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ARTICLE

Prediction and Modelling of Land Use Change in Pesawaran District Lampung Using ANN and Cellular Automata

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ABSTRACT

The simultaneous increase in development in Pesawaran Regency is closely correlated with the intense competition for land use. However, low policy implementation effectiveness has led to construction beyond designated spatial plan. The study used a quantitative survey using Landsat images in 2016, 2019, and 2022. The data analysis techniques used geographic information systems integrated with Artificial Neural Network (ANN) and Cellular Automata (CA) models. This study aims to predict land-use change in 2031, evaluate its alignment with spatial planning, and provide guidance for controlling land-use change. The results showed that there has been an increase in land use. In 2019, built-up land reached 7,069.65 Ha. The model shows its ability to predict land simulation and transformation, where it is predicted that built-up land in 2031 will experience an increase of up to 40.10%, so development and change cannot be avoided every year. This study also suggests that decision-makers and local governments should reconsider spatial planning strategies. This study shows that there have been many land use changes from 2016 to 2022. The model shows its ability to predict simulation and land transformation. When using the model, there are many changes in the land use area in 2031. This is due to wet agricultural land turning into built-up land by almost 70%. This study shows that road network influence land-use change. The cellular automata model managed to capture the complexity with simple rules. Predictions for future research should focus on conserving wetlands and primary forests.

Keywords: Land Use Model; System Information Geography; Cellular Automata; Artificial Neural Network (ANN)

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1. Introduction

Land is an area that has specific characteristics such as geology, atmosphere, hydrology, vegetation, and land use. Land is an essential and limited natural resource that natural and anthropogenic activities can modify [1]. Land as a geographic appearance needs to be studied by observing its use and influence on human life. Land use changes according to space and time because land, as one of the natural resources, is the most important element in human life. An increase in the number of people inhabiting a land accompanied by the development of business and cultural activities results in an increase in the demands of life that are desired to maintain their survival for the sake of sustainable development [2,3].

Pesawaran Regency is a district formed from expanding the South Lampung Regency area. Officially becoming a Regency in 2007 with an area of 117,373 ha [4], consisting of 15,465 Ha of rice fields and 101,912 Ha of garden/cultivation land and other land. It comprises 11 sub-districts, namely Gedong Tataan, Negeri Katon, Tegineneng, Kedondong, Way Khilau, Way Lima, Punduh Pedada, Marga Punduh, Padang Cermin, Way Ratai dan Teluk Pandan [5]. Increasing development in Pesawaran Regency, which is running simultaneously, will be closely related to competition for land use for development activities. Land use and management arrangements have been regulated in each region's Regional Spatial Plans (RTRW). However, the development of Pesawaran Regency is influenced by its proximity to Bandar Lampung City, both in terms of territorial boundaries and accessibility. The center of growth and spatial interaction makes Bandar Lampung City one of the growth centers with the highest spatial interaction with Pesawaran Regency [6].

Pesawaran Regency, a buffer zone (Hinterland) for Bandar Lampung City, shows that the population of Pesawaran Regency in 2010 was 398,848 people, and in 2020, it will be 477,468 people. If calculated, within a period of 10 years (2010 – 2020), the population growth rate increased significantly by 1.76% (78,621 people) [7]. Population density per km^2, according to the Central Statistics Agency of Pesawaran Regency, Subdistrict in Pesawaran Regency (people/km^2), is also above 160 people/km^2 on average. One of the sub-districts with the highest density figure is Gedongtataan Sub-district with 1 106.23 people/km^2 in the very dense category [8]. The most apparent impact of this condition is the rampant change in land use. Unsurprisingly, commercial and residential areas on non-built-up land have started to emerge in Pesawaran Regency. Comprehensive problems to meet the need for houses are also increasing, while the available land for housing is increasingly limited.

The scarcity of land has led to the development of new, uncontrolled settlements, with slums also emerging along riverbanks, coastal regions, and hilly areas. Observations and field surveys reveal that in Pesawaran Regency, homes are being constructed on riverbanks and rice fields [9–11]. Land use change refers to the transformation of land from one type of use to another, often accompanied by a reduction in other land uses over time, or a shift in the function of the land at different periods [12].To address these challenges, a land use change model is required to understand how land transitions over time and to predict future land use patterns. This model is crucial for evaluating and analyzing the impacts of development on environmental conditions, resources, and disaster risk. This study examined land use changes and predictions using a spatial approach with Geographic Information Systems, incorporating Artificial Neural Networks (ANN) and integrating Cellular Automata (CA) models with multitemporal raster data. These models are effective in simulating changes in land use [13]. The primary objectives of this study are to map land use changes for the periods 2016–2019 and 2016–2022, analyze the factors influencing land use change during these periods, and create a prediction model for land use changes through 2031.

Various studies have applied ANN and CA to analyze land-use changes, each with different approaches and focus. Zhang and Liu enhanced land-use modeling by incorporating deep learning techniques, specifically Neural Cellular Automata (NCA) and Convolutional Neural Networks (CNNs), to improve spatial detail accuracy [14]. Arman examined land-use changes in Muzaffarpur, India, emphasizing the transformation of agricultural land into urban areas due to rapid development [15]. Meanwhile, Zhou combines CA with Long Short-Term Memory (LSTM) neural networks, which excel in capturing temporal dependencies and long-term trends in sequential data

[16]. Mubarok studied urban sprawl in Delhi, India, where rapid expansion was the central concern [17]. Unlike these studies, which primarily focused on dense urban regions, this research applies ANN and CA using the MOLUSCE plugin in QGIS to analyze a broader land-use transition in Pesawaran Regency.

Land use change in Pesawaran Regency also directly impacts food security. Agricultural land, especially wet rice fields, has experienced a significant decline in line with the increasing conversion to built-up land. Boedingsih's study (2023) corroborates these findings, showing that conversion of agricultural land can reduce local food production capacity and threaten national food security [18]. Therefore, there is a need for stricter land conversion control policies that are based on spatial data. Zoning policies and the protection of wet agricultural land are important strategies that must be implemented immediately in peri-urban areas. Other recommendations include improving land conservation and forestry through incentives for farmers and local communities. An integrated land management strategy, taking into account social, economic, and environmental aspects, will be the basis for sustainable planning. Thus, ecosystem sustainability and food security in Pesawaran Regency can be maintained even under the pressure of growing urbanization [19].

This study not only examines urban expansion but also considers changes in agricultural areas, wetlands, and forests, providing a more comprehensive perspective on regional land-use planning. The results of the ANN and CA models in this study show a significant increase in built-up land from 2016 to 2022. This finding strengthens the evidence that artificial intelligence-based approaches can be a reliable predictive tool in regional spatial planning, especially in areas experiencing development and urbanization pressures. The methodological framework is adapted to accommodate mixed land-use transitions, making it distinct from studies that focus solely on urban growth. Through the integration of ANN and CA, this study presents a more advanced, data-driven, and dynamic land-use change simulation model. The results not only enhance prediction accuracy but also provide deeper insights for sustainable land-use planning in Pesawaran Regency. Having established the importance of monitoring and predicting land-use changes, this study adopts a methodological approach that integrates Artificial Neural Networks (ANN) and Cellular Automata (CA). The following section details the study area, data sources, and analytical techniques employed to develop an accurate land-use change model.

2. Methods

This study uses a quantitative approach with artificial intelligence-based spatial modeling methods and dynamic simulations, through the integration of Artificial Neural Network (ANN) and Cellular Automata (CA). This study constructs a hybrid model that combines data-driven learning with rule-based spatial simulation to predict future land use changes. The main objective of this approach is to model and predict spatial changes in land use accurately based on biophysical and socio-economic influencing factors [20]. Artificial Neural Network (ANN) was chosen for its ability to understand complex relationships between factors influencing land use change, such as distance to roads, slope, and population density. Meanwhile, Cellular Automata (CA) helps simulate spatial dynamics by applying simple transition rules between neighboring areas. By combining both, this study aims to produce predictions that are not only data-driven but also spatially realistic [21,22].

The research was carried out in Pesawaran Regency, which is situated geographically between 104.92°–105.34° East Longitude and 5.12°–5.84° South Latitude, covering an area of approximately 1,173.86 km² or 117,386 hectares (with a slight variation of 117,373 hectares) (**Figure 1**). Research was conducted to predict land use changes with a dynamic spatial model. This research aims to produce a land use change map and evaluate land use against the regional spatial plan. Land use change control directions are being developed based on the 2031 land use change prediction map (**Table 1**).

Landsat image data from 2016, 2019, and 2022 were sourced from BAPPEDA and the US Geological Survey (USGS) Earth Explorer website (earthexplorer.usgs.gov). BAPPEDA of Pesawaran Regency provided data regarding the driving factors of land change. Data processing was performed on a computer with Microsoft Windows specifications, 8 GB of RAM, and a 64-bit operating system. Software used included ArcGIS 10.4, Microsoft Office 2010, and MOLUSCE. A mobile phone camera was used to capture images. The research was carried out in the following stages.

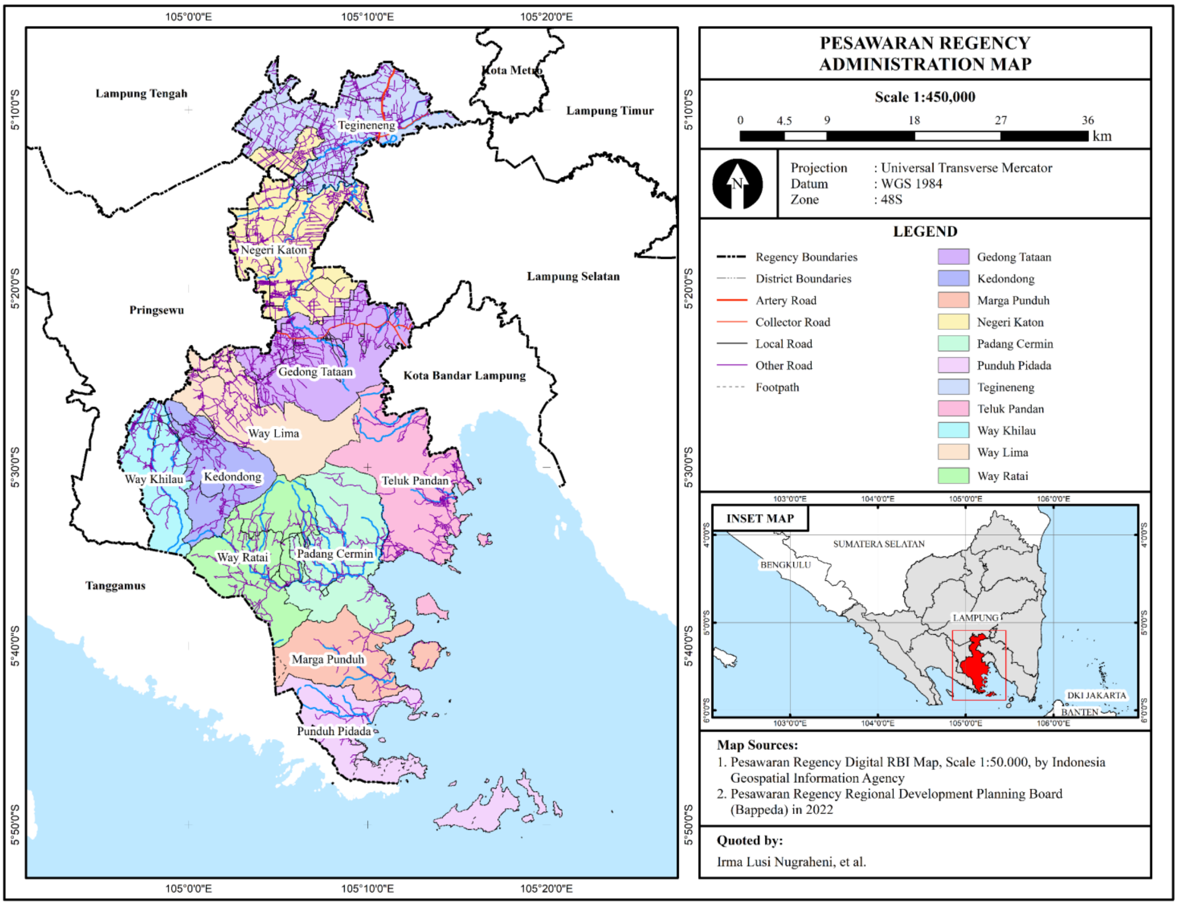


Figure 1. Administrative Map of Pesawaran Regency.

Table 1. Land Use Change 2016–2022 (Ha).

No	Land Use	2016 (ha)	2019 (ha)	2022 (ha)
1	Ponds	5,258	6,806	8,549
2	Built-up Land	6,535	10,558	17,627
3	Open Land	1,075	795.08	575.22
4	Dry Land Agriculture	29,955	28,780	22,305
5	Wetland Agriculture	13,718	14,904	14,902
6	Primary Forest	3,108	3,107	3,457
7	Secondary Forest	68,974	63,673	61,209

The Artificial Neural Network (ANN) used in this study follows a Multi-Layer Perceptron (MLP) architecture with the following parameters: Hidden Layers: The ANN model consists of one hidden layer with five neurons, which was determined through iterative testing to balance computational efficiency and prediction accuracy. Activation function: the sigmoid activation function was used to model transition probabilities between land-use types. Sigmoid is suitable for this task as it ensures smooth probability distribution and stable gradient descent during training. Learning Rate: A learning rate of 0.01 was selected to optimize model convergence without causing overshooting or slow learning.

2.1. Preparation Stage

A literature review was undertaken to gather initial survey data on the technical and community aspects. This involved conducting field observations, documenting conditions, taking photographs, and conducting interviews with key personnel including the head of the Public Works and Public Housing Office, head of the Health Office, head of the Regional Planning Agency, head of the BPBD of Pesawaran Regency, sub-district head, village head, and community members. The interview data pertains to the general causes of land use change, zoonotic diseases, and environmental health impacts. Additionally, it covers annual floods, construction of buildings on riverbanks, new housing developments replacing rice fields, and implementing regional regulations related to RTRW.

2.2. Data Processing Stage

Landsat image processing is analysed through on-screen digitisation in ArcGIS 10.4 software to generate land use maps for 2016, 2019, and 2022. Using ArcGIS 10.4, data on the factors that influence land change, including an accessibility map, public service distribution map, land characteristics map, density map, and housing distribution location map, are also processed. The technique used to achieve research goals is Molecule-Cellular Automata data analysis. The land usage change maps for 2016, 2019, and 2022 are overlaid to obtain a land change model map for 2016–2022.

Next, the model map and the land use change factors map undergo transition modeling. This study integrates two primary approaches in land-use change modeling: Artificial Neural Network (ANN) and Cellular Automata (CA). ANN is used to analyze land-use change patterns based on historical data and driving factors, while CA is applied to simulate the spatial dynamics of land transitions based on the transition probabilities predicted by ANN. The combination of these methods allows for a more accurate analysis of land-use changes over time and provides highly precise future scenario predictions.

The transition probabilities derived from these maps are then modeled using Artificial Neural Network (ANN) and Cellular Automata (CA). Cellular Automata has been run to model LULC changes in the study area and to predict future land use changes [23,24]. Compared to more conventional, this combination allows it to capture complex, multi-dimensional interactions more effectively. CA-ANN models show excellent predictive accuracy and flexibility which makes them a reliable option for precise and thorough land use forecasting [25]. By integrating ANN and CA, this study dynamically models land-use changes and improves prediction accuracy compared to conventional methods. The CA model was utilised to predict future land cover changes in the study area using the Modules for Land-Use Change Simulation (MOLUSCE) [26]. A pre-set threshold value is applied to regulate the rate of land use change, ensuring that conversions occur gradually. The prediction year is determined by adding the previous year to the year range, which is the difference between the end year and the start year [27]. The cell remains unchanged if the highest transition probability is lower than the threshold value of 0.9. The threshold value can vary from 0 to 1. To validate the land use simulation, the accuracy of the prediction model is assessed using the statistical kappa coefficient, with values greater than 0.80 considered satisfactory [28]. **Figure 2** illustrates the research methodology and data analysis process, which is used to assess and compare the accuracy of the actual land use map with the predicted 2031 land use map.

With the methodological framework in place, the next step is to apply these techniques to analyze land-use changes over time. The following section presents the findings, highlighting the major land-use transitions observed and the model's predictive capabilities.

3. Results

3.1. Land Use Change in 2016–2019 and 2019–2022

Table 1 shows the land use change data (Ha) processing results for 2016, 2019, and 2022.

Built-up land in 2019 showed the most extensive changes, adding 4,022.66 ha. Similarly, wetland agriculture experienced an increase in land area to 1,186.05 ha. Secondary forests experienced a reduced area from 2016 to 2019 to 5301 ha. Furthermore, **Table 2** shows the condition of land use change from 2016 to 2022.

Table 2 shows that over the past seven years, there has been an increase in land area in the use of ponds, built-up land, and wetland agriculture. The reduction of land area occurred due to the use of open land, dry land farming, primary forest, and secondary forest. The most significant increase in area is in the use of built-up land, and a substantial reduction in land area occurs in the use of dry land.

The next stage looks like a land change from 2019 to 2022. This can be seen in **Table 3**. Land use change in 2019–2022 based on **Table 3** found an increase in land use area from 2019–2022, namely on built-up land of 7,069.65 Ha. Land use that experienced a reduction in land area was open land (−219.86 ha), dry land agriculture (−6,445.42 ha) and secondary forests (−2,463.75 ha). The most obvious area of land change is dry land agriculture, which has experienced a significant reduction in area. As shown in **Figure 3**, the map of land use changes from 2016–2022 can be seen in **Figure 3a–c**.

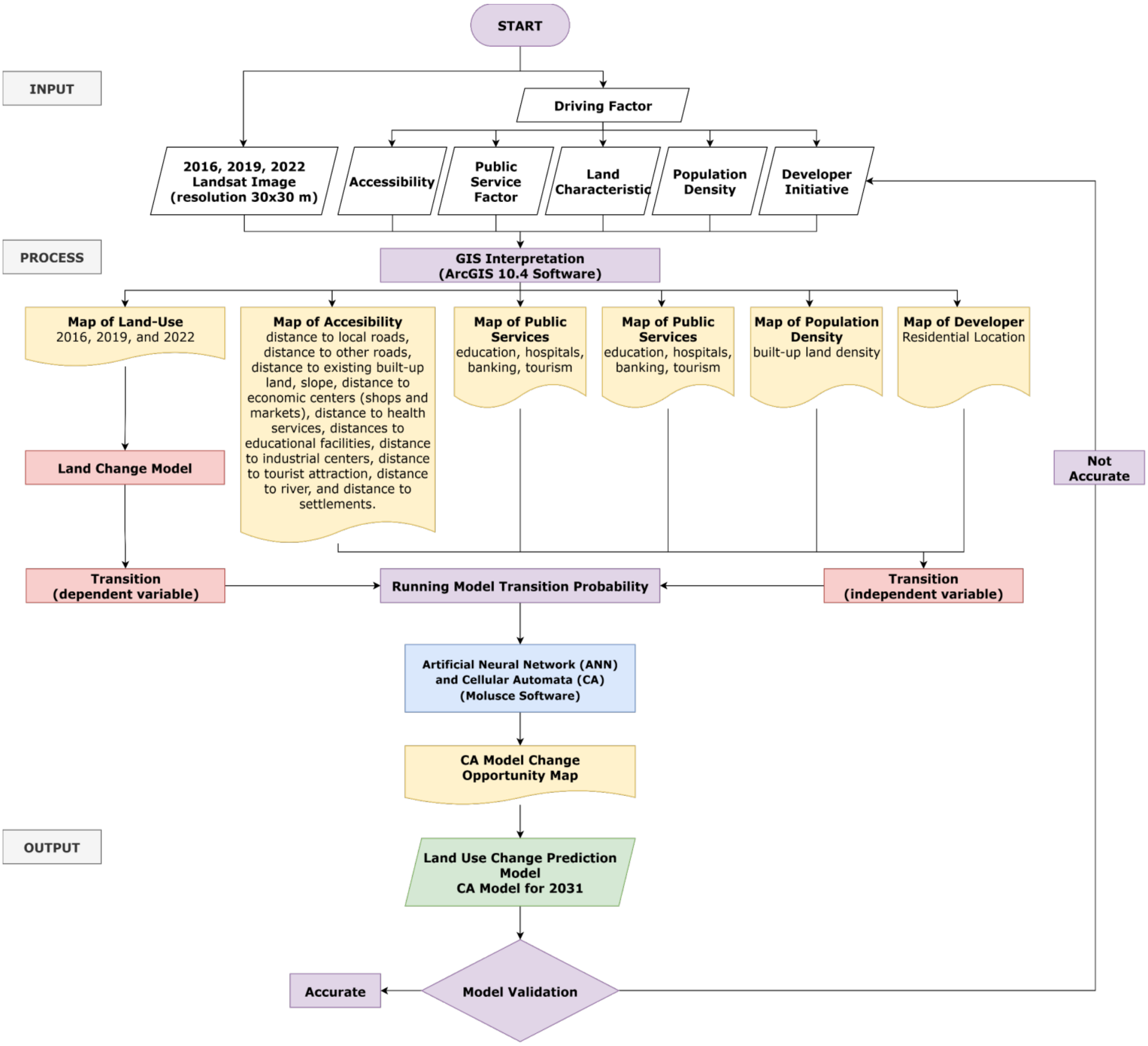


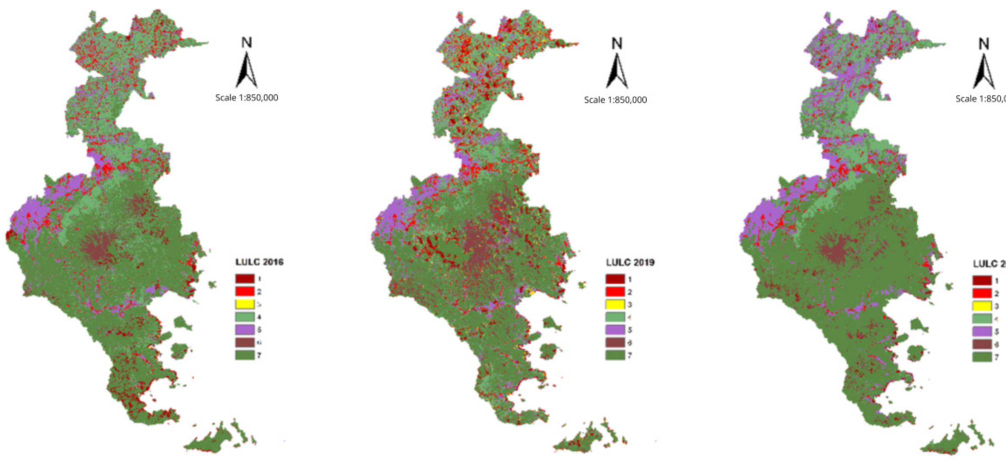
Figure 2. Data Analysis Process.

Table 2. Area of Land Use Change 2016–2022 (Ha).

No	Land Use	2016–2019 (ha) +/−	%	2019–2022 (ha) +/−	%
1	Ponds	1,547	29.44	1,743	3.98
2	Built-up Land	4,022	61.55	7,069	39.86
3	Open Land	−280	6.06	−219	89.69
4	Dry Land Agriculture	−1,175	3.92	−6,445	10.24
5	Wetland Agriculture	1,186	8.65	0	3.16
6	Primary Forest	−0.19	0.01	349	8.04
7	Secondary Forest	−5,301	7.69	−2,463	2.47

Table 3. Pearson Correlation.

Drivers Land	Type Soil	Tourism	School Distribution	Population Density	Market	Road	Slope	Health Facility	River
Banking	0.00	−0.06	0.18	0.00	0.53	0.26	0.00	0.33	0.06
type Soil	--	−0.00	0.00	0.02	0.00	0.00	1.0	0.00	0.00
Tourism		--	−0.02	−0.00	−0.18	−0.02	−0.00	−0.03	−0.06
School Distribution			--	0.00	0.52	0.84	0.00	0.04	−0.01
Population Density				--	0.00	1.0	0.75	0.00	0.00
Market					--	0.5	0.00	0.00	0.02
Road						--	0.00	1.0	0.02
Slope							--	0.00	0.00
Health facility								--	−0.06
River									--



(a) **(b)** **(c)**

Figure 3. (a) Land Use 2016, **(b)** Land Use 2019, **(c)** Land Use 2022.

With land use classifications of 1 = Pond, 2 = Built-up Land, 3 = Open Land, 4 = Dry Land Agriculture, 5 = Wet Land Agriculture, 6 = Primary Forest, and 7 = Secondary Forest.

3.2. Modelling Land Use Change Using ANN and Cellular Automata Methods

Modelling is one approach to studying natural phenomena. Dynamic modelling can predict future conditions. Before modelling, the independent variables or driving factors to be included are first determined.

Land use change modelling in this study uses the Artificial Neural Network (ANN) method for land modelling and Cellular Automata (CA) to predict land contained in the MOLUSCE (Model for Land Use Change Simulation) Plug in Quantum GIS 2.81 Software [29]. The molusce plugin consists of six stages [30], namely inputs, evaluating correlation, area changes, transition potential modelling, cellular automata simulation, and validation where each stage has a different role and is mutually sustainable so that if one of the stages has an error or error, it cannot be continued at the next stage. Before modelling and predicting land use, land cover data and variables driving land cover change are processed using ArcGIS software. The process stages in the Mollusca plugin will be explained as follows.

3.2.1. Stages of Predicting Land Use in MOLUSCE Software

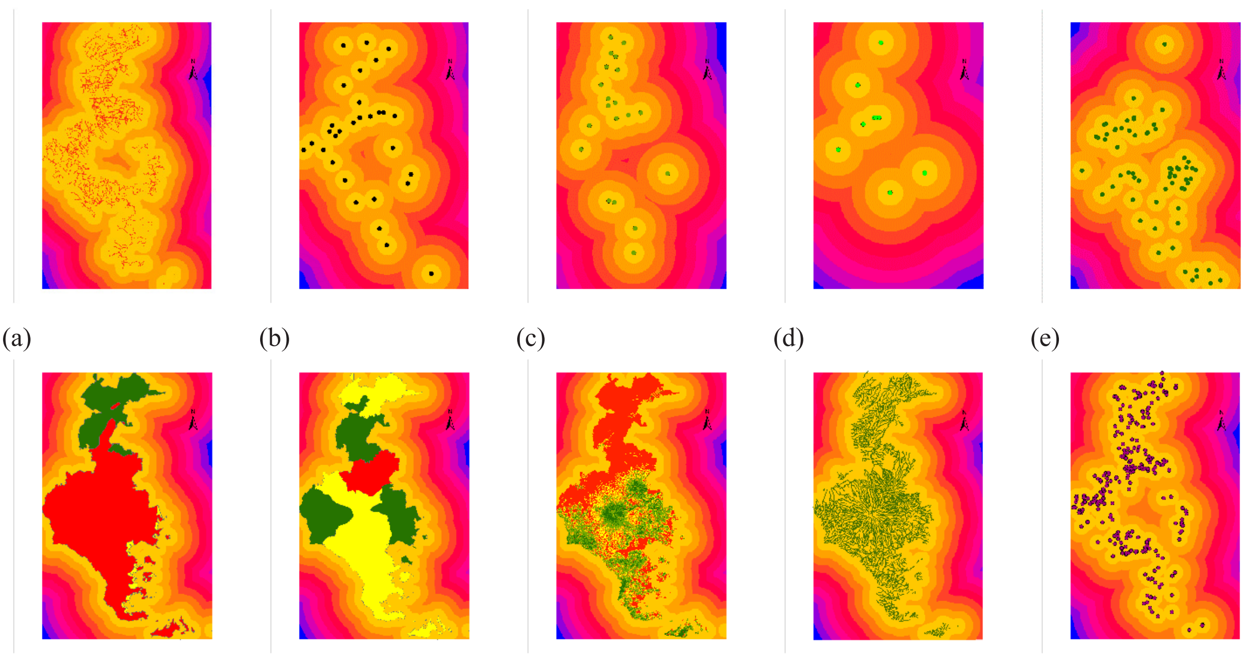
In the first stage of the land use prediction process, spatial data is inputted to generate land use predictions. The data includes land use information from 2016, 2019, and 2022, essential for validating the model and identifying driving factors. These driving factors include five main items: accessibility, public service factors, land characteristics, density, and developer initiatives.

Driving factors are variables that contribute to the transition probability model. They influence development, progress, and growth, often leading to land-use changes. When land use changes, these factors significantly affect its development and/or expansion. There are two primary categories of driving forces for land use change: biophysical factors and socio-economic factors [31,32]. Biophysical factors refer to natural characteristics and processes such as climate change, topographical alterations, geomorphological processes, and natural disasters. Socio-economic factors involve human activities, including demographics, social dynamics, economic conditions, cultural aspects, politics, industry, technology, etc.

Five key factors influence land use change: 1) Biophysical factors (potential and limitations), 2) Economic factors, 3) Social factors, 4) Spatial policies, and 5) Spatial interactions and neighborhood characteristics [33]. These driving forces for land use change are interconnected, with social, political, economic, technological, and environmental factors playing a role. These factors can be categorized into direct and indirect influences. Direct factors include urbanization, agriculture, and wood processing, which are shaped by indirect factors such as demographic changes, economic conditions, technological advancements, policies, culture, and physical environmental conditions.

Several factors cause land drivers to change, but these factors are interrelated, such as social, political, economic, technological, and physical environmental factors. These factors are categorised into two categories: direct and indirect factors. Direct factors are activities that include urbanisation, agriculture, and wood processing. These activities are influenced by demographic, economic, technological, policy, cultural, and physical environmental variables, which are indirect factors [34].

In general, land use or land cover changes can be caused by many factors (Driving Factors), especially factors relating to land use. Some factors influence the process of land use change because these factors interact with each other. Driving Factors are then processed using Euclidean distance to determine the distance to the factors or variables driving change (**Figure 4**). The following driving variables have been generated through Euclidean distance (**Figure 4(a–j)**) [35].



(a) (b) (c) (d) (e)

(f) (g) (h) (i) (j)

Figure 4. **(a)** Distance to Road, **(b)** = Distance to Health Facility, **(c)** = Distance to Market, **(d)** = Distance to Bank, **(e)** = Distance to Tourism Sites, **(f)** = Soil Type, **(g)** = Population Density, **(h)** = Slope, **(i)** = Distance to River, **(j)** = Distance to School.

Furthermore, evaluating the correlation between the driving factors used using Pearson's correlation [36]. The matrix of correlation test results is shown in **Table 3**.

Pearson correlation shows the relationship between variables using a value range of 0–1. The closer the number 1 is, the stronger the correlation, and the value 0 means the correlation is small or has no relationship. **Table 3** shows that the variables at number 1 are soil type with slopes, population density with roads, and school distribution with roads. This indicates that the closer the land use is to the road, the greater the potential for land use changes. Meanwhile, driving factors with a low correlation or zero (0) mean that the driving variable has little potential for change.

Data on land cover changes in 2010–2015 and the land use transition matrix were obtained at the next stage. Land cover change is presented in **Table 4** with Land Use Change 2016–2019 (Ha) below.

Over a three-year period, land change experienced an increase and decrease in the area of specific land uses. Built-up land in 2019 showed the change, with the most extensive addition of 4,022 Ha. Similarly, wetland agriculture experienced an increase in land area to 1,186 ha. Secondary forests experienced a reduced area from 2016–2019 to 5,301 ha.

Table 4. Land Use Change 2016–2019 (Ha).

No	Land Use	2016 (ha)	2019 (ha)	Change (ha)
1	Ponds	5,258	6,806	1,547
2	Built-up Land	6,535	10,558	4,022
3	Open Land	1,075	795	−280
4	Dry Land Agriculture	29,955	28,780	−1,173
5	Wetland Agriculture	13,718	14,904	1,186
6	Primary Forest	3,108	3,107	−0,19
7	Secondary Forest	68,974	63,673	−5,301

This stage generates change in land cover area and a change transition matrix that shows the proportion of pixels that changed from one land cover to another (**Table 5**).

Based on **Table 5**, open land has the potential to become dryland agriculture, which can also become built-up land. Wetland agriculture has the potential to become built-up land and dryland agriculture, and primary and secondary forests have the potential to become dryland agriculture.

Table 5. Land Use Change Matrix.

No	Land Use	Ponds	Built-Up Land	Open Land	Dry Land Agriculture	Wetland Agriculture	Primary Forest	Secondary Forest
1	Ponds	0.854	0.000	0.000	0.000	0.291	0.000	0.000
2	Built-up Land	0.010	0.176	0.00	0.00	0.026	0.000	0.000
3	Open Land	0.00	0,198	0.658	0.176	0.04	0.00	0.021
4	Dry Land Agriculture	0.003	0.181	0.975	0.587	0.030	0.00	0.000
5	Wetland Agriculture	0.004	0.198	0.00	0.164	0.677	0.000	0.000
6	Primary Forest	0.00	0.005	0.00	0.211	0.000	0.347	0.010
7	Secondary Forest	0.00	0.00	0.00	0.149	0.000	0.000	0.534

3.2.2. Artificial Neural Network (ANN) Modelling

The network topology used is Multi-Layer Perception (MPL) with a 4-5-2 structure: 4 nodes in the input layer, 5 in the hidden layer, and 2 in the output layer. Each node in the layer will be associated with other nodes. The results of modelling using ANN can be seen in **Table 6**.

The training or learning model results are shown in **Table 6**. The value of each parameter affects the overall error of the min validation. This process is usually repeated until it gets the most minor error value. Parameters for this study with an error of 0.07498 are considered good performance to continue to the next stage. Momentum determines the amount of weight change from training. Momentum with a value of 0.060 is supposed to have the best performance.

Table 6. Model Training Results.

Neighbourhood	1 px
Learning rate	0,010
Maximum iterations	100
Hidden layer	5

Table 6. *Cont.*

Neighbourhood	1 px
Momentum	0,060
Overall accuracy	−0.00275
Min validation kappa	0.07498
Current validation kappa	0.65691

3.3. Cellular Automata Simulation

The next stage in Mollusks is to predict land use using cellular automata. At this stage, land use data for 2022 is produced as existing data and data for 2022 is predicted. The expected land use can be seen in **Table 7** below.

Table 8 shows that the difference between the existing land use in 2022 and the modelled land area is not very different, so the model can be used.

3.4. Model Validation

The ANN model was validated using the ROC curve and AUC to assess its classification accuracy. The ROC curve was used to assess the model's ability to classify pixels into change and no-change categories. The AUC value provides a single metric summarizing this capability, where a score closer to 1.0 indicates excellent model performance. In this study, an AUC value above 0.80 was considered to reflect strong predictive accuracy. To assess the spatial accuracy of the CA simulation, the predicted land use map was compared with the actual land use map for the target year. Kappa statistics were employed to quantify the agreement between simulated and observed land use patterns. The validation of the model was carried out using the kappa accuracy value, which measures the level of agreement between the simulated land use in 2016 and the actual land use in 2022. A higher kappa accuracy value indicates a greater level of accuracy in the predicted land use compared to the real land use. A kappa accuracy value between 0.89 and 1.00 signifies a very good match, between 0.61 and 0.80 indicates a good match, 0.41 to 0.60 represents a moderate match, 0.21 to 0.40 shows a less than moderate match, and a value below 0.20 reflects a poor match [37].

The kappa accuracy value for the model validation in this study is 0.741 (**Figure 5**), which indicates a good agreement between the simulated land use and the digitized land use in 2022. This high kappa accuracy suggests that the model is reliable and can be used to predict land use changes in 2031.

The prediction of land use change in 2031 is done using the same method using molusce (**Figure 5**). The first input in making the land use change prediction model is to use the 2022 map as the base map of initial conditions. The second input is the transition area matrix obtained from the mollusk analysis of the 2016–2022 map.

Table 7. Comparison of Existing Land Use Area (Ha) with Modelled Land Use Area in 2022.

No	Land Use	Existing Land Use Year 2022 (Ha)	Modelled Land Use Year 2022 (Ha)	Difference in land area difference
1	Ponds	8,549	6,535.44	2,014.52
2	Built-up Land	17,627	14,767.21	2,860.72
3	Open Land	575	1,508.22	933
4	Dry Land Agriculture	22,305.06	25,833.84	3,528.78
5	Wetland Agriculture	14,902.66	14,433.84	468.82
6	Primary Forest	3,457.73	3,357.73	100
7	Secondary Forest	61,209.82	62,103.87	894.05

Table 8. Predicted Land Use Change in Pesawaran Regency 2022–2031.

No	Land Use	2022	Area %	2031	Area %
1	Pond	6,535.44	5.08	10,559.28	8.34
2	Built-up Land	14,767.21	11.49	20,688.17	16.34
3	Open Land	1,508.22	1.17	424.01	0.33
4	Dry Land Agriculture	25,833.84	20.10	21,830.93	17.24
5	Wetland Agriculture	14,433.84	11.23	11,849.40	9.36
6	Primary Forest	3,357.73	2.61	3,552.92	2.81
7	Secondary Forest	62,103.87	48.31	57,692.60	45.57
	Total	**128,540.15**	**100.00**	**126,597.31**	**100.00**

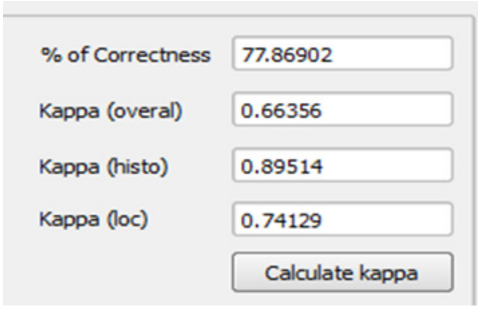


Figure 5. Validation Results.

The results of the land use change prediction for 2031 (**Figure 6**) indicate that the most notable projected change will be in dryland agriculture, with an increase of 21,830 hectares (17.2%).

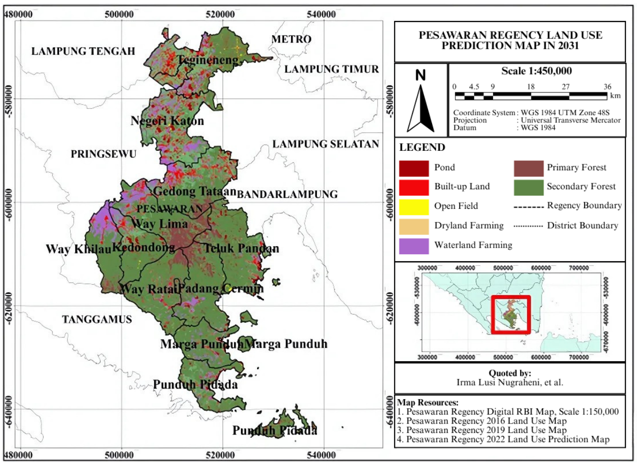


Figure 6. Predicted Land Use Map for 2031.

The results of the ANN-CA simulation provide a detailed view of how land-use patterns have evolved and how they are projected to change in the future. In the next section, these findings are critically examined in the context of existing research, policy implications, and environmental impacts.

4. Discussion

The analysis of land use change trends that occurred in Pesawaran Regency during the period 2016–2022, based on the overlay results on the land use map processed using ArcGIS 10.3 software, revealed that the addition of land use area for ponds, which was originally 1547.92 hectares, changed to 1276.92 hectares.

The area of ponds decreased to 1547.92 hectares (29.44%). Wetland agriculture increased to 1186.05 hectares (8.65%). Changes in the use of open land, dry land agriculture, primary forest, and secondary forest increased the built-up land area to 4,022.66 hectares (61.55%). In 2019, more open land was converted into built-up land, so its area decreased to only 280.16 hectares. For more details, see **Table 9**.

The change of land use in 2016–2022 from **Table 9** shows that the increase in land use area is still dominated by built-up land, which increased by 8,232.21 hectares. While the decrease in land area occurred in dry land agriculture, secondary forest, and open land. Dryland agriculture experienced the most significant reduction in area at 4.121,16 hectares. This decrease can occur because people convert one land to another, such as built-up land, which increases due to the need for housing caused by population growth, and wetland agriculture, which also increases due to people's needs for food and economy. The land use change in Pesawaran Regency increased significantly from 2016–2022, namely on built-up land, which increased by 70%. This occurred due to the development of the local government and the central government building infrastructure. This resulted in significant use/cover and better access to the provincial capital, making land conversion to built-up land unavoidable.

Table 9. Land Changes From 2016–2022.

No	Land Use	2016–2019 (ha) +/–	%	2019–2022 (ha) +/–	%	2016–2022 (ha) +/–	%
1	Ponds	1,548	29.44	-270.56	-3.98	1,277.44	24.30
2	Built-up Land	4,023	61.56	4,209.21	39.87	8,232.21	125.97
3	Open Land	–280	-26.05	713.22	89.71	433.22	40.30
4	Dry Land Agriculture	–1,175	–3.92	–2,946.16	–10.24	–4,121.16	–13.76
5	Wetland Agriculture	1,186	8.65	–470.16	–3.15	715.84	5.22
6	Primary Forest	–1	–0.03	250.73	8.07	249.73	8.04
7	Secondary Forest	–5,301	–7.69	–1,569.13	–2.46	–6,870.13	–9.96

4.1. Predicted Land Use Change Year 2031

This prediction is made based on the historical trends observed in 2016, 2019, and 2022. According to simulation results and land use change forecasts for Pesawaran Regency over the next nine years, the analysis indicates that wetland agriculture will decline by 17.91% (2,584.44 hectares) (**Table 10**). This reduction is attributed to the expansion of infrastructure in wetland areas, as well as the population growth in Pesawaran Regency. Changes in land use and land cover (LULC) are driven by both natural and human activities [38,39].

Open land is predicted to decrease by as much as 71.88%. Dry land is also expected to shrink by 15.49%, while primary and secondary forests will see area reductions of 5.81% and 7.10%, respectively.

The area of ponds, however, is forecasted to increase by 61.57%, from 6,535.44 hectares in 2022 to 10,559.28 hectares in 2031. The expansion of these ponds may be influenced by rising sea levels, which could affect long-term ecosystem stability [40]. Growing pond areas raise concerns about zoonotic diseases like malaria, as water bodies such as deep, shallow, and shaded waters, wetlands, and ponds are known breeding grounds for malaria vectors [41].

Table 10. Predicted Land Use Change 2022–2031.

No	Land Use	2022	%	2031(Ha)	%	2022–2031 (ha) +/−	%	Land conversion to
1	Ponds	6,535.44	5.08	10,559.28	8,3	4,023.84	61.57	Increase in pond area
2	Built-up Land	14,767.21	1.49	20,688.17	16,3	5,920.96	40.10	Increase in built-up area
3	Open Land	1,508.22	1.17	424.01	0,6	–1,084.21	–71.88	Built-up land, ponds
4	Dry Land Agriculture	25,833.84	20.10	21,830.93	17,2	–4,002.91	–15.49	Built-up land, ponds
5	Wetland Agriculture	14,433.84	11.23	11,849.40	9,3	–2,584.44	–17.91	Built-up land
6	Primary Forest	3,357.73	2.61	3,552.92	2,8	195.19	–5.81	Built-up land
7	Secondary Forest	62,103.87	48.31	57,692.60	45,5	–4,411.27	–7.10	Built-up land
	Total	128,540.15	100	126,597.31	100	-	-	-

The prediction for land use changes in 2031 reveals several significant shifts. Open land is expected to decrease by 71.88%, while dryland agriculture will see a decrease of 15.49%. Primary and secondary forests are projected to shrink by 5.81% and 7.10%, respectively. On the other hand, pond areas are forecasted to grow by 61.57%, from 6,535.44 hectares in 2022 to 10,559.28 hectares in 2031. This expansion may be influenced by rising sea levels, which could destabilize ecosystems in the long term [40]. As pond areas increase, concerns arise about the spread of zoonotic diseases like malaria, since water bodies such as ponds, wetlands, and shallow waters are known breeding grounds for malaria vectors [41].

Built-up land is expected to grow by 40.10% by 2031. Although this growth could negatively affect other land uses, such as natural vegetation, its expansion is inevitable as urban areas continue to develop each year [42]. During the period between 2022 and 2031, residential areas will likely expand at the cost of natural vegetation, especially if proper management measures are not in place. These land use changes highlight the significant impact of human activities on land use dynamics. As Talukdar suggests [39], landscape dynamics are a major event in human-dominated environments, with the composition and configuration of landscapes changing over time. This leads to habitat loss and fragmentation, which affects landscape patches and their class levels. Land use patterns vary across different landscapes, influenced by factors like agricultural land use, which often has larger patch sizes and higher patch densities compared to residential land use [43].

Land use changes also impact the emergence of diseases [44]. Anthropogenic land-use changes are major drivers of infectious diseases, such as agricultural encroachment, deforestation, road construction, dam building, irrigation, wetland modification, mining, urban expansion, and coastal zone degradation. Human migration further exacerbates this process, facilitating the spread of diseases and modifying the transmission of endemic infections [45,46]. These activities contribute to the rise of mosquito-borne diseases, such as dengue fever, which are most prevalent in built-up, residential areas [47,48]. The 61.57% increase in pond areas predicted for 2031 may further contribute to the spread of zoonotic diseases, with mosquitoes using stagnant water in ponds and rice fields as breeding grounds [49].

The rapid land use changes in Pesawaran Regency, which is close to Bandarlampung City, support Forkuor's observation that agricultural land is being converted into built-up areas, especially on the outskirts of cities [50]. As populations grow and cities expand, competition for land intensifies. This results in challenges for poor farmers, who struggle to compete with plantation managers, foreign investors, and others. The unfavorable land tenure system exacerbates the situation, causing farmers to lose their land and livelihoods [51]. The conversion of agricultural land into housing, industry, and other uses has led to the gradual loss of productive land. This reduction in agricultural production is expected to increase reliance on external sources for food, which could raise food prices due to transportation costs [37,38]. The built-up land expansion also significantly impacts environmental services, contributing to frequent flooding and land degradation in Pesawaran Regency.

Changes in land use will affect various aspects, including farmers who lose their livelihoods as their land is converted into built-up areas [52]. Additionally, the decrease in agricultural land will result in food needs being met from outside the region, which could drive up food prices due to distribution costs. These changes also contribute to the erosion of local wisdom and cultural values within the community [53]. The instability in the implementation of the Regional Spatial Planning (RTRW) policy regarding land use is a part of the broader negative impact of land use changes on the environment, as demonstrated by the recurrent flooding and land damage in Pesawaran Regency [54]. Future research should focus on conservation scenarios, particularly preserving wetlands and primary forests.

Controlling land use change requires policies based on scientific approaches and modern spatial technology [55]. Strengthening spatial planning policies, especially through preparing and regularly updating the Regional Spatial Plan (RTRW), is essential to prevent uncontrolled land conversion [56,57]. With the support of technologies such as Artificial Neural Network (ANN), Cellular Automata (CA), and geospatial information systems (GIS), planning can be directed more precisely towards the dynamics of land change. Implementing strict protection zones in forest and wetland areas is a strategic step in maintaining the ecosystem [58]. In addition, developing sustainable infrastructure such as greenways, urban parks, and green spaces is also important to reduce the negative impacts of urbanization and provide adaptive space for local climate change.

Furthermore, food security can be strengthened by protecting agricultural land from massive land conversion [59]. This policy includes incentives for farmers to maintain environmentally friendly farming practices, such as agroforestry, and restrictions on converting agrarian zones [60]. In addition, GIS and land change modeling technologies should be extended to the local level for more effective planning and monitoring [61]. The use of interactive spatial data can increase transparency and engage community participation in managing a more equitable and sustainable spatial layout. Developing integrated geospatial databases will support accuracy in impact evaluation and policy making that is more responsive to environmental dynamics [62].

Finally, public participation is important in an inclusive land use planning process. The active involvement of local communities, businesses, and environmental organizations will result in more targeted policies. Participatory forums, public training, and location-based technology can accelerate the identification of problems and solutions at the site level. On the other hand, ecosystem conservation and restoration efforts must also be strengthened with an ecosystem-based approach and by incentivizing those active [63]. Data-driven planning, public participation, and strengthened conservation are the main pillars to create sustainable land use, resilience to climate crisis, and improvement in the overall quality of life of the community.

The discussion highlights key insights into land-use transformation and its broader implications. The final section synthesizes these findings, emphasizing their significance for regional planning and offering recommendations for future research.

5. Conclusions

This study shows that there have been many land use changes from 2016 to 2022. The model shows its ability to predict simulation and land transformation. When using the model, there are many changes in the land use area in 2031. This is due to wet agricultural land turning into built-up land by almost 70%. In this study, road network data is one of the influential driving factors. The cellular automata model managed to capture the complexity with simple rules. Predictions for future research should use conservation scenarios, namely, maintaining wetlands and primary forests.

Author Contributions

Conceptualization, I.L.N. and M.U.; methodology, M.U.; software, I.L.U.; validation, I.L.N., M.U. and S.S.; formal analysis, I.L.N.; investigation, M.U.; resources, M.U.; data curation, M.U.; writing—original draft preparation, I.L.N.; writing—review and editing, I.L.N.; visualization, I.L.N.; supervision, M.U.; project administration, S.S.; funding acquisition, S.S. All authors have read and agreed to the published version of the manuscript.

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Data Availability Statement

Data will be made available on request. Declaration of Interest Statement: The authors declare no conflict of interest.

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Conflicts of Interest

The authors declare no conflict of interest. The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript; or in the decision to publish the results.

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