Exploring the Effects of Land use Land Cover (LULC) Change on Menhir in 2053: Utilizing the Cellular Automata-Artificial Neural Network (CA-ANN) Algorithm: A Case Study of Menhir Tourist Site in Nagari Maek, Indonesia

Antomi, Y.,* Angraina, D., Arif, D. A. and Fitriawan, D.
Department of Remote Sensing & GIS, Vocational School, Universitas Negeri Padang
E-mail: antomi_y@fis.unp.ac.id,* angrainadilla@fis.unp.ac.id, dianadhetyaarif@fis.unp.ac.id, dedy.fitriawan@fis.unp.ac.id
**Corresponding Author*

DOI: https://doi.org/10.52939/ijg.v20i11.3685

Abstract
The construction of tourism facilities related to physical aspects triggers changes in land use. This research aims to model Land Use Land Cover (LULC) by 2053 and determine the influence of LULC on the existence of the menhir tourist attraction as the main object in historical tourism in Nagari Maek. The method used to produce LULC predictions is the CA-ANN model via the MOLUSCE plugin in QGIS Desktop 2.18.11. The research results show that the 2023 prediction map has an accuracy value of 68.43 with a correctness percentage of 83.11458%. This means the resulting model is highly suitable, and the prediction results can be trusted. The LULC prediction for 2023 to 2053 results in significant land changes occurring in the dry land forests, which experienced a decrease of 6.75%, and plantations of 13.67%, while the increase occurred in the mixed plantations by 17.46%, rice fields 1.57% and built-up area 1.39%. If the LULC conversion is linked to the existence of menhirs (the main object in historical tourism), then by 2053, there will be a reduction from 30 sites to 24 menhir sites. Each site has a different number of menhirs, and there will be at least 20. The loss of 6 sites or 120 menhirs caused the inherent characteristic of Nagari Maek, as it was named as the Nagari of 1000 menhirs, to disappear.

Keywords: Artificial Neural Network, Cellular Automata, LULC, Menhir, MOLUSCE Plugin

1. Introduction

Indonesia is a nation renowned for its exceptional natural beauty and wide-ranging cultural treasures spanning from Sabang to Merauke, all complemented by the warm hospitality of its people. Indonesia's popularity as a tourist destination attracts visitors [1] from different nations, resulting in a beneficial economic impact at the national and local stages [2]. Additionally, this serves as a strategy to address various social and economic concerns [3]. Hence, when fostering tourism, it is imperative to consider the local community's physical, economic, and socio-cultural dimensions, as they are fundamental in establishing sustainable tourism [4], characterized by community participation and involvement [5] in tourism activities.

The development of tourism facilities related to physical aspects triggers changes in land use with the expansion urbanized regions [6] via the transformation of cultivable land [7]. This conversion of agricultural land has economic and environmental impacts [8] [9] [10] and [11], loss of biodiversity [12], and endangering natural resources and food security [3] and [13]. In addition, land use changes that could be better planned can also change the earth's energy equilibrium and biogeochemical cycles, influencing climate change [14], thereby affecting the nature of the land surface and ecosystem services [15]. To mitigate these effects, conducting a spatial-temporal analysis of land use and land use change (LULC) is imperative before building tourism infrastructure. This analysis will offer a comprehensive understanding of the policies that need to be implemented in the future [16], including sustainable land management [17] through remote sensing and geographic information systems (GIS) [18] [19] and [20].

ISSN: 1686-6576 (Printed) | ISSN 2673-0014 (Online) |

Remote sensing and geographic information systems (GIS) are increasingly used in ecosystem assessment, biodiversity, and climate change studies [21] due to their ability to detect land use changes. Several analysis tools that have been used were Dinamica [22], Markov-FLUS [23], SLEUTH cellular automata [24], Cellular Automata-Markov (CA-Markov), Land Change Modeller, Composite Analysis, Image Differentiating, Image, Rationing [25], Artificial Neural Network (ANN) [21] and [26] Cellular Automata - Artificial Neural Network (CA-ANN) [27] and [28], Artificial Neural Network - Markov Chain (ANN-Markov) [29][30] and [31], and CLUE-S [32], LULC [33]. The Cellular Automaton (CA) model is commonly employed for accurate land use predictions and dynamics. It is particularly effective when integrated with other models like the Artificial Neural Network (ANN), which excels in translating non-linear and spatially probabilistic land use data [34]. Artificial neural networks (ANN) provide the capability to identify and comprehensively understand causative elements and intricate patterns accurately [35]. The process by which Artificial Neural Networks (ANN) simulate Land Use and Land Cover (LULC) follows a similar pattern to that of the human brain and nervous system [36]. The CA-ANN model is based on what-if conditions, so it is suitable in the LULC scenario [37] to determine the potential changes in land use utilizing temporal land use data in conjunction with the topographical characteristics of a region [38].

Nagari Maek is a tourist village with a pioneering category [39], which shows that tourism facilities still need to be improved. To enhance Nagari Maek's attraction, particularly in developing tourism infrastructure that will transform land use, it is crucial to initially forecast Land Use and Land Cover (LULC) patterns through spatial-temporal analysis [40]. It is also essential to monitor and predict changes in land use and land cover (LULC) in an area, particularly for ecosystem conservation and sustainable development management techniques.

The analysis is carried out using real-time and time series remote sensing data, which is integrated with GIS through the LULC simulation module in open-source QGIS, employing Artificial Neural Networks (ANN) as the primary algorithm. While other algorithms such as multi-criteria evaluation (MCE), weights of evidence (WoE), and logistic regression (LR) were considered good algorithms [41], ANN was selected due to its superior performance in modeling complex, non-linear relationships in land use change prediction. The data used includes LULC data, with driving factors such as the distance from the river and main road, chosen based on the unique geographic and landscape conditions of the mountainous region. This research aims to predict LULC in 2053 and assess its impact on the preservation of the menhir tourist attraction, a key historical tourism asset in Nagari Maek.

2. Methods

LULC and its influence on the development of historical tourism in Nagari Maek are studied by analyzing spatial-temporal data using a Cellular Automata-Artificial Neural Network (CA-ANN) using the LULC or MOLUSCE simulation module plugin in QGIS.

2.1 Study Area

The research was conducted in area called Nagari Maek, Bukik Barisan District, Limapuluh Kota Regency, West Sumatra Province, Indonesia as presented in Figure 1. Nagari Maek is the largest Nagari in Bukik Barisan District, covering 12 jorongs and covering an area of 244.14 km^2. This village, known as the village of 1,000 menhirs, had a population of 9,744 people in 2022 [42]. The research methodology is presented in Figure 2.

2.2 *Materials*

The LULC model in Nagari Maek was analyzed from Landsat Imagery as remote sensing data [43]. This satellite image covers Nagari Maek, Bukik Barisan District, and Limapuluh Kota Regency and has a temporal interval of 5 years, namely 2013, 2018, and 2023. In predicting land use, driving factor attribute data consists of distance parameters, physical characteristics, and neighbor relationships [44]. In this study, the drifting factors used were data on distance from the river and the main road. Road and river proximity were prioritized in the analysis due to their direct and significant influence on land use changes, particularly in facilitating access to infrastructure and natural resources, which are primary drivers of settlement patterns. Conversely, while DEM slope and settlement proximity are important, they were deemed less critical within the context of this study, where the expansion of infrastructure plays a more decisive role in guiding development. The sources of the data used is presented in Table 1.

Administrative boundaries use shapefile data from the Geospatial Information Agency (BIG) such as the *Rupa Bumi Indonesia* Map (RBI Map) of Limapuluh Kota Regency which has been corrected geometrically and radiometrically. Corrected image Necessary to achieve optimal image quality with suitable pixel values and accurate geographic positioning of pixels. Next, data on the distribution of menhirs is needed to find out the influence of LULC on the distribution of these menhirs.

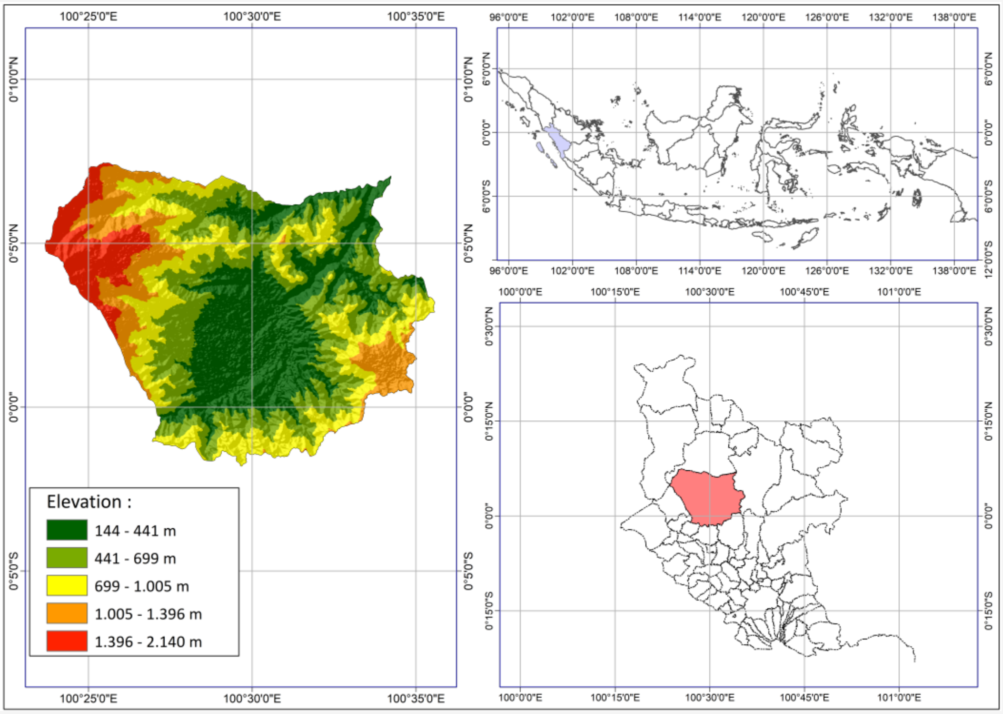


Figure 1: Menhir tourist site in Nagari Maek, Indonesia

2.3 Data Preparation and Analysis

2.3.1 Satellite image processing

Landsat images, which are remote sensing data, undergo geometric and atmospheric distortion correction processes using ENVI software. Geometric correction is carried out to ensure that the data is spatially aligned [10]. The procedure includes identifying and rectifying distortions induced by variations in the sensor platform's position and orientation as well as topographical and atmospheric influences. Geometric correction requires selecting a series of geographic coordinate reference sites called ground control points (GCP).

2.3.2 LULC classification

The LULC classifier in this study refers to the 2014 SNI (*Standar Nasional Indonesia*) with several modifications. The Landsat images for 2013, 2018, and 2023 used have a spatial resolution of 30 meters (medium resolution), so they are appropriate for use at the optimum scale of 1:100,000 [45]. Land use is classified into five classes [46]: dry land forest, Built-up land, plantations, mixed plantations and rice fields (Table 2). This LULC classification uses pixel-based Maximum Likelihood Classification (MLC) [46] and [47] using ArcGIS 10.8. The maximum likelihood method was selected because of its ability to account for the mean value across bands and the variability between bands within distinct classes, hence minimizing mistakes and achieving optimal accuracy with an average of 94.04%, 85.04%, 99.61 % in heterogeneous areas [48] and the most widely used [49]. Apart from that, the algorithm contained in MLC also has good capabilities in processing images and simulating variables sourced from satellite images [50]. A total of 40 sample points were selected for the study, distributed across all land use types using proportional random sampling. This method ensures the number of samples in each land use category is proportional to its area within the study region. By employing this approach, the sampling distribution reflects the true spatial distribution of land use types, reducing bias and enhancing the accuracy of the analysis. Field surveys were conducted to collect data at these points, ensuring that the sample was representative of the overall landscape and land use patterns. The data were analyzed using kappa statistical test.

2.3.3 Change analysis and transition potential modeling

LULC changes were analysed using the Modules for Land-Use Change Simulation (MOLUSCE) plugin found in QGIS [51]. This MOLUSCE plugin was used to estimate spatiotemporal changes and calculate LULC transitions (2013–2018 and 2018–2023). The plugin's capabilities are that it can effectively calculate spatio-temporal changes in land use, model potential transitions, and carry out simulations for future scenarios [52].

Table 1: Data used

No	Data	Acquired Information	Sources
1	Landsat 8 OLI imagery in 2013	LULC in 2013	USGS (https://earthexplorer. usgs.gov/) (Acquisition dates 28 August 2013)
2	Landsat 8 OLI imagery in 2018	LULC in 2018	USGS (https://earthexplorer. usgs.gov/) (Acquisition dates 30 January 2018)
3	Landsat 9 OLI imagery in 2023	LULC in 2023	USGS (https://earthexplorer. usgs.gov/) (Acquisition dates 20 May 2023)
4	RBI Map of Limapuluh Regency	Geospatial data (in shapefile)	BIG (https://tanahair.indonesia.go.id/ portal-web)
5	Menhir data in 2023	Distribution of menhirs, size, materials, menhir directions, menhir conditions	Field survey
6	Driving factors	Distance from the river and distance from the road	BIG (https://tanahair.indonesia.go.id/ portal-web)

Table 2: Land Use/Land Cover classes

LULC Type		Description
Dryland Forest	DF	Forests that grow in hilly/mountainous areas
Built-up Land	BU	Housing, commercial and industrial areas, transportation networks
Plantations	PL	Land planted with one type of plant
Mix Plantation	MP	Plantations planted with various types of perennial plants that produce flowers, fruit and brittle without needing to be cut down
Rice fields	RF	Wet rice fields and dry fields

LULC prediction using the MOLUSCE plugin is carried out using the Artificial Neural Network (ANN), Cellular Automata (CA) and Multi-Layer Perceptron (MLP) methods. To produced LULC predictions, six processing stages need to be carried out, namely data input, evaluation of correlation results, land change analysis, transition potential modelling (TPM), cellular automata (CA) simulation, and validate the results of the predictions [53]. In preparing potential transition modelling, a multilayer ANN with a perceptron approach was used. The driving factors were distance from the river and distance from the main road. These factors can influence LULC dynamics because they are related to physical conditions and anthropogenic activities [54] and [55].

2.4 Prediction and Simulation Models

This research estimates land-use change prediction modelling using a combination of ANN (artificial neural network) and CA (Cellular Automata). These two combinations were chosen because they produce accurate LULC predictions [56] [57] [58] [59] and [60]. Artificial Neural Network (ANN) have emerged as the predominant in remote sensing and GIS for precise modeling and classification of land use changes [61]. This ANN consists of neurons with the same mechanism as the human brain and uses it to recognise data trends [62]. It can be applied to areas with limited data and unknown factors that influence the growth of built-up land [63] and [64]. In addition, the ANN approach is objective in determining weights based on regression analysis by considering a few statistical assumptions so that it can model variables that have non-linear relationships [63] and [65]. The ANN model or artificial neural network can have good accuracy when the driving indicators for built-up land growth have a non-linear relationship to built-up land growth [63] and [65].

In the MOLUSCE plugin in QGIS Desktop version 2.18.11, the ANN algorithm recognises potential changes with output as a transition potential matrix. The ANN-CA simulation utilizes raster data, including land use classifications, spatial parameter rasters, and transition potential models, under the ANN algorithm. The simulation evaluates a predetermined quantity of pixels, determining the most probable transition with the highest certainty, and subsequently modifies the pixel classification. The parameters used in the simulation to find the best RMS value are neighborhood 1px, learning rate 0,010 and 0,001, maximum iterations 100 and 1000, and hidden layers 1-5. The model will stop when it has reached the specified condition.

2.5 Validation Model

Validation was conducted on the MOLUSCE plugin to assess the accuracy of the LULC prediction model. If the validation results of the LULC prediction model are with an accuracy of more than 75%, then it can be continued for predictions for the following year [60].

Land use change prediction results are validated by comparing the 2023 prediction map with the actual 2023 map. If the 2023 prediction results are valid, then land use predictions can be continued for 2053 and subsequent years. If not, the process is repeated by adding, reducing or modifying driving factors. Predictions were extended to 2053 to align with established policy planning horizons and to maintain the reliability of the projections, while 5-year intervals were chosen to capture detailed trends, ensuring a balance between analytical complexity and data consistency. The method used is the Kappa statistical test, which is carried out using an error matrix (confusion matrix) [66]. The Kappa accuracy test formula is below. Based on this calculation formula, the Kappa test results are classified into several classes that indicate the accuracy of the predictions, with the criteria presented in Table 3. If the simulation results have a strong Kappa value, predictions can be modelled for the desired target year.

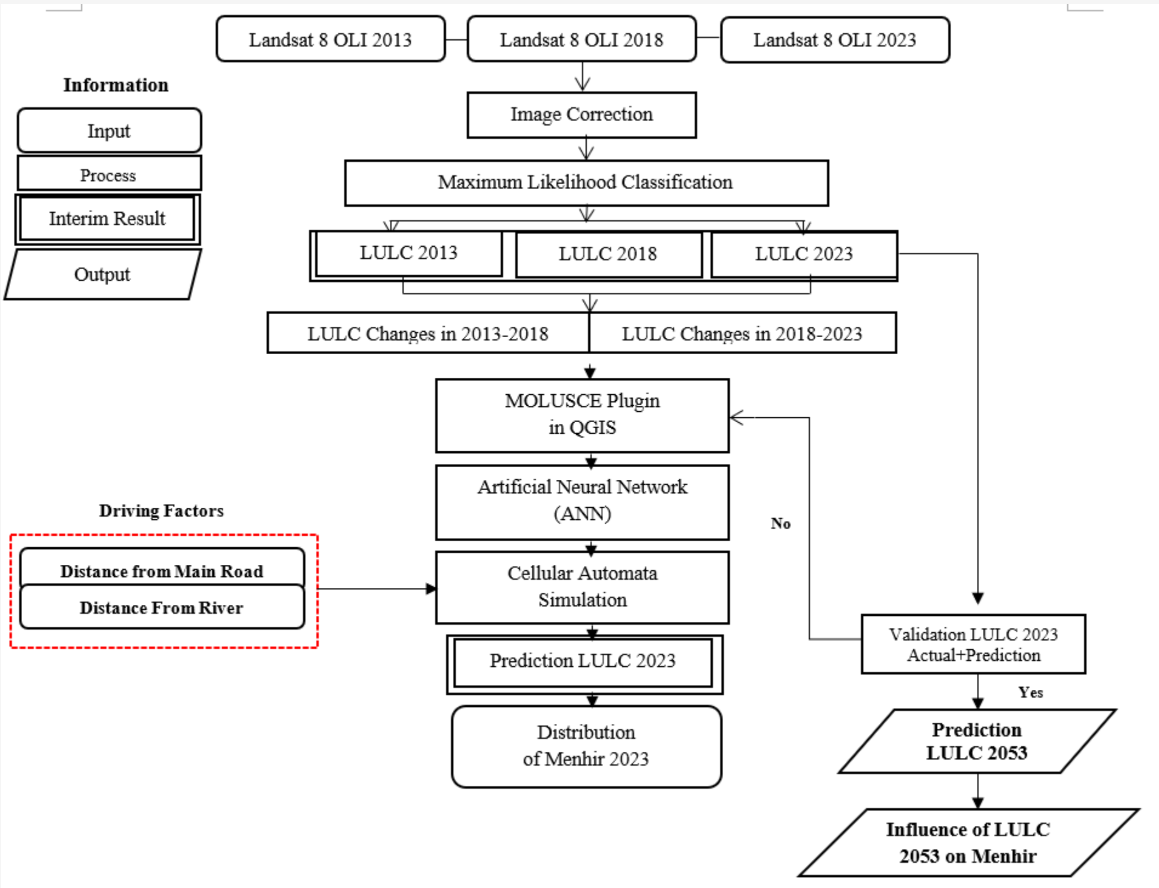


Figure 2: Methodology workflow

Table 3. Classification of Kappa values

Coefficient Value	Value Interpretation
<0.2	Poor
0.21-0.40	Fair
0.41-0.60	Moderate
0.61-0.80	Good
>0.80	Very Good

ISSN: 1686-6576 (Printed) | ISSN 2673-0014 (Online) | © Geoinformatics International

3. Results and Discussion

3.1 Spatiotemporal Change Analysis

Nagari Maek, a Nagari known to have thousands of menhirs, has the potential to develop into a "menhir" historical tourist attraction. It has five land use classes: dry land forests (DF), built-up land (BU), plantations (PL), mixed plantations (MP) and rice fields (RF). These dynamic land use changes require continuous assessment, analysis and monitoring using social, economic and geospatial data to obtain more accurate and integrated results [67]. In this research, a study of LULC changes in Nagari Maek was carried out using geospatial data, and the five LULC classes were spatially distributed for 2013, 2018, and 2023, as seen in Figure 3. Furthermore, the temporal area of each LULC class can be seen in Table 4, where the total area of Nagari Maek obtained from the classification results is 24,413.76 ha which is in accordance with data from [42], namely 244.14 Km^2. LULC Nagari Maek from 2013 to 2023 has the broadest LULC class in the dry land forest class with an average of 62.59% covering Nagari Maek, followed by the plantation class with an average of 25.21%, mixed plantations 10.39%, plantations 1.18%while the largest area the least is built-up land, namely 0.63%. The low area of built-up land is caused by Nagari Maek having a population of 9,744 people with a population density classified as not dense, namely 39.91% [42].

Furthermore, Table 5 presents the changes in LULC that occurred in 2013-2018, 2018-2023, and 2013-2023. Positive changes in LULC indicate an expansion in the area of that particular land use or land cover class, whereas negative changes signify a reduction in the area of that class. Of the five land use classes, it is known that the largest reduction in LULC area, namely – 3.48%, occurred in the dry land forest class, where in 2013, the area was 15,809 ha to 14,958.86 ha in 2023, while those experiencing an increase in area were plantations of 3.43% or 5,646.46 ha to 6,485.46 ha. Built-up land in Nagari Maek from 2013 to 2023 only experienced an increase of 0.19%. This means that within ten years, Nagari Maek has not shown a significant regional transition, but there has been an increase in built-up land which an increase in population can cause.

From the results of the analysis of these changes, it is known that changes in LULC in Nagari Maek were more due to anthropogenic and socio-economic activities that occurred from 2013 – 2023, especially in the dry land forest and plantation classes, while the rice field use class only experienced an increase of 0.18 % or 44.57 ha. These results are in accordance with research [68], which explains that changes in land use occur due to anthropogenic factors or an increase in human population and the need for natural resources, especially land for settlements [69].

Table 4: LULC distribution for the years 2013, 2018, and 2023

LULC Class	2013		2018		2023		2013-2023
	Area (ha)	% area covered	Area (ha)	% area covered	Area (ha)	% area covered	% Average area covered
DF	15,809.00	64.75	15,077.18	61.76	14,958.56	61.27	62.59
BU	128.45	0.53	154.14	0.63	176.38	0.72	0.63
PL	5,646.46	23.13	6,335.06	25.95	6,485.46	26.56	25.21
MP	2,560.78	10.49	2,564.87	10.51	2,479.72	10.16	10.39
RF	269.07	1.10	282.51	1.16	313.64	1.28	1.18
Total	24,413.76	100.00	24,413.76	100.00	24,413.76	100.00	100.00

Table 5: LULC change analysis for the years 2013, 2018, and 2023

LULC Class	2013-2018		2018-2023		2013-2023	
	Area (ha)	Changing area (%)	Area (ha)	Changing area (%)	Area (ha)	Changing area (%)
DF	-731.82	-2.99	-118.62	-0.49	-850.44	-3.48
BU	25.69	0.1	22.24	0.09	47.93	0.19
PL	688.60	2.82	150.40	0.61	839.00	3.43
MP	4.08	0.02	-85.14	-0.35	-81.06	-0.33
RF	13.44	0.06	31.13	0.12	44.57	0.18

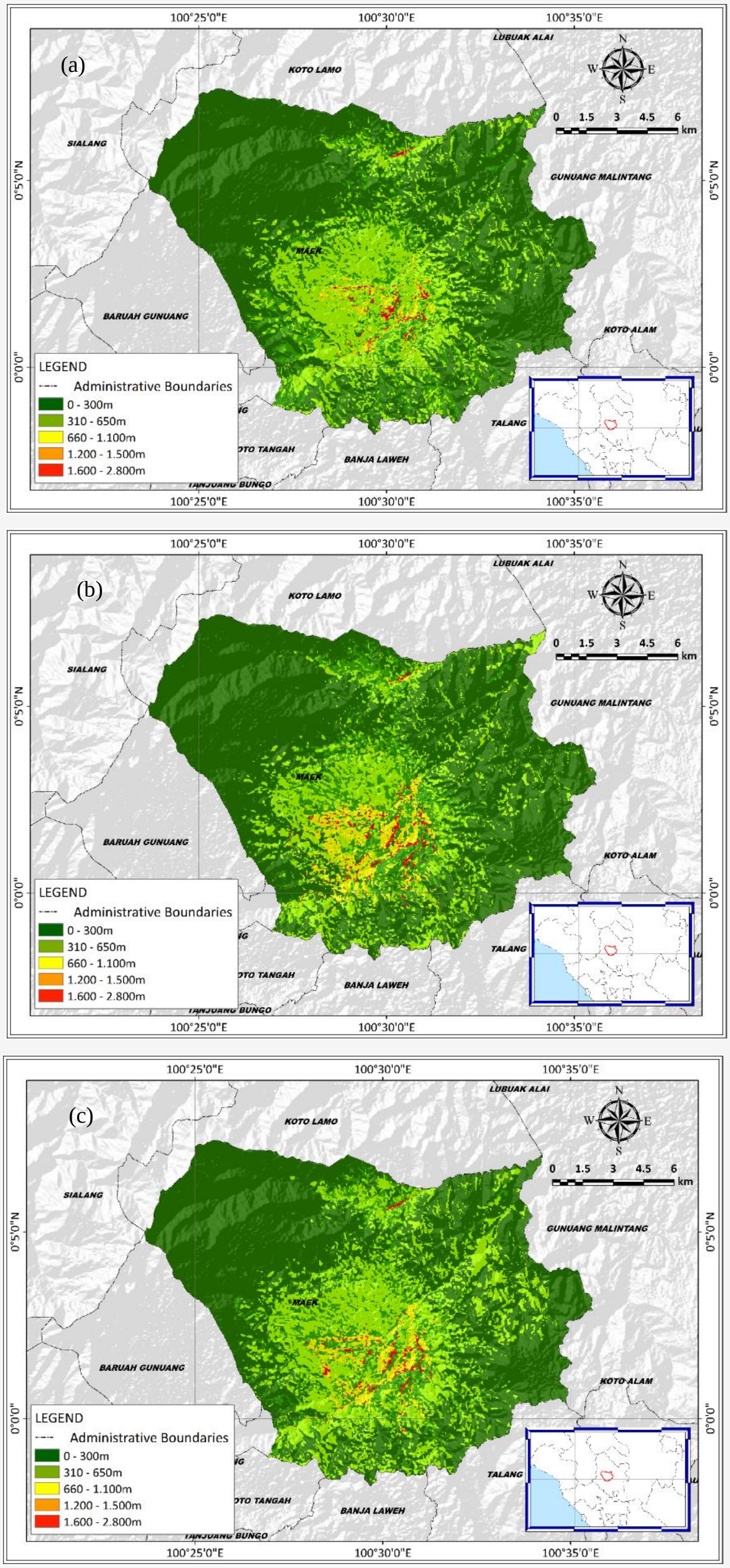


Figure 3: LULC maps for the years (a) 2013 (b) 2018 and (c) 2023

3.2 LULC Transition Analysis

Land use changes in an area depend on the driving factors that cause these changes [54] the driving factors used are proximity to rivers and proximity to roads (refer to Figure 4), which are most often used when considering driving factors in land use changes [70]. These factors were chosen because Nagari Maek is a Nagari surrounded by hills, far from the district center so road access is still minimal and has many tributaries, so it is an access that is needed by the community and there is potential for the area around this factor to experience changes.

Determining the distance between roads and rivers is executed via the Euclidean Distance technique. The statistical tests using Pearson correlation show that the relationship between the road and the river is 1, which means it has a very strong relationship. The transition matrix plays a very important role in predicting LULC. It looks at how the proportion of pixels changes from one land use class to another. Many researchers use transition matrices to determine temporal changes in each region [71].

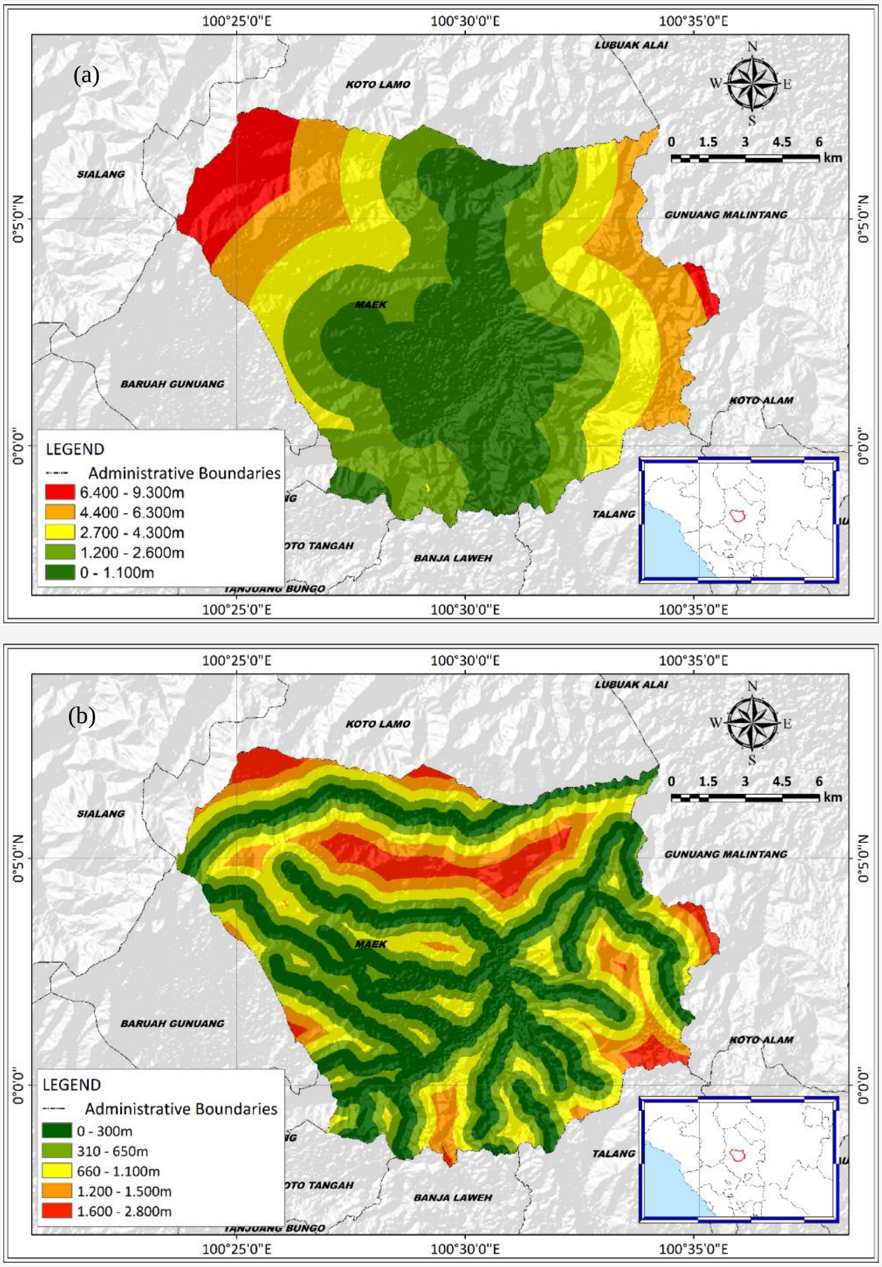


Figure 4: Driving factors: (a) distance from main roads (b) distance from river

Table 6: Transition matrix of LULC 2013-2023

Transition Matrix	DF	BU	PL	MP	RF
DF	**0.875**	0.000	0.036	0.086	0.002
BU	0.000	**0.436**	0.093	0.053	0.418
PL	0.065	0.014	0.178	**0.663**	0.079
MP	0.305	0.003	**0.359**	0.318	0.015
RF	0.005	0.018	0.166	0.109	**0.700**

The potential magnitude of these changes is the basis for predicting LULC in the future. In this research, the transition matrix was carried out with the help of the MOLUSCE plugin in the period 2013–2023. The 2013–2023 Nagari Maek LULC transition matrix can be seen in Table 6, where the rows in the matrix table represent the magnitude of changes in land use classes, the columns show the order of the same LULC categories in the last year, while the diagonal in the matrix shows the measure of class stability, and each number outside the diagonal represents the size of the transition from one class to a different class [56]. Table 6 presents the transition matrix values ranging from 0 to 1, where off-diagonal elements are particularly significant, as they indicate substantial land cover changes or transitions within the study area. Values between 0.01 and 0.99 suggest the possibility of land use changes, with values of 0 indicating no transition and values of 1 indicating a complete transition from one land cover class to another. The focus should be on the largest off-diagonal elements, as these represent the most notable transitions observed [19]. The greater the transition value, the greater the changes that occur in the type of land use.

Nagari Maek has the greatest probability of change in the dryland forest (DF) class of 0,875 and the rice field (RF) class of 0,700. This value means that the probability of switching from DF to DF class is 87,5% and switching from RF to RF class is 0,70%. This means that the potential for changes in the DF and RF classes to other land use classes is very small, almost even close to a value of 1, which means there tends to be no change. Nagari Maek exhibits a high stability value in terms of DF (forest) land use change, primarily due to its geographical characteristics, being surrounded by hills and valleys. These natural barriers significantly limit the likelihood of DF conversion to other land uses, particularly to built-up areas (BU). Furthermore, the considerable distance between Nagari Maek and Sarilamak, the capital of Limapuluh Kota Regency, contributes to the community's tendency to preserve RF (forest reserve) land use, as it plays a crucial role in sustaining their daily needs. However, the most notable transitions occur in the off-diagonal elements of the transition matrix. These off-diagonal values highlight the potential for land cover change, albeit small. The transitions from PL to MP (0.633) and from MP to PL (0.359) are more frequent, particularly in recent years. Overall, while DF and RF demonstrate high stability, the plantation classes exhibit more dynamic changes, primarily between PL and MP. These changes can be attributed to the increasing human population and demand for land, particularly for settlement expansion and its supporting areas [69]. Additionally, a transition map (Figure 5) corroborates the matrix results, showing that from 2013 to 2018, transitions were primarily from PL to MP, and in the 2018 to 2023 period, shifts occurred between PL, MP, and some DF conversions to PL. These findings align with the transition matrix for the 2013-2023 period (Table 6).

3.3 Prediction and Simulation Models

Before predicting the 2053 LULC in Nagari Maek, a potential transition modeling using Artificial Neural Network (ANN) is first carried out to produce a neural network graph. Modeling using ANN consists of several parameters which can be seen in Figure 6. In this study, using a neighborhood of 1 px, learning rate 0.1; maximum iteration 100, hidden layer 10 and momentum 0.05. The ANN modeling that was carried out resulted in an overall accuracy value obtained of -0.01157, minimal validation overall error of 0.05987 with a current validation kappa value of 0.68. The smaller the error value, the higher the performance of the model created. This value can be used, because it has an error value close to 0 and a kappa value close to 1 with a moderate category because it is in the range of 0.40 to 0.60 [60][72] and [73]. The values obtained from the training results are influenced by the iteration value, momentum value, or even the pixel cell size in the initial modeling data. This means that if the Kappa validation value is greater, the factor values used will generalize the results of the computational values in the ANN process. More iteration factors will also improve the modelling, but require longer processing time [53]. Subsequently, LULC prediction was conducted using cellular automata simulation, resulting in a prediction of LULC 2023 (Figure 7).

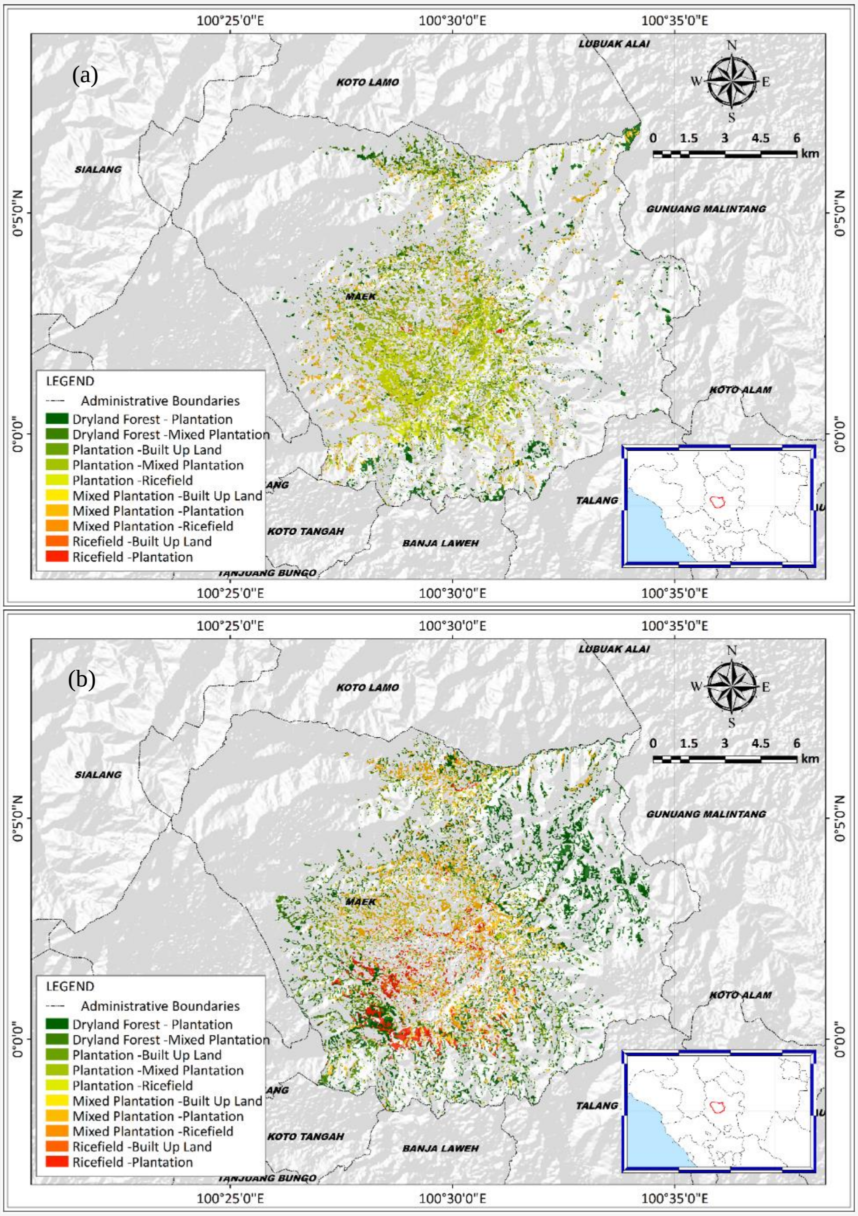


Figure 5: Transition map (a) LULC 2013-2018 (b) LULC 2018-2023

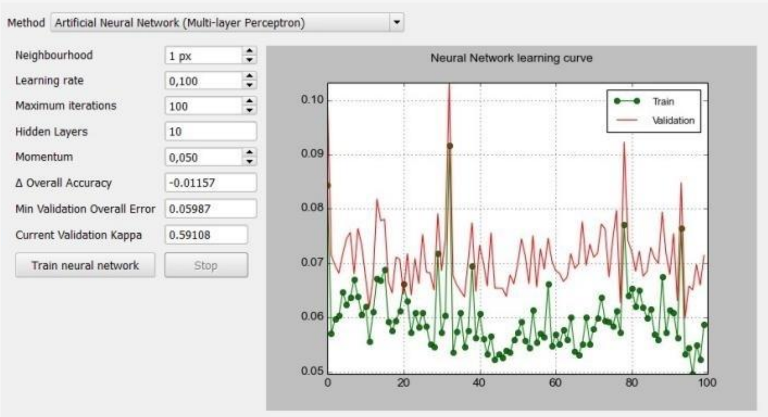


Figure 6: Transition potential modeling

ISSN: 1686-6576 (Printed) | ISSN 2673-0014 (Online) | © Geoinformatics International

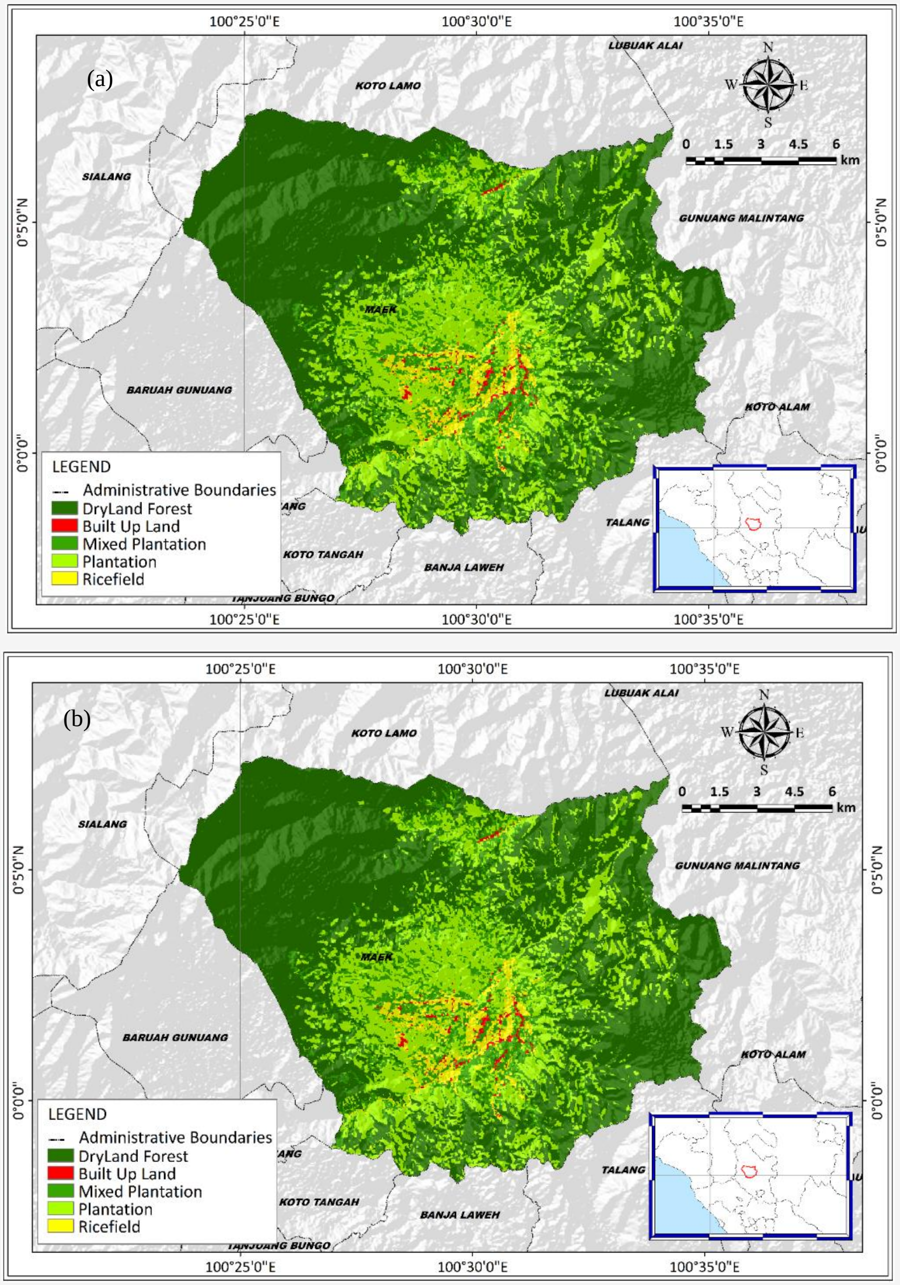


Figure 7: LULC in 2023 (a) actual (b) predicted

The LULC prediction results for 2023 were then compared with the actual data for 2023 which can be seen in Figure 7 and Table 7 The analysis results in Table 7 show that there is a slight difference in the LULC area between the predicted and actual results, especially in the PL class with a difference of up to 16,36% and MP up to 17.84%. The overall statistical accuracy test was 68.43 with a correctness percentage of 83.11%. The Kappa value shows that the modeling has a strong suitability [19] and [73] because it is in the Kappa coefficient category of 0.61–0.80. Meanwhile, this correctness value represents a reliable prediction result and can be used as a reference in the formation of subsequent policies and of course a review of the prediction results with physical conditions in the field is needed. The Kappa value results show that there is a strong match between the simulation results and actual conditions, so the prediction simulation process can be carried out. In this study, predictions were made for the year 2053 which spatially can be seen in Figure 8. Temporally in Figure 8 it is known that from 2023 to 2053 or the next 30 years there will be significant changes in all LULC classes.

Table 7: Actual and projected LULC of 2023

LULC Class	Actual 2023		Projected 2023		Projected and actual difference (%)	Kappa Value	
	Area (ha)	Changing area (%)	Area (ha)	Changing area (%)		Correctness (%)	Overall Kappa
DF	14,958.56	61.27	13,698.08	56.11	-5.16		
BU	176.38	0.72	176.21	0.72	0		
PL	6,485.46	26.56	2,490.19	10.20	-16.36	83.11	0.68
MP	2,479.72	10.16	6,836.23	28.00	17.84		
RF	313.64	1.28	1,213.05	4.97	3.60		
Total	24,413.76	100.00	24,413.76	100.00	0		

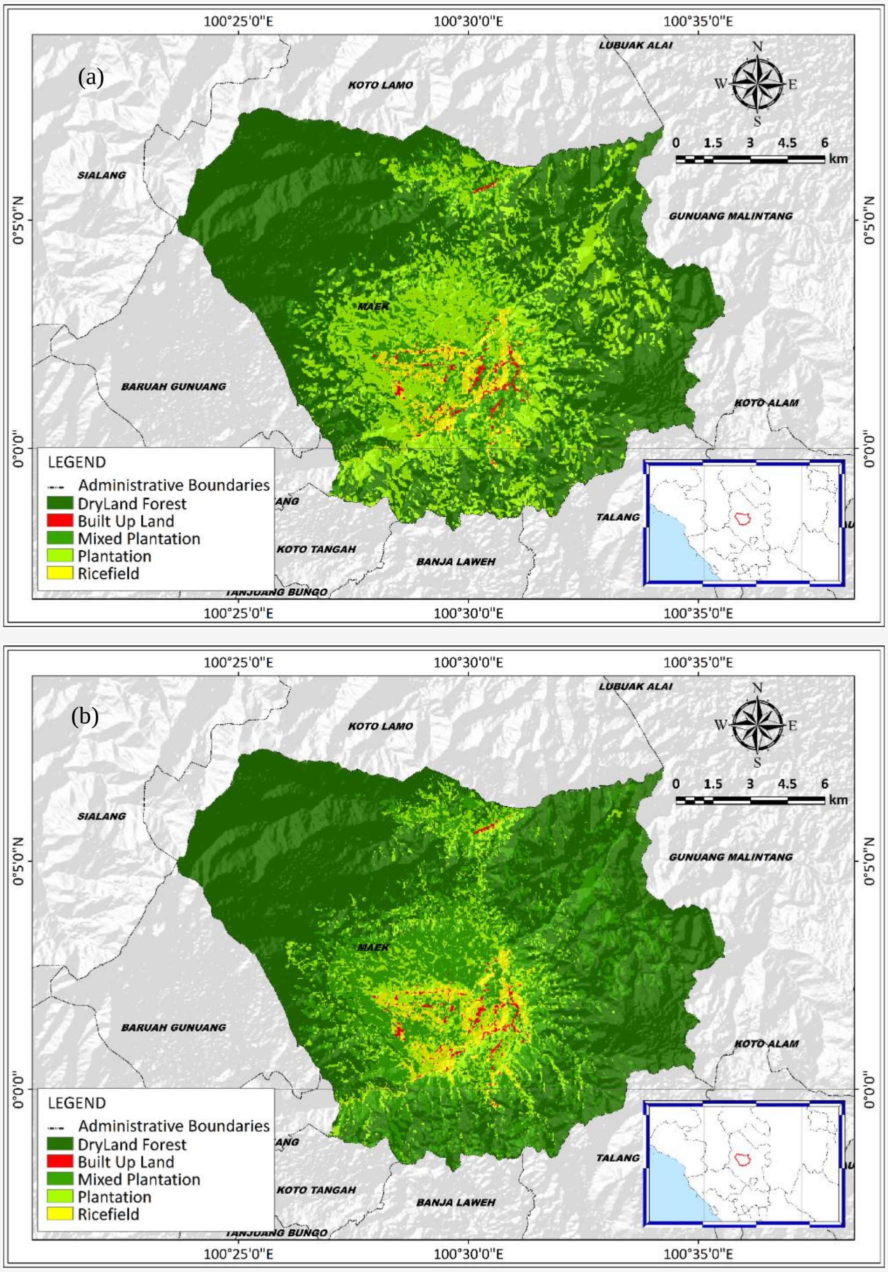
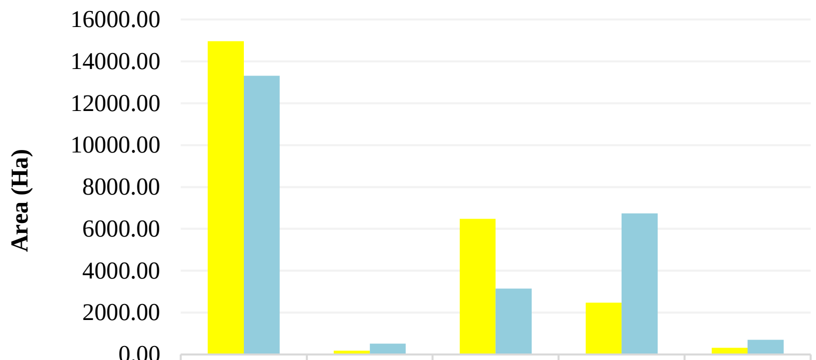


Figure 8: Predicted LULC: (a) in 2023 (b) in 2053

ISSN: 1686-6576 (Printed) | ISSN 2673-0014 (Online) | © Geoinformatics International



	Dryland Forest	Built-up Land	Plantations	Mix Plantation	Rice fields
Actual 2023	14958.56	176.38	6485.46	2479.72	313.64
Projected 2050	13,311.07	515.54	3,147.66	6,742.55	696.29
Difference (%)	**-6,75%**	**1,39%**	**-13,67%**	**17,46%**	**1,57%**

Figure 9: LULC change analysis from 2023 to 2053

Significant changes occurred in the PL class which experienced a decrease of -13.67% and MP experienced an increase in 2053 of 17.46% while other land use classes such as DF, BU and RF did not experience a significant increase or decrease (Figure 9). The decrease and increase in LULC in Nagari Maek can be caused by various factors, including in the next 27 years the population will increase, accompanied by the need for land, especially land for natural resource settlements, and socio-economic development plans [18] and [69].

3.5 LULC and Historical Tourism Menhir

Nagari Maek is famous for its interesting and unique natural menhirs and geoparks. This is a potential for the Nagari to have historical tourism potential, especially regarding the menhirs facing Mount Sago. However, the history of menhirs is starting to be forgotten in society, and some people do not know the origins of the menhirs in Nagari Maek. Menhirs found in Maek have a variety of shapes such as animal and weapon shapes in accordance with the circumstances and beliefs of the previous community and some have motifs. The survey results showed that in Nagari Maek there were 30 menhir sites spread across various LULC classes (Table 8) and there were still many sites that had not been fenced, so the menhirs were distributed unevenly and many were not maintained. There are even people who use the menhir stones for household purposes.

Should the predicted Land Use Land Cover (LULC) conversion in Nagari Maek occur by 2053, many menhirs are likely to be neglected or even lost due to the repurposing of their locations for other land uses. As indicated in Table 8, there were 30 menhir sites identified in 2023. However, by 2053, it is estimated that there will be a reduction of 13 menhir sites. Specifically, in 2053 it is known that the dominant changes occur in PL and MP, so it is predicted that 8 menhir sites contained in these land uses will also be disturbed, namely Domo Hill Menhir III, Menhir Ateh Sudu I, Menhir Jalan Baliak IV, Menhir Ampang Gadang A, Menhir Below the Ditch, Menhir Tanjung Kayu Kaciak II, Village Menhir I, Menhir Kampung II. Each site contains at least 20 menhirs; thus, the loss of 13 sites would result in the disappearance of at least 260 menhirs. Consequently, this would erode the distinctive characteristic of Nagari Maek as a site with 1,000 menhirs over time.

In Figure 10, it can also be seen that in 2023, there are 30 menhir sites spread across various land uses in Nagari Maek. This menhir in megalithic culture has a main function related to the worship of ancestral spirits or related to burial activities [74]. The extent of the menhir distribution area in Nagari Maek shows that Nagari Maek has a high cultural and historical value, so if it is properly utilized, it has the potential as a cultural and historical tourism area. However, with land use change, especially in the PL and MP classes in 2053, it can impact the 8 menhir sites shown in Figure 9(b). When people make land use changes, they tend to ignore the position and location of the menhirs, so that for some people the menhir stone is used as a seat or chili grinder. If this continues, Nagari Maek will lose its identity as a Nagari of 1,000 menhirs. This, careful planning is essential for land conversion, particularly for areas with potential value for development as historical tourism sites.

Table 8: Historical tourism menhir in Maek

No	Name	E	N	LULC 2023	LULC 2053
1	Bandar Lintang Island Menhir (Fence)	100° 28' 56.268" E	0° 2' 9.992" N	Mix Plantation	Mix Plantation
2	Menhir Bukit Domo I (Padang Hilalang)	100° 30' 22.206" E	0° 1' 55.531" N	Mix Plantation	Mix Plantation
3	Domo Hill Menhir II	100° 30' 18.924" E	0° 1' 53.660" N	Mix Plantation	Mix Plantation
4	Menhir Bukit Domo IV	100° 30' 20.153" E	0° 1' 43.513" N	Mix Plantation	Mix Plantation
5	**Domo Hill Menhir III**	**100° 30' 22.991" E**	**0° 1' 48.762" N**	**Plantations**	**Mix Plantation**
6	Menhir Ronah I	100° 30' 13.254" E	0° 1' 36.077" N	Built-up Land	Built-up Land
7	**Menhir Ateh Sudu I**	**100° 30' 43.274" E**	**0° 1' 6.357" N**	**Mix Plantation**	**Built-up Land**
8	Menhir Ateh Sudu II	100° 30' 47.797" E	0° 1' 9.346" N	Mix Plantation	Mix Plantation
9	Menhir Jalan Baliak III	100° 30' 26.496" E	0° 0' 56.521" N	Mix Plantation	Mix Plantation
10	Pentingan Menhir	100° 30' 24.136" E	0° 0' 56.657" N	Mix Plantation	Mix Plantation
11	**Menhir Jalan Baliak IV**	**100° 30' 26.955" E**	**0° 0' 54.423" N**	**Dryland Forest**	**Mix Plantation**
12	**Menhir Ampang Gadang A**	**100° 29' 46.029" E**	**0° 0' 43.802" N**	**Plantations**	**Mix Plantation**
13	Menhir Ampang Gadang B	100° 29' 43.717" E	0° 0' 42.724" N	Mix Plantation	Mix Plantation
14	**(Fence) Menhir Below the Ditch**	**100° 29' 40.705" E**	**0° 1' 38.570" N**	**Plantations**	**Mix Plantation**
15	(Fence) Menhir Balai Batu	100° 30' 34.350" E	0° 0' 57.065" N	Mix Plantation	Mix Plantation
16	Bandar Lintang Island Menhir	100° 28' 56.357" E	0° 2' 10.024" N	Mix Plantation	Mix Plantation
17	**Menhir Tanjung Kayu Kaciak II**	**100° 29' 38.572" E**	**0° 1' 18.209" N**	**Plantations**	**Mix Plantation**
18	Menhir Tanjung Kayu Kaciak I	100° 29' 39.256" E	0° 1' 21.229" N	Mix Plantation	Mix Plantation
19	Menhir Ronah II	100° 30' 12.335" E	0° 1' 41.929" N	Mix Plantation	Mix Plantation
20	Menhir Ronah III	100° 30' 15.402" E	0° 1' 39.243" N	Built-up Land	Built-up Land
21	Sopan Land Menhirs	100° 30' 46.074" E	0° 1' 51.407" N	Built-up Land	Built-up Land
22	Menhir Jalan Baliak II	100° 30' 28.905" E	0° 0' 56.202" N	Mix Plantation	Mix Plantation
23	Menhir Jalan Baliak I	100° 30' 26.390" E	0° 0' 49.648" N	Mix Plantation	Mix Plantation
24	**Village Menhir I**	**100° 30' 30.779" E**	**0° 0' 45.032" N**	**Mix Plantation**	**Plantations**
25	**Menhir Kampung II**	**100° 30' 29.732" E**	**0° 0' 43.219" N**	**Mix Plantation**	**Plantations**
26	Sopan Tanah	100° 30' 45.438" E	0° 1' 50.938" N	Built-up Land	Built-up Land
27	Menhir Tanjung Jirat I	100° 29' 36.221" E	0° 0' 48.215" N	Mix Plantation	Mix Plantation
28	Menhir Lubuak Kambiang	100° 29' 39.488" E	0° 0' 50.830" N	Built-up Land	Built-up Land
29	Menhir Tanjung Jirat II	100° 29' 37.851" E	0° 0' 47.012" N	Mix Plantation	Mix Plantation
30	Menhir Lubuak Kubang	100° 29' 18.153" E	0° 0' 35.556" N	Ricefields	Ricefields

Effective development of historical tourism could generate significant income for the Nagari. Conversely, if land conversion is not executed with thorough planning, it may result in the loss of menhirs and negatively impact ecosystem services, including provisioning, regulation, cultural, and biodiversity functions [75]. This is because ecosystem services that provide food sources, clean water, and biodiversity are low due to the change in plantation land (vegetation) to built-up land. Therefore, the results of LULC predictions are essential for planners and stakeholders [76]. Especially for Wali Nagari Maek, Bukik Barisan District, Limapuluh Kota Regency. The integration of menhir distribution into the LULC model enhances its practical relevance by including cultural factors, enabling better decision-making for balancing development and heritage conservation. However, the model is limited by the resolution of menhir data, which may miss smaller or undocumented sites, and by assuming that cultural landscapes remain static, ignoring potential changes in preservation efforts.

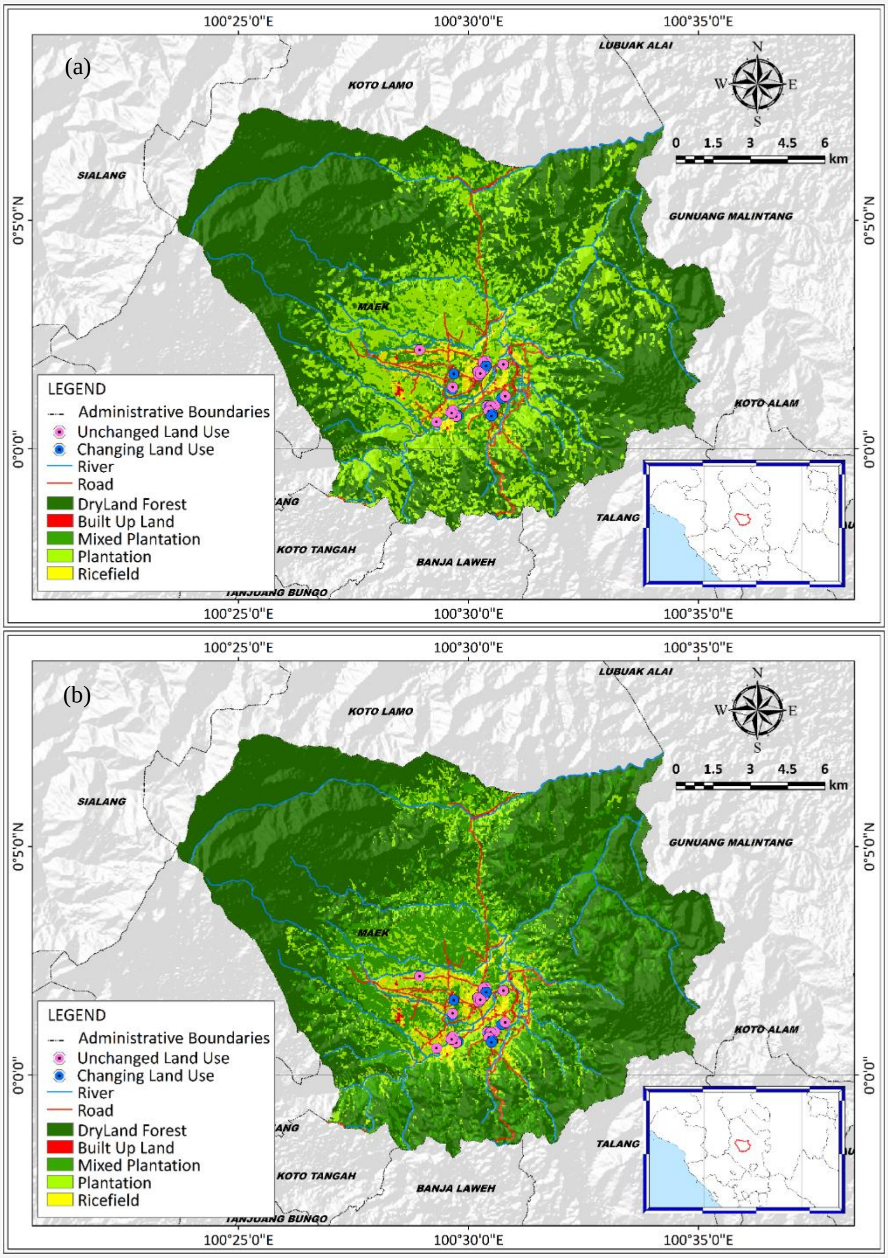


Figure 10: Influence of LULC change on menhir tourism:
(a) actual LULC in 2023 (b) predicted LULC in 2053

Future research could improve the model by incorporating more detailed cultural information, such as community involvement or tourism potential, and by considering dynamic factors like evolving environmental policies to create a more flexible and accurate predictive tool.

4. Conclusions

Nagari Maek is a Nagari famous for its menhirs, which can be used as a historical menhir tourist attraction. To increase historical menhir tourism in Nagari Maek, land needs to be converted in several locations to build private infrastructure. Therefore, a 2053 LULC prediction was carried out to determine the menhirs condition in 2053 after land conversion. LULC predictions in Nagari Maek were carried out using the CA-ANN method from 2013 to 2023, where the results of changes from 2018 to 2023 were used as the basis for determining the LULC class in 2053. The overall statistical accuracy test showed that the prediction results had an accuracy of 68.43 with a correctness percentage amounting to 83.11%. This means that the resulting modeling has strong suitability and the prediction results can be trusted so that it can be used as a reference in the formation of subsequent policies and of course a review of the prediction results is needed with the physical conditions in the field. LULC 2053 resulted in significant land changes only occurring in the DF or dry land forest class which experienced a decline of 6.75% and PL or plantations of 13.67%. Apart from the decrease. LULC Nagari Maek also experienced an increase in the MP or mixed plantation class by 17.46%. RF or rice fields by 1.57% and BU or built-up land by 1.39%. The decrease and increase in LULC in Nagari Maek can be caused by various factors, including in the next 30 years the population will increase, accompanied by the need for land, especially land for settlement, natural resources for survival.

If the LULC conversion is linked to the existence of menhirs (the main object in historical tourism), then in 2023 there will be 30 menhir sites discovered. However, in the 2053 estimate there will be a reduction in 6 menhir sites, where in 2053 Menhir Ronah I will experience residential development. Menhir Ateh Sudu I will experience land conversion from mixed gardens to built-up land. Menhir Ronah III, Menhir Sopan Tanah and Menhir Lubuak Kambiang will experience development, settlement. Each site has a different number of menhirs and has at least 20 menhirs. If 6 sites are lost, then at least 120 menhirs are also lost. This caused the characteristic inherent in Nagari Maek, namely as a Nagari with 1,000 menhirs, to disappear. This means that there needs to be good planning in carrying out land conversion, especially for land that has potential value to be developed as historical tourism.

References

[1] World Trade Organization, (2020). *International Tourism Highlights. In UNWTO*. https://doi.org/10.18111/9789284422456.

[2] Haryana, A., (2020). Economic and Welfare Impacts of Indonesia's Tourism Sector. *Jurnal Perencanaan Pembangunan: The Indonesian Journal of Development Planning*, Vol. 4(3), 300-311. https://doi.org/10.36574/jpp.v4i3.127

[3] Rasool, H., Maqbool, S. and Tarique, M., (2021). The Relationship between Tourism and Economic Growth Among BRICS Countries: a Panel Cointegration Analysis. *Future Business Journal*, Vol. 7(1), 1–11. https://doi.org/10.1186/s43093-020-00048-3.

[4] World Trade Organization, (2013). *Sustainable Tourism for Development Guidebook-Enhancing Capacities for Sustainable Tourism for Development in Developing Countries*. First Edition: 2013. [Online]. Available: https://lib.ncdd.gov.kh/storage/app/public/test_library/CAT_24829_1/2013.SustainableTourism-Guidebook-en.pdf. [Accessed: Dec. 15, 2023].

[5] Warouw, F. F., Langitan, F. W. and Alamsyah, A. T., (2018). *Community Participation for Sustainable Tourism Model in Manado Coastal Area*. IOP Conference Series: Materials Science and Engineering, Vol. 306(1), 1-7. October 25–26. 2018. Manado, Indonesia. IOP Publishing Ltd. https://doi.org/10.1088/1757-899X/306/1/012039.

[6] Widaningrum, D. L., Surjandari, I. and Sudiana, D., (2020). Analyzing Land Use Changes in Tourism Development Areas: A Case Study of Cultural World Heritage Sites on Java Island, Indonesia. *International Journal of Technology*, Vol. 11(4), 688–697. https://doi.org/10.14716/ijtech.v11i4.4097.

[7] Mao, X. Y., Meng, J. J. and Wang, Q., (2014). Tourism and Land Transformation: a Case Study of The Li River Basin, Guilin, China. *Journal of Mountain Science*, Vol. 11(6), 1606–1619.

[8] Yang, R., Chen, H., Chen, S., and Ye, Y. M., (2022). Spatiotemporal Evolution and Prediction of Land Use/Land Cover Changes and Ecosystem Service Variation in The Yellow River Basin, China. *Ecological Indicator*, Vol.145, 1-13. https://doi.org/10.1016/j.ecolind.2022.109579.

[9] Li, S., Nadolnyak, D. and Hartarska, V., (2019). Agricultural Land Conversion: Impacts of Economic and Natural Risk Factors in Coastal Areas. *Land Use Policy*, Vol. 80, 380–390. https://doi.org/10.1016/j.landusepol.2018.10.016.

[10] Xiao, J., Watanabe, T., Lu, X., Chand, M. B., Umarhadi, D.A., Chen, X. and Avtar, R., (2021). Integrating Land Use/Land Cover Change with Change in Functional Zones' Boundary of the East Dongting Lake National Nature Reserve, China. *Physics and Chemistry of the Earth, Parts A/B/C*, Vol. 126. https://doi.org/10.1016/j.pce.2021.103041.

[11] Fedele, G., Locatelli, B., Djoudi, H. and Colloff, M. J., (2018). Reducing Risks by Transforming Landscapes: Cross-Scale Effects of Land-Use Changes on Ecosystem Services. *PLOS ONE*, Vol. 13(4), 1-21. https://doi.org/10.1371/journal.pone.0195895.

[12] Yadav, P. K., Kapoor, M. and Sarma, K., (2012). Land Use Land Cover Mapping. Change Detection and Conflict Analysis of Nagzira-Navegaon Corridor, Central India Using Geospatial Technology. *International Journal of Remote Sensing and GIS*, Vol. 1(2), 90–98.

[13] Abbas, Z., Yang, G., Zhong, Y. and Zhao, Y., (2021). Spatiotemporal Change Analysis and Future Scenario of LULC Using the CA-ANN Approach: A Case Study of the Greater Bay Area, China. *Land*, Vol. 10(584), 1-26. https://doi.org/10.3390/land10060584.

[14] Li, D., Tian, P., Luo, H., Hu, T., Dong, B., Cui, Y., Khan, S. and Luo, Y., (2020). Impacts of Land Use and Land Cover Changes on Regional Climate in the Lhasa River Basin, Tibetan Plateau. *Science of the Total Environment*, Vol. 742. https://doi.org/10.1016/j.scitotenv.2020.140570.

[15] Song, X. P., Hansen, M. C., Stehman, S. V., Potapov, P. V., Tyukavina, A., Vermote, E. F. and Townshend, J. R., (2018). Global Land Change from 1982 to 2016. *Nature*, Vol. 560, 639-643. https://doi.org/10.1038/s41586-018-0411-9.

[16] Aniah, P., Bawakyillenuo, S., Codjoe, S. N. A. and Dzanku, F. M., (2023). Land Use and Land Cover Change Detection and Prediction Based on the CA-Markov Chain in the Savannah Ecological One of Ghana. *Environmental Challenge*, Vol.10, 1-11 https://doi.org/10.1016/j.envc.2022.100664.

[17] Tadese, S., Soromessa, T. and Bekele, T., (2021). Analysis of the Current and Future Prediction of Land Use/Land Cover Change using Remote Sensing and the CA-Markov Model in Majang Forest Biosphere Reserves of Gambella, Southwestern Ethiopia. *The Scientific World Journal*, Vol. 2021(1), 1-18. https://doi.org/10.1155/2021/6685045.

[18] Wang, J., Lin, Y., Glendinning, A. and Xu, Y., (2018). Land-use Changes and Land Policies Evolution in China's Urbanization Processes. *Land Use Policy*, Vol. 75, 375-387. https://doi.org/10.1016/j.landusepol.2018.04.011.

[19] Hapsary, M. S. A., Subiyanto, S. and Firdaus, H. S., (2021). Analisis Prediksi Perubahan Penggunaan Lahan Dengan Pendekatan Artificial Neural Network dan Regresi Logistik di Kota Balikpapan. *Jurnal Geodesi Undip*, Vol. 10(2), 88-97. https://doi.org/10.14710/jgundip.2021.30637.

[20] Rane, N. L., Achari, A., Choudhary, S. P. and Giduturi, M., (2023). Effectiveness and Capability of Remote Sensing (RS) and Geographic Information Systems (GIS): A Powerful Tool for Land Use and Land Cover (LULC) Change and Accuracy Assessment. *International Journal of Innovative Science and Research Technology*, Vol. 8(4), 1411–1446. https://doi.org/10.5281/zenodo.7845418.

[21] Kafy, A. A., Rahman, M. S., Hasan, M. M. and Islam, M., (2020). Modelling Future Land Use Land Cover Changes and their Impacts on Land Surface Temperatures in Rajshahi, Bangladesh. *Remote Sensing Applications: Society and Environment*, Vol. 18. https://doi.org/10.1016/j.rsase.2020.100314.

[22] Soares-Filho, B. S., Cerqueira, G. C. and Pennachin, C. L., (2002). DINAMICA-a Stochastic Cellular Automata Model Designed to Simulate the Landscape Dynamics in an Amazonian Colonization Frontier. *Ecological Modelling*, Vol. 154(3), 217–235. https://doi.org/10.1016/S0304-3800(02)00059-5.

[23] Chen, Z., Huang, M., Zhu, D. and Altan, O., (2021). Integrating Remote Sensing and a Markov-FLUS Model to Simulate Future Land Use Changes in Hokkaido, Japan. *Remote Sensing*, Vol. 13(13), 1-23. https://doi.org/10.3390/rs13132621.

[24] Liu, X., Sun, R., Yang, Q., Su, G. and Qi, W., (2012). Simulating Urban Expansion Using an Improved SLEUTH Model. *Journal of Applied Remote Sensing*, Vol. 6, 1-19. http://dx.doi.org/10.1117/1.JRS.6.061709.

[25] Rismara, F., (2014). *Land Use Change and Its Impact on Water Availability*. Bogor: Bogor Agricultural University.

[26] Shatnawi, N. and Abu Qdais, H., (2019). Mapping Urban Land Surface Temperature Using Remote Sensing Techniques and Artificial Neural Network Modelling. *International Journal of Remote Sensing*, Vol. 40(10), 3968–3983. https://doi.org/10.1080/01431161.2018.1557792.

[27] Asori, M. and Adu, P., (2023). Modeling the Impact of the Future State of Land Use Land Cover Change Patterns on Land Surface Temperatures Beyond the Frontiers of Greater Kumasi: A Coupled Cellular Automaton (CA) and Markov Chains Approach. *Remote Sensing Applications: Society and Environment*, Vol. 29. https://doi.org/10.1016/j.rsase.2022.100908

[28] Phonphan, W., Arunplod, C., Wongsongja, N., Utarasakul, T., Niemmanee, T., Kayee, P., Daraneesrisuk, J., & Thongdara, R. (2024). Evaluating Spatiotemporal Dynamics: A Comparative Study of Predictive Efficacy in Land Use Land Cover Change Models-Markov Chain, CA-ANN, and PLUS. *International Journal of Geoinformatics*, Vol. 20(6), 13–25. https://doi.org/10.52939/ijg.v20i6.3329.

[29] Thammaboribal, P., and TRIPATHI, N. (2024). Predicting Land Use and Land Cover Changes in Pathumthani, Thailand: A Comprehensive Analysis from 2013 to 2023 Using Landsat Satellite Imagery and CA-ANN Algorithm, with Projections for 2028 and 2038. *International Journal of Geoinformatics*, Vol. 20(5), 13–27. https://doi.org/10.52939/ijg.v20i 5.3225.

[30] Kaswanto, R. L., Aurora, R. M., Yusri, D. and Sjaf, S., (2021). Analisis Faktor Pendorong Perubahan Tutupan Lahan Selama Satu Dekade di Kabupaten Labuhanbatu Utara. *Jurnal Ilmu Lingkungan*, Vol. 19(1), 107-116. https://doi. org /10.14710/jil.19.1.107-116.

[31] Mehdi, N. and Mosavi, A., (2021). An Integrated CA-Markov Model for the Simulation and Prediction of Future LULC Changes in Boushehr Province, Iran. *Journal of Environmental Management*, Vol. 293, 112–116. https://doi.org/10.1016/j.jenvman.2021.1 12850.

[32] Verburg, P. H., Veldkamp, W. S. A., Espaldon, R. L. V. and Mastura, S. S. A., (2020). Modeling the Spatial Dynamics of Regional Land Use: The CLUE-S Model. *Environmental Management*, Vol. 30(3), 391-405. https://doi. org/10.1007/s00267-002-2630-x.

[33] Rahman, M., Begum, R. A. and Aryastana, P. D., (2020). Land-Use/Land-Cover Change Prediction Using an Integrated Approach of Markov Chain Model. CA-ANN. And The Multi-Layer Perceptron in Serang Regency. Indonesia. *The Egyptian Journal of Remote Sensing and Space Science*, Vol. 23(3), 341-353. https://doi.org/10.1016/j.ejrs.2020.05.003.

[34] Sang, L., Zhang, C., Yang, J., Zhu, D. and Yun, W., (2011). Simulation of Land Use Spatial Pattern of Towns and Villages Based on CA-Markov Model. *Mathematical and Computer Modelling*, Vol. 54(3-4), 938-943. https://doi. org/10.1016/j.mcm.2010.11.019.

[35] Zhou, Y., Li, Y., Qian, L. and Yang, Y., (2019). CA-Markov Model-Based Study of Land Use/Land Cover Spatiotemporal Change and Simulation in Bao'an District, Shenzhen City, China. *Ecological Indicators*, Vol. 109. https://doi.org/10.1016/j.ecolind.2019.105838.

[36] Dewan, A. M. and Yamaguchi, Y., (2009). Land Use and Land Cover Change in Greater Dhaka. Bangladesh: Using Remote Sensing to Promote Sustainable Urbanization. *Applied Geography*, Vol. 29(3), 390-401. https://doi. org/10.1016/j.apgeog.2008.12.005.

[37] Baig, M. F., Mustafa, M. R. U., Baig, I., Takaijudin, H. B. and Zeshan, M. T., (2022). Assessment of Land Use Land Cover Changes and Future Predictions Using CA-ANN Simulation for Selangor, Malaysia. *Water*, Vol. 14(3). https://doi.org/10.3390/w14030402.

[38] Klanreungsang, B., and Nilsonthi, P. (2024). Urban Land Use Changes Simulation with CA-ANN Model: A Case Study of Mae Sot District, Tak Province, Thailand. *International Journal of Geoinformatics*, Vol. 20(6), 69–81. https:// doi.org/10.52939/ijg.v20i6.3339.

[39] Desa Wisata 1000 Menhir. *Kementrian Pariwisata dan Ekonomi Kreatif*. [Online]. Available: https://jadesta.kemenparekraf.go.id/ desa/1000_menhir. [Accessed: Feb. 21, 2023].

[40] Mandal, J. and Reja, M. S., (2021). Application of CA-Markov Model for Prediction of Land Use/Land Cover Change in a Rapid Growing Urban Area of West Bengal, India. *Journal of Urban Management*, Vol. 10(2), 155-166. https://doi.org/10.1016/j.jum.2021.01.003.

[41] Gollnow, F. and Lakes, T., (2014). Policy Change, Land Use, and Agriculture: The Case of Soy Production and Cattle Ranching in Brazil. 2001–2012. *Applied Geography*, Vol. 55, 203-211. https://doi.org/10.1016/j.apgeog. 2014.09.003.

[42] Kecamatan Bukik Barisan dalam Angka 2023. Badan Pusat Statistik. [Online]. Available: https://limapuluhkotakab.bps.go.id/id/publicati on/2023/09/26/8a9819aa3825a937a42aecda/ke camatan-bukik-barisan-dalam-angka-2023 .html. [Accessed: Feb. 21, 2023].

[43] Ambarwulan, W., Syetiawan, A., Rahadiati, A. and Rahmawan, G. A., (2022). Monitoring Thirty Years of LULC Change (1990 2021) from Landsat Images of Jatabek, Indonesia. *IOP Conf. Series: Earth and Environmental Science*. https://doi.org/10.1088/1755-1315/11 09/1/012059.

[44] Moffat, K., Sanchez, L. and Hanney, N., (2022). Application of CA-Markov Chain Models for Land Use Change Prediction: A Review. *Ecological Modelling*, Vol. 471. https://doi.org/10.1016/j.ecolmodel.2022.110051.

[45] Klasifikasi Penutup Lahan. *Standar Nasional Indonesia*. SNI 7645-1:2014. [Online]. Available: https://www.big.go.id/assets/download/sni/SNI/15.%20SNI%207645-2010%20Klasifikasi%20penutup%20lahan.pdf. [Accessed: May 09, 2023].

[46] Rana, I. A., Bhatti, S. S. and Hussain, F., (2017). Exploring Future Urban Expansion in a Metropolitan Area Using the SLEUTH Model. *Journal of Urban Planning and Development*, Vol. 143(2).

[47] Amiri, S., Sheikhahmadi, A. and Ghasemi, S., (2022). Land Use Change Detection and Future Modeling Using an Integrated Approach of Remote Sensing and CA-Markov Model in Mazandaran Province, Iran. *Modeling Earth Systems and Environment*, Vol. 8, 1521–1536.

[48] Li, T. and Zeng, Y., (2014). Multiple Land Use Change Simulation with Monte Carlo Approach and CA-ANN Model, a Case Study in Shenzhen, China. *Environmental Systems Research*, Vol. 4(1), 1-10.

[49] Xu, D., Zhang, K., Cao, L., Guan, X. and Zhang, H., (2022). Driving Forces and Prediction of Urban Land Use Change Based on the Geodetector and CA-Markov Model: a Case Study of Zhengzhou, China. *International Journal of Digital Earth*, Vol. 15(1), 2246-2267. https://doi.org/10.1080/17538947.2022.2147229.

[50] Dey, N. N., Al Rakib, A., Al Kafy, A. A. and Raikwar, V., (2021). Geospatial Modelling of Changes in Land Use/Land Cover Dynamics Using Multi-Layer Perception Markov Chain Model in Rajshahi City, Bangladesh. *Environmental Challenges*, Vol. 4, 1-11. https://doi.org/10.1016/j.envc.2021.100148.

[51] Ramadan, G. F. and Hidayati, I. N., (2022). Prediction and Simulation of Land Use and Land Cover Changes Using Open Source QGIS: A Case Study of Purwokerto, Central Java, Indonesia. *Indonesian Journal of Geography*, Vol. 54(3), 344-351.

[52] Satya, B. A., Shashi, M. and Deva, P., (2020). Future Land Use Land Cover Scenario Simulation Using Open Source GIS for the City of Warangal, Telangana, India. *Applied Geomatic*s, Vol. 12(3), 281–290. https://doi.org/10.1007/s12518-020-00298-4.

[53] Sahu, G. and Vidyarthi, V. K., (2024). Modeling Land Use/Land Cover Transformations in Mahanadi River Basin in Chhattisgarh, India: Trends and Future Projections. *GeoJournal*, Vol. 89. https://doi.org/10.1007/s10708-024-11152-0.

[54] Roy, P. S., Ramachandran, R. M., Paul, O., Thakur, P. K., Ravan, S., Behera, M. D., Sarangi, C. and Kanawade, V. P., (2022). Anthropogenic Land Use and Land Cover Changes-A Review on Its Environmental Consequences and Climate Change. *Journal of the Indian Society of Remote Sensing*, Vol. 50(8), 1615–1640. https://doi.org/10.1007/s12524-022-01569-w.

[55] Yadav, Y., Chhetri, B. B. K., Raymajhi, S., Tiwari, K. R. and Sitaula, B. K., (2019). Dynamics of Land Use Land Cover Change and Mapping of Tree Outside Forest (TOF) in Terai, Nepal. *International Journal Environment Sciences and Natural Resources*, Vol. 19(1), 4-9.

[56] Jayabaskaran, M. and Das, B., (2023). Land Use Land Cover (LULC) Dynamics by CA-ANN and CA-Markov Model Approaches: A Case Study of Ranipet Town, India. *Nature Environment and Pollution Technology an International Quarterly Scientific Journal*, Vol. 22(3), 1251-1265. https://doi.org/10.46488/NEPT.2023.v22i03.013.

[57] Jafari, H., Sharifi, A. and Najafi, A., (2019). Forecasting Land Use/Land Cover Changes Using CA-Markov Model and Multi-Layer Perceptron Neural Network in The Coastal Area of Bandar Abbas, Iran. *Applied Geomatics*, Vol. 11, 57–67.

[58] Shahfahad Naikoo, M. W., Das, T., Talukdar, S., Asgher, S., Asif and Rahman, A., (2022). Prediction of Land Use Changes at a Metropolitan City Using Integrated Cellular Automata: Past and Future. *Geology, Ecology, and Landscapes*, Vol. 8(3), 287–305. https://doi.org/10.1080/24749508.2022.2132010.

[59] Mzava, P., Nobert, J. and Valimba, P., (2019). Land Cover Change Detection in the Urban Catchments of Dar Es Salaam, Tanzania Using Remote Sensing and GIS Techniques. *Tanzania Journal of Science*. Vol. 45(3), 315–329.

[60] Sajedi-Hosseini, F., Shamsi, S. R. F. and Mohammadi, A., (2020). Predicting Land Use and Land Cover Changes in Karaj River Basin Using Integrated CA-Markov and Artificial Neural Network Models. *Modeling Earth Systems and Environment*, Vol. 6(2), 1063-1075.

[61] Dumdumaya, C. E. and Cabrera, J. S., (2023). Determination of Future Land Use Changes Using Remote Sensing Imagery and Artificial Neural Network Algorithm: A Case Study of Davao City, Philippines. *Artificial Intelligence in Geosciences*, Vol. 4, 111–118. https://doi.org /10.1016/j.aiig.2023.08.002.

[62] Mas, J. F. and Flores, J. J., (2008). The Application of Artificial Neural Networks to the Analysis of Remotely Sensed Data. *International Journal of Remote Sensing*, Vol. 29(3), 617-663. https://doi.org/10.1080/014311 60701352154.

[63] Xu, T., Gao, J. and Coco, G., (2019). Simulation of Urban Expansion Via Integrating Artificial Neural Network with Markov Chain – Cellular Automata. *Land*, Vol. 11, 1-15. https://doi.org /10.3390/land11071074.

[64] Pijanowski, B. C., Tayebi, A., Delavar, M. R. and Yazdanpanah, M. J., 2009. Urban Expansion Simulation Using Geospatial Information System and Artificial Neural Networks. *International Journal of Environmental Research*, Vol. 3(4), 493–502.

[65] Mustafa, A., Van Rompaey, A., Cools, M., Saadi, I. and Teller, J., (2018). Addressing the Determinants of Built-Up Expansion and Densification Processes at the Regional Scale. *Urban Studies*, Vol. 55(15), 3279-3298. https://doi.org/10.1177/0042098017749176.

[66] Rwanga, S. S. and Ndambuki, J. M., (2017). Accuracy Assessment of Land Use/Land Cover Classification Using Remote Sensing and GIS. *International Journal of Geosciences*, Vol. 8, 611-622. https://doi.org/10.4236/ijg.2017.840 33.

[67] Lukas, P., Melesse, A. M. and Kenea, T. T., (2023). Prediction of Future Land Use/Land Cover Changes Using a Coupled CA-ANN Model in the Upper Omo–Gibe River Basin, Ethiopia. *Remote Sensing*, Vol. 15, 1-24. https://doi.org/10.3390/rs15041148.

[68] Findell, K. L., Berg, A., Gentine, P., Krasting, J. P., Lintner, B. R., Malyshev, S., Santanello, J. A. and Shevliakova, E., (2017)., The Impact of Anthropogenic Land Use and Land Cover Change on Regional Climate Extremes. *Nature Communications*, Vol. 9(989), 1-10.

[69] Genet, A., (2021). Population Growth and Land Use Land Cover Change Scenario in Ethiopia. *International Journal of Environmental Protection and Policy*, Vol. 8(4),77-85.

[70] Setiawan, O., Rahayu, A. A. D., Dharmawan, I. W. S., Samawandana, G., Rachmat, H. H., Tata, H. L., Suharti, S., Windyoningru, A. and Khotimah, H., (2024). Unraveling Land Use Land Cover Change, their Driving Factors, and Implication on Carbon Storage through an Integrated Modelling Approach. *The Egyptian Journal of Remote Sensing and Space Sciences*, Vol. 27, 615–627. https://doi.org/10.1016/j. ejrs.2024.08.002.

[71] Chardon, V., Staentzel, C., Skupinski, G. and Herrault, P. A., (2022). Using Transition Matrices to Assess the Spatio-Temporal Land Cover and Ecotone Changes in Fluvial Landscapes from Historical Planimetric Data. *Earth Surface Processes and Landforms*,1-35. http://dx.doi.org/10.1002/esp.5437.

[72] Mondala, M. S., Sharmab, N., Gargc, P. K. and Kappasa, M., (2016). Statistical Independence Test and Validation of CA Markov Land Use Land Cover (LULC) Prediction Results. *The Egyptian Journal of Remote Sensing and Space Sciences*, Vol. 19, 259–272. http://dx.doi.org /10.1016/j.ejrs.2016.08.001.

[73] Gasirabo, A., Xi, C., Hamad, B. R. and Edovia, U. D., (2023). A CA–Markov-Based Simulation and Prediction of LULC Changes Over the Nyabarongo River Basin, Rwanda. *Land*, Vol. 12, 1-20. https://doi.org/10.3390 /land12091788.

[74] Haj, F. A. E., Ouadif, L. and Akhssas, A., (2023). Simulating and Predicting Future Land-Use/Land Cover Trends Using CA- Markov and LCM Models. *Case Studies in Chemical and Environmental Engineering*, Vol. 7, 1-11. https://doi.org/10.1016/j.cscee.2023.100342.

[75] Sarastika, T., Kusumawardani, M., Triyadi, R. A. and Putro, S. T. J., (2023). Analysis of Ecosystem Services Performance in Peri-Urban Areas of Sleman Regency for Sustainability Development. *BIO Web of Conferences*, Vol. 69. https://doi.org/0.1051/bioconf/2023690401 5.

[76] Welde, K. and Gebremariam, B., (2017). Effect of Land Use Land Cover Dynamics on Hydrological Response of Watershed: Case Study of Tekeze DAM Watershed, Northern Ethiopia. *International Soil Water Conservation Research*, Vol. 5, 1-16. https:// doi.org/10.1016/j.iswcr.2017.03.002.