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Spatial Analysis Model of Land Use Change and Prediction in Ciawi District Using Cellular Automata - Artificial Neural Network

Model Analisis Ruang dan Ramalan Perubahan Guna Tanah di Daerah Ciawi Menggunakan Automata Selular - Rangkaian Neural Tiruan

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ABSTRACT

Land use change is an important issue that occurs massively in the Ciawi Regency area, mainly due to rapid population growth and the increasing need for residential space, public facilities, and infrastructure. The problem that arises from this phenomenon is the occurrence of intensive land use conversion, especially the increase in built-up land area which has the potential to disrupt the environmental balance. This study aims to analyze land use changes from 2003 to 2023, as well as predict land use conditions in 2033. The study covers the entire administrative area of Ciawi Regency, Bogor, with a focus on seven land use classes, including built-up land, forests, rice fields, and gardens. The methodology used includes classification of Landsat 5 and 8 images using the Random Forest algorithm through the Google Earth Engine (GEE) platform, as well as predictive modeling using the Cellular Automata – Artificial Neural Network (CA-ANN) method through the MOLUSCE plugin in QGIS. The driving variables used in the prediction include distance to road, distance to settlement, and distance to river. The results of the study show a significant increase in built-up land from 291.45 hectares (2003) to 1,262.37 hectares (2023), and is predicted to reach 1,073.07 hectares in 2033. Prediction model validation showed an overall accuracy of 92.92% and a Kappa coefficient value of 0.82, which signifies excellent model quality. These findings are expected to be the basis for consideration in spatial planning and sustainable development policies in Ciawi Regency.

Keywords: land use; built-up land; Google Earth Engine; CA-ANN; spatial prediction; remote sensing

INTRODUCTION

Land use change and closure are dynamic phenomena that occur as a result of increasing human activity and the need for space for development. Land conversion, especially from agricultural and forest areas to built-up areas, is often the main indicator of regional development, but also has the potential to cause various environmental problems if not managed properly. One of the areas that is experiencing quite high pressure on land use change is Ciawi District, Bogor Regency, which is characterized by population growth, settlement expansion, and rapid infrastructure development.

Some of the main factors that affect land cover changes include population density, accessibility to activity centers and road networks, land economic value, topography, and the availability of regional facilities and infrastructure. Data from the Central Statistics Agency shows that Ciawi District has an area of 77.55 km² with a population of 115,816 people and a growth rate of 1.09% (BPS, 2023). The population surge has a direct impact on the increase in demand for built land for residential purposes and public facilities. If not balanced with planned spatial management, these changes can lead to environmental degradation such as reduced water catchment areas, increased flood risk, and ecosystem fragmentation.

For this reason, a scientific approach is needed that is able to analyze land use dynamics and predict future change trends. One of the approaches that is currently rapidly developing is the use of remote sensing technology and geographic information systems (GIS). Satellite data processing can be done through cloud-based platforms such as Google Earth Engine (GEE) which provides access to medium-resolution imagery such as Landsat as well as large-scale computing capabilities. In the land use classification process, the Random Forest algorithm was chosen for its ability to handle complex data, reduce overfitting, and provide stable and accurate classification results (Breiman, 2001).

In addition to historical spatial analysis, predictive modeling is needed to forecast land-use scenarios in future periods. One of the methods used in this study is a combination of Cellular Automata (CA) and Artificial Neural Network (ANN), which is implemented through the MOLUSCE plugin in QGIS. CA has the ability to model spatial change locally, while ANN is able to capture non-linear relationships between driving variables and land change. The combination of these two approaches, known as CA-ANN, has been shown to provide good predictive results in various land-use studies.

Thus, this study aims to analyze land use changes in Ciawi District in three time periods (2003, 2013, and 2023) and predict land use patterns in 2033 based on driving variables such as proximity to roads, settlements, and rivers. The results of this study are expected to provide a scientific basis in spatial planning and sustainable land use change control.

PROBLEM STATEMENT

From the initial background that has been explained, the formulation of the problem in this study is:

1. What is the pattern of land use change in Ciawi District in 2003, 2013, and 2023?
2. How is the prediction of land use in Ciawi District in 2033 using the Cellular Automata – Artificial Neural Network (CA-ANN) method?

LITERATURE REVIEWS

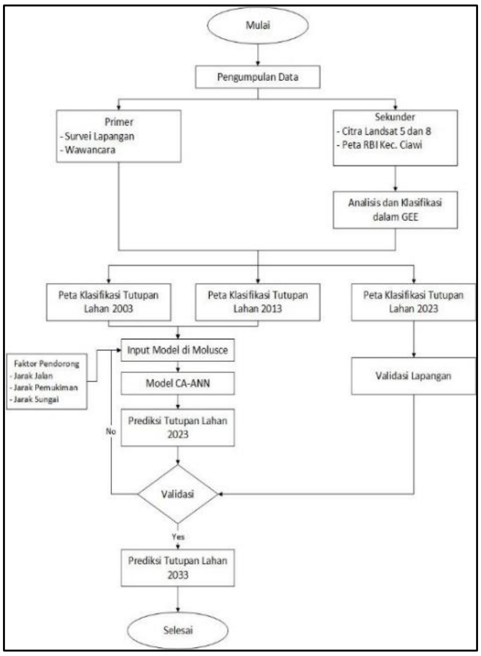
Table 1: Literature reviews

No	Researcher (Year)	Method	Study Location	Key Findings	Weaknesses / Gaps
1	Rahmah et al. (2020)	ANN	Semarang City	The predicted land cover according to the RTRW is 69.30%.	Excludes explicit driver spatial variables.
2	Asriani et al. (2021)	CA-ANN	Kabupaten Pati	The RMSE is very small (0.00117), accurately modeling coastal zones.	Limited to coastal areas; does not study land conversion at large.
3	Bahagia et al. (2021)	ANN Regresi Logistics	Balikpapan City	The prediction is 72.81% in accordance with the forecast.	It does not use cloud platforms or GEE-based remote sensing technologies.
4	Rizkiyanto et al. (2020)	Cellular Automata (CA)	Pekalongan City	A Kappa value of 0.907 indicates high accuracy.	It does not combine ANNs to capture non-linear relationships between variables.
5	Kusniawati et al. (2020)	ANN	Salatiga City	Identification of land use transfer, Kappa value 0.972.	It does not explicitly present long-term predictions.

METHODOLOGY

Below are the steps taken to support the research process so that the research carried out can run more structured and systematic, as shown in Figure 1.

Figure 1: Research flow diagram



In the Flowchart above, explain that the preliminary is done by conducting a needs analysis. As for the preliminary study, there are three types of data collection, namely literature studies, observations, and interviews.

1. Preparation Stage

The preparation carried out was a literature review as a reference and collection of research data. The data collected is in the form of primary data and secondary data. Primary data include Field Surveys and Interviews. And secondary data includes Landsat 5 and 8 imagery, Ciawi Regency RBI Map and Ciawi Regency DEM Map.

2. Image Processing Stage

This stage aims to make a land use classification with a total of 7 classes. This classification was carried out using Google Earth Engine by utilizing Landsat 5 and 8 imagery to produce land use maps for 2003, 2013 and 2023 using the Random Forest method.

3. Stages of Processing Driving Factors

In the modeling process, several driving factors are needed that can influence these changes. This study uses driving factors in the form of distance to roads, distances to settlements, and distances from rivers with Euclidean distance features in ArcGIS.

4. Modeling and Prediction Stage

At this stage Modeling and Prediction uses CA-ANN with QGIS 2.18 software and uses the MOLUSCE plugin. The land use maps used are the 2003 and 2014 land use maps, and the 2023 land use maps are used for validation. After that, an overall accuracy test is carried out to determine the overall value. The purpose of overall accuracy is to determine the accuracy of land cover map data with data in the field. The overall accuracy value required for the next stage is above 80%, if the overall accuracy value is below 80%, it is necessary to re-digitize it until the value is above 80%.

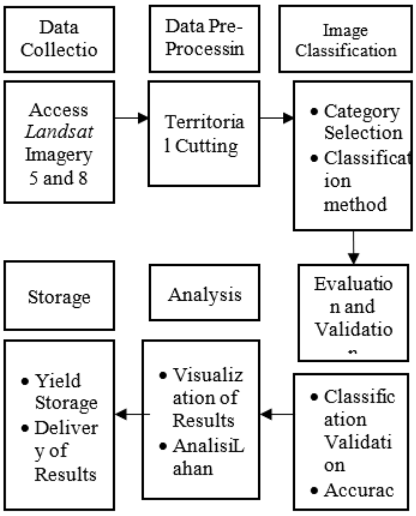
RESULTS AND DISCUSSION

Modeling

1. Land Use of Ciawi Regency

The land use of Ciawi district was obtained from classification processing in Google Earth Engine using Landsat 5 and 8 imagery. Data processing and analysis were carried out using spatial data, including images of Bogor City in 2003 obtained with Landsat 5 TM, and images in 2013 obtained with Landsat 8 OLI/TIRS. This is shown in Figure 2.

Figure 2: Spatial Data Processing Flowchart in Google Earth Engine



2. Land Use Classification of Ciawi Regency

At the land use classification stage, the researcher used secondary data in the form of the administrative area of Ciawi Regency to determine the geographical area. The data is then exported to Google Earth Engine for the land use identification process in Bogor City. Identification was carried out using Landsat 5 TM imagery from 2003, specifically using bands 3, 2, and 1.

A tape is a wavelength of light recorded by a satellite. The combination of bands 3, 2, and 1 on Landsat 5 is used for agricultural monitoring, with the aim of identifying vegetation and non-vegetation. Images showing green, yellowish green, and bright green indicate vegetation, while light brown images are used for non-vegetation monitoring. Water bodies are typically characterized by dark colors, such as dark green and dark brown, as seen in Figure 3.

Figure 3: Visualization of GEE Landsat 5 TM Imagery Year 2003 Composite Bands 5, 4 and 1

The Landsat imagery used for land use identification in 2013 and 2023 is the OLI/TIRS Landsat 8 image with a combination of bands 5, 6, and 4. These bands represent the range of light waves recorded by satellites, and the combination of bands 5, 6, and 4 on Landsat 8 is designed to monitor agriculture, including vegetation and non-vegetation. Images with green, yellowish green, and bright green colors show vegetation, while light brown colors are used to identify non-vegetation. Water bodies are characterized by dark colors, such as dark green and dark brown, as seen in Figure 4 and Figure 5.

Figure 4: Visualization of GEE Landsat OLI TIRS 8 Year 2013 Composite Band 5, 6, and 4

Figure 5: Visualization of GEE Landsat OLI TIRS Year 8 Year 2023 Composite Band 5, 6, and 4

The following is the source code for the 2003 and 2013 Landsat 5 TM OLI/TIRS images used in this study:

Figure 6: Landsat 5 TM Data Filtering Cloud Source code

```
var dataset = ee.ImageCollection('LANDSAT/LT05/C02/T1_L2')
                  .filterDate('2003-01-01', '2003-12-30')
```

Figure 7: Source code of Landsat OLI TIRS 8 Data Filtering Cloud

```
var dataset = ee.ImageCollection('LANDSAT/LC08/C02/T1_L2')
                  .filterDate('2013-01-01', '2013-12-31')
```

Figure 8: Landsat OLI TIRS 8 Cloud Filtering Data Source code

```
var dataset = ee.ImageCollection('LANDSAT/LC08/C02/T1_L2')
                  .filterDate('2023-01-01', '2023-06-28')
```

Figure 6 shows the source code for calling a set of TIR1 Landsat 5 TM Collection 2 imagery and filtering the dataset for the specified period, from January 1, 2003 to December 30, 2003. Figure 7 shows the source code for calling a set of TIR1 Landsat 8 OLI/TIRS Collection 2 images and filtering the dataset for the specified period, from December 1, 2013 to December 30, 2013. Figure 8 shows the source code for calling a set of TIR1 Landsat 8 OLI/TIRS Collection 2 imagery and filtering the dataset for the specified period, from January 1, 2023 to June 28, 2023.

Figure 9: Source code Scale Factor and Landsat 5 and Landsat 8 Mosaic

```
function maskL8sr(image) {
  // Bit 0 - Fill
  // Bit 1 - Dilated Cloud
  // Bit 2 - Cirrus
  // Bit 3 - Cloud
  // Bit 4 - Cloud Shadow
  var qaMask = image.select('QA_PIXEL').bitwiseAnd(parseInt('11111', 2)).eq(0);
  var saturationMask = image.select('QA_RADSAT').eq(0);

  // Apply the scaling factors to the appropriate bands.
  var opticalBands = image.select('SR_B.').multiply(0.0000275).add(-0.2);
  var thermalBands = image.select('ST_B.*').multiply(0.00341802).add(149.0);

  // Replace the original bands with the scaled ones and apply the masks.
  return image.addBands(opticalBands, null, true)
      .addBands(thermalBands, null, true)
      .updateMask(qaMask)
      .updateMask(saturationMask);
}
```

Scale and mosaic factors are stages in image processing that involve mixing scale factors with specific optical parameters of images in a dataset. After that, the image is cropped (cropped) based on the area boundary.

Figure 10: Clip of Ciawi Lansat 5 TM and Landsat OLI 8 Sub-district Source code

```
var composite = dataset.median().clip(table);
```

The above source code is used to crop the image to fit the administrative boundaries of Ciawi District, and produce an image with True Color using ribbons 3, 2, 1 and 4, 3, and 2. True Color represents natural colors in Landsat imagery.

Figure 11.1: Source code Visualization Launched 5 TM

```
Map.addLayer(composite, {bands: ['SR_B3', 'SR_B2', 'SR_B1'], min: 0, max: 0.3});
```

Figure 1.2: Source code Visualization Launch OLI TIRS 8

```
Map.addLayer(composite, {bands: ['SR_B4', 'SR_B3', 'SR_B2'], min: 0, max: 0.3});
```

The above source code is used to display the imagery in a color composite by selecting bands B5, B4, and B1 for Landsat 5 TM, as well as bands B5, B6, and B4 for Landsat OLI/TIRS 8. In addition, this code performs visualization parameters with a value range of min: 0 – 30000 to improve the contrast of satellite imagery and display the image as layers.

3. Building the 2003, 2013, and 2023 Land Use Classes on Gooogle Earth Engine (GEE*)*

At this stage, the class of building land use is carried out through a classification process using data that has been collected from the observation results. Training samples were made for categories such as water bodies, built-up land, gardens, rice fields, forests, open land, and shrubs. Data from the training samples that have been compiled are then classified using the Random Forest method.

Figure 2: Source code Building a Land Use Class

```
//Membangun kelas tutupan lahan
var classNames = BadanAir.merge(LahanTerbangun).merge(Sawah).merge(Kebun)
.merge(Hutan).merge(LahanTerbuka).merge(SemakBelukar);
print(classNames)
```

The above source code is used to define seven classes of land use, namely: water bodies, built-up land, gardens, rice fields, forests, open land, and shrubs.

Figure 3: Source code Group Group for Classification

```
//Memilih band yang akan digunakan klasifikasi
var bands = ['SR_B1','SR_B2','SR_B3','SR_B4','SR_B5','SR_B7'];
```

The above source code is used to select a set of bands when classifying using Random Forest.

Figure 14: Random Forest Accuracy Source Code

```
// Get a confusion matrix representing resubstitution accuracy.
var trainingImage = training.randomColumn();
var trainingData = trainingImage.filter(ee.Filter.lt('random', 0.7));
var validation = trainingImage.filter(ee.Filter.gte('random', 0.7));
```

The above Source Code is used to see the accuracy of 70% of the training data and 30% of the test data

Figure 15: Random Forest Classification Source code

```
//Sample the reflectance values for each training point
var labelcover = 'TL';
var training = composite.select(bands).sampleRegions({
  collection: classNames,
  properties: ['TL'],
  scale: 20,
});
print(training)

//Train the classifier - in this case using a CART regression tree
var classifier = ee.Classifier.smileRandomForest(50).train({
  features: trainingData,
  classProperty: 'TL',
  inputProperties: bands
});

//Run the classification
var classified = composite.select(bands).classify(classifier);
```

The above source code is used to determine the TL cover label on each training sample data, as well as apply a classifier using the Random Forest algorithm. This process involves training with the features: training, classProperty: TL, and Properties: input band.

Figure 16: Source code Display Classification

```
//Display classification
Map.centerObject(classNames, 11);
Map.addLayer(classified.clip(geometry), {min: 0, max: 6,
palette: ['blue', 'red', 'yellow', 'green','darkgreen','white','black']},
'classification');
```

The source code above displays different land identification image colors for each category: blue water bodies, red woke lands, light green orchards, yellow rice fields, dark green forests, brown open fields, and purple shrubs. The results of the land cover classification can be seen in Figure 17, Figure 18 and Figure 19.

Figure 17: Land Cover Classification in 2003

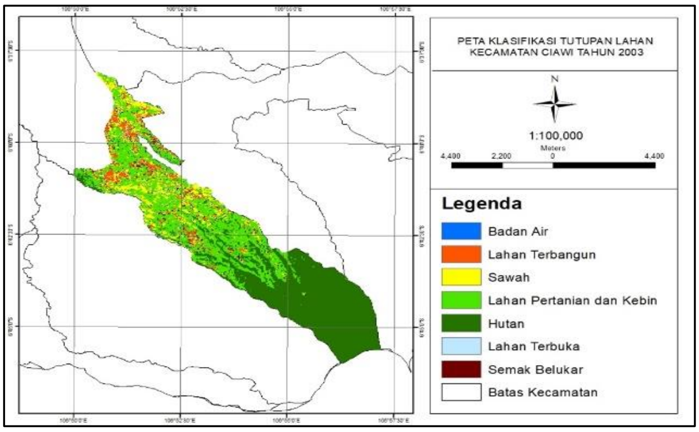


Figure 18: Land Cover Classification in 2013

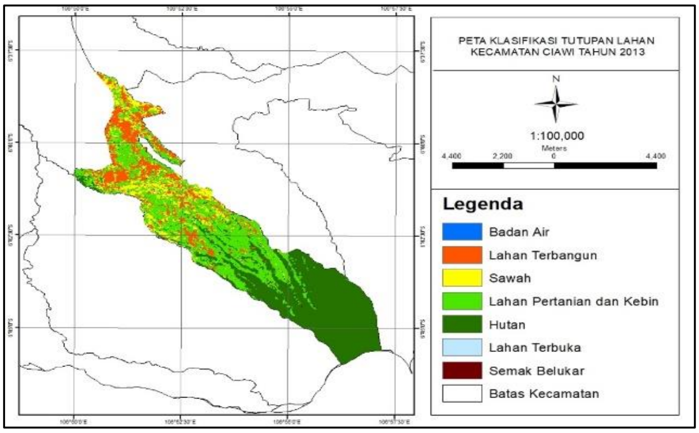
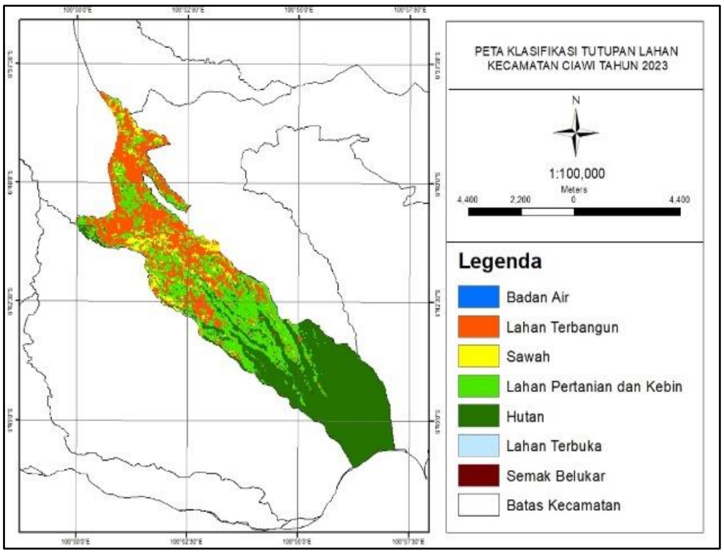


Figure 19: Land Cover Classification in 2023



The area of each land use in Ciawi Regency in 2003, 2013 and 2023 can be seen in Table 2.

Table 2: Land Use in Ciawi Regency

Land Use	2003 (ha)	2013 (ha)	2023 Title (Ha)
Water bodies	18,51	14,80	8,34
Built-up Land	291,45	688,66	1262,37
Paddy	531,20	518,10	291,19
Agriculture and Dryland Gardens	1685,38	1605,87	1354,40
Forest	2003,56	1863,51	1772,60
Open Ground	55,93	2,79	4,04
Bushes and Meadows	121,29	13,59	14,37
Entire	4707,32	4707,32	4707,32

Based on Table 2, the most dominant land use in 2003 was 2003.56 ha of forest. (42.56%). In 2013, forest use decreased to an area of 1863.51 ha. (39.59%) and there will be another decrease in 2023 of around 1772.60 ha. (37,67%). The use of shrubs and pasture land in 2003 had an area of 121.29 ha. (2.58%) and in 2013 there was a decrease so that the land area was only 13.59 ha. (0.29%). In 2003 the land was built with an area of 291.45 ha. (6.19%) and there was a significant increase in 2013 to 688.66 ha. (14.63%) and experienced a re-addition in 2023 of 1262.37 ha (26.54%).

a. Analysis of Land Use Change in Ciawi Regency

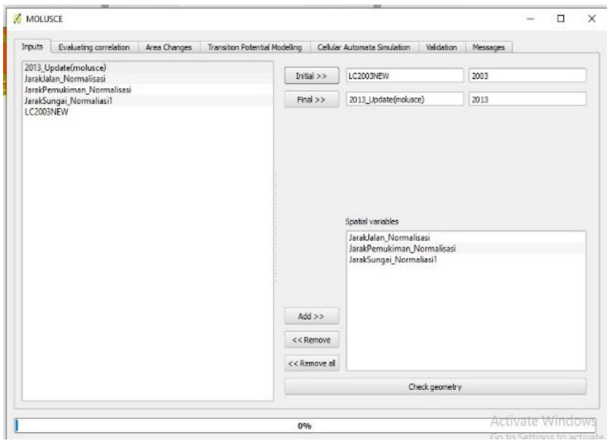
Land use changes in Ciawi Regency were obtained by using intersect overlays in the ArcGIS application.

b. Modeling Land Use Change with Mobile Automata – Artificial Neutral Networks
Modeling of land use change was carried out using the QGIS application with the Molusce plugin. The steps are as follows:

1. Input Model

The input data in the modeling process is the 2003 land use map as a Beginning and land use maps in 2013 as last. The variables of the driving factors used are distance to roads, distance to settlements and distance from rivers. This data is entered as shown in Figure 20.

Figure 20: Model inputs



2. Evaluating Correlation

A correlation test of people is done to measure the strength of the relationship between factors. The results of the correlation test can be seen in Table 3.

Table 3: Correlation test

	River Distance	Completion Distance	Distance
River Distance	…..	0.187768493764	0.174768627516
Completion Distance		…..	0.864619946502
Distance			…..

Based on Table 3, it shows that the correlation between roads and settlements is very strong because it is close to the number 1, which is 0.864. This can be interpreted that the closer land use is to settlements and roads, the faster it changes. Due to the factor of roads that have accessibility or ease of reaching an area, the area will develop faster.

3. Area Change

This stage produces a table of changes in the use of cultivated land mollusk shown in Table 4.

Table 4: Land use change

Not	Land Use	2003 (ha)	2013 (ha)	Difference
1	Water bodies	18,55	14,75	-3,80
2	Built-up Land	287,40	684,41	397,01
3	Paddy	530,98	517,25	-13,73
4	Agriculture and Dryland Gardens	1683,73	1605,83	-77,90
5	Forest	2003,17	1862,72	-140,45
6	Open Ground	55,99	2,77	-53,22
7	Bushes and Meadows	121,51	13,59	-107,92

Based on Table 4, the land use that has increased in area is 397.01 hectares of built land while other uses have decreased. And the most reduced is the use of forest land covering an area of 140.45 hectares. This stage also produces a transition matrix that shows the magnitude of the opportunity to change land use to another land use. The transition matrix has a value of 0-1, i.e. if the value ranges from 0.01-0.99, it has a chance to change to another land use and if the value is 0 or 1, it means that the land has not changed (fixed). In the diagonal component of the forest matrix, it has the greatest chance value, which is 0.92, meaning that the use of forest land does not change or remains forest land, but the use of forest land has the highest chance value of 0.06 to change to other land uses, namely agricultural land and gardens. Meanwhile, rice fields have a fixed tendency of 0.49 and have a tendency to turn into agricultural and garden land (0.21) and assisted land (0.29).

4. Potential Transition Modeling

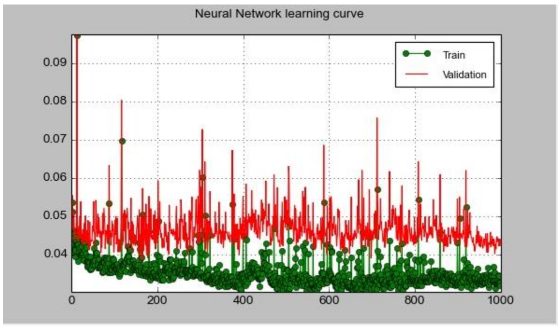
The network topology used in ANN modeling is MultiLayer Perception (MLP) with 10 nodes on the hidden layer. Each node in the layer will correlate with the other nodes, indicating a relationship or connection path denoted by (W) as the weight in the matrix. The results of modeling using ANN can be seen in Table 5.

Table 5: ANN modeling results

Milieu	1 px
Learning level	0.100
Maximum iteration	1000
Hidden Layers	10
Momentum	0.050
Best Accuracy	-0.00376
Overall Error Validation Min	0.03869
Current Validation Kappa	0.70680

The training and network learning process from the input data is carried out repeatedly by adjusting the number of each parameter which will affect the error value or Min Validation Overall Error. The error value obtained is 0.03869 and is considered to have been met to proceed to the next stage. The value of the learning level and the value of large iterations does not guarantee that it will provide good results and accuracy, meaning that other parameters such as momentum have an influence in giving good results. The momentum parameter determines the magnitude of the change in the weight of the exercise. The curve of the ANN modeling results is presented in Figure 21.

Figure 21: Modeling curve

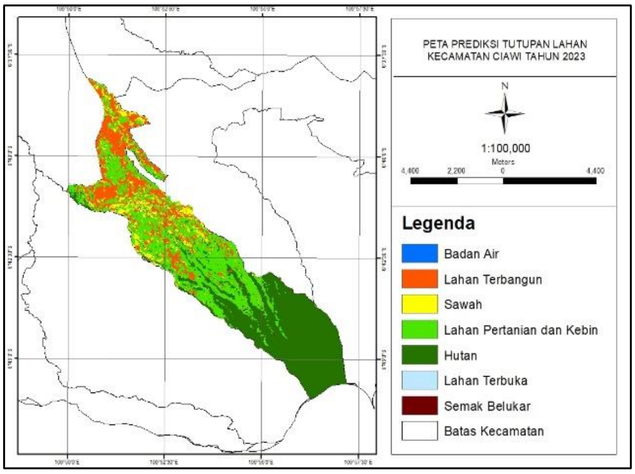


The car results are in the form of an ANN graph that shows the comparison between the RMS and the iteration of the ANN modeling results with the best parameter values. From the results in the form of network simulations carried out, it is shown that the variation of different parameters is very influential, especially learning rate, hidden layer, momentum and iteration.

5. Mobile Automata Simulation

The mobile automata simulation stage produced a map of land use predictions in 2023 based on data from 2003 and 2013 which can be seen in Figure 22.

Figure 22: Land Use Prediction Map of Ciawi Regency in 2023



The results of the prediction of land use modeling in 2023 using the ANN method show that the most dominant land use in Ciawi Regency is forests with an area of 1849.45 hectares. Agricultural land and gardens along with rice fields have declined respectively. Meanwhile, the use of assisted land continues to increase to an area of 822.17 hectares. And the following is the extent to which the use of modeling prediction results can be seen in Table 6.

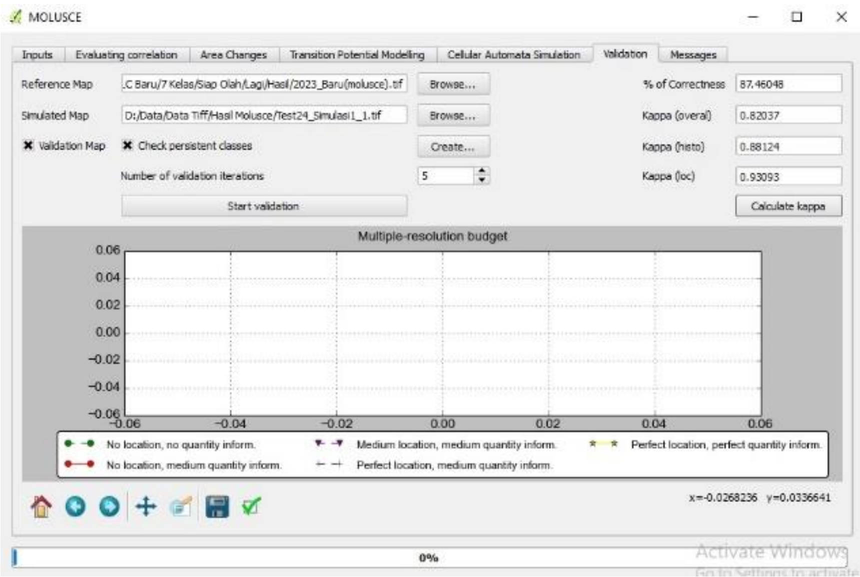
Table 6: Predicted land use areas for 2023

Land Use	Prediction 2023 (Ha)	Percentage
Water bodies	11.02	0.31%
Built-up Land	872.95	14.63%
Paddy	394.90	10.96%
Agriculture and Dryland Gardens	1581.17	34.13%
Forest	1840.72	39.56%
Open Ground	0.21	0.06%
Bushes and Meadows	6.34	0.35%
Entire	4707,32	

6. Validation

The prediction model that has been created is then validated using the Kappa method. The validation result using Kappa was 0.82 which indicates that this modeling has a fairly good accuracy value for classified land use in 2023 with predicted results in 2023. The validation results can be seen in Figure 23.

Figure 23: Kappa validation



In addition to the kappa method to strengthen the validity of the model, an overlay method is used between the sample of field survey results and the map of the 2023 prediction results. Sampling was carried out using a stratified random sampling method. The validation results can be seen in Figure 24.

Figure 24: Survey Validation

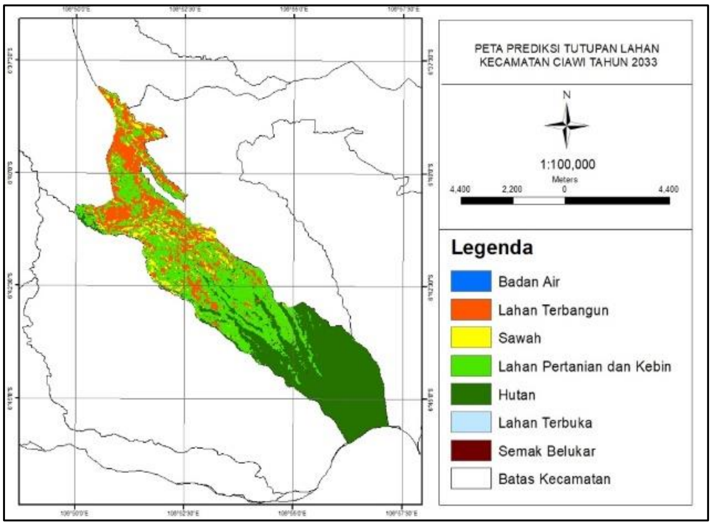
		Lokasi Hasil GroundCheck Lapang									
		Badan Air	Lahan Terbangun	Sawah	Pertanian Lahan Kering/Kebun	Hutan	Lahan Terbuka	Semak Belukar dan Rumput	Total Baris	User Accuracy	Commission Error
Lokasi Hasil Interpretasi Citra	Badan Air	2	0	0	0	0	0	0	2	100.00	0.00
	Lahan Terbangun	0	57	0	0	0	0	0	57	100.00	0.00
	Sawah	0	1	14	0	0	0	0	15	93.33	6.67
	Pertanian Lahan Kering/Kebun	0	2	1	21	0	0	0	24	87.50	12.50
	Hutan	0	0	0	2	7	0	0	9	77.78	22.22
	Lahan Terbuka	0	1	0	0	0	1	0	2	50.00	50.00
	Semak Belukar dan Rumput	0	1	0	0	0	0	3	4	75.00	25.00
	Total Kolom	2	62	15	23	7	1	3	113		
	Produscer Accuracy	100.00	91.94	93.33	91.30	100.00	0.00	100.00			
	Omission Error	0.00	8.06	6.67	8.70	0.00	100.00	0.00			
	Overall Accuracy	92.92			total diagonal (A)	105					
	Koefisien Kappa	89.21			B	4392					

Figure 24 shows that the overall accuracy value is 92.92 and the kappa coefficient value is 89.21. Using 7 land use classes, image classification data can represent what is on the ground and land use maps can be used as modeling comparisons.

Analysis of Land Use Prediction Results in Ciawi Regency 2033

The prediction of land use in 2033 is based on the changes that occurred in 2003-2013 by adding 2 iterations to the mobile automata simulation. The results of land use prediction in 2033 can be seen in Figure 25.

Figure 25: Land Use Prediction Map in 2033



The results of the 2033 land use prediction in Ciawi Regency show that there will be an expansion of built land and a decrease in other land use as shown in Table 7.

Table 7: Land use area in Ciawi Regency 2033

Land Use	Area (Ha)	Percentage
Water bodies	7,21	0.18%
Built-up Land	1073,07	26.82%
Paddy	235,35	6.19%
Agriculture and Dryland Gardens	1580,58	28.77%
Forest	1806,50	37.66%
Open Ground	0,09	0.09%
Bushes and Meadows	4,51	0.31%
Entire	4707,32	

CONCLUSION

Based on the discussion and implementation carried out in the research, several conclusions can be obtained as follows:

Land use changes in Ciawi Regency in 2003-2013 were dominated by a decrease in the area of water bodies, rice fields, dryland agriculture and gardens, forests, open land and shrubs and grasslands, as well as an increase in built-up land. The largest decrease in area occurred in dry agricultural land and plantations by 38.60% or 363.93 Ha, with the growth of built-up land by 42.13% or 397.21 Ha.

Modeling of land use changes using CA-ANN in 2003 and 2013 with the variables of distance to road, distance to settlement and distance from river showed good model accuracy results (% correctness 87.46%), kappa (overall) 0.82 kappa (histo) 0.88 and kappa (loc) 0.93 so that it can be used as a modeling comparator.

On the other hand, the satellite imagery used must have better spatial accuracy so that it can facilitate the classification of land use classes. Using more driving factors such as land prices, slopes, proximity to public facilities, regional income, and other factors that support land development and change. Further research is suggested to compare multiple modeling methods to obtain a high probability matrix so that the best method can be known. This study also combines the power of satellite image classification through GEE and spatial change prediction using CA-ANN, with spatial driving variables such as distance to roads, rivers, and settlements. This model is expected to provide faster, more efficient, and applicable predictions for developing areas such as Ciawi Regency.

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