



Modeling Land Use and Land Cover Dynamic Using Geographic Information System and Markov-CA

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Abstract

The need for built-up area increases along with a rise in population growth in many regions. This phenomenon leads to a tremendous change in agricultural land and decrease in the environmental carrying capacity. Therefore, this study aims to determine Land Use and Land Cover (LULC) dynamics and the drivers used for its modeling in 2030. This is a quantitative study, which uses the dynamic models of Geographic Information System (GIS) and Markov-CA. Data were obtained from the CNES-Airbus satellite imageries in 2009, 2014, and 2019 by using Google Earth at East Cirebon. The drivers include road density, distance to CBD, total population, distance to settlements, land slope and distance to rivers. The interaction between drivers and LULC change was analyzed using binary logistic regression. The results showed that the rise of built-up area reached 36.4 percent and causes the loss of 0.78 km² of agricultural land from 2009 to 2019. The LULC simulation in 2030 shows an increase in the built-up area by 82.85 percent with probabilities above 0.6. Meanwhile the significant drivers for changes include road density and distance to settlements. In conclusion, efforts to reduce LULC change in agricultural land into built-up area is by re-strengthening spatial planning-based environmental awareness for the community.

Keywords: Built-up area; GIS; LULC; Markov-CA; Spatial modeling

1. Introduction

Land is a valuable resource formed from biotic and abiotic components on the earth's surface (Asselen & Verburg, 2013). Its various forms and uses are referred to as land use and land cover (LULC) (Aspinal & Hill, 2008). Land growth rates and human needs have varying patterns, although it is a limited resources— its value typically appreciates over time. It has both direct and indirect impacts on humans which leads to the dynamic phenomenon of LULC, such as the transformation of agricultural land into built-up area (Gashaw *et al.*, 2017).

This condition is caused by several factors or drivers, from the physical and social environment (Kusratmoko *et al.*, 2017). In Indonesia, the rate of land conversion follows a linear pattern from 1.8 percent to 2.1 percent (BPS, 2013). There is an increase in the demand for built-up areas such as housing, amenities, infrastructure as well as employment in the industrial sector due to the 2030 demographic dividend. This led to the shrinkage of productive-agricultural lands that served as food barns. Cirebon is one of the regions which has agricultural comparative-advantage, as well as a similar pattern of LULC conversion (Dede *et al.*, 2016; Dede *et al.*, 2019). This is evident in the emergence of its Regional Planning (RTRW) from 2018 to 2038 and Regional Regulation on Sustainable Agricultural Land (LP2B), these two policies have the directives to protect 45,000 hectares of agricultural land against LULC change.

LULC change in the western region of Cirebon occurred due to industrialization, while in the Eastern part, it is caused by the development of new residential and industrial areas for numerous multinational companies. Another region that experiences this change is Gebang Sub-District. Its development is rapidly instigated by the local government because this region has poor economic growth than The Western Region of Cirebon. This actualization was realized by the residential and industrial projects carried out on lands formerly used for agricultural purposes. Assuming, the rate of LULC change is not properly controlled, it tends to cause several impacts as well as a decline on environmental carrying capacity (Hidajat *et al.*, 2013). The factors that affects this phenomenon is geographically determined through an efficient method referred to as spatial modeling . Its dynamic nature is predicted using spatial modeling and geographic information system (GIS) subsequently, the use of vector and raster data based on remote sensing imageries is ideal for future purposes (Dan-Jumbo *et al.*, 2018). An LULC spatial modeling relating to physical and social factors is capable of determining (didactic) and illustrating the dynamic process (heuristic) to produce useful outcomes for the regional development planning (Sanders, 2007; Kangalawe

& Lyimo, 2010). It is also used to evaluate the changes in probability, the influence of the factors or drivers, and dynamic scenario based on certain trends in space and time (Kumar *et al.*, 2015).

Markov-Cellular automata (CA) is a dynamic spatial model composed of cells (pixels or grids), each of which is systematically arranged. It is also robust in predicting the transitions or spatial and temporal dynamics among a number of LULC types.... 2014). This model is a computational method for determining dynamic systematic changes that depend on certain rules developed temporally (Liu, 2012). It functions in accordance with the principle of game play, it is sensitive to cell size, and neighborhood configuration or similar to three or more existent parcels (Moreno, 2008). Markov-CA, when compared with other dynamic models has advantages such as the ability of individuals to boost information that has under the regular principles, regulates their evaluation, and analysis of the spatial (space) characteristics, used to easily predict land use in the future (Gambo *et al.*, 2018).

Knowledge of existing LULC changes and the probability of its dynamics in the future is important for regional development, particularly in rural areas proposed as growth centers such as Gebang District, and Cirebon Regency. Previous studies generally examined the LULC changes in critical watershed, peri-urban, metropolitan, and megapolitan regions (Lahti, 2008; Chavula *et al.*, 2011; Li *et al.*, 2019). Furthermore, the studies carried out in rural areas, primarily focuses on the use of land for agricultural purposes and forestry (Sodikin *et al.*, 2018; Voight *et al.*, 2019). According to previous studies, its factors or drivers tend to have an effect on the biogeophysical aspects rather than the regional socio-economic conditions. Therefore, efforts to examine LULC changes in rural areas with potentially significant landscapes are essential for adaptive and sustainable regional development policies. This study aims to determine the dynamics of LULC in Gebang District representing the Eastern Cirebon and the future application of GIS and Markov-CA models.

2. Methods

2.1 Study Area

This research was carried out at Gebang Sub-District, East Cirebon Regency, West Java. This area is situated between Cirebon, Kuningan and Brebes Regency. It has a tropical climate characterized by an average temperature of 32° Celsius and annual rainfall of approximately 2000 to 2500 mm. Gebang has an altitude of 0 to 37 m above sea level and the region is suitable for the cultivation of rice, pulses and sugarcane, however it is quite susceptible to flood and tidal rising. This study applied saturated sampling in 14 villages

(Figure 1). Subsequently, LULC dynamic model is an input for environmental conservation as well as efforts to protect productive agricultural land.

2.2 Data Acquisitions

Basic information on LULC was obtained using the 2009 CNES-Airbus imagery which had a spatial resolution of 0.96 meters. The analysis of land changes were initiated based on a temporal span of 10 years which was due to the independent implementation of development policies in the region – in the early 2000s, Gebang was separated from Babakan. The second temporal (time) data was obtained with the 2014 CNES-Airbus imagery. Meanwhile, the first law of geography refers to the dynamics of LULC's spatial modeling - which stated that everything is related, however those that are closer are more influential than distant things (Sui, 2004; de Smith *et al.*, 2007; Foresman & Luscombe, 2017). Consequently, all spatial phenomena are formed due to reciprocal relationships with their neighboring environment, which leads to geographical closeness that offers stronger and more influential interactions. This is common in cross-sectional phenomena such as land use, therefore the Markov-CA, is a suitable mathematical model (Hamad, *et al.*, 2018; Hua, 2017).

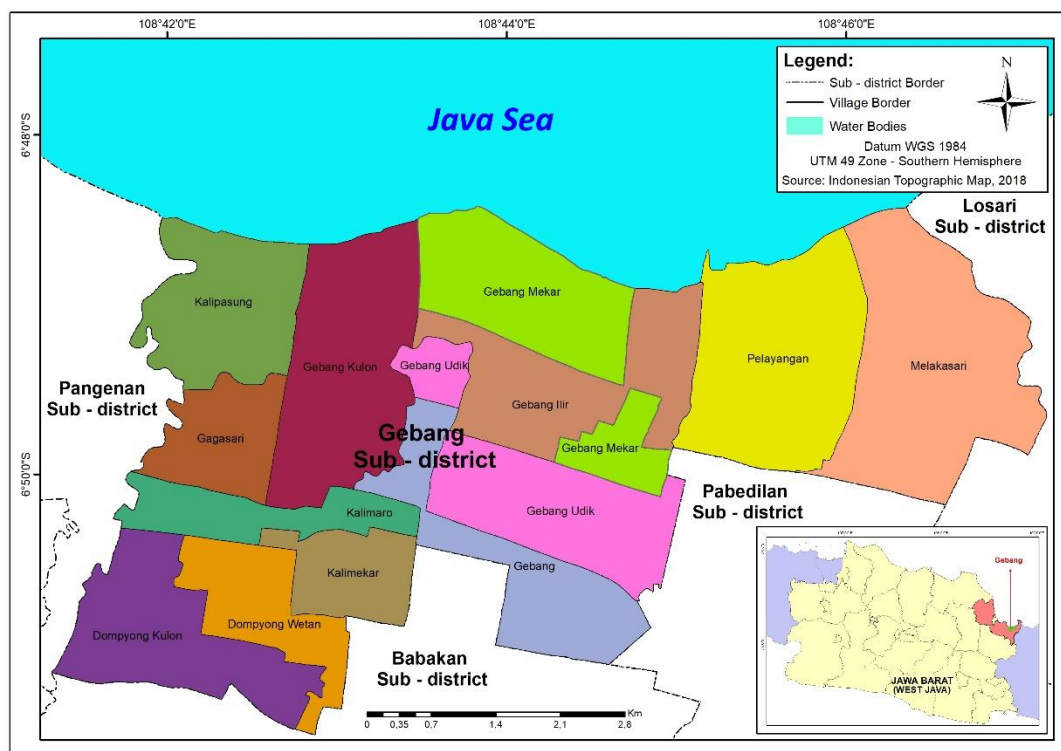


Figure 1. Study Area

This study utilized primary data obtained from field surveys carried out as part of testing land use in 2019, however secondary data was derived from reliable sources, namely

scientific articles, official reports of government and non-governmental institutions (Table 1). These data are validated according to geospatial criteria in order to enable LULC dynamic spatial modeling.

Table 1. Data Acquisition and Research Variables

Variable or driver	Data	Data acquisition
Land slope (X ₁)	Raster	ASTER DEM (2019)
Distance to rivers (X ₂)	Vector	Field survey (2019) and buffering HOT-OSM BNPB data (2019)
Distance to CBD (X ₃)	Vector	Buffering based on field survey (2019)
Total population (X ₄)	Atribut	Indonesian Statistical Agency (BPS) (2019)
Road density (X ₅)	Vector	BIG <i>Tanah Air</i> -Geoportal (2019)
Distance to settlements (X ₆)	Vector	Buffering based on visual-supervised classification of CNES-Airbus (2019)
Land use and land cover (Y)	Vector and raster	Visual-supervised classification of CNES-Airbus Imageries (2019) and field survey (2019)

2.3 Data Analysis

This research applied a quantitative approach for making interpretation and drawing inferences from changes in the dynamic system which occurs due to its drivers and the LULC predictions by the Markov-CA model. Supposing the outcome is combined with non-parametric statistical analysis, the determinants or drivers influencing this phenomenon are discerned (Quan *et al.*, 2006; Deng *et al.*, 2009). Therefore, the results from Markov-CA were combined with the logistic regression method to obtain the probability value in the modeling of LULC in Gebang (Equation 1). Logistic regression is defined as a type of non-parametric statistics, which involves the interaction between variables relating to an actual situation in the absence of classical assumption test. The models produce potential LULC dynamics in the future. The probability of spatial dynamics is determined by the transformation of standardized Z values (Hosmer, 2013). Through this model, the intervention of independent variables that are highly significant produces several scenarios of LULC probabilities.

$$\ln\left(\frac{p}{1-p}\right) = \alpha + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_n X_n \quad (1)$$

where \ln is the natural logarithmic, p probability value, α regression constant, and β predictor coefficient.

The results from the validation of spatial modeling were obtained using data from ground truth which involves 30 LULC samples from all villages in Gebang Sub-District. This

effort is evident in the overall accuracy and kappa values (as shown in Equation 2 and 3) (Widiawaty *et al.*, 2018).

$$\text{overall accuracy} = \frac{L_1 + L_2 + \dots + L_n}{n} \quad (2)$$

$$\text{overall kappa} = \frac{OA - EA}{1 - EA} \quad (3)$$

Where L is LULC types, n total samples, OA observed, and EA expected agreement.

3. Results and Discussion

The analysis of LULC dynamics started in 2009 because the study area showed the independent implementation of development policies after it was separated from Babakan Sub-District in the early 2000s. During this period LULC was dominated by agricultural land and salt-fisheries with an area of approximately 29.11 km² (82.38 percent), other large proportion consist of built-up areas (2.93 km²) and plantations (2.60 km²). In 2014, the built-up area gained a significant increase of approximately 0.93 km², five years later. However, various conditions caused a decline at the plantations and agricultural lands to relatively 0.26 – 0.58 km² (as shown in Figure 2). In accordance with the aquacultural sector, there was a decline in areas utilized as salt-fisheries and they were transformed into mangrove forests due to lack of management.

It is assumed that the prediction of LULC information during the final periods are based on the interpretation and classification of imageries, obtained in 2019 and 2030 using GIS and Markov-CA model. The model used a redundant temporal dynamics with pixel resolution 5 m x 5 according to the geospatial regulation in Indonesia (Law 4/2011 of Geospatial Information). The LULC model has an overall accuracy of 93.33 percent and kappa of 0.92, therefore it is valid and needs to be recommended for future purposes. The high-level of accuracy is considered prevalent due to the detection of LULC using high satellite imagery resolution with an accuracy of relatively 0.80 (Ustuner *et al.*, 2017). The LULC model in 2019 showed several changes in built-up areas, furthermore its increase caused a decline in agricultural lands, plantation, etc (Figure 3). The occurrence of accretion led to the development of mangrove vegetation of approximately 0.02 km². Sediment materials from Ci Beres and Ci Sanggarung accumulated in the shoreline of Gebang.

In 2030, Gebang Sub-District is expected to be highly-dynamic because the built-up areas was approximately 20.67 percent, tend to increase to 3.99 km² due to the function of non-vegetated land and plantations with a probability of 0.43 – 0.45. Changes in LULC were

also detected in agricultural land and shrubs with a probability of relatively 0.10 as shown in Table 2. The direction of the dynamics in this region starts with the exhaustion of agricultural land which is converted to non-vegetated land till it is covered with marshes and woody plants. Initially, it was made up of agricultural land which gradually became compact and used to build settlements as well as other infrastructures to support human needs. This is common in various parts of the world to prevent subsidence thereby resulting in the conversion and utilization of inappropriate human activities to manage the environment (Minderhoud *et al.*, 2018). Therefore, the agricultural land is directly converted to built-up areas. Figure 2 shows that agricultural land decrease every time.

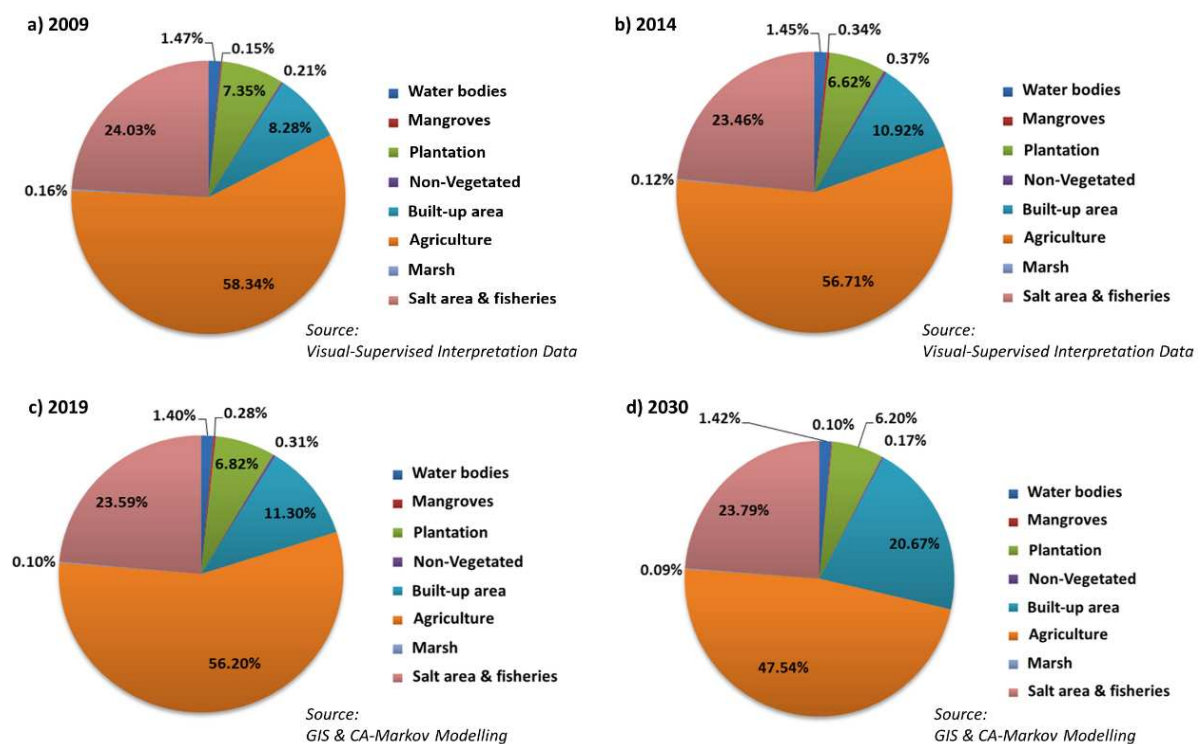


Figure 2. LULC Change in Gebang and Prediction in the Future

Table 2. LULC Change Probabilities

LULC Type	Probability							
	WB	MA	Pt	NV	BA	AL	Mr	SF
Water bodies (WB)	0.322	0.049	0.171	0.002	0.114	0.089	0.023	0.231
Mangroves (MA)	0.182	0.029	0.047	0.003	0.038	0.029	0.008	0.666
Plantations (Pt)	0.029	0.002	0.346	0.001	0.447	0.167	0.002	0.007
Non-vegetated (NV)	0.015	0.005	0.042	0.009	0.437	0.162	0.001	0.331
Built-up area (BA)	0.021	0.001	0.090	0.000	0.870	0.015	0.001	0.002
Agricultural land (AL)	0.003	0.000	0.063	0.009	0.122	0.789	0.000	0.014
Marsh (Mr)	0.042	0.007	0.158	0.002	0.126	0.149	0.078	0.439
Salt area & Fisheries (SF)	0.047	0.022	0.011	0.007	0.053	0.054	0.001	0.804
Mean	0.083	0.014	0.116	0.004	0.276	0.181	0.014	0.312

LULC transition shows that human intervention in agricultural activities has the tendency to change the land into a built-up area. This condition is driven by lack and the pragmatic attitude of young people to become farmers – due to the fact that poverty aided in accelerating the rate of land conversion in the Cirebon Regency, particularly in Gebang District. The results from the gain and loss analysis show that the developed area was approximately 4.38 km², while the agricultural land was reduced to 4.22 km² as shown in Table 3. The LULC dynamics shows that a significant interaction exists between the decline in agricultural land and increase of built-up area. This pattern leads to food inequality because the human population continues to grow while there is a decline in agricultural lands, particularly in developing countries due to modernization and industrialization (Ouedraogo *et al.*, 2010; Mhawish & Saba, 2016). Figure 3 shows the expansion of built-up area in previous periods tends to be close to the road.

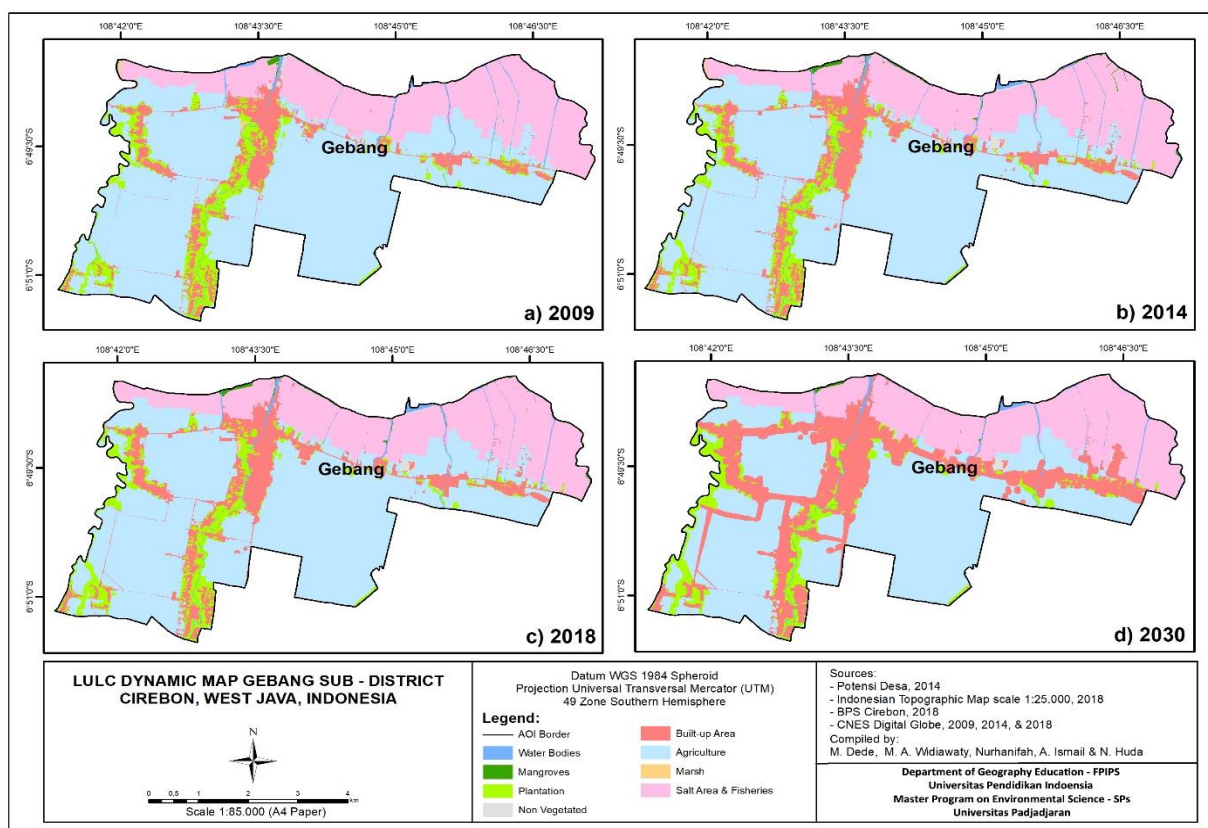


Figure 3. LULC Dynamic Map of Gebang

3.1 Driven Factors of LULC Change

LULC change in a dynamic system occurs due to various factors. The CA model produces predictions which combines with non-parametric statistical analysis useful in

determining the various factors that influences this phenomenon referred to as drivers (Kamwi *et al.*, 2018; Munthali *et al.*, 2019). Therefore, the LULC modeling in Gebang Sub-District is combined with the Markov-CA logistic regression methods to obtain the probability value of the dynamics. The testing involved 6 (six) factors or drivers known as independent variables namely land slope, distance to rivers, distance to CBD, population, road density, and distance to the built-up area which were analyzed and reclassified as shown in Figure 4. LULC change is a dependent variable which consists of both changed and non-changed lands.

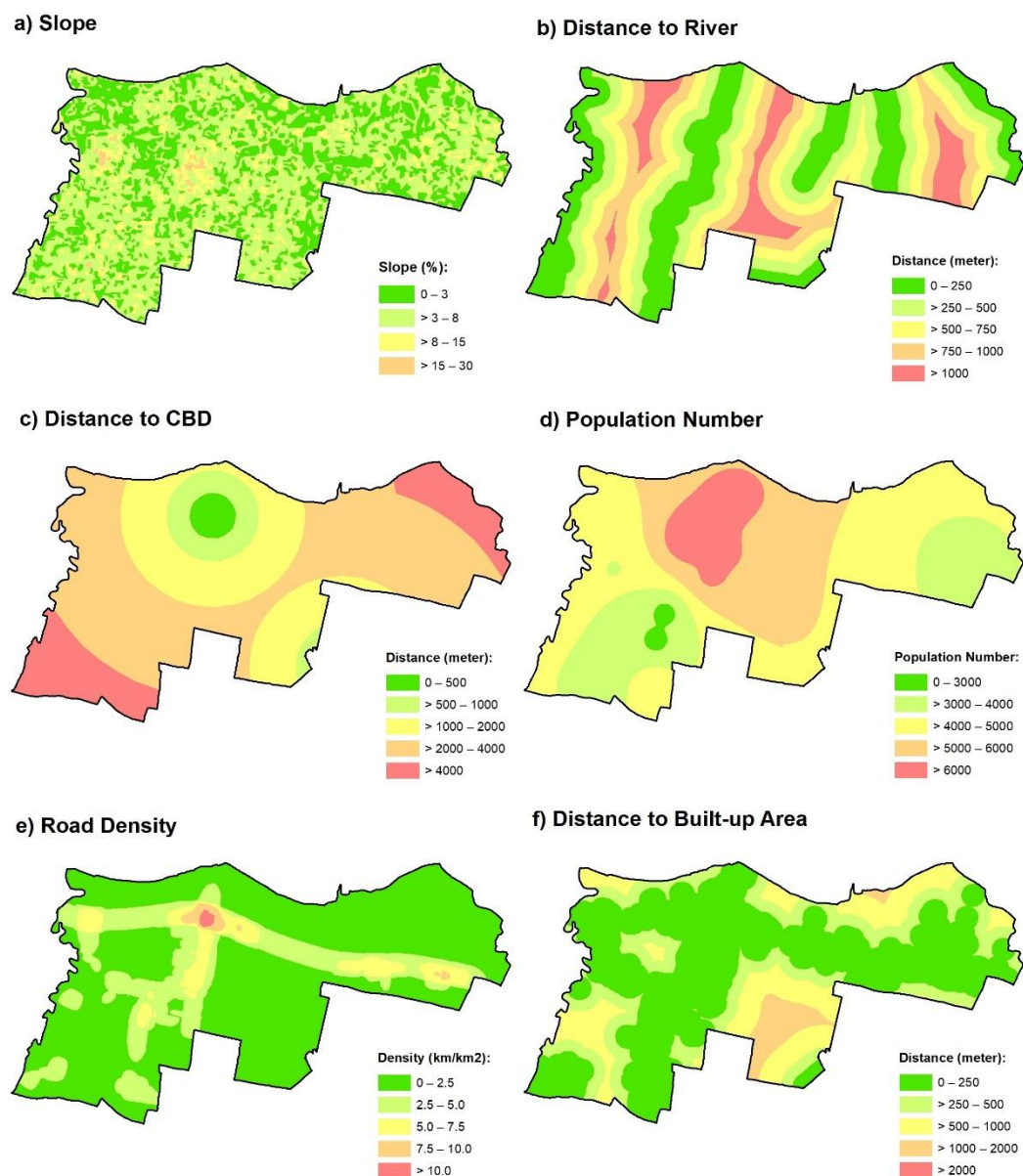


Figure 4. Drivers of LULC Changes

Table 3. Gain and Loss All Types of LULC in Gebang

LULC Type	Area (km ²)				Gain & Loss (%)			
	2009	2014	2019	2030	2009	2014	2019	2030
Water bodies (WB)	0.52	0.51	0.49	0.50	-	-0.89	-3.93	2.10
Mangroves (MA)	0.05	0.12	0.10	0.04	-	129.5	-18.02	-62.78
Plantations (Pt)	2.60	2.34	2.41	2.19	-	-9.96	3.01	-8.99
Non-vegetated (NV)	0.08	0.13	0.11	0.06	-	74.27	-16.83	-43.62
Built-up area (BA)	2.93	3.86	3.99	7.30	-	31.79	3.52	82.94
Agricultural land (AL)	20.6	20.0	19.9	16.8	-	-2.78	-0.92	-15.36
Marsh (Mr)	0.05	0.04	0.03	0.03	-	-25.46	-14.99	-3.59
Salt area & Fisheries (SF)	8.49	8.29	8.34	8.41	-	-2.36	0.54	0.86

Table 4. Interaction between Drivers and LULC

Variable or driver	B	Exp(B)	Sig.	Status
Land slope (X ₁)	0.021	1.021	0.746	Not significant
Distance to rivers (X ₂)	0.032	1.033	0.442	Not significant
Distance to CBD (X ₃)	-0.090	0.914	0.254	Not significant
Total population (X ₄)	-0.061	0.941	0.415	Not significant
Road density (X ₅)	0.228	1.256	0.001	Significant
Distance to settlements (X ₆)	1.776	5.907	0.000	Significant
Constant	-8.647	0.000	0.000	Significant

Table 5. LULC Dynamic Model Validity

Model accuracy and drivers influence					
Accuracy (percent)		Nagelkerke test (r and r ²)	Significance		
Without drivers	Using drivers		p-value	A	
50.2	66.0	0.493 and 0.243	0.00	0.05	
<i>Goodness of fit</i> (GoF) Hosmer-Lameshow					
Chi-square value	Chi-square table	DoF	p-value	α	Status
10.61	15.51	8	0.225	0.05	Fit
<i>Relative operative characteristics</i> (ROC)					0.73

$$\ln\left(\frac{p}{1-p}\right) = -8.65 + 0.02 X_1 + 0.03 X_2 - 0.09 X_3 - 0.06 X_4 + 0.23 X_5 + 1.18 X_6 \quad (4)$$

The result from logistic regression test implies that road density and distance to built-up area have a significant influence of approximately 95 percent confidence level (Table 4). This condition shows that the pattern of LULC changes tends to be close to the existing built-up area which has quality accessibility (Saputra & Lee, 2019). In addition, six drivers simultaneously have a significant influence on LULC change, the r-value obtained from the

Nagelkerke test is 0.493, and an increase was detected in the value of Markov-CA based on GoF and ROC (as shown in Table 5). However, LULC changes also occur without influencing the drivers. This is evident in the 0.757 value of the epsilon which shows that other factors such as socio-economic conditions and political policies also influence the LULC preferences (Yirsaw *et al.*, 2017). The interaction value between the drivers and LULC change in the regression model is shown in Equation 4.

The statistical results also known as the drivers of socio-economic aspects are more influential than the biogeophysical aspects in Gebang. These are certainly different from previous studies which stated that slope and distant water bodies are significant drivers (Hassen & Assen, 2017; Dibaba *et al.*, 2020). This shows that abrupt knowledge of the socio-economic condition is necessary in the analysis of LULC change, although the nature of these drivers tends to be dynamic and difficult because they are the two main causes of urbanization – in the context of the development of rural and urban landscape (Han *et al.*, 2015).

3.2 Probability LULC in 2030

The values of the input independent variable (drivers) stated in Equation 4 predicts the probability of LULC change in 2030. Out of the six drivers, four of them are constant namely slope, distances to the river, built-up area, and CBD. Therefore, the spatial probability of LULC in Gebang is only affected by two dynamic drivers namely population number and road density which are both significant variables. Population number in 2030 is obtained from the prediction of the population growth from 2009 to 2019. Gebang Sub-District has a population growth of 1.42 percent per year, therefore in 2030 it is predicted to be 67,449 people (approximately 10.77 percent). The increasing road density in 2030 is derived from the national average road development which is relatively 0.12 percent per year (Istiono, 2014). The results from processing and inputting data for the drivers into a logistic regression equation produced a probability scenario of LULC change as shown in Figure 5. This pattern of change is similar to the research carried out by Mienmany (2018) which predicts that almost all types of LULC have a potential change towards the built-up area.

In 2030, the probability of LULC change is predicted to be high in four villages – Gebang Kulon, Gebang Ilir, Gebang Mekar, and Gebang Udik. These areas are close to the Gebang CBD and have high density, due to the influence of national arterial roads (pantura). Its existence offers a variety of socio-economic benefits for the population due to the role of

interregional interaction, and the presence of built-up areas (McAndrews *et al.*, 2017; Yesuph & Dagnew, 2019). The total area of 0.55 km² has a probability of approximately 0.4. This value is smaller when compared to the land probability of 0.001 – 0.1 with an area of 3.06 km², irrespective of the changes.

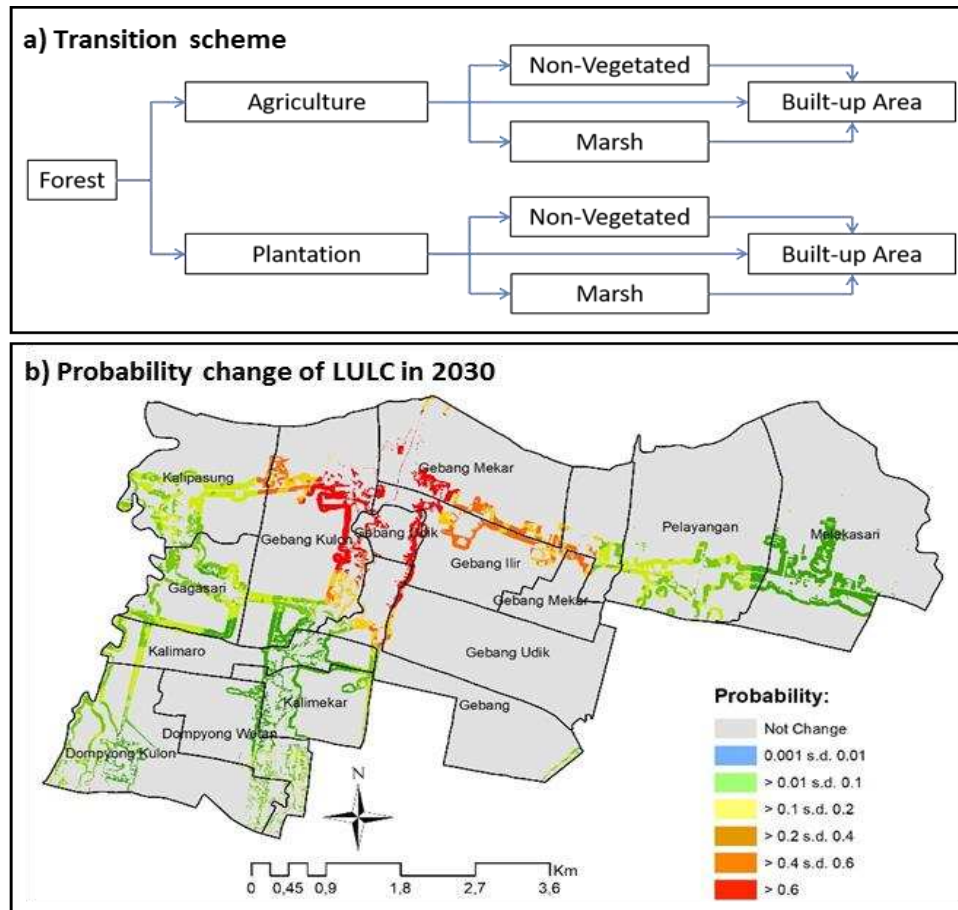


Figure 5. a) Pattern of LULC Change Transition and b) Probability Change of LULC Gebang in 2030

4. Conclusion

The integration of GIS and Markov-CA led to the emergence of a dynamic LULC model and information on various factors which influenced its changes in the Gebang Sub-District. This research discovered that from 2009 to 2030 there tends to be an increase in built-up area accompanied by a decline in agricultural land and plantations. The predictions of 2030 also showed that the developed area was expanded to approximately 20.67 percent, while the largest land loss of relatively 18.5 percent occurred in agricultural land. Two drivers that have significant influence on LULC change is road density and distance to built-

up area. In addition, the total chances of LULC occurrence in this region was approximately 4.31 km².

Conflict of Interest

The authors declare that there is no conflict of interest with any financial, personal, or other relationships with other people or organizations related to the material discussed in the article.

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