer data

Fuzzy is an analysis technique used to reduce bias or value discrepancies during the model development process. Therefore, the distance calculations obtained from Euclidean distance are reanalysed using the fuzzy method. According to Abdillah et al (2021), fuzzy helps to transform all the driving factor data used into a uniform value range. In this study, the desired value range is 0-1, with the assumption that values closer to 1 (one) have a higher probability of LU/LC change. The fuzzy method formula is as follows:

$$Sstd_{x,y} = \frac{Smax_{x,y} - Si_{x,y}}{Smax_{x,y} - Smin_{x,y}} \tag{2}$$

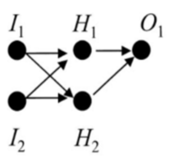
Where: $Sstd_{x,y}$ is Standard value in a specific cell (x,y); $Si_{x,y}$ is Conformity value/distance value relative to a specific cell; Max is Maximum value of the conformity value/distance value; Min is Minimum value of conformity value/distance value.

Population density map to obtain standardised values, each class is given a value with an interval of 0-1, so that the values are consistent with other factors. All data used for land use prediction is in raster form.

2.3. Prediction Stage of Land Use/Land Cover Change (LU/LC)

Predictions of LU/LC changes are made using a Geographic Information System (GIS), namely QGIS 3.40.6 software with the molusce plugin. Molusce is an advanced open source geospatial tool used to simulate LU/LC changes with input data in the form of predictive algorithms such as artificial neural networks and weights (Kumari and Arijit, 2025). According to Hapsari et al (2021), the LU/LC prediction process with molusce involves the following six stages:

1. Input is the initial stage, which involves entering land use map data from 2013 and 2018, as well as the driving factors for geometric verification. The next process can be carried out once the geometry of all input data is uniform;
2. Evaluating Correlation is a stage that shows the extent of correlation between LU/LC change factors using Pearson's correlation method. According to Hauke and Tomasz (2011), Pearson's correlation is a measure of the strength of the linear relationship between two variables. The closer the correlation test value is to 1 (one), the stronger the correlation or relationship;
3. Area Change, is a stage that provides information about changes in the area of each LU/LC and a transition matrix that shows the likelihood of land use change occurring.
4. Transition Potential Modelling is the stage of constructing a model of possible land transitions by utilising probabilities based on actual changes from the 2013 and 2018 LU/LC maps and their driving factors. Several methods are available for this stage, but this study uses Artificial Neural Networks (ANN). ANN is a machine learning method consisting of simple processing units in the form of neurons and nodes arranged in layers and interconnected. ANN works by mimicking the way the human brain processes information by connecting neurons and changing connection weights based on the data learned. An example of a network scheme built by ANN is shown in Figure 2.



Description:
I : Input layer
H : Hidden layer
O : Output layer

Figure 2. ANN Network Diagram

ANN uses several parameters in performing LU/LC predictions. The settings for each parameter are obtained based on literature studies that have been modified to obtain a current validation kappa value of ≥85%. A current validation kappa result of ≥85% indicates excellent training results and can be used for further processes (Subandi, 2019). The ANN parameters are as follows:

a. Neighbourhood is a parameter set to determine the surrounding neuron area that is affected or the surrounding region that is taken into consideration when training the model. In this study, the neighbourhood used is 1 (one) px. This means that the neighbours considered form a 3x3 window formation. The 3x3 window neighbourhood formation is presented in Figure 3.

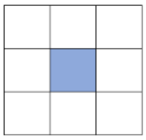


Figure 3. Windows 3x3 Neighbourhood Formation

b. The learning rate is a parameter that regulates the magnitude of weight changes in each learning iteration. The smaller the learning rate, the slower but more stable the training will be, whereas the larger the learning rate, the faster but less stable the training will be. In this study, the learning rate used was 0.005.
c. Momentum is the velocity component from the previous iteration when updating the network weights. The momentum function helps the network escape local minima and accelerate convergence.
d. The hidden layer is a parameter that determines the number of middle layers between the input and output in a neural network where the main computational process occurs. The more hidden layers a model has, the stronger it will be, but it will also be more complex and prone to overfitting. In this study, five hidden layers were used.
e. Maximum iteration is a parameter that determines the maximum number of training cycles allowed when training a network. This parameter prevents training from running indefinitely and controls computation time. In this study, a maximum iteration of 350 was used.

5. Cellular Automata Simulation (CA) is a method used by molusce to predict LU/LC by utilising ANN results in the transition potential modelling stage. In CA model applications, geographical space is represented as a regular cell grid and the environment is defined as a collection of cells based on a physical approach that has the ability to produce different spatial patterns based on locally defined transition rules. CA consists of the following five elements:
   a. Cells, in CA, are arranged in spatial tessellation, namely a two-dimensional grid. Cells are the most common form of CA used in modelling LU/LC change;
   b. State, meaning that each cell can only take one condition from a series of conditions at a given time. Cell condition is a description of cell characteristics that can change. In this study, the cell condition referred to is the type of LU/LC;
   c. The neighbourhood, or area considered in the CA process in this study, is a 3x3 window. This neighbourhood concept is standardised with the neighbourhood in the ANN analysis process;
   d. Transition Rule, referring to the results of ANN analysis obtained at the transition potential modelling stage; and
   e. Time-Step is the time dimension used during the iteration process from time to time. According to Kusniawati et al (2020) in molusce, the length of the prediction time is set automatically using the following formula.

$$Time\ Period = t1 + (t1 - t0) \quad (3)$$

Where: t1 is Final Year and t0 is Early Year

Land use data was inputted for the period from 2013 to 2018. This means that the prediction period is five years. In this study, the target time frame is 2033. Therefore, the desired land use predictions are for 2023, 2028, and 2033. The predictions were made for 2028 and 2033 because in those years the Gorontalo Province Spatial Plan will undergo its second and third review stages. It is hoped that the results of these predictions can be used as consideration in revising the spatial plan.

6. Validation is the stage of assessing the accuracy between the results of the first iteration simulation and the real/existing data in the same year. The accuracy assessment reflects the actual difference between the LU/LC simulation results and the reference LU/LC. The accuracy assessment method used by molusce is kappa accuracy, with a feasibility value of ≥85% (Subandi, 2019). If the first iteration simulation results have a kappa accuracy value of ≥85%, then the simulation can be continued for the next iteration. The LU/LC prediction process flow diagram is presented in Figure 4.

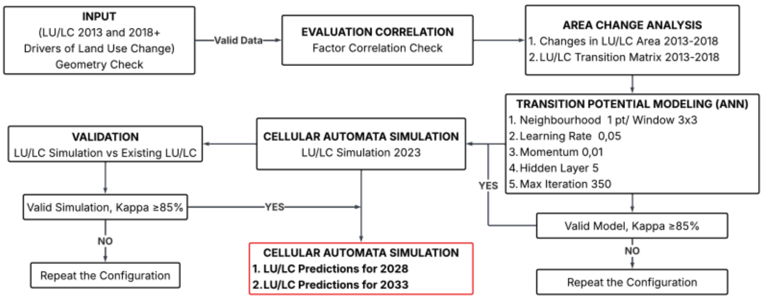


Figure 4. LU/LC Prediction Process Flowchart with Molusce Plugin

3. RESULTS AND DISCUSSION

3.1. Factors Driving Land Use/Land Cover Change (LU/LC)

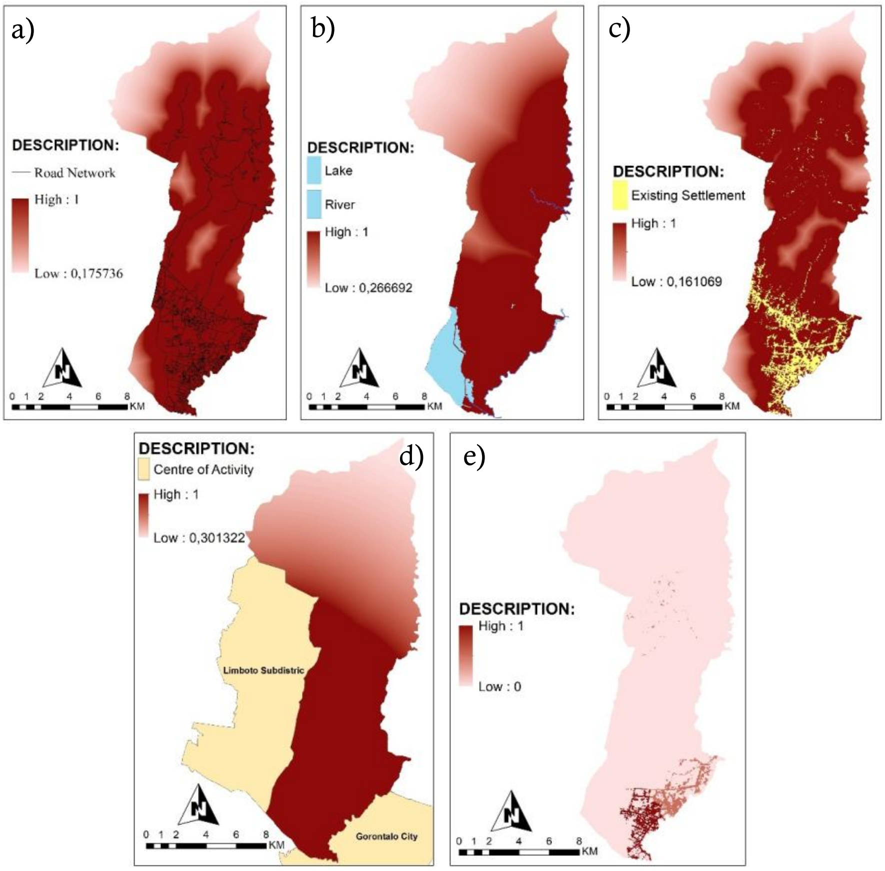


Figure 5. a) Distance Map from Roads; b) Distance Map from Water Bodies; c) Distance Map from Existing Settlements; d) Distance Map from Activity Centers; e) Population Density Map

The LU/LC change factors are represented through continuous distance raster maps, such as distance from roads, distance from water bodies, distance from existing settlements, and distance from activity centres obtained through Euclidean distance analysis. These factors are scaled to facilitate the modelling process, namely at intervals of 0-1. Specifically for the population density factor, in order to have scale equivalence, a constraint value is given based on the population density level per sub-district, as presented in Table 1. The results of the scale value equalisation are presented in Figures 5. Based on the results of the scaling of LU/LC change factors, it can be observed that the southern part of the Telaga City planning area has a fairly strong potential for LU/LC change.

Table 1. Population Density Constraint Values

Subdistrict	Population Density (People/Area of Existing Settlements)	Constraint value
Telaga Biru	1,3	0,25
Telaga	1,4	0,5
Telaga Jaya	1,5	0,75
Tilango	1,9	1

3.2. Prediction of Land Use/Land Cover (LU/LC) Change with Molusce

Input is the stage of entering data in the form of LU/LC maps for 2013 as the initial year and LU/LC maps for 2018 as the final year, as well as factors driving LU/LC changes. The data is standardized in the Universal Transverse Mercator zone 51 Northern Hemisphere (UTM 51 N) coordinate system so that the process can continue to the next stage. The coordinate system settings are adjusted to the research location.

Evaluating Correlation measures correlation between LU/LC change factors using Pearson correlation method. The correlation levels are classified into three classes. Factors with low correlation, shown by population density, indicate minimal LU/LC changes near settlements and activity centers, despite increasing land needs. This shows the spatial system's complexity, making it ideal for modeling.

Second, there are factors with moderate correlation levels, as indicated by the distance from roads to activity centers, the distance from water bodies to existing settlements, and the distance from existing settlements to activity centers. These values indicate the existence of interrelated spatial patterns, such as activity centers that are generally connected by road networks and residential areas that tend to be located close to water sources.

Several driving factors show high correlation, including distances between roads to settlements, roads to water bodies, and water bodies to activity centers. Correlation values > 0.7 typically require reduction to a single variable to avoid prediction errors. The study found correlations of 0.72 for roads to water bodies and 0.83 for roads to settlements. However, since LU/LC change is multifactorial and nonlinear, all driving factors were retained. Correlation results are in Table 2.

Table 2. Correlation Values of Factors Driving LU/LC Change

	Population Density Map	Distance Map from Roads	Distance Map from Water Bodies	Distance Map from Existing Settlements	Distance Map from Activity Centers
Population Density Map	-	0,13	0,16	0,14	0,21
Distance Map from Roads		-	0,72	0,83	0,55
Distance Map from Water Bodies			-	0,59	0,66
Distance Map from Existing Settlements				-	0,56
Distance Map from Activity Centers					-

Area change data reveals LU/LC patterns for 2013-2018. LU/LC information is shown through class statistics and transition matrices for neural network prediction. Highland forest, gardens with mixed crops, and dryland seasonal crops each comprise about 20% of Telaga City's planning area. From 2013-2018, highland forests, lowland forests, seasonal wetland crops, freshwater ponds, and shrubs decreased in area, while other LU/LC types increased.

The LU/LC transition matrix shows change probabilities between classes. Diagonal values indicate stability, while off-diagonal values show change likelihood. Most classes show high persistence: Residential/Mixed Buildings (0.99), High Forest (0.93), Lowland Forest (0.94), Natural Rock/Sand Area (0.97), Mixed Plantation/Cropland (0.99), Lake (0.96), River (0.95), and Reservoir (1). Other Natural Open Land (0.58), Annual Crop Plantations (0.84), Wetland/Rice Field Crops (0.90), Dry Season Crops (0.89), and Shrubs (0.75) show lower persistence, indicating higher vulnerability. Details are in Tables 3 and 4.

Table 3. Class Statistics

LU/LC Code	2013 (Ha)	2018 (Ha)	Δ (Ha)	2013%	2018%	Δ %
1	862,74	1.120,03	257,29	4,57	5,94	1,36
2	5.348,86	4.999,25	-349,61	28,37	25,51	-1,85
3	1.119,98	1.056,73	-63,25	5,94	5,60	-0,33
4	45,34	128,27	82,94	0,24	0,68	0,43
5	8,14	23,40	15,26	0,04	0,12	0,08
6	3.429,25	3.542,69	113,44	18,18	18,79	0,601
7	309,44	316,91	7,47	1,64	1,68	0,03
8	1.115,37	1.004,22	-111,15	5,91	5,32	-0,58
9	3.406,99	3.865,30	458,30	18,07	20,50	2,43
10	1.938,94	1.503,94	-434,99	10,28	7,97	-2,30
11	2,75	0,99	-1,75	0,01	0,005	-0,009
12	1.223,17	1.242,70	19,53	6,48	6,59	0,10
13	38,99	45,52	6,53	0,20	0,24	0,03
14	2,50	2,50	0	0,01	0,01	0

Table 4. Transition Matrix

	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1	0,99	0	0	0	0	0	0	0	0	0	0	0	0	0
2	4,20	0,93	0	0	0	0	0	0	0,05	0	0	0	0	0
3	0	0	0.94	0	0	0	0	0	0,05	0	0	0	0	0
4	0,25	0	0	0,58	0	0	0	0	0,04	0,10	0	0	0	0
5	0,02	0	0	0	0,97	0	0	0	0	0	0	0	0	0
6	0	0	0	0	0	0,99	0	0	0	0	0	0	0	0
7	0,14	0	0	0	0	0	0,84	0	0	0	0	0	0	0
8	0,02	0	0	0,01	0	0	0	0,90	0	0	0	0,05	6,05	0
9	0,04	0	0	0,01	0	0,02	0,01	0	0,89	0	0	0	0	0
10	0	0	0	0	0	0	0	0	0,22	0,75	0	0	0	0
11	0,03	0	0	0,10	0	0	0	0	0	0,5	0,36	0	0	0
12	0	0	0	0,03	0	0	0	0	0	0	0	0,96	0	0
13	0	0	0	0,01	0	0	0	0	0,01	0,01	0	0	0,95	0
14	0	0	0	0	0	0	0	0	0	0	0	0	0	1

LU/LC Code Description:

1. Residential/Mixed Buildings
2. Highland Forest
3. Lowland Forest
4. Other Natural Open Land
5. Natural Rock/Sand Deposits
6. Mixed Gardens and Crops
7. Seasonal Crops Plantations
8. Wet Season Crops (Rice Fields)
9. Dry Season Crops
10. Shrubbery
11. Freshwater Ponds
12. Natural Lakes/Ponds
13. Rivers
14. Reservoirs and Artificial Lakes

Diagonal Matrix

Transition potential modeling is the stage of building a LU/LC prediction model by utilizing the probability of LU/LC changes in 2013-2018 and the factors driving LU/LC changes using the ANN method. The ANN training results show that data training was successful. This success rate is indicated by the current validation kappa value approaching 1 (one), namely 0.87. In the neural network learning curve, there is a green line with round dots indicating the loss error value of the training data, and a red line indicating the loss error of the validation data. Data validation is needed to ensure that the resulting model is not only suitable for the training data, but can also be used to generalize well on new data. In this study, the patterns of the train and validation data graphs are almost directly proportional, or the differences between the patterns are not too significant. This indicates that the model does not experience serious overfitting or underfitting. Based on the neural network learning curve graph, it can be observed that the training data error and validation error values decreased significantly in the early iterations, then tended to stabilize until the end of the iteration process. This condition shows that the model successfully learned the relationship pattern between the input variables and LU/LC changes consistently, without any strong indications of overfitting. The ANN training results are presented in Figure 6.

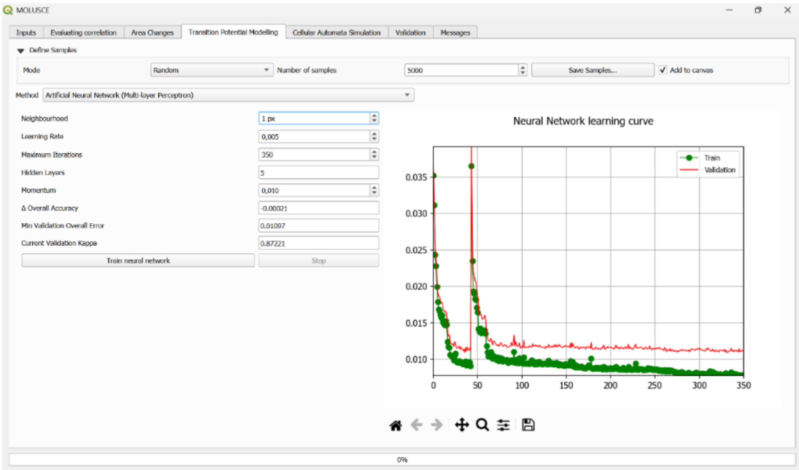


Figure 6. ANN Training Results in the Transition Potential Modeling Stage

Cellular Automata (CA) Simulation is an activity of predicting LU/LC by utilizing models generated by ANN. The probability of LU/LC changes in 2013-2018 has an interval of 5 (five) years, so that the prediction of LU/LC usage in the first iteration is in 2023 and the same interval applies to subsequent iterations. The CA prediction results are presented in Table 5. The next iteration of LU/LC prediction can be carried out if the 2023 LU/LC simulation results obtain a feasibility value of ≥85% at the validation stage.

Table 5. LU/LC CA Prediction Results for 2023

LU/LC	LU/LC Area in 2023 (Ha)
Residential/Mixed Buildings	1.230,37
Highland Forest	4.998,14
Lowland Forest	1.057,23
Other Natural Open Land	105,97
Natural Rock/Sand Deposits	19,43
Mixed Gardens and Crops	3.546,51
Seasonal Crops Plantations	316,54
Wet Season Crops (Rice Fields)	1.004,49
Dry Season Crops	3.806,24
Shrubbery	1.495,92
Freshwater Ponds	0,95
Natural Lakes/Ponds	1.242,76
Rivers	40,72
Reservoirs and Artificial Lakes	1,98
Total	18.867,25

Validation is the final stage of LU/LC prediction, where accuracy is checked by comparing 2023 prediction simulation with existing 2023 data. The kappa value of 91.69% indicates acceptable simulation results for future predictions. The next prediction requires returning to Cellular Automata Simulation with increased simulations for 2033, conducted in three iterations: 2023, 2028, and 2032. Prediction validation results are shown in Figure 7.

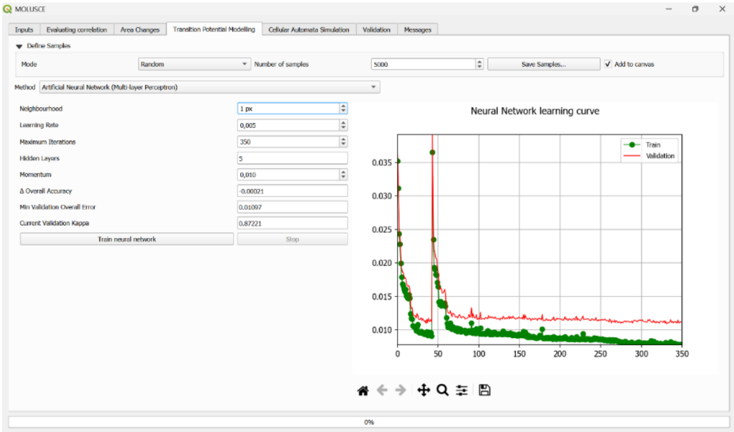


Figure 7. Validation of LU/LC Prediction Simulation Results for 2023

3.3. Predicted Results of Land Use/Land Cover (LU/LC) Change

The 2023-2033 LU/LC predictions show highland forests, plantations, mixed crops, and dryland seasonal crops remain dominant. The northern region features forests and plantations, while the southern part is mainly developed land. This aligns with regional characteristics, as the north has slopes exceeding 15% and is designated as protected forest by Gorontalo Province Spatial Plan. The southern area, bordering the provincial capital, has flat terrain that enables rapid development. The prediction results are shown in Table 6 and Figures 7-8.

The same LU/LC change pattern is observed for both 2023-2028 and 2028-2033 periods, as shown in Figures 14-15. The average LU/LC pattern shows area decreases, except for Residential/Mixed Buildings, indicating increasing development pressure and land use shifts from vegetation to cultivated land in the Telaga City planning area. Residential/Mixed-Use Buildings growth is expected to continue as per its new city development plan. Proper land use planning is needed for sustainable development, ensuring WP Kota Telaga meets developed land demand while preserving the environment through appropriate land utilization.

Table 6. LU/LC Prediction Results for 2023-2033

LU/LC	LU/LC Code	2023 (Ha)	2028 (Ha)	2033 (Ha)
Residential/Mixed Buildings	BP	1.230,37	1.247,87	1.255,19
Highland Forest	HT	4.998,14	4.997,49	4.997,04
Lowland Forest	HR	1.057,23	1.057,07	1.056,98
Other Natural Open Land	LT	105,97	97,88	93,79
Natural Rock/Sand Deposits	HB	19,43	18,10	17,25
Mixed Gardens and Crops	KC	3.546,51	3.546,48	3.546,12
Seasonal Crops Plantations	PK	316,54	316,36	316,34
Wet Season Crops (Rice Fields)	SW	1.004,49	1.004,22	1.004,16
Dry Season Crops	TK	3.806,24	3.804,12	3.804,50
Shrubbery	SB	1.495,92	1.492,46	1.491,24
Freshwater Ponds	KA	0,95	0,95	0,95
Natural Lakes/Ponds	DN	1.242,76	1.242,56	1.242,47
Rivers	SG	40,72	39,75	39,34
Reservoirs and Artificial Lakes	WD	1,98	1,94	1,89
Total		18.867,25	18.867,25	18.867,25

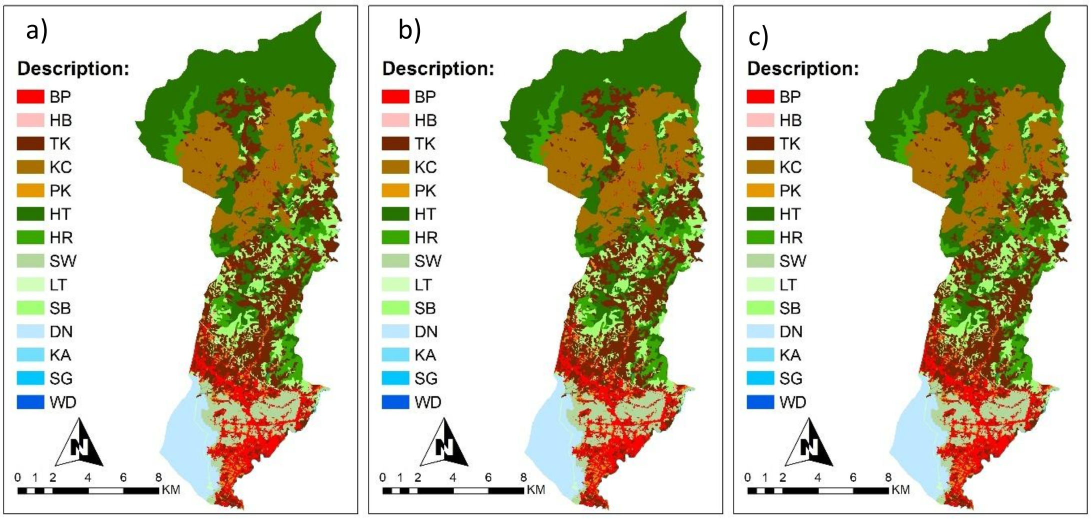


Figure 7. a) LU/LC Prediction Map for 2023; b) LU/LC Prediction Map for 2028; c) LU/LC Prediction Map for 2033

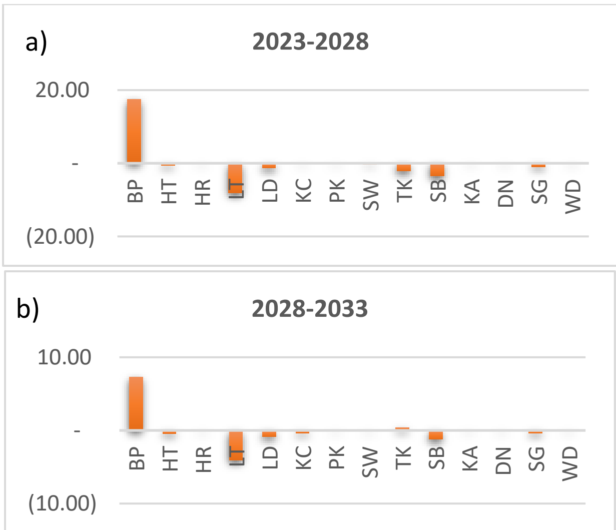


Figure 8. a) LU/LC Change Pattern 2023-2028; b) LU/LC Change Pattern 2028-2033

4. CONCLUSIONS

This study shows that changes in land use/land cover (LU/LC) in the Telaga New City Planning Area are influenced by multifactorial interactions between distance from roads, water bodies, existing settlements, activity centers, and population density. The integration of the Artificial Neural Network (ANN) and Cellular Automata (CA) methods through the Molusce plugin was able to model the nonlinear relationship between the driving factors well, as evidenced by a validation kappa accuracy value of 91.69%. The prediction results for the 2023–2033 period show that vegetated areas still dominate the study area, but residential/mixed-use building land is experiencing consistent growth, especially in the southern part, indicating strong urban development pressure. The scientific contribution of this study lies in the use of high-resolution SPOT 6/7 image interpretation land use/land cover maps, which can improve the accuracy of prediction analysis, especially in the context of peri-urban areas planned as new cities. The limitations of this study are that it does not explicitly include policy variables and socio-economic factors, and the prediction period is limited to 2033. Therefore, further research is recommended to develop policy scenario-based modeling and dynamic variables to support more adaptive and sustainable spatial planning.

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