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Monitoring and prediction land cover in Prabumulih City, South Sumatera Province, Indonesia using land change modeler and multi-temporal satellite data

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ABSTRACT

Monitoring and prediction of land cover can be a strategy in determining policies for sustainable development. This research aims to analyze the use, change, and prediction of land cover in Prabumulih City. The method used in this research was the Geographic Information Systems (GIS) approach using spatial analysis and the Land Change Modeler on Landsat imagery with CA Markov. The results showed that the largest area of land cover in Prabumulih City was in the form of plantations, reaching 70% of the total area of Prabumulih City. Land cover changes in Prabumulih City from 2008 to 2020 with the highest area increasing were water bodies by 527.43%, and the place that decreased the most was an open area by 40.67%. The prediction that in 2030 the area that will increase would be the most settlement by 47.73%, and the area that will decrease the most is oil palm plantations by 21.90%.

Key words : *Land cover, Land change modeler, CA-Markov, Geographic Information Systems*

Introduction

The rapid increase iof population in the world, which requires increased anthropogenic activity, has resulted in fast land use and land cover, leading to forest destruction and transforming arable land into urban construction, significantly impacting ecosystems (Al-sharif and Pradhan, 2014). Environmental issues related to forest degradation, deforestation, and other environmental problems have become discussion topics in several environmental forums that discuss measures to reduce these impacts (Goll *et al*., 2014). The acceleration of human activity rate significantly changes land cover to each country's heterogeneity (Wang *et al*., 2016).

Population growth can increase the need for land for activities. According to Adhiatma *et al*., (2020) economic development will increase an area's growth very well. Economic development and population growth are also the causes of converting agricultural land into other areas of use besides agriculture. Economic development and population growth are also the causes of converting agricultural land into other areas of use besides agriculture. The main factor in land cover change is the human factor and the socio-economic factor that triggers land

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cover change because social and economic aspects are always human needs (Yusuf *et al*., 2018).

Land cover classification is one of the most critical remote sensing applications to identify land use features using multispectral satellite imagery in general (Osei *et al*., 2014). Currently, an understanding of the mapping of land use land cover (LULC) changes has occupied an important position in making policies related to natural resource management and environmental monitoring changes. LULC changes are essential expressions of human interaction with the environment and are characterized and influenced by many factors in time and space at different magnitudes. These factors include natural, political, socio-economic, cultural, and several other factor interaction with the environment (Sharma *et al*., 2018).

Interpretation land use/cover change creating a matrix with Geographic Information System (GIS) analysis, we can determine changes in land use/cover every year (Edwin *et al.,* 2015). Remote sensing technology is a helpful tool for detecting land use and land change (Suhartono *et al*., 2020). In addition to the results in the form of maps, GIS observes the impact of factors on the studied phenomena such as the geology of heavy metals, anthropogenic content, or the migration of organic contaminants in the soil (Rozpondek *et al.*, 2016).

Prabumulih City is one of Indonesia's cities, located on the island of Sumatera. Prabumulih City is a developing city where there are many new infrastructures to support community activities. Land cover changes will occur, threatening the existence of vegetated land that functions as life support. This research aimed to analyze, monitoring and predict land cover changes in Prabumulih City, South Sumatera Province, Indonesia.

Materials and Methods

Study area and field data

The location of this research was Prabumulih City, South Sumatera Province, Indonesia. The location of this research is at 3°20'09,01 "- 3°34'24,7" LS and 104°07'50,4 "- 104°19'41,6" LT. The area of Prabumulih City is a land area of 434.50 km^2. This study conducted random field surveys in various Prabumulih cities to identify land cover classes according to each existing class type. The specified land cover classes were matched with similar types observed in the satellite images to interpret the different spectral signatures of the LULC class on each image.

Data and software used

The data used in this study used two satellite images within 12 years to analyze the dynamics of land cover change in Prabumulih City. This image consists of Landsat TM 7 for 2008 and Landsat TM 8 for 2014 and 2020. Image data was obtained from the freely accessible data portal in https://earth explorer.usgs.gov/, in the zone 48S Universal Transverse Mercator (UTM) with the WGS84 datum. Data processing using ArcGIS 10.7.1 and TerrSet 18.31 software.

Table 1. Source of land cover time series data

Satellite data	Image date	Path row	Spatial resolution
Landsat 7ETM+	27 April 2008	124/62	30 m
Landsat 8 OLI	20 April 2014	124/62	30 m
Landsat 8 OLI	06 Mei 2020	124/62	30 m

Image data analysis and land cover change

Data analysis in this study consisted of land cover analysis, land cover change, and prediction of land cover in Prabumulih City. The method used in this study consists of satellite data pre-processing, image classification, accuracy assessment, identification of land cover changes, and prediction of land cover using the CA-Markov model.

Pre-processing satellite data

Satellite data pre-processing was carried out to prepare the image before it is processed, such as conducting a gap fill to improve Landsat 7, which contains scan line errors and geometric corrections.

Land cover change monitoring

The land cover analysis in this study consists of two stages, namely the classification of images and changes in land cover. Data processing for image classification using ArcGIS 10.7 software and for land cover changes using TerrSet 18.31 software. Image classification functions to detect, identify and classify different images based on the actual land cover represented on the earth's surface (Kalra *et al.*, 2013).

Image classification is carried out using the supervised classification method using the Maximum

Likelihood Classifier (MLC). Land cover types were composed into seven classes: swamp scrub, rivers, settlement, open area, mixed plantations, oil palm, and grassland. Land cover change was analyzed using the TerrSet software with the Land Change Modeler module by analyzing three land cover change models for 2008-2014, 2014-2020, and 2008-2020.

Accuracy

Accuracy assessment determines the accuracy and accuracy of the interpretation results using an error matrix by comparing the actual field data. The accuracy value consists total accuracy, and kappa accuracy. Confusion matrices consist of an array of numbers displayed in rows and columns indicating the number of pixels or polygons associated with a particular land cover class relative to the actual class in the field (Congalton, 1991; Provost and Kohavi, 1998).

Land cover prediction

The prediction of land cover in this study uses cellular automata (CA), where land cover is the basis for land classification and prediction of changes in land cover at specific intervals. The main constituents of the cellular automata method, according to Chen *et al*., (2002) is a pixel (cell) as the basic unit of spatial interaction in space, state, neighborhood, and the transition function is a response to changes in a cell in response to the current situation and neighborhood conditions.

Land cover prediction to get an overview of the land cover in the study area in 2030, which consists of land cover in 2020 as the reference year with a default filter of 5x5, suitability of land cover, and land cover change transition matrix between 2014-2020. The land cover prediction simulation in this study uses the TerrSet 18.31 software with the Markov cellular automata module (CA-Markov).

Results and Discussion

Accuracy assesment

The results of Landsat interpretation with the Maximum Likelihood Classification method resulted in land cover classification in 2008 with a total accuracy value of 88.24% with a Kappa value of 0.85, in 2014 the total accuracy value was 92% with a Kappa value of 0.90, and for 2020 the total accuracy value was 88.75% with the Kappa value is 0.86. Kappa values ranging from 0.86 - 0.99 are excellent (Nouri *et a*l., 2014; Wang *et al*., 2012). Overall, the kappa value in this study in 2008, 2014, and 2020 has been included in a good category to take the land cover analysis step.

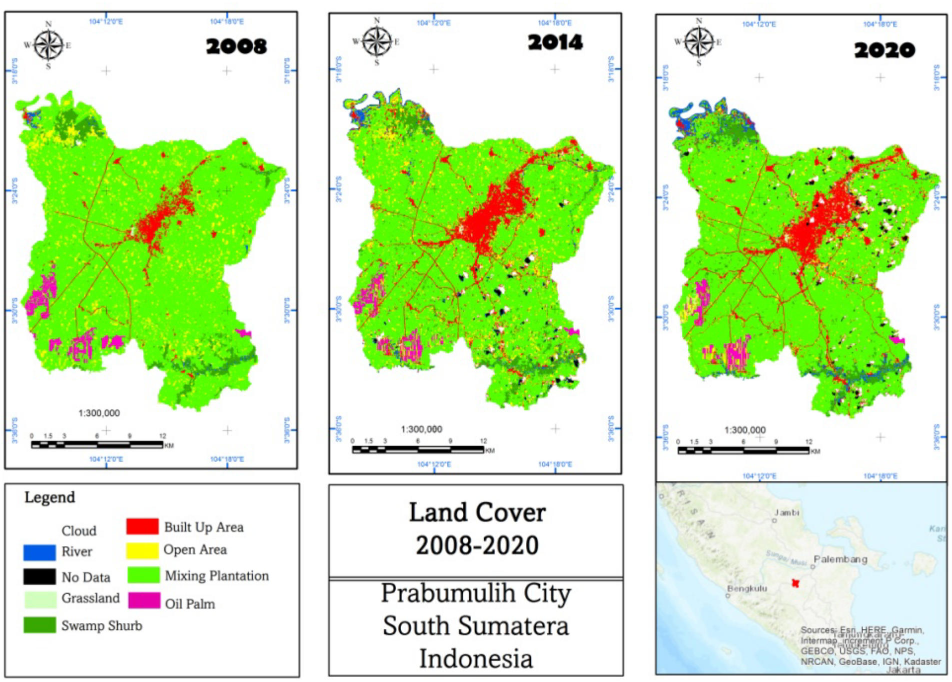

Fig. 1. Land cover in Prabumulih City 2008, 2014 and 2020

Land Cover Change Monitoring

Based on the analysis results, mixed plantations in 2008, 2014, and 2020 were the dominating land cover covering 70% of the total area of Prabumulih City (Fig. 1). Generally, farms in Prabumulih City are in the form of rubber plantations and pineapple plantations. Pineapple plantations in Prabumulih City were generally intercrops between rubber (intercropping) which function as ground cover, prevent erosion and leaching of nutrients and suppress weed growth. Pineapple plantations that became intercrops hamper the classification of the land cover types of pineapple plantations. Oil palm plantations in Prabumulih City in 2008 covered 1135.33 ha or 2.48% of the total area of Prabumulih City and continued to experience a reduction until 2020, namely to 764.12 ha.

The most comprehensive land cover after the plantation has built land consisting of settlements, roads, offices, industrial areas, and recreational areas. During 2008, 2014, and 2020 there were changes in the built-in land cover with a percentage of 4.05%, 10.83%, and 11.77%. Prabumulih City has a population in 2019 of around 186834 people with a population growth rate of 1.30%.

Swamp scrub cover based on analysis results in 2020 was decreasing in the area. The area of swamp scrub in 2008 was 4288.07 ha. In 2014 it became 2062.74 ha and decreased to 1746.06 ha in 2020 or about 3.81% of the total area of Prabumulih City (Table 2). Swamp scrub changes were estimated to be due to land cover differences, either into plantations, open land, or built-up land.

In addition to building up, open area has also changed from 2008 to 2020. In 2008, the percentage of open area in Prabumulih City was 9.30%, in 2014, it became 9.23%, then in 2020, the open became 5.52%. This change was due to the change in land use from an open area to plantations, built-up area, and other cover types. Besides, the open area, which is consistently available, is in oil wells, considering that Prabumulih is an oil-producing city. According to Pratiwi *et al*., (2016) land conversion is a consequence of increased activity and population. According to Adhiatma *et al*. (2020), social, economic, and cultural factors such as population growth, human food needs, and the fulfillment of other pri-

Table 2. Area and percentage of land cover in Prabumulih City

LC classification	2008		2014		2020	
	Area (ha)	%	Area (ha)	%	Area (ha)	%
Cloud	37.8	0.08	495.34	1.08	786	1.71
No Data	3.7	0.43	265.28	0.58	398.80	0.87
River	198.57	0.01	801.53	1.75	1245.89	2.72
Swamp shrubs	2008.44	4.38	2062.74	4.50	1746.06	3.81
Built-up land	1856.15	4.05	4967.23	10.83	5398.55	11.77
Open area	4263.52	9.30	4232.37	9.23	2529.71	5.52
Mixing plantation	36329.52	79.22	31937.94	69.64	32716.35	71.34
Oil palm	1135.33	2.48	852.80	1.86	764.12	1.67
Grassland	25.62	0.06	244	0.53	274.46	0.60
Total	45859	100	45859	100	45859	100

Table 3. Land cover change 2008-2020 in Prabumulih City

Land cover	2008-2014		2014-2020		2008-2020	
	(ha)	%	(ha)	%	(ha)	%
Cloud	457.54	1210.42	290.66	58.68	748.2	1979.37
River	602.96	303.65	444.37	55.44	1047.32	527.43
No Data	261.58	7069.73	133.51	50.33	395.09	10678.11
Swamp scrub	54.30	2.70	-316.68	-15.35	-262.38	-13.06
Built-up land	3111.08	167.61	431.10	8.68	3542.18	190.83
Open area	-31.15	-0.73	-1702.67	-40.23	-1733.82	-40.67
Mixing plantation	-4391.58	-12.09	778.41	2.44	-3613.17	-9.95
Oil palm	-283.12	-24.94	-89.15	-10.46	-372.27	-32.79
Grassland	218.38	852.39	30.46	12.48	248.84	971.27

mary requirements make changes in land cover/use from forest to non-forest factors that cause land change. Grassland cover was the land cover with the smallest space, which was less than 1%. In general, grass cover is in golf courses, soccer fields, and open land with grass growth.

Land cover changes in Prabumulih City from 2008 to 2020 with the highest area increasing were a river of 527.43% (Table 3). The increase occurred due to the overflowing river flow during the rainy season and the possibility of classification errors. The built-up area also increased where the built-up area increased by 3111.08 ha from 2008 to 2014. From 2014 to 2020, it increased by 431.10 ha due to residential areas such as national housing and other infrastructure. The open area was the area that has decreased the most, wherein 2008 to 2014 it decreased by 31.15 ha, and from 2014 to 2020 it decreased by 1702.67 ha.

This study presents data on land cover change with gains and losses on each type of land cover and net changes for three periods, period 1 (2008-2014), period 2 (2014-2020), and period 3 (2008-2020). This study's changes in land cover produce a graph of wide gains and losses in each land cover. The purple color on the graph depicts a the decrease in land cover area, while the green color shows that a type of land cover has increased in the area.

The land cover change analysis shows significant changes and transitions during the last 12 years between 2008 and 2020, incredibly mixed plantations and swamp scrub (Fig. 2). Vegetated land cover in swamp scrub, mixed plantations, oil palm, and grass plantations experienced the most significant reduction in area. The decrease in the area was accompanied by an increase in non-vegetation land covers such as open land and built-up land. According to

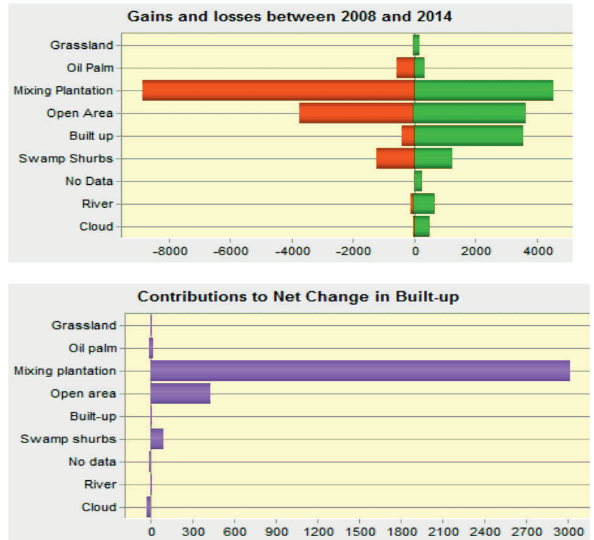

Fig. 2a. Gains, losses and net change periode 1 (2008-2014)

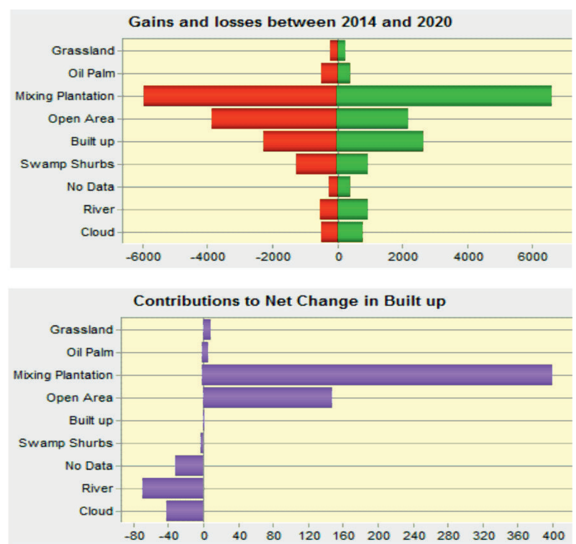

Fig.2b. Gains, losses and net change periode 2 (2014-2020)

Table 4. Prediction land cover change 2030 in Prabumulih City

Land cover classification	2020		2030		2020-2030	
	Area (ha)	%	Area (ha)	%	Area (ha)	%
Cloud	786	1.71	761.23	1.67	-24.77	-3.15
No Data	398.80	0.87	375.10	0.82	-23.7	-5.94
River	1245.89	2.72	1809.29	3.97	563.4	45.22
Swamp shrubs	1746.06	3.81	1763.16	3.87	17.1	0.98
Built-up land	5398.55	11.77	7975.33	17.49	2576.78	47.73
Open area	2529.71	5.52	2271.64	4.98	-258.07	-10.20
Mixing plantation	32716.35	71.34	29725.95	65.18	-2990.4	-9.14
Oil palm	764.12	1.67	596.75	1.31	-167.37	-21.90
Grassland	274.46	0.60	328.96	0.72	54.5	19.86

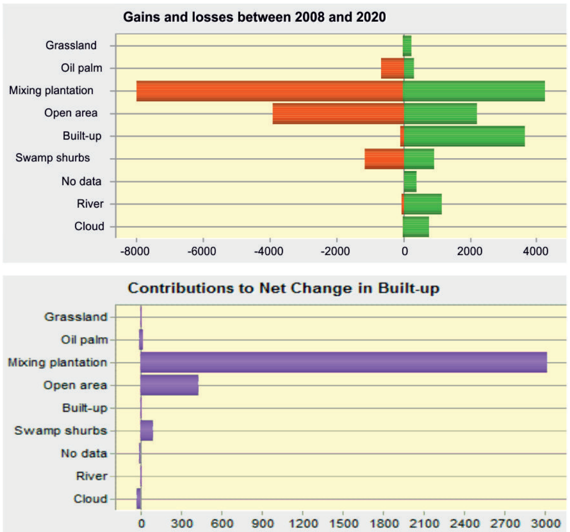

Fig. 2c. Gains, losses and net change periode 3 (2008-2020)

Koko *et al*. (2020), the decline in vegetated land is related to the expansion and development of cities due to population growth and uncontrolled human activities.

Prediction of Prabumulih City's land cover in 2030

The land cover prediction uses a change model that follows a historical pattern in the previous year (Business As Usual) using the Markov chain method in raster form. According to Adhiatma *et al*., (2020), the difference in raster and vector formats causes the difference in total area to be not significantly different. The land cover change that will change the most in 2030 is the increase in built-up land and the reduction in mixed plantations and oil palm plantations. The plantation land change in 2030 has decreased by 2,990.4 ha, and oil palm plantations have decreased by 167.37 ha.

The reduction in vegetated land was the result of its conversion to open land and built-up land. Built up area will become 7975.33 ha in 2030. According to *Karimi et al*., (2018), the increase in built-up land was accompanied by infrastructure, education, and medical facilities in each fog, increasing the urban population and changing land use that can affect the natural environment.

With the reduction of vegetated land due to land conversion to built-up land, it was necessary to have scenarios and monitor to maintain vegetated land cover that functions to absorb CO_2 emissions. According to Koko *et al*., (2020), monitoring land use/cover change dynamics plays an important role in formulating strategies and policies for effective planning and sustainable development in rapidly developing cities.

The change in the area has presented in Table 4, and the land use prediction map has shown in Figure 3.

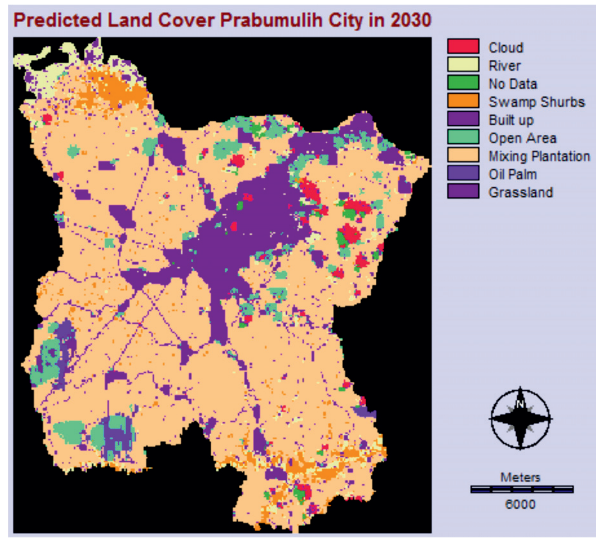

Fig. 3. Predicted land cover Prabumulih City in 2030

Conclusion

In 12 years, there was a decrease in the area of swamp scrub (-262.38 ha), open area (-1733.82 ha), mixed plantations (-3613.17 ha), and oil palm (-372.27 ha). Generally turned into a mixture of plantations and built up area. The increase in area from 2008 to 2020 occurred in rivers (1,047.32 ha), built-up area (3,542.18 ha), and grassland (248.84 ha), with additional areas resulting from changes in mixed plantations and open areas. In 2030, it was estimated that the land cover in Prabumulih City would experience changes, such as an increase in the area of development and a reduction in mixed plantations and oil palm.

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