Land cover change modeling to identify critical land in the Ciletuh Geopark tourism area, Palabuhanratu, Sukabumi Regency.

R A Putri1, S Supriatna*
1 Departement of Geography, Faculty of Mathematics and Natural Sciences, Universitas Indonesia

rizky.amellia71@ui.ac.id

Abstract. Ciletuh Geopark is one of UNESCO's tourist attractions as one of the Global Geopark located in Sukabumi Regency, West Java, one of the most visited tourist destinations because of its beauty and role in knowledge development. It caused Geopark Ciletuh to have significant growth in facilities and accessibility, which generated land cover change that triggered the critical land. This study aims to analyze the land cover change in Ciletuh Geopark until 2030 to identify essential land. The method used in this study is Cellular Automata-Markov Chain to detect the land cover change and predict its transformation in the future with several driving factors built based on fuzzy logic. The variable contains proximity to the road, the settlement, the coastline, slope, and population density. Land cover map obtained processing Landsat 7 ETM+ and Landsat 8 OLI/TIRS 2010, 2015, and 2020. This study proves that land cover changes are mainly due to housing and facilities' need to support tourism activities. The conversion from the agricultural area that abandoned becomes shrubs. This research was expected to become a medium that will move the government and local people to make the land used well and still be the sustainable geopark.

1. Introduction
Sukabumi Regency is famous for its various beautiful natural tourist attractions. One of the most visited natural tourist destinations in Sukabumi is the Ciletuh Geopark, which UNESCO recognized as a Global Geopark. The Ciletuh Geopark reflects the geological diversity resulting from millions of years ago with volcanic landscapes and the south coast's beauty. Also, it has a role as a means of developing science [1]. It causes the surrounding area to create supporting infrastructure for tourist areas, consisting of road construction, lodging, mosques, restaurants, and settlements. Besides, the Ciletuh Geopark also attracts residents to live around tourist areas due to job opportunities in the tourism sector, which will help the population's economy.

Land degradation is a crucial ecological and environmental problem facing the world today, which causes the loss of available land resources and a decrease in soil quality, which ultimately leads to the occurrence of degraded lands [2]. Critical land causes environmental losses by decreasing land quality and productivity, impacting the surrounding population's socio-economic life. The need for land for infrastructure development that supports tourist areas and human settlements triggers land cover changes. If there is no control over these changes, the Ciletuh Geopark will lose its function as a tourist area that pays attention to environmental balance and will create critical land.
One approach to seeing the potential of degraded land is to assess changes in land cover. The difference in land cover related to degraded land has changed its surface, which was dense and then became barren. Examples are forest land turning into agricultural land, settlements, shrubs, and open fields [3]. The prediction of critical land in the future is crucial to prevent the future's actual land occurrence. Previous research on identifying critical land was carried out by Siti Hadjar Kubangun in 2016 using the Artificial Neural Network (ANN) method. The difference between previous studies lies in the technique, which this study uses, the Cellular Automata-Markov Chain (CA-MC) method, which is considered very good in identifying changes and predicting future changes. This study also uses more driving factors for land change from previous studies, namely the proximity from the river and the coastline's proximity. These two factors are deemed necessary to identify and predict land changes because infrastructure development will pay attention to these two factors under applicable laws.

The Ciletuh Geopark is located in Sukabumi Regency, West Java, which borders Ciletuh and Palabuhanratu Bay. Eight districts become the Ciletuh Geopark Tourist Area, namely Ciamis, Ciracap, Cisolok, Cikakak, Palabuhanratu, Simpenan, Waluran, and Surade. The area of the Ciletuh Geopark is 128,000 Ha. This study uses multi-temporal land cover data to process the Cellular Automata-Markov model using physical data and population data as driving factors. Land cover was obtained from the processing of Landsat 7 ETM + and Landsat 8 OLI / TIRS. Physical data consists of road networks, river networks, slopes, settlements, and coastlines. Population data includes population density. Physical data and demographic data are overlayed with fuzzy methods to create driving factors.

2. Methodology

Markov Chain and Cellular Automata are discrete dynamic models in time and state. This method consists of the Markov Chain and Cellular Automata methods, which complement each other. Markov is one of the most reliable, accurate, and useful land cover change approaches for predicting spatial and temporal variations of long-term land change in complex systems combined with geographic information systems.

CA is used to simulate and predict land changes spatially and temporally in the future with accuracy. In this system, the value of raster data can be defined as binary or discrete data, and its behavior is influenced by neighbors [4,5]. CA-Markov combines biophysical and socio-economic data to stimulate future land changes' accuracy and is used in management, planning, modeling, and spatial processes [6].

The CA-Markov model needs a driving factor, which in this study consists of physical and demographic characteristics. Physical factors include slope, proximity to the road, proximity to the coastline, proximity to the river, and proximity to the settlement. The population factor consists of population density. The process of creating the driving factor is to use fuzzy logic with fuzzy overlay techniques. Fuzzy logic is an excellent tool for interpreting continuous data effectively and efficiently. It is a perfect way to model CA-based modeling because fuzzy logic uses parallel computation, which contains interconnected units (cells) and has a continuous value [7]. The model is executed with Idrisi Selva software as a medium for simulating land cover in the Ciletuh Geopark because it can integrate Markov and CA very well [8].

3. Results and discussion

3.1. Land cover change analysis

3.1.1. The spatial pattern of land cover has changed. The land cover classification is divided into five (5) classes: built-up areas, agricultural areas, water bodies, non-agricultural areas, and open fields. Based on the data processing results that have been carried out, from 2010 to 2020, the non-agricultural area experienced the highest increase compared to other land uses, as seen in figure 1.
Conversion results from agricultural land dominated the increase in the non-agricultural area. The farm area in the study area decreases due to the land's neglect, which then becomes shrubs. In this study, the shrubs are included in the non-agricultural area. Then, the built-up area is the land cover with the second-highest increase, and the growth is dominated by the results of agricultural area conversion, as seen in table 1. Therefore, the agricultural area is the land cover with the highest decrease due to land conversion with the non-agricultural area's dominance and built-up area. The built-up area continues to experience growth in line with population growth and the tourism area's development. The non-agricultural area is the dominance in the study area.

![Figure 1. Graph of Increase and decrease in the land cover area (in hectares).](chart)

### Table 1. Land cover conversion (in hectares).

| The Land Change                  | Area (Hectare) |
|----------------------------------|----------------|
| Agricultural Area to Built-up Area | 2204.24        |
| Non-agricultural Area to Built-up Area | 581.82        |
| Open Field to Built-up Area     | 138.94         |
| Water Bodies to Agricultural Area | 177.83         |
| Non-agricultural Area to Agricultural Area | 216.62 |
| Open Field to Agricultural Area | 298.66         |
| Agricultural Area to Water Bodies | 1775.33        |
| Open Field to Agricultural Area | 389.06         |
| Agricultural Area to Non-agricultural Area | 10478.09 |
| Open Field to Non-agricultural Area | 624.01        |

3.1.2. Transitional probability matrix. Markov Chain works by analyzing land cover classes from different times, generating a transition probability matrix. The matrix shows the number of pixels that are likely to change from one land cover type to another within a specific period in the value range 0-1. Value 0 means it is possible to change, and value one means indeed happening [9]. The transitional probability matrix is presented in table 2.

### Table 2. Transitional probability matrix.

| Land cover          | Built-up Area | Agricultural Area | Water Bodies | Non-Agricultural Area | Open Field |
|---------------------|---------------|-------------------|--------------|-----------------------|------------|
| Built-up Area       | 0.74          | 0.23              | 0            | 0.01                  | 0          |
| Agricultural Area   | 0.04          | 0.73              | 0            | 0.21                  | 0          |
| Water Bodies        | 0.03          | 0.48              | 0.36         | 0.11                  | 0          |
| Non-Agricultural Area | 0.11        | 0.05              | 0            | 0.81                  | 0          |
| Open Field          | 0.05          | 0.65              | 0            | 0.22                  | 0.06       |
3.2. Landcover prediction

3.2.1. Driving factor. Driving factors are essential in modeling land cover change to understand the change process. In this case, it functions to determine the possibility of land change with pixel values. In this study, the driving factors consisted of 5 types; proximity to the road, proximity to the river, proximity to the settlement, proximity to the coastline, and population density. Then, each of the factors is classified to determine the level of suitability and then overlaid with fuzzy overlay.

3.2.2. Land cover change prediction. Prediction of landcover change in 2030 in the Ciletuh Geopark Tourism Area is shown in figure 2. The built-up area continues to develop from year to year. It proves that the growth of the built-up area in the study area is very significant. In general, the ease of accessibility determined the development of the built-up area, which means it is close to the road network. The flat slopes also affect the built-up area's growth and proximity to the previous building, namely settlement. As can be seen on the map, it is predicted that the built-up area will increase in 2030 in the north due to conversion from the non-agricultural area and agricultural area. From 2020 to 2030, the built-up area will increase by 6645.18 hectares or 152%. The non-agricultural area will continually grow until 2030, dominated by the non-agricultural area's conversion. Water bodies also From 2020 to 2030, the non-agricultural area has increased by 11839.19 hectares or 34%. Water bodies also experience a significant increase in each span of the year. Other land covers, agricultural areas, and open fields are predicted to decrease in 2030 due to the built-up area's growth and open field. A graph of land change from 2010 to 2030 is shown in figure 3.

![Figure 2. Landcover change prediction.](image1)

![Figure 3. Landcover change graph 2010-2030.](image2)

3.2.3. Accuracy test. The accuracy test using the validate GIS analysis tool in the Idrisi Selva software, the K-standard accuracy test results in this study were 0.8425 kappa index, which means that the modeling carried out is quite useful and accurate.

3.3. Identify critical land-based on land cover change

Critical land is one of the degraded lands which causes a temporary or permanent decrease in productivity and land capability. Necessary land is characterized by reducing soil properties
physically, chemically, and biologically [10]. This study's definition of critical land focuses on the land cover that has changed from previously dense and then switched to infrequent or changes in potentially critical lands. It causes necessary land because the changes that occur cause the mismatch of land use, causing the land's productivity to be not optimal.

In this study, the conversion of land cover from dense to infrequently consisted of six changes. The six land covers were changed. There are agricultural area to built-up area, non-agricultural area to built-up area, non-agricultural area to agricultural area, agricultural area to non-agricultural area, non-agricultural area to open field, and water bodies to the agricultural area. It is indicated that these land changes can cause critical land to occur. Changes predictions that occur between 2020-2030 trigger a wider essential area of land than changes in 2010-2020, as seen in table 3. In 2010-2020, a change in land cover triggered critical land scattered in almost all study areas, predominantly in the central and northern regions. Likewise, the change prediction results in 2020-2030 are concentrated in the study area's north and central parts, as shown in figure 4. From the effects of the accumulated changes in land cover, land changes have occurred, which triggered critical land from 2010-2030 in the central and northern areas. The total critical land area predicted in 2030 is 18% of the whole study area.

Table 3. The area of land cover change that triggers critical land (in Hectares).

| Landcover Change                        | 2010-2020 (Ha) | 2020-2030 (Ha) |
|----------------------------------------|----------------|----------------|
| Agricultural Area to Built-up Area     | 2204.24        | 2841.04        |
| Non-agricultural Area to Built-up Area | 581.82         | 3878.10        |
| Non-agricultural Area to Agricultural Area | 216.62        | 0              |
| Agricultural Area to Non-agricultural Area | 10478.09       | 15831.95       |
| Non-agricultural Area to Open Field   | 0              | 120.96         |
| Water Bodies to Agricultural Area     | 177.83         | 0              |
| Total                                  | 13658.6        | 22672.05       |

Figure 4. The map of landcover change that determines critical land.
4. Conclusion
Land cover change using the CA-Markov method was successfully carried out in this study. The results of the modeling that have been done show that the trend of each land cover is different. From 2020 to 2030, the built-up area and non-agricultural area experienced a significant increase due to the agricultural area's conversion. Therefore, the agricultural area has also decreased significantly in each period. Two other land covers, open land, and water bodies experienced changes but were not significant. Based on the analysis of changes that have been carried out, there are six types of changes that are considered to result in critical land. This study indicates that the prediction of crucial land in 2030 in the study area is 18% of the total study area.

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