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Modeling of land use and cover changes (LUCC) in Deli Serdang Regency, North Sumatra Province

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***Abstract**. Land use/cover (LUC) is a substantial factor in land management and can influence policy in an area. LUC has the potential to change due to physical, economic, and social aspects. This study aims to analyze the spatial land use and cover changes (LUCC) in Deli Serdang Regency for the 2010 to 2020 period and predict LUC in 2030. The analysis was run by applying the Cellular Automata-Markov Chain method. The driving factors used in this modeling are the distance to the road, the distance to the river, population density, the distance to the district capital, and the distance to Medan city. The results showed that Kappa for image classification was 0.86. The dominant type of LUC in Deli Serdang Regency is a plantation, with a total area of more than 45%, followed by paddy fields, dryland agriculture, forests, and settlements/built-up areas. LUCC model validation obtained a kappa value of 0.89 (very good category) and can be applicated for predicting land use change models in 2030. By 2030, the settlements/built-up area and dryland agriculture will increase significantly, which 21,060 ha and 4,587 ha, respectively, while forests, plantations, and paddy fields will decrease significantly by around 9,266 ha, respectively, respectively 8,306 ha and 7,806 ha.*

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INTRODUCTION

Land use and land cover here in after referred to as LUC, are two different terms but often used alternately by researchers. Land use is a form of dynamic human intervention on land on the earth's surface as an effort to meet the needs of life, both material and spiritual (Kusumaningrat et al. 2017), while land cover represents biophysical characteristics spread over the surface of the earth such as grassland, bare soil and water bodies (Gregorio and Jansen 2005). The population growth is in line with people's need for land, but on the other hand, the available land area is limited. This condition causes competition in land demand for particular needs and encourages changes in land use or land conversion. According to Rustiadi (2007), LUCC can be considered a logical consequence of the growth and transformation of changes in developing societies' social and economic structure. These developments are reflected in the presence of (a) the growth of land resource utilization activities due to the increasing population and (b) a shift in the contribution of the agricultural and natural resource processing sectors to the activities of the secondary (manufacturing) and tertiary (services) sectors. In the market economy law, LUCC occurs from activities with lower land rents to activities with higher land rents. One of them is converting agricultural land into non-agricultural land uses, such as settlements, roads, industry, health facilities, education, and others. Compared to other land use types, agricultural land (paddy fields) is currently the main producer of rice, the staple food for Indonesians, including the people of Deli Serdang Regency. However, paddy fields are one of the conversion targets for developers because, in general they have flat land relief, high accessibility, and are close to water sources (Mulyani et al. 2016).

Deli Serdang Regency is one food crops center in North Sumatra Province (Handayani et al. 2019). Based on BPS data (2020a), rice production in 2019 reached 491,109 tons of MDR, or equivalent to 296,579 tons of rice, while rice demand (consumption) was around 251,869 tons (BPS 2020b). This data shows that in 2019 Deli Serdang Regency had 44,710 tons of rice surplus. Based on data on the paddy fields area in North Sumatra Province in 2019, the paddy fields area in Deli Serdang Regency was 34,135 ha, while in 2015, it was 40,721 ha (BPS 2020a). There was a decrement in paddy fields area of around 6,586 ha in 4 (four) years or 16.2%, in an average per year of 4.0%. The decline of paddy fields area has an impact on decreasing rice production produced and will decrease more if the land conversion of paddy fields is uncontrolled or unwisely managed. Then, food self-sufficiency becomes harder to achieve.

Modeling of Land Use/Land Cover Changes in Deli Serdang Regency is urged to research because this regency is the largest rice-producing area and food crop center area in North Sumatra Province. On the other hand, the shrinkage of paddy fields occurs every year. In addition, administratively, Deli Serdang Regency is directly adjacent to Medan City and is a hinterland that supplies land needs, especially for residential and industrial areas. In addition, the issue of conversion of agricultural land is considered one of the primary issues in developing areas, even though the policy for controlling the conversion of agricultural land based on this information is still limited (Ruswandi et al. 2007). Therefore, it is necessary to restrain the conversion of paddy fields amid massive development activities in various sectors, such as roads, industrial areas, and other public facilities. If proper planning and control are not implemented, the conversion of agricultural land will continue uncontrollably. As a result, the area of paddy fields continues to decline, the amount of production decreases, and it has an impact on the ability of local governments to achieve food self-sufficiency.

LUCC was analyzed three different times (2010, 2015, and 2020) to obtain an overview of the pattern of change so that it can be used as a basis for future land use projections. CA-Markov method is used to analyze and modeling of LUC. Mondal et al. (2016) stated that the Markov model has been widely used and reliable for understanding the stochastic nature and stability of land use/land cover (LUC). In the CA-Markov model, the detection of LUCC is analyzed by the possibility of land change from one condition to another based on local rules, spatial filters of cellular automata, and a map of potential changes in the transition's probabilities (Hedge et al. 2008). LUC map is structured based on neighboring and physical (land) factors that trigger changes in land cover/use. Previous researchers used Markov Chains Cellular Automata Modeling to analyze spatial and temporal changes in land cover are Salakory and Rakuasa(2022), Adhiatma et al. (2020), Prayitno et al. (2020), Roseana et al. (2019), Shen et al. (2020), Pravitasari et al. (2020), Sugiyanto (2019), and Fadilla et al. (2017).

This study aims to analyze land use/land cover changes (LUCC) in Deli Serdang Regency in 2010, 2015, and 2020 and also to predict land use/land cover (LUC) in Deli Serdang Regency until 2030. 2030 is taken because it is expected to be used as material for consideration in the review of Deli Serdang Regency Spatial Plan.

METHOD

Study Area

The study is located in Deli Serdang Regency, North Sumatra Province. Astronomically, Deli Serdang Regency is situated at 2°57'–3°16' N and 98°33'–99°27' E. Meanwhile, geographically, the Deli Serdang Regency is bordered by Langkat Regency and the Malacca Strait in the north, Serdang Bedagai Regency in the east, Karo and Simalungun Regencies in the south, Langkat Regency, Karo Regency, and Binjai City in the west.

Administratively, Deli Serdang Regency has an area of about 2,576.4 km^2, and consists of 22 districts, namely Gunung Meriah District, Sinembah Tanjung Muda Hulu (STM Hulu) District, Sibolangit District, Kutalimbaru District, Pancur Batu District, Namorambe District, Biru-biru District, Sinembah Tanjung Muda Hilir (STM Hilir) District, Bangun Purba District, Galang District, Tanjung Morawa District, Patumbak District, Deli Tua District, Sunggal District, Hamparan Perak District, Labuhan Deli District, Percut Sei Tuan District, Batang Kuis District, Pantai Labu District, Beringin District, Lubuk Pakam District, and Pagar Merbau District. The research location is presented in Figure 1.

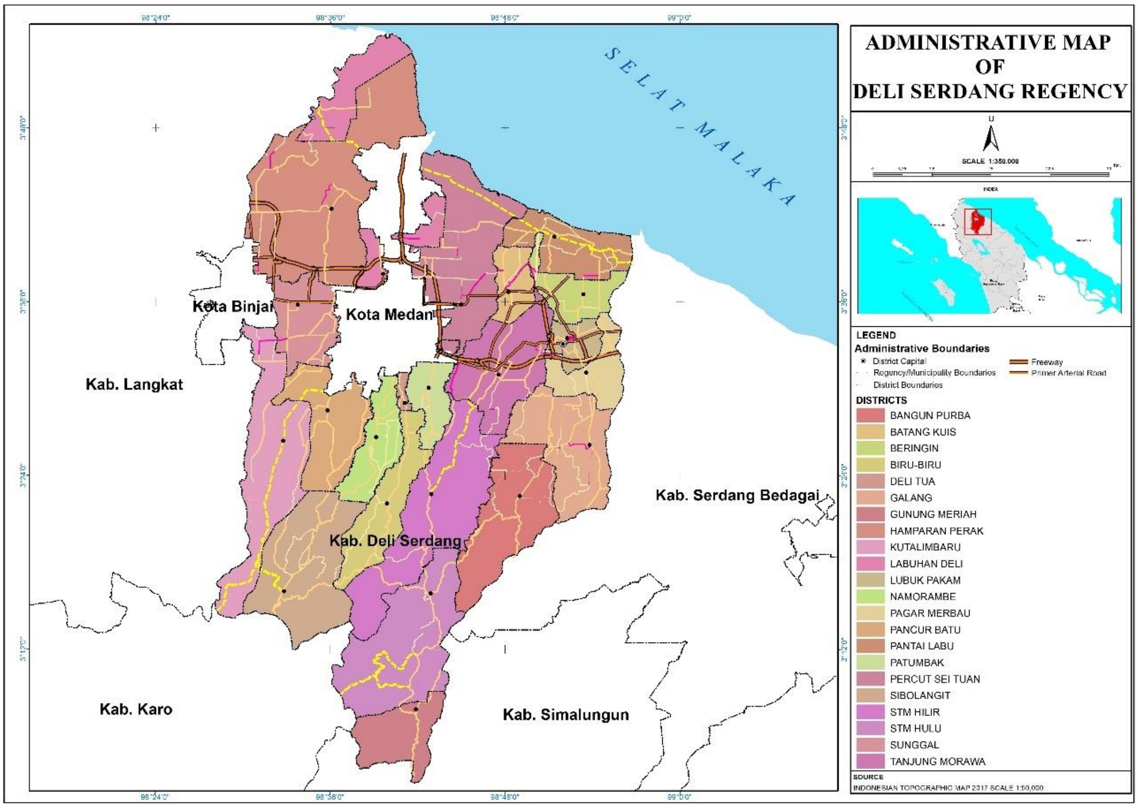


Figure 1 Study area

Data and Tools

The data used in this study are SPOT 4 images in 2010, SPOT 6 images for 2015, and SPOT 7 images in 2020 obtained from National Institute of Aeronautics and Space of Indonesia. Map of administrative boundaries obtained from the Topographic Map with a scale of 1:50,000. The tools used in this research are a camera, computer software (Microsoft Office, ArcGIS, IDRISI), and the Global Position System (GPS). GPS and camera are used for documentation of LUC survey activities (ground check), ArcGIS is software used for image analysis, and IDRISI is software used for analyzing LUCC models using the CA-Markov model.

Data Analysis Method

Visual Interpretation of LUC and Analysis of LUCC

Lillesand and Kiefier (1994) state that there are 8 (eight) elements of interpretation that are used centrally or convergently to identify an object in the image. The 8 (eight) elements are color/hue, shape, size, shadow, texture, pattern, association, and site. Based on these elements, an image visual interpretation of several types of LUC in the Deli Serdang Regency was carried out. The classification of LUC in this study is followed by the classification system based on the Indonesian National Standard (SNI) in 2010. Visual LUC classification is carried out by delineating each land cover class on a computer screen using ArcGis.10 software at a scale of

1:10,000. Visual image classification has better accuracy for distinguishing or separating land cover classes than digital classification (Kosasih et al. 2019).

This interpretation result will be verified and validated to find out the compatibility level of the classification process. The verification process is conducted by taking real points in the field (ground check points) using a stratified random sampling method. It is a method of taking stratified points randomly based on the proportion of the area of each land use class, so the class with the larger area will have more test points. The validation process is analyzed by performing the accuracy test, which consists of an overall accuracy test and a kappa accuracy test based on the misclassification matrix presented in Table 1. A kappa value equal to 1 (one) indicates the classification results get perfect agreement, while the Kappa value equal to 0 (zero) indicates the classification results cannot be agreed (no agreement). The accuracy value required in the interpretation of land use is at least 85% (Anderson 1971). Kappa Accuracy equation by Lillesand et al. (2004) expressed in:

$$K = \frac{N \sum_{i=1}^{r} X_{ii} - \sum_{i=1}^{r}(X_{i+} \times X_{+i})}{N^2 - \sum_{i=1}^{r}(X_{i+} \times X_{+i})}$$

where K is Kappa value; N is the number of observations; r is the total number of rows/columns in the error matrix; X_{ii} represents the number of observations in row i and column i; and X_{i+} and X_{+i} represents the total number of row i and column i, respectively.

Table 1 Confussion matrix

Interpreted LUC	**Reference land use (validation)**					
	P_{i+}	**P_{i+}**	**P_{i+}**	**….**	**P_{i+}**	**Sum**
P_{+i}						X_{+i}
P_{+i}						X_{+i}
P_{+i}						X_{+i}
………..						X_{+i}
P_{+i}						X_{+i}
Sum	X_{i+}	X_{i+}	X_{i+}	X_{i+}	X_{i+}	N

Note: P_{+i} : Type of interpreted LUC; P_{i+} : Type of validation LUC

: Correct number of pixels; : Wrong number of pixels

Furthermore, land use change analysis is analyzed by overlaying land use maps at the point of the observation year, 2010, 2015, and 2020 to see the transition to land use changes in the observation year period as shown in Table 2. The process result is land cover change data and also a trend of land cover change in Deli Serdang Regency.

Table 2 Transition matrix of LUCC in time t0 – t1

	LUC	**Time t_1**						**Sum**
		1	**2**	**3**	**4**	**…**	**n**	
Time t_0	1							1 t_0
	2							2 t_0
	3							3 t_0
	4							4 t_0
	…							…
	n							n t_0
	Sum	1 t_1	2 t_1	3 t_1	4 t_1	…	n t_1	N

Note: : Changed; : Consistenly; 1,2,3 etc: code of LUC

Land Use Change and Prediction Models

Land use is predicted using a spatial approach using the IDRISI (TerrSET) software. At this stage, Cellular Automata-Markov Chain (CA-Markov) modeling method approach is used, and the model is simulated using land use data in 2010 and 2015 to produce a predictive map of land use in 2020. This land cover prediction uses a Business as Usual (BaU) scenario approach, which is a case scenario based on past and present socio-economic trends assuming the first's year trends (2010) and the final year (2020) will continue in the future (Hamad et al. 2018). The driving factors used in this spatially modeling LUC are the distance to the road, the distance to the river, population density, the distance to the district capital, and the distance to Medan City. Road and river maps were available from the Topographic maps. The distance to the road maps, the distance to the river maps, the distance to the district capital maps, and the distance to Medan City maps are created using the Distance module on Idrisi Selva. The distances are calculated based on Euclidean, which is the distance from one object to another. Meanwhile, population density data is used to create a map of population density per pixel.

Ridwan et al. (2017) and Kubangun (2015) informed that the analysis stages of making a land use change model using the IDRISI software consist of several steps, namely (i) change analysis, (ii) land use change modeling (Transition Potential), and (iii) land use projections (change prediction). In the first step (i), change analysis will analyze land uses changes in a different year of input data. A graph of changes in the area of each LUC is presented at this step. Next step (ii), land use change modeling, aims to predict locations with potential land use changes and determine driving variables to build the model. Dependent variables are modeled one by one, called Sub-Model, with independent variables included in each of these sub-models. The driving variables are tested for each Cramer's V value to see the relationship between these variables and land use classes. Value of Cramer's ranges from 0 (zero) to 1 (one). A value of 0 (zero) indicates there is no relationship between the dependent and independent variables, while a value of 1 (one) indicates a perfect relationship. Losiri et al. (2016) state that if the Cramer's value is more than 0.15, then the association can be used so the driving factor can be used in the model, and if the value is more than 0.4, then the association is good. After the Cramer's V of all variables is tested, the model will be run by choosing the Multilayer Perceptron (MLP) approach. The multilayer perceptron is an algorithm that adopts the workings of neural networks in living things. MLP is the most common topology in ANN, where each perceptron is connected to form several layers. MLP has an input layer, at least one hidden layer, and an output layer (Purwaningsih 2016; Oktavianti et al. 2019).

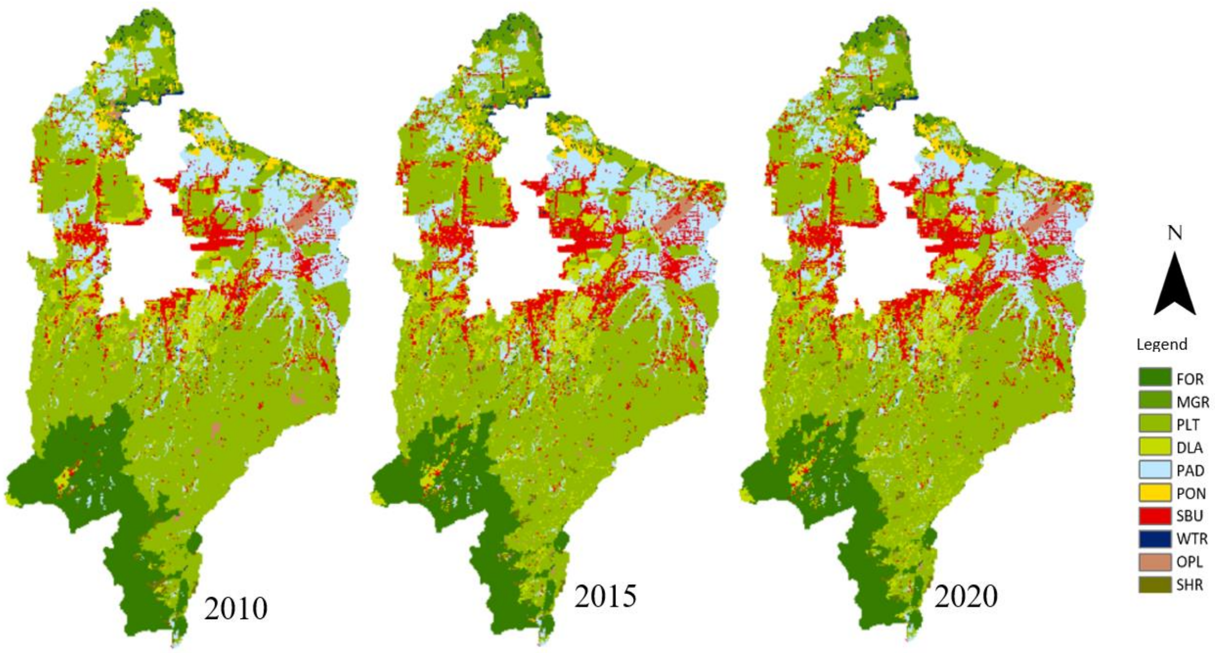
The third step is the land use projections using the Markov Chain Method. The Markov process is a process in which the system's future state can be modeled based on the previous state (Eastman 2012). Markov chain analysis will describe changes in land use from one period to another and use it as a basis for projecting future changes. This is achievable by developing a transition probability matrix of land use change from the first time to the second time, which will be the basis for forecasting the next time. At this step, it produces a change opportunity matrix based on changes in land use in 2010–2015. This method assumes changes that occur in the future have a similar pattern and probability to the pattern of change during the past period changes. The forecasting is executed to create a 2020 prediction map so it can be validated by the 2020 actual LUC map. A transition matrix will be generated by Markov Chain as the basis for making the projection map. Validation of the model using the Kappa value is by comparing the predicted 2020 map with the actual 2020 LUC map.

RESULT AND DISCUSSION

Land Use/Land Cover (LUC)

Based on the results of the image interpretation carried out, Deli Serdang Regency has 10 (ten) land use/land cover classes, namely (1) forest, (2) mangrove, (3) plantation, (4) dryland agriculture, (5) paddy fields, (6) ponds, (7) settlements/built-up area, (8) water bodies, (9) open land, and (10) shrubs. The accuracy test of LUC classification using 200 ground checkpoints with a stratified random sampling method. The Kappa coefficient is considered substantial and illustrates that the classification results can be used for further research (Rwanga and Ndambuki 2017). Based on the analysis of the error matrix in this study, the Kappa accuracy was 0.86. This value indicates that the interpretation of satellite imagery is in the very good category and complies the criteria required by Anderson (1971) so that the interpretation results can be applied for further land use analysis. The results of research by El-Hallaq and Habboub (2015), Yusuf et al. (2018), Zhu et al. (2022), and Sandi (2020) also show that Kappa scores ranging from 0.86 to 0.99 is in the very good category.

The LUC map of Deli Serdang Regency based on the classification results in 2010, 2015, and 2020 is presented in Figure 2. Furthermore, the area and proportion of each type of land use can be seen in Table 3, where it shows that the plantation has the largest proportion, reaching more over 45% of the entire administrative area. In 2010, 2015 and 2020 the plantation area was 123,157 ha (47.8%), 119,072 ha (46.2%) and 116,907 ha (45.4%). The second largest proportion is paddy fields with 37,570 ha (14.6%), 33,860 ha (13.1%) and 32,710 ha (12.7%) respectively, and so on. Based on the information in Table 3, it can also be seen that the area of forests, mangroves, plantations, paddy fields, and ponds has a declining trend at every point of the year of observation. Meanwhile, the dryland agriculture and settlements/built-up area tends to increase at every point of the year of observation.



Note: FOR=forest, MGR=mangrove, PLT=plantation, DLA=dryland agriculture, PAD=paddy fields, PON=ponds, SBU= settlements/built-up area, WTR=water bodies, OPL=open land, and SHR=shrubs

Figure 2 Map of LUC in Deli Serdang Kabupaten Regency

The transition matrices of LUC from 2010 to 2015 and 2015 to 2020 are served in Table 3 and Table 4. From Table 3, we can get information that from 2010 to 2015, the highest proportion of land use changes was in the residential/built-up area, where in 2015 the area increased significantly to 6,915 ha from 2010, followed by dryland agriculture which increased to 5,022 ha. Moreover, forest, plantation, and paddy fields decreased significantly compared to the area in 2010 about 4,181 ha; 4,085 ha; and 3,710 ha, respectively. Whereas Table 4 shows information about changes from 2015 to 2020, the dryland agricultural increased significantly to 2,759 ha from 2015, followed by settlements/built-up areas, which also increased by 2,522 ha. Meanwhile, the plantation decreased to around 2,165 ha and was followed by paddy fields which decreased more or less to 1,150 ha.

Tabel 3 Matrix of LUC transition for 2010–2015 (ha)

LUC 2010	**2015**										
	FOR	**MGR**	**PLT**	**DLA**	**PAD**	**PON**	**SBU**	**WTR**	**OPL**	**SHR**	**Sum**
FOR	30,408		2,823	505	29		36		124	665	34,589
MGR		6,555	236	206	13	397	32		143	25	7,606
PLT			110,993	8,701	225	27	1,453		1,467	292	123,157
DLA			1,139	17,591	2	3	3,737		480	84	23,036
PAD			1,885	452	33,500	83	1,465		155	31	37,570
PON		291	357	200	31	3,578	64		30	11	4,561
SBU							19,896				19,896
WTR								2,025			2,025
OPL			1,320	116	1	75	126	8	1,763	69	3,477
SHR			320	287	59		3		25	1,027	1,720
Sum	30,408	6,847	119,072	28,057	33,860	4,163	26,811	2,033	4,185	2,202	257,637

Note: FOR=forest, MGR=mangrove, PLT=plantation, DLA=dryland agriculture, PAD=paddy fields, PON=ponds, SBU= settlements/built-up area, WTR=water bodies, OPL=open land, and SHR=shrubs

Fuadina et al. (2020) also found that the built land and mixed plantations in the Metropolitan Area of Bandung continued to increase from year to year, while the paddy fields continued to decline during the period 1983–2015. Meanwhile, LUC that occurred in Ciamis Regency and its proliferated regions (Banjar City and Pangandaran Regency) from 2000 to 2018 was also dominated by an increase in dryland cover followed by a decrease in rice fields and plantation areas (Pravitasari et al. 2021). The results of the analysis are in line with research conducted in Pakistan where built-up land experienced significant growth while open spaces and green areas, on the contrary, decreased quite a lot (Khan et al. 2020).

Table 3 shows that forests changed or converted into other land use, and so other types of land use. The conversion of forest to plantations is in the highest changes area with 2,823 ha. In the mangroves, the higher potential in function is the change into a pond, which is 397 ha. Furthermore, in plantation, the widest conversion is the change to dry land agriculture which reaches 8,701 ha, followed by open land at 1,467 ha and settlements/built-up area at 1,453 ha. In the dryland agricultural, the largest conversion is to become a settlements/built-up area, which is 3,737 ha. In the paddy fields conversion, the most potent change was the conversion to plantations of 1,885 ha, followed by settlements/built-up area of 1,465 ha. In open land, the highest change function is the conversion into plantations getting 1,320 ha.

Table 4 Matrix of LUC transition for 2015–2020 (ha)

LUC 2015	**2020**										
	FOR	**MGR**	**PLT**	**DLA**	**PAD**	**PON**	**SBU**	**WTR**	**OPL**	**SHR**	**Sum**
FOR	29,874		197	195			2		39	101	30,408
MGR		6,402	152	97		89	2		106		6,847
PLT			113,737	4,258	123	16	342		450	146	119,072
DLA			631	25,639	39	20	1,402		300	27	28,057
PAD			716	112	32,476	32	452		72		33,860
PON		176	329	17	32	3,581	6		20	2	4,163
SBU							26,811				26,811
WTR								2,033			2,033
OPL			834	256	14	16	313	2	2,511	240	4,185
SHR			312	243	28	1	4		22	1,594	2,202
Sum	29,874	6,578	116,907	30,816	32,710	3,754	29,332	2,035	3,519	2,111	257,637

Table 4 shows that the majority of land use has changed into another form of land use in the 2015 to 2020 period. Although, it can be noticed that the change is smaller than the transition from 2010 to 2015. The conversion of forest to plantation is in the highest where the area reaches 197 ha, and followed by dryland agriculture at 195 ha. Mangrove has the widest change into plantation, which is 152 ha. Furthermore, in the plantation, the widest change area is the change to dry land agriculture which reaches 4,258 ha, followed by open land 450 ha and settlement/built-up area of 342 ha. In the dryland agricultural, the largest conversion area is into settlements/built-up area, which is 1,402 ha, and plantations, about 631 ha. In the paddy fields conversion, the highest change area was its conversion to plantations of 716 ha, followed by settlements/built-up area of 452 ha. In the open land, the largest conversion is the conversion to plantations reaching 834 ha, followed by settlements/built-up area at 313 ha. In general, the kind of land use changes in the period 2010 to 2015 has almost the same trend but with different areas from 2015 to 2020.

Land Use and Cover Modelling

The land use/land cover change (LUCC) model in this study uses two-year points, 2010 as the base point and 2020 as the end point of the study. The initial stage is the analysis of LUCC from 2010 to 2020, which produces a diagram of the addition and decrease of the area in each land use/land cover (Figure 3). The purple color in the graph illustrates there is a decrease in the area of LUC, while the green color indicates that LUC has increased in the area. Changes in LUC forests are very significant because they tend to decline from 2010 to 2020 with irreversible changes. It means that if the forest has changed its function, it is difficult to return it to its original use. On the other hand, settlements/built-up areas are land use classes that tend to increase each year due to the increase in population. In addition, plantations and dryland agriculture have decreased as well as increased in the area, meaning that dryland agriculture and plantations have reversible changes. In the northern region with relatively flat land topography, several key players have converted their oil palm plantations into paddy fields. Meanwhile, on the south side with hilly topography, many smallholder rubber plantations have also experienced conversion into dry land agricultural crops. This happens because it is considered more profitable economically. But some of them actually did the opposite, so that the area of plantations and dry land agriculture can increase or decrease in the research area. It is appropriate with the results of research by Kubangun (2015), which states that secondary forests and paddy fields have irreversible changes, while agricultural land and mixed gardens have reversible properties. As for the water body is a relatively fixed land use at each point of the year of observation.

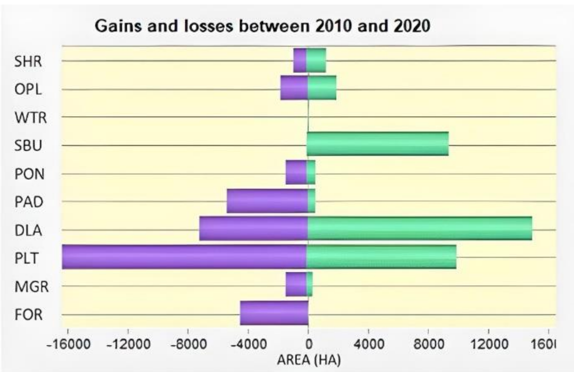


Figure 3 LUCC in 2010-2020

This simulation of land cover/use change is supported by the driving factors influencing the result in LUCC. In his research, Wijaya (2011) used several factors driving changes in land use/land cover come from economic, social/cultural, and environmental (land) factors, namely access to roads, rivers, settlements, population density, soil fertility, climate, and land topography. In this analysis, the driving factor in this model includes; the distance to the road, the distance to the river, population density, the distance to the district capital, and the distance to Medan City. Before entering the driving variable into the model, the Cramer's V is tested first to find out whether the driving variable has an influence on LUCC. Based on the analysis results, the Cramer's V values obtained are 0.2228, 0.2207, 0.1676, 0.2588, and 0.2839, respectively. As Losiri et al. (2016) state, if the Cramer's value is more than 0.15 then the correlation can be used, and the variables are adequate to use in modeling. Based on the model simulation, the locations of land use that potentially change can be predicted. The greater the Cramer's value is greater the effect to land use change (Fitriyanto et al. 2019). From the analysis results, it found that the variable distance to Medan city is the variable with the greater Cramer's value, meaning that the distance to Medan city has a greater influence on land use changes in Deli Serdang Regency when compared to other variables. Medan City is the largest center of economic activity in North Sumatra Province. This is a force that also influences changes in land use in the study area. As research from Fajarini et al. (2015) states, the distance to collector roads and the distance to the center of economic activity have a significant effect on increasing changes in land use. It shows that the closer the distance to the collector street and center of economic activity, the higher the opportunity for land use change.

Furthermore, based on the trend of land use/land cover changes in the previous stage, a land use/land cover prediction is made. Prediction/forecasting of land use is done by using the Markov Chain Method. At this stage, it produces a matrix of transition probabilities based on changes in land use from 2010 to 2015. The change opportunity matrix is presented in Table 5, which has a value of 0–1 which indicates an opportunity for the magnitude of land use change. Land use tends to change if the value is more than 0.00 or less than 1.00; otherwise, the value of 0.00 or 1.00 means the land has not changed (fixed). For example, in Table 5, settlements and built-up areas have a value of 1.00; As for other uses, the value is 0.00 so that settlements and the built-up area in the future will not change. The same situation also occurs in water bodies, which tend to be constant or unchanging. If the value ranges from 0.01 to 0.99, then it has the opportunity to change to other uses. The magnitude of this change opportunity depends on the change opportunity value. The closer to 0.01, the smaller the opportunity for the land use to change to another land use. On the contrary, the closer to 0.99, the greater the preponderant to change.

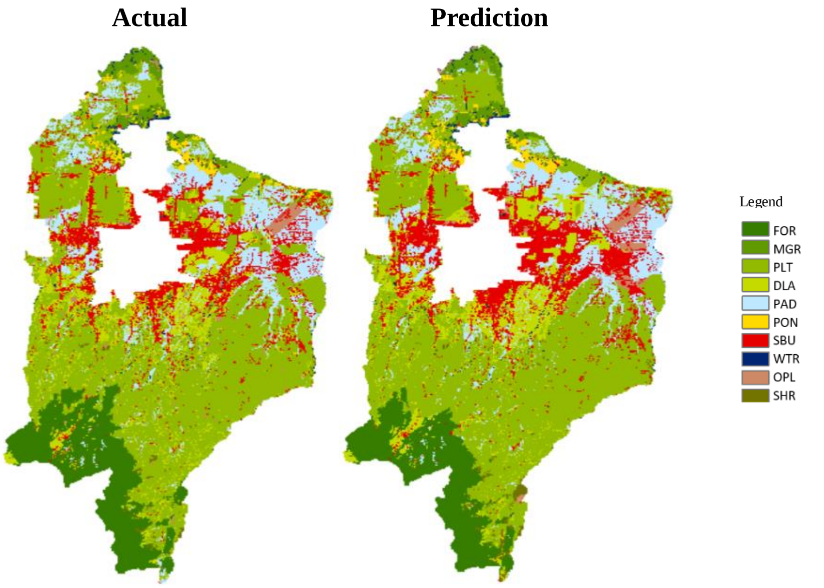
Table 5 Probabilities transition matrix

PL	FOR	MGR	PLT	DLA	PAD	PON	SBU	WTR	OPL	SHR
FOR	0.878	0.000	0.082	0.015	0.001	0.000	0.001	0.000	0.004	0.020
MGR	0.000	0.862	0.031	0.027	0.002	0.052	0.004	0.000	0.019	0.003
PLT	0.000	0.000	0.901	0.071	0.002	0.000	0.012	0.000	0.012	0.002
DLA	0.000	0.000	0.049	0.763	0.000	0.000	0.163	0.000	0.021	0.004
PAD	0.000	0.000	0.050	0.012	0.892	0.002	0.039	0.000	0.004	0.001
PON	0.000	0.064	0.079	0.044	0.007	0.785	0.014	0.000	0.007	0.002
SBU	0.000	0.000	0.000	0.000	0.000	0.000	1.000	0.000	0.000	0.000
WTR	0.000	0.000	0.000	0.000	0.000	0.000	0.000	1.000	0.000	0.000
OPL	0.000	0.000	0.381	0.033	0.000	0.022	0.037	0.000	0.506	0.022
SHR	0.000	0.000	0.186	0.166	0.035	0.000	0.002	0.000	0.014	0.598

On the forest, it tends to remain forest (0.878), while the highest value of the potential conversion is to change to plantation (0.082); Thus, in the future, the forest potentially be converted into plantations and has a greater chance of being converted into other land uses. Paddy fields have a tendency to remain as paddy fields (0.892), but there is an indication to change in dryland agriculture, plantations, settlements/built-up area, ponds, and others. This is also proven by the reduction in the area of forests and paddy fields every year. Settlements/built-up areas do not have the opportunity to turn into any land use, but almost all types of land use have the potential to become settlements/built-up areas except for water bodies. This result also proves the increasing area of settlements/built-up areas every year.

Model Validation

The modeling results produce a predictive map of land cover/use change based on the change opportunity matrix created for 2020. The modeling structure will be validated first to test whether the model could be used to predict LUC in the coming year. Validation was run out by comparing the prediction results of 2020 land use/land cover map with the 2020 actual land use map (Figure 4). Prediction of LUC in 2020 is obtained from the results of the Markov Chain analysis by utilizing data on land use/land cover in 2010 as the base/initial year and land use/land cover in 2015 as the second year. The prediction of 2020 land use is compared with the actual 2020 land use/land cover (interpretation results) using the crosstab method (cross-tabulation), as presented in Table 6.



Note: FOR=forest, MGR=mangrove, PLT=plantation, DLA=dryland agriculture, PAD=paddy fields, PON=ponds, SBU= settlements/built-up area, WTR=water bodies, OPL=open land, and SHR=shrubs

Figure 4 LUC Map of Deli Serdang Regency in 2020

Table 6 Cross-validation of the predicted and actual LUC 2020 (pixel)

LUC	**Actual**										
Predict	**FOR**	**MGR**	**PLT**	**DLA**	**PAD**	**PON**	**SBU**	**WTR**	**OPL**	**SHR**	**Sum**
FOR	294,061	0	75	1,385	0	0	23	0	309	757	296,610
MGR	0	62,795	1,510	227	0	2,858	0	0	1,099	0	68,489
PLT	27,322	1,485	1,161,346	49,558	17,582	3,881	4,385	15	9,444	7,259	1,282,277
DLA	4,882	2,112	83,854	23,4113	5,502	2,083	10,205	0	3,960	4,069	350,780
PAD	231	122	8,195	1,408	32,3088	648	4,059	0	757	673	339,181
PON	0	4,689	3,689	461	1,156	3,1042	61	0	1,208	64	42,370
SBU	324	311	15,205	45,861	14,048	642	30,4268	0	1,354	377	382,390
WTR	0	0	0	0	0	0	0	22,578	0	0	22,578
OPL	1,254	1,394	16,429	6,375	1,490	427	3,039	0	19,876	531	50,815
SHR	6,322	169	6,210	3,069	492	158	264	10	998	9,481	27,173
Sum	334,396	73,077	1,296,513	342,457	363,358	41,739	326,304	22,603	39,005	23,211	2,862,663

Note: FOR=forest, MGR=mangrove, PLT=plantation, DLA=dryland agriculture, PAD=paddy fields, PON=ponds, SBU= settlements/built-up area, WTR=water bodies, OPL=open land, and SHR=shrubs

It should be noted that the kappa accuracy value or the match value (similarity) between the number of columns and the maximum row is 1.00. From the analysis results, it was found that the Kappa value was 0.897. This value indicates that this model is fit and classified as having "very good" agreement or similarity to the existing conditions of LUC in 2020. Since high Kappa value, this model can be used to predict the distribution pattern and area of land cover/use for prediction 2030, based on historical trends in the modeling projections.

Land Use/Land Cover Prediction

Predictions have been constructed in this study using one type of model, namely the Business as Usual (BAU) Model, where the model changes follow the historical pattern that has occurred from the previous year. The prediction method of LUC in 2030 uses the same method, namely the Markov Chain. The prediction of land use/landcover map in 2030 can be seen in Figure 5, while the proportion of the area of each type of land use is presented in Table 7.

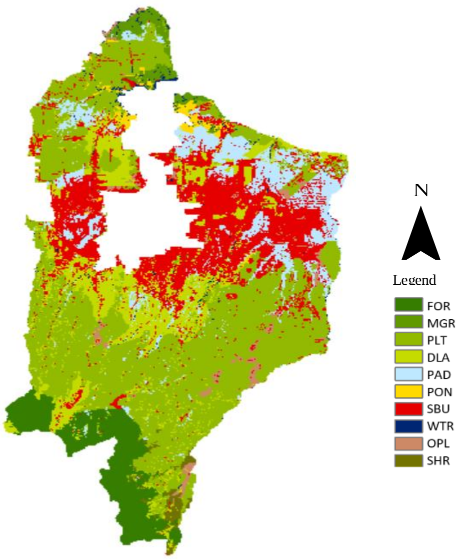


Figure 5 Predicted map of LUC 2030

Table 7 Predicted LUC area in 2030

LUC	2020		2030		2020–2030	
	Area (Ha)	%	Area (Ha)	%	Area (Ha)	%
Forest	29,874	11.6	20,608	8.0	–9,266	–31.0
Mangrove	6,578	2.6	4,979	1.9	–1,599	–24.3
Plantation	116,907	45.4	108,601	42.2	–8,306	–7.1
Dryland Agriculture	30,816	12.0	35,403	13.7	4,587	14.9
Paddy fields	32,710	12.7	24,904	9.7	–7,806	–23.9
Pond	3,754	1.5	3,194	1.2	–561	–14.9
Settlement and built-up area	29,332	11.4	50,392	19.6	21,060	71.8
Water bodies	2,035	0.8	2,032	0.8	–3	–0.2
Open land	3,519	1.4	4,852	1.9	1.333	37.9
Shrub	2,111	0.8	2,672	1.0	561	26.6

Based on the predicted map for LUC for 2030, shows that land use is still dominated by plantations (Table 7). Settlements/built-up areas are increasingly dense and concentrated in areas directly adjacent to the road, the Medan city, and the district capital. This is in line with research conducted by Widiatmaka et al. (2013)

which stated that the relatively rapid growth of residential land in areas that directly intersect with roads, where the farther the distance from the road, the smaller the percentage of change into settlements. Furthermore, Firmansyah (2016) also states that paddy fields have decreased in area, especially in areas close to urban and metropolitan areas or in areas with relatively good accessibility.

Figure 6 presents trends in land use areas from 2010, 2015, and 2020 and predictions for 2030. The graph shows that forests, mangroves, plantations, paddy fields, and ponds are land uses with a decreasing trend of changes in the area every year. However, forests, plantations, and paddy fields have a steeper slope of decline compared to mangroves and ponds. It means that the decreasing area is greater than the relatively flat slope. The forest, plantations, and paddy fields decreased significantly, around 9,266 ha; 8,306 ha; and 7,806 ha, respectively. LUC predictions carried out in regencies around the Citarum watershed also occurred similarly, where based on the results of the 2030 prediction, the area of rice fields continued to decline continuously (Firmansyah et al. 2015). Meanwhile, the decline in the area of mangroves and ponds was 1,599 ha and 561 ha, respectively.

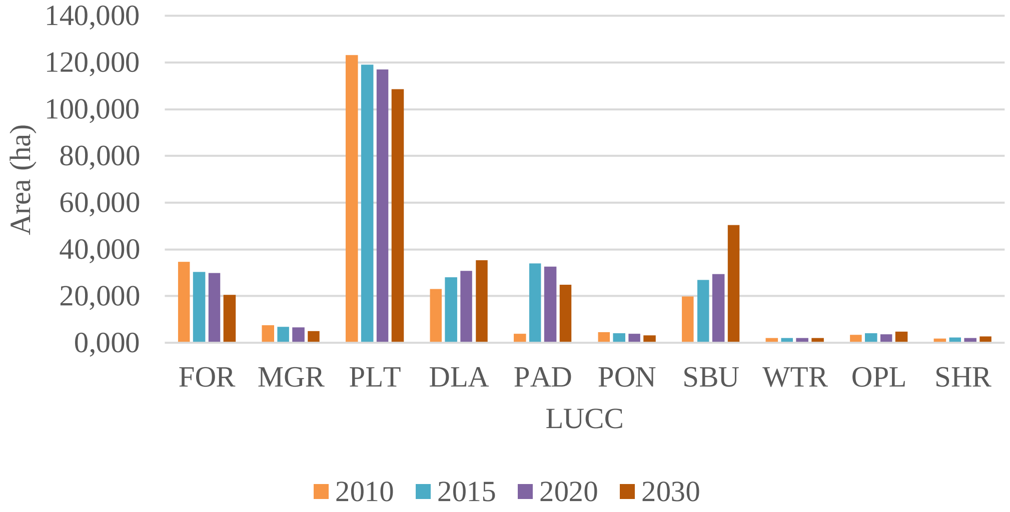


Figure 6 Trends in LUCC in Deli Serdang Regency

On the other hand, dryland agriculture, settlements/built-up area actually have an increasing trend of area changes every year. And the largest area change is settlements/built-up area, which has increased to 21,060 ha, equivalent to 71.8% of the area in the previous year. This result is also in line with the prediction of LUC in the Citarum watershed by Firmansyah et al. (2015), who found that settlements were the LUC that experienced the fastest increase (84.4%). The increase of settlements/built-up areas is due to a massive increasing infrastructure as a result of economic development that caused conversion from cultivated or non-built into a built-up areas (Adhiatma et al. 2020). In addition, dryland agriculture has a significant increase of 4,587 ha from the previous observation period. Meanwhile, water bodies tend to have a constant trend of change, while open land and shrubs are relatively fluctuating but insignificant. The pattern and distribution of land use changes in this study are influenced by the driving factors used in the model course, where all the variables used in this study have good association values for land use changes that occur in Deli Serdang Regency.

As the prediction results of land use in 2030, as presented in Table 7, the paddy fields continue to decline significantly and obviously will impact rice production and potentially impair the government's ability to meet the food needs (food self-sufficiency) of the region. Based on the research of Widiatmaka (2015), the same thing also happened in rice production centers such as Karawang Regency, where there has been a reduction in paddy fields, from 120,865 ha in 2000 to 95,926 ha in 2011, which resulted in a reduced ability of the region to supply rice outside its territory. If the same thing happened to some production centers in Indonesia, it could result in a continuous reduction in the supply of staple food in the next few years, which of course, had implications for national food sovereignty. Therefore, hopefully, the results of this study can be used as considerations for evaluation and anticipation to reduce or control the rate of land conversion rate through local government policies so that food self-sufficiency will continue in Deli Serdang Regency. There is a need for synergy between Regional Spatial Planning, in this case including the regulation of spatial patterns and land use, with the calculation of food needs in order to meet regional food needs, as well as the capability and suitability of the agricultural land itself. So that it can produce a protected paddy field that is designated as sustainable food field.

CONCLUSION

Visual interpretation of the image resulted in land use/land cover classes of forest, mangrove, plantation, dryland agriculture, paddy fields, ponds, settlements/built-up area, water bodies, open land, and shrubs, with a kappa accuracy value of 0.86. The dominant land use in Deli Serdang Regency is plantations, with a portion of more than 45% of the total area, followed by paddy fields, dryland agriculture, forests, and settlements/built-up area. Land use change in the period 2010 to 2015 and 2015 to 2020 tend to have the same patterns. The validation of the land use/land cover change model is in the "very good" category with a kappa value of 0.897 and can be used as a predictive model of LUC in 2030. Changes in LUC in Deli Serdang Regency from 2010 to 2020, with the highest increase, are settlements/built-up areas, followed by dryland agriculture. Meanwhile, LUC that have a significant decrease are plantations, paddy fields, and forests area. Based on the predicted results of land use/cover in 2030, this pattern will continue, where settlements/built-up land will increase significantly, but plantations and paddy fields will continue to decline.

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