

Preliminary Study of Land Cover Changes on Mangrove Area Using Markov Chain – Cellular Automata (Case study: Teluk Batang, West Kalimantan Province Indonesia)

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Abstract— Ecosystem of mangrove forest is one of wetlands forest which land cover changing because of human activities. On this study we utilized spatio-temporal data to investigate the classification methods and to predict the model of mangrove land-use change using CA- Markov model in Teluk Batang, West Kalimantan. The data collection was used Landsat 5 (TM), Landsat 7 ETM, and Landsat 8 OLI in 1997, 2002, 2011, and 2018. The classification method were compairing for the supervised classification of the minimum distance, parallelepiped and support vector machine (SVM). The result showed that the SVM method was the best classification. Mangrove forest areas in the years until 2018 has decreased from 2499.66ha to 2016.36ha. Based on the predicted image for 2025 with the 2018 classification result image, the area of mangrove forest will increase from 2018 to 2025 of 3093.3ha from 2016.36ha to 5109.66ha.

Keywords— Mangrove, Landcover changes, Markov chain -Cellular automata

I. INTRODUCTION

Mangrove forests in Indoneisis is the largest of all mangrove forests in the world [1]. Kalimantan island is part of the territory of Indonesia, which has the capacity for mangrove forests with an area of approximately 735.906 ha [2]. According to Indonesia Forest and Environment Help (IFACS) (2014), there are 17,780 ha of mangrove forests in the Kayong Utara region. Teluk Batang Utara Town, Teluk Batang District, Kayong Utara Regency, West Kalimantan Province is one of the villages with a 354.83 ha mangrove ecosystem area [3]. Teluk Batang Village is a village with large peatlands and mangroves on its alluvial soils. Peatlands before they were plantations, as they are now are forests with a variety of flora, particularly hardwoods, which are also habitats for the fauna that inhabits them [4]. However, along with the growing activity and high demands of people in coastal areas, mangrove forests are under pressure that could endanger their life and operation [5]. In addition, it is necessary to monitor and forecast the condition of the mangrove forest environment so that physical changes can be identified.

Technological advancements have provided to identify physical improvements in mangrove forest areas, one of which is the utilization remote sensing technologies. Several previous studies have successfully used the cellular automata (CA) approach to made a model of the propagation of forest fires. One of them is Alexandridis (2008), which uses a cellular automation model to simulate cases of forest fires that occurred in Spetses Island in August 1990 (Sofiani et al., 2018). Feng et al., (2016) estimated and simulated urban growth in Shanghai-China using the Markov-Cellular Automata integration model based on machine learning [6]. Earlier, Darmawan et al (2020) had succeed of identified and predicted landuse-landcover change on the mangrove area in National Sembilang Park using Markov-CA [7]. The objective of this study is to investigate the classification methods of Land-use in mangrove forest area (1997, 2002, 2011 and 2018) and to predict the model in 2011, 2018 and 2025 to estimate the mangrove forest area using the Cellular Automata (CA-Markov).

II. MATERIAL AND METHOD

A. Study Area

Teluk Batang is located in West Kalimantan Province, Indonesia. The geographic coordinate are in 0° 43' 5.15" until 1° 46' 35,21" South Latitude and 108° 40' 58,88" until 110° 24' 30,05" East Longitude (figure 1).



Fig 1. Study Area in Teluk Batang, West Kalimantan, Indonesia [8].

B. Methodology

The steps of this research include data selection, land cover classification, configuration matrix, markov chain, cellular automation (CA) model, Kappa index validation.

a) Data Collection

Data ware used Landsat Imagery for identified the classification. One Landsat Thematic Mapper 5 (TM) for 1997 and two Landsat 7 Enhanced Thematic Mapper Plus (ETM+) images in 2002 and 2011, and one Landsat 8 OLI in 2018. The images were downloaded from USGS. The images were registered to the geographic coordinate projection using World Geodetic System 1984 (WGS-84). And auxiliary data include tide data, Sea level data, and rainfall data.

b) Processing

Fisrtly, selection of band combinations which would make it easier to identify mangrove forest area objects by choosing a combination of land and water. Secondly, the classification method will be comparing to find out the best classification method by identified the accuracy [9]. Land use/cover classification was adopted using the classification approach of the supervised classification of the minimum distance, parallelepiped and support vector machine (SVM) classification categories. Thirdly, matrix confussion. The classification accuracy allow the data be implemented in order to test the accuracy of use of the map derived from the digital classification process [10] with test samples were taken from google earth for the accuracy test. The sample was taken at different location in Teluk Batang. Fourthly, the markov-chain using the transition probabilities from 2018 to 2025 can be determined by multiplying the transition probabilities matrix from 2002 to 2018 by the transition probabilities matrix from 1997 to 2002. The Markov first-order process is a Markov process where the transition from one class to another does not include intermediate transitions to other classes. Statistical dependency may be evaluated as in every confusion matrix indicating land use/cover change [11]. Fifthly, using cellular automata model is a method of representing predictions [12]. For Mangrove forest area, the prediction for 2011, 2018 and 2025 were calculated from the transition matrix data from the Markov Chain method. Sixthly, the validation was carried out to assess how accurate the data prediction can be verified [13]. Validation was carried out by comparing the classified land cover image with the predicted image based on the kappa value [14]. Finally, the 2025 predictions should be made after the analysis of the 2011 and 2018 images have been validated. If the results of the 2011 and 2018 image validation indicate consistency then the predictions for 2025 could be developed.

III. RESULT

1) Comparisson of Classification Method

The classification approach used in this analysis were using the supervised classification of the minimum distance, parallelepiped, and support vector machine (SVM) classification classes. However the SVM classification category was used as the image for a model in the Markov CA method, because this method of classification provides the most accurate result (figure 2).



Fig 2. Land use/Land Cover using SVM method

TABLE 1. Comparisson of classification method

		1997	2002	2011	2018
Support Vector	Overall Accuracy (%)	99,5138	99,8607	100	100
Machine	Kappa Coefficient	0,9904	0,9976	1	1
Minimum Distance	Overall Accuracy (%)	77,221	76,1838	87,1849	88,3058
	Kappa Coefficient	0,6652	0,6398	0,8099	0,7871
Parallelepiped	Overall Accuracy (%)	76,3098	96,5181	95,1681	97,3013
	Kappa Coefficient	0,5682	0,9406	0,9283	0,9456

Based on Table 1, the Support Vector Machine (SVM) classification had the highest accuracy performance above 99% and the kappa index above 0.99, which indicated that the classification processed would be prevent minor misinterpretation. The classification process shall result in the area or land cover of each class being determined, including mangroves, non-mangroves and waters.

TABLE 2. The Area of Land-Use (ha)

	1997	2002	2011	2018
<i>Mangrove</i> (ha)	2499,66	2399,49	2237,49	2016,36
<i>Non-mangrove</i> (ha)	19845,72	19963,8	20046,96	20203,29
Perairan (ha)	12709,08	12691,17	12770,01	12834,81

According to Table 2 showed the classification of the Support Vector Machine (SVM) resulting in a mangrove area in 1997 of 2499.66 ha until 2018 of 2016.36 ha, which showed that the mangrove area had been decreased.

2) Image Analysis Predictions for 2011 and 2018

The prediction land use in 2011 and 2018 has an area for each land cover (mangrove, non-mangrove, and water). The area of the prediction with the results of the classification has differences from 2011 to 2025. Mangrove area would be increased around 2871 ha (Table 3).

TABLE 3. Comparisson of prediction (ha)					
Area	Klasifikasi (2011)	Prediksi (2011)	Klasifikasi (2018)	Prediksi (2018)	Prediksi (2025)
Mangrove (ha)	2237,49	6237,45	2016,36	5661,81	5109,66
Non-mangrove (ha)	20046,96	17883,54	20203,29	18245,52	18775,71
Perairan (ha)	12770,01	10933,47	12834,81	11147,13	11169,09

Kappa analyzes how well identification or modeling performs apart from a chance agreement [15]. In this analysis, kappa was used to evaluate the relationship between actual land cover maps and simulations between 2011 and 2018. The highest were Klocation and KlocationStrata in 2011 around 0.98, while the lowest is Kstandard 0.78 in 2018.

Indatas IZ anna	Years		
Indeks Kappa	2011	2018	
Kstandard	0,7918	0,7866	
Kno	0,8178	0,8161	
Klocation	0,9844	0,9605	
KlocationStrata	0,9844	0,9605	

3) Analysis of 2025 Land Use Prediction

The prediction change of Land-use in 2025 was obtained from the map of land-use in 2011 and 2018.



Fig 3. The Land-Use Prediction in 2025

The prediction image of land use in 2025 produces an area which shows that there is a change in the area in 2025, especially in the mangrove forest area which is the object of research. The area of the predicted image can be seen in Table 5.

TABLE 5. Area of Mangrove in 2025			
Class	Area		
Mangrove (ha)	5109,66		
Non-mangrove (ha)	18775,71		
Water (ha)	11169,09		

This graph in figure 4 and 5 showed that the area of the mangrove forest area in the predicted image decreased from 2011, 2018 to 2025. Similar to the predicted map, the mangrove forest area in the classification image also decreased. However if you look at the 2025 prediction, classification in 2018, the area of mangrove forest will increase from 2018 to 2025 of 3093.3ha.



Fig 4. The area of prediction



Fig 5. The area of classification

IV. CONCLUSSION

The development of mangrove forest areas in the years until 2018 has decreased from 2499.66ha to 2016.36ha. This data is obtained from the results of the Support Vector Machine (SVM) classification which has the highest accuracy. In the image prediction results using the CA_Markov method, the results are the area of mangrove forest in 2011 to 2025, from 6237.45ha to 5109.66ha. Then the area of the mangrove forest in the predicted image has decreased as in the classification result image. Based on the predicted image for 2025 with the 2018 classification result image, the area of mangrove forest will increase from 2018 to 2025 of 3093.3ha from 2016.36ha to 5109.66ha. The area of non-mangrove areas has decreased by 1427.58ha from 20203.29ha to 18775.71ha. The water area also decreased by 1665.09ha from 12834.81ha to 11169.09ha.

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