Modeling Land Cover Change Using Markov

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Modeling Land Cover Change Using Markov Chain-Cellular Automata in Sorong, West Papua Province

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ABSTRACT
Land cover change is a complex interaction of environmental and socioeconomic factors. The purpose of this article is to determine changes in land cover using satellite imagery data, predict land cover in the next ten years and determine the factors that affect land cover change. The Markov Chain and Cellular Automata (Markov-CA) approach have been applied to create land-use change modeling dynamics in Sorong Regency, Papua Barat, Indonesia. The multi-temporal remotely sensed data, Landsat 7 TM in 2003 and Landsat 8 OLI in 2017, were used to produce the landcover maps. The results showed that land cover change during 2003-2017 is dominated by reducing forested land and becoming settlement and shrub area. The integration of Markov Chain and Cellular Automata can construct a spatial prediction of land cover change in 2017-2025 in Sorong City. Therefore, this modeling can be used to create maps of land cover change in the future.

Keywords: *Markov Chain, Cellular Automata, Land cover change, Sorong City*

1. INTRODUCTION

Land cover is the physical surface of the land [1]. Land cover change is determined by complex environmental and socioeconomic factors, a complex, dynamic process that links together natural and human systems [2,3,4]. The major causes of land-use change vary depending on the area that it occurs. Recently, land use changes mostly caused by urban area growth and expanding agricultural land [4,5].

Remote Sensing and Geographic Information System (GIS) have been used as powerful and practical tools to detect land use and land cover changes and the broader aspect of land use science [6,7,8,9]. The availability of data sources and technologies in RS and GIS can predict future land-use change. The commonly used model for prediction and simulation of future land cover change are Markov Chain Analysis [6], Cellular Automata [10], Cellular Automata-Markov model (CA-Markov) [11,12], Artificial Neural Network (ANN) [8], and Binary Logistic Regression [13] or the mix between those models [14].

Markov chain analysis describes land cover change from one period to another and uses this as the necessary time to project future changes. Cellular Automata (CA) has been initially introduced around 1940 to provide a framework for a complex system [7]. Stochastic models' application to simulate dynamic systems such as a land cover change in a developing nation is rare. Therefore, much work needs to be done to develop an operational procedure that integrates the techniques of satellite remote sensing, GIS, and CA-Markov modeling for monitoring and modeling land cover changes.

The city of Sorong is surrounded by other regions that have potential natural resources. This will make Sorong city a city of industry, trade, and services in West Papua Province that will invite domestic and foreign investors to invest. Moreover, this city has the highest population density in Papua Barat Province.

Therefore, the need for land for development and settlement will increase.

The study's objectives are: (1) to predict the land cover change scenario for the year 2025, (2) to determine the influence of land-use change drivers in Sorong City.

2. MATERIALS AND METHODS

1.1. Land use change analysis

Land cover changes were analyzed using the supervised classification method and field checking. Supervised classification is an activity of a self-defined category of image classes [15]. The satellite image used in this study was Landsat imagery obtained from the USGS website. Landsat imagery has been used for land cover mapping purposes since 1990 in Indonesia [16]. Land cover change analysis used Landsat satellite imagery for 2009, 2013 (LANDSAT 7 TM), and 2017 (LANDSAT 8 OLI). The results of the study obtained land-use data for 2009, 2013, and 2017. Based on the classification used, land use in Sorong City is divided into nine categories: Secondary dryland forest (HLKS), primary mangrove forest, secondary mangrove forest, shrubs, settlements, bare land, water bodies, agriculture (PLKCS), and airports.

2.2. Land use prediction modeling

In this study, Cellular Automata-Markov Chain (CA-Markov) model is used to predict the land-use change in Sorong city. Cellular Automata-Markov is a combined Cellular Automata-Markov Chain land-use change prediction procedure. The CA-Markov method is a method for adding space characters based on the application of rules. This ensures that land cover change is not completely random but based on rules [17]. Markov's analysis leads to a quantitative technique used to analyze current behavior from some variables intended to predict these variables' future behavior [18]. Markov method is formulated as $M_{LC} \,.\, M_t = M_{t+1}$

$$\begin{pmatrix} LC_{uu} & LC_{au} & LC_{uw} \\ LC_{au} & LC_{aa} & LC_{aw} \\ LC_{wu} & LC_{wa} & LC_{ww} \end{pmatrix} \begin{pmatrix} U_t \\ A_t \\ W_t \end{pmatrix} = \begin{pmatrix} U_{t+1} \\ A_{t+1} \\ W_{t+1} \end{pmatrix}$$

Notes: MLC = Probability, Mt = Prob

The transition areas produced from the Markov model of the land use map 2003 and 2009 establish the quantity of expected land-use change from each existing category to each other class in the next period, i.e., 2013. The base land-use image of 2017 is used as the starting point for change simulation.

3. RESULTS AND DISCUSSIONS

3.1. Land cover change analysis

The land cover map is based on the supervised classification in ArcGis 10.4. Supervised classification is a classification that is carried out with the direction of the analysis (supervised). Class grouping criteria are determined based on the class founder (signature class) obtained through the creation of training areas [19] [20]. Land cover maps based on supervised classification results for each land cover category in Sorong City in 2009 and 2017 are shown in Figures 1 and 2. Based on these maps, the area of each land cover category was calculated. The distribution of each land use category in 2009 and 2017 in the study area results are shown in Table 5. The classification of land cover/land use for 2009 Landsat 7 imagery and Landsat 8 imagery in 2017 show that land cover is dominated by forest (Secondary dryland forest). This land use category occupied a proportion of more than 48% in 2017. Changes in each land cover/use class for the 2009-2017 period had an increasing and decreasing trend in the area. The land cover class that experienced the largest decrease in the area was a forest, while the cover/use class that experienced an increase in size was the settlement. Table 1 shows the land cover area in Sorong City in 2009 and 2017 based on image analysis.

Table 1. Land use in Sorong

Land Cover	Area (ha)	
	2009	2017
Secondary dryland forest	35,266	26,485
Primary mangrove forest	2.003	1,038
Secondary mangrove forest	447	1,630
Shrubs	5.543	6,913
Settlement	2,520	2,764
Bare land	1.7671	2,328
Waterbody	278	679
Agriculture	6,633	11,559
Airport	24	84

Changes in the cover area in Table 1 occurred in dryland forests and primary mangrove forests, which had decreased their size. It is inversely proportional to the residential area, which has increased in the region over the last four years.

The results of the image analysis are shown on the map in Figure 1 and Figure 2 below. Figure 1 shows the land cover map in 2009, and Figure 2 is the land cover map processed by imagery in 2017. Meanwhile, Figure 3 shows the location of the observation points in Sorong City.

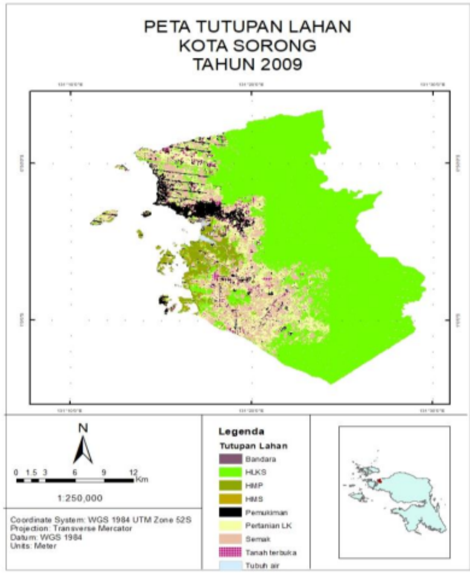

Figure 1 Land cover map of 2009

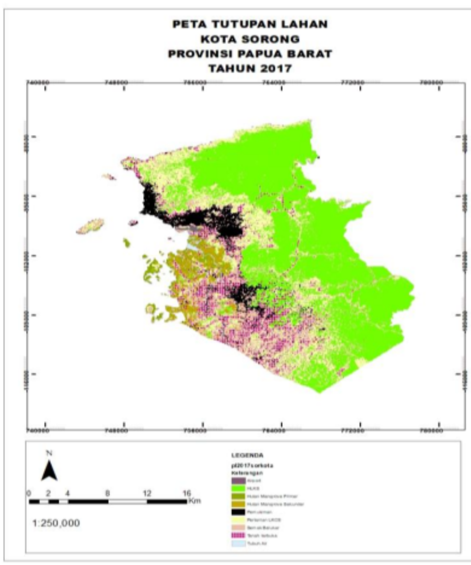

Figure 2 Land cover map of 2017

Figure 3 shows the point of coordinate data collection to determine land cover changes in Sorong City. There are 37 ground checking locations in Sorong City. Coordinate point data is collected using GPS and the Avenza Map application on a smartphone. The data collected is based on areas experiencing degradation and deforestation in the City of Sorong.

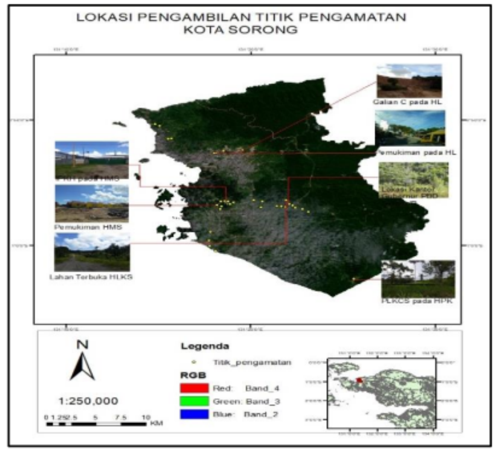

Figure 3 The location of data collection

This change in land-use area is due to an increase in development in the City of Sorong, where this area is the main gateway to the Provinces of Papua and West Papua. This is supported by an increase in this area's population due to births and migration outside Papua. During these ten years, the number of people in Sorong City has increased by 70%. Compared to all West Papua districts where Sorong City is the area with the highest population density in West Papua. The increase in population will have implications for the increased need for land.

3.2. Land cover prediction analysis

Land cover prediction analysis was carried out using data analysis of Landsat 7 ETM and Landsat 8 OLI imagery in 2009, 2013, and 2017 which were downloaded from http://earthexplorer.usgs.gov. The selected data is data that has minimal cloud cover. Image data that has been made of land cover in the ArcGIS 10.4 software are then carried out by predicting land cover in the Idrisi software. The land cover analysis used land cover data with an interval of 8 years, namely 2009 to 2017. The results of the study of land cover for the past eight years can be used to make predictions eight years later, namely the prediction data for 2025. This analysis was carried out using the Markov Chain and Cellular Automata methods. The prediction of land-use change in 2017-2025 is, in principle, a simulation of land-use change in 2017-2025. The simulation input is a land-use map for 2017 and a probability matrix for the transition to land-use change in 2009-2017. According to the Markov Chain theory, changes that occurred during the eight periods can be used as a basis for predicting changes in the next eight years (2017-2025 period).

Table 2. Transition probability matrix

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Given : Probability of changing to :

	Cl. 1	Cl. 2	Cl. 3	Cl. 4	Cl. 5	Cl. 6	Cl. 7	Cl. 8	Cl. 9
Class 1 :	0.6015	0.0070	0.0179	0.1318	0.0095	0.0209	0.0040	0.2071	0.0002
Class 2 :	0.0527	0.5961	0.1174	0.0145	0.0249	0.0450	0.1224	0.0229	0.0041
Class 3 :	0.0403	0.3115	0.2886	0.0651	0.0407	0.0750	0.0436	0.1291	0.0060
Class 4 :	0.0952	0.0314	0.0810	0.2009	0.0487	0.0791	0.0156	0.4469	0.0010
Class 5 :	0.0754	0.0343	0.0337	0.1399	0.4256	0.1153	0.0338	0.1265	0.0156
Class 6 :	0.0977	0.0203	0.0446	0.1471	0.2237	0.1750	0.0153	0.2717	0.0048
Class 7 :	0.0143	0.0512	0.0238	0.0310	0.1426	0.0977	0.4903	0.1367	0.0123
Class 8 :	0.1117	0.0067	0.0448	0.2450	0.0948	0.1013	0.0035	0.3912	0.0010
Class 9 :	0.0000	0.0000	0.0241	0.0040	0.1484	0.4370	0.0321	0.1403	0.2141

Note: Class 1: Secondary dryland forest; Cl.2. Primary mangrove forest; Cl.3. Secondary Mangrove Forest; Cl.4. Shrubs; Cl.5. settlement; Cl.6. open land; Cl.7.body of water; Cl.8. dryland bush farming; Cl.9. airport.

Transition probability means the likelihood of a change from one land use category to another land use category [18]. The data used to calculate the probability of this transition results from cross-tabulation between land use data for 2009 and 2017. The likelihood of land change transition is manifested in an n x n dimension matrix, where n is the number of land cover classes used. Figure 4 below shows the transition probability matrix for the City of Sorong with dimensions of 9x9.

The rows and columns in the transition probability matrix follow rows and columns on the cross tab. In Figure 4, row 1 and column 1 or denoted by p11, is the probability of change from secondary dryland forest to secondary dryland forest with a value of 0.6015 and so on.

Prediction of change location is made through spatial integration simulation between Markov Chain and Cellular Automata. This simulation process is the same as the change simulation process for 2009-2017. The difference is in the input data as the basis for simulation. This simulation's input, which acts as a prediction basis, is land use in 2017. The transition probability and the prediction of the changing area from the Markov Chain application are used as the basis for the Cellular automata to determine the predicted location to change. Change locations are represented in pixels. The simulation output is defined in the form of a land cover prediction map for 2025.

Sorong City is an area that no longer has primary dryland forest. This is due to land clearing activities for the wood industry in the 90s. The predictive analysis of the land area and land-use change in Sorong City based on the KLKH land cover data is shown in Table 2 and Figure 5.

Based on Table 2, it is predicted that secondary dryland forest will reduce up to 10% in 2025, while the area of settlement and scrub area will increase. When viewed from the total population and population density in the City of Sorong, this triggers changes in forest areas and other areas for infrastructure development activities, especially housing, and industrial buildings. Figure 5 is a map of the prediction results of land cover in Sorong City in 2025.

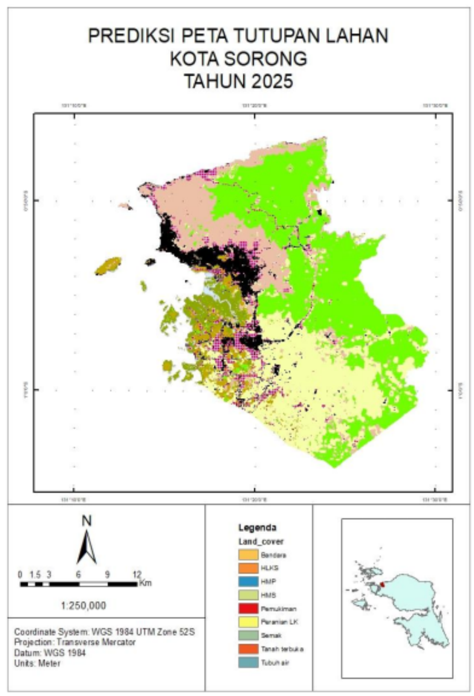

Figure 4 The prediction of land cover change in Sorong City in 2025

Table 3. Prediction of Area and Land Cover Change in Sorong City

Land Cover	The land cover area in Sorong					
	2017		2025		Change	
	ha	%	ha	%	ha	%
Secondary dry land forest	30,646.26	56.27	25,119.23	46.13	5,527.02	10.14
Primary mangrove forest	695.65	1.28	947.26	1.74	251.61	0.46
Shrubs	2,559.88	4.70	4,430.29	8.14	1,870.41	3.44
Settlement	7,911.92	14.53	12,607.32	23.15	4,695.39	8.62
Bareland	71.68	0.13	185.03	0.34	113.34	0.21
Savana	168.26	0.31	159.98	0.29	-8.27	-0.02
Water body	98.74	0.18	92.55	0.17	6.19	0.01
Secondary mangrove forest	2,289.50	4.20	1,734.09	3.18	-554.40	-1.02
Swamp	374.54	0.69	371.26	0.68	-3.28	-0.01
Agriculture	9,501.57	17.45	7,403.24	13.64	-2,071.32	-3.80
Airport	81.03	0.12	141.95	0.26	78.90	0.14
Mining	63.06	0.21	141.95	0.26	78.90	0.14
Total	54,462.07	100.00	54,454.32	100.00		

Figure 5 shows a map of predicted land cover in 2025 in Sorong City. The area of land cover for airports has increased because the pixel value in land cover for settlements is close to the pixel value at the airport, so that the reading of this prediction shows an increasing result. This error can be seen in the land cover prediction map in 2025 in Sorong, where the airport cover is located in residential areas. Therefore, it is recommended that the predicted results be reclassified logically to predict land cover change location.

4. CONCLUSION

As a result of the CA-Markov model, settlement and shrub area expansion will occur in the future, while forest areas will decline due to this expansion. The combination of the satellite image, GIS, and Markov models provides useful information on land cover change trends in the future, which can be used to make a better decision by policymakers in Sorong City.

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