Prediction of Land Change for Oil Palm Plantations in Penajam Subdistrict, Penajam Paser Utara Regency, East Kalimantan Province

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Abstract. Penajam Subdistrict is the center of government and economy of the North Penajam Paser Regency. It has an area of oil palm plantations that continues to grow every year. The massive growth of oil palm plantations has resulted in converting agricultural land to oil palm plantations. The transformation of land function occurs because oil palm plantations are considered more profitable than planting rice. This study aims to analyze and predict land-use changes for oil palm in Penajam Subdistrict in 2031. The method used in this study uses a Geographical Information System (GIS) approach with the CA-Markov prediction model. The drivers of land-use change as input to the CA-Markov model consist of distance from the road, distance from the river, distance from the forest, elevation, and slope. The results showed an increase in the area of oil palm plantations and a decrease in the forest area. The Kappa test results show a value of 88%, which means it has an adequate accuracy level. In 2031, the location of oil palm plantations in the Penajam Regency will reach 11,542.57 ha or 23.1%.

1. Introduction

Utilization of remote sensing data and spatial analysis can be carried out with a geographic information system (GIS), which is used to obtain factual and temporal land use information and its consequences by linking driving factors with changes that occur [1,2]. Land-use change modeling is one way to understand and explain land-use change dynamics and a tool to support the analysis of the causes and consequences of land-use dynamics [3,4]. The land-use change model can be an instrument to understand the dynamics of land change for oil palm and as an early warning system of future land-use change impacts.

Oil palm (Elaeis guineensis Jacq) is a leading plantation commodity in Indonesia because it is a significant source of state income and a provider of employment [5,6]. Oil palm (Elaeis guineensis Jacq.) is a vegetable oil producer needed for human consumption and can be fuel oil [7]. Based on Indonesian Plantation Statistics data, the Directorate General of Plantation in Penajam Paser Utara Regency has 17,131 hectares of oil palm, with production reaching 25,195 tons in 2016 [8]. The oil palm land is spread across four sub-districts in Penajam, Babulu, Waru, and Sepaku Subdistricts. The oil palm commodity is the main plantation crop in Penajam Paser Utara Regency, with extensive oil palm...
plantations concentrated in Penajam Subdistrict. Penajam Subdistrict was chosen as the research area because it has the largest oil palm plantation area and a high production level.

Based on the Central Bureau of Statistics (2019) Penajam Paser Utara Regency, oil palm production has increased [9]. The increase in land area and oil palm production is thought to be converting agricultural land and forest to oil palm land. The conversion of land functions significantly affects the area of land and yields of oil palm production. Land clearing for plantation areas is considered a contributing factor to natural forest loss (deforestation) [10]. Meanwhile, the conversion of paddy fields occurred due to the farmers' difficulty in getting water for irrigating their fields.

Various spatial approaches have been developed in the GIS environment to model land-use change. *Cellular Automata (CA) Markov* is a dynamic model used for spatial simulations with a predetermined time [11]. Land-use change modeling with the CA-Markov model's application is one way of predicting land-use change [12], which has been widely applied by many researchers. Research conducted in Kuala Langat District to develop land-use models for oil palm in Malaysia [13]. And predictions of land-use change were carried out in Rokan Hulu Regency, Riau Province, which is experiencing deforestation, using physical factors as input from the CA-Markov model [14].

Unlike the previous research, this research is based on oil palm plantations in the Penajam Subdistrict, which has increased in the area every year. Using a driving factor that consists of distance from the road, distance from the river, forest, height, and slope. These driving factors are assumed to influence the spatial change model of oil palm plantations in 2031. Based on this background, this study aims to analyze land-use changes in 2009–2019 and predict land-use changes for oil palm in Penajam Subdistrict, Penajam Paser Utara Regency, in 2031. This research is expected to provide technical recommendations to prepare regional planning according to trends in land-use change.

2. Study Area and Data

2.1. Study Area

This research was conducted in Penajam Subdistrict, North Penajam Paser Regency, East Kalimantan Province, with 1,207.37 km² and an altitude of more than 500 meters above sea level. Penajam Subdistrict is the center of government as well as the capital of the North Penajam Paser Regency. Penajam Subdistrict has 19 urban villages and four villages. Geographically, Penajam District is located between 116°44' and 09°85' East Longitude and 01°18' North Latitude and 9°63' South Latitude (Figure 1).

![Figure 1. Research Area](image-url)
Penajam District in the north is bordered by Kembang Janggut Subdistrict, to the south with Muara Kaman Subdistrict. In contrast, the east and west are bordered by Kota Bangun Subdistrict and West Kutai Regency.

2.2. Data
This research requires some data that must be collected. The data used in this study are secondary, in the form of Image Landsat/Copernicus images in 2009, 2014, and 2019. Also, the driving factors for land-use change are input from the CA-Markov model, which consists of distance from the road, distance from the river, distance from the forest, elevation, and slope. The following data can be seen in Table 1.

| No. | Dataset                             | Year | Source |
|-----|-------------------------------------|------|--------|
| 1   | Image Landsat/Copernicus            | 2009 | Google Earth |
| 2   | Image Landsat/Copernicus            | 2014 | Google Earth |
| 3   | Image Landsat/Copernicus            | 2019 | Google Earth |
| 4   | Administration of Penajam Subdistrict | 2013 | BIG |
| 5   | Road                                 | 2013 | BIG |
| 6   | River                                | 2013 | BIG |
| 7   | Forest                               | 2013 | BIG |
| 8   | DEMNAS                               | 2019 | BIG |

3. Methodology
The leading software used in this study is ArcGIS 10.1, Google Earth Pro, and IDRISI Selva. The prediction model for land-use change in this study uses the Cellular Automata model. The data used in this study are presented in Table 1.

In this study, an analysis of land-use changes for oil palm in Penajam Subdistrict, Penajam Paser Utara Regency from 2009 to 2019, was conducted. To predict future land use of the study area, the method used in this study used a Geographical Information System (GIS) approach. With the Cellular Automata (CA) Markov Chain prediction model. The drivers of land-use change as input to the CA-Markov model consist of distance from roads, distance from rivers, distance from forest, elevation, and slope. This study's land use was classified into six classes: forest, oil palm plantations, non-oil palm plantations, developed land, lakes, and grass / bare land based on SNI 6502.2: 2010 with modifications [15]. These driving factors also need to be carried out by Cramer's v Test to know the weight of the influence of the driving factors on land-use change with the help of IDRISI Selva software [14].

Furthermore, the application of the CA-Markov model is used as a way to predict land-use change. The CA-Markov model is one commonly used model among many land-use modeling tools and techniques, which model spatial and temporal changes [16]. The CA-Markov model combines cellular automata and Markov chains to predict trends and characteristics of land-use change over time [17]. Before the CA-Markov model was used, land-use changes in 2009 and 2014 were projected for the 2019 land use prediction. The projection results were used to validate the projection map for modeling. Good analysis and predicting outcomes, an accuracy test is required. The validation test is measured by the Kappa Index of Agreement (KIA). Kappa value ≥ 75% indicates an excellent agreement [2]. Then it can be continued with the CA-Markov process to get predictions of land use in 2031.
4. Results and Discussion

4.1. Analysis of Land Use Change

The image data processing results show changes in land use in 2009, 2014, and 2019. This land use is used as a basis for analyzing changes in land use in Penajam Subdistrict over the last ten years. From the image interpretation results, land use is classified into six classes: forests, oil palm plantations, non-oil palm plantations, developed land, lakes, and grass/bare land (Figure 2). A descriptive spatial and temporal analysis was carried out related to changes in oil palm land use in Penajam Subdistrict 2009-2019, as shown in Table 2. The results of the research in 2009 were dominated by forest land and oil palm plantations. However, in 2014 the forest area had decreased in space until 2019.

Meanwhile, oil palm plantation land has always increased in the location from 2009 to 2019. An increase has always followed a decrease in the forest area in the area of oil palm plantations. From this land use pattern, it can be seen that humans tend to use forest land as land for oil palm plantations.

| Land Use                  | Year         |
|---------------------------|--------------|
|                           | 2009         | 2014         | 2019         | LULC 2009-2019 |
|                           | Area (Ha)    | Percent (%)  | Area (Ha)    | Percent (%)  | Area (Ha)    | Percent (%)  |
| Lake                      | 15,99944     | 0,03         | 40,78301     | 0,08         | 51,75428     | 0,10         | 35,7548 | 0,07         |
| Forest                    | 42,348,02    | 84,6         | 41,420,67    | 82,8         | 38,586,79    | 77,1         | 3,761,23 | -7,5         |
| Grass/Bare Land           | 871,6843     | 1,74         | 1,092,175    | 2,18         | 820,5035     | 1,64         | 51,1808 | -0,10        |
| Oil Palm Plantations      | 5,344,949    | 10,7         | 5,981,512    | 12,0         | 7,804,364    | 15,6         | 2,459,41 | 4,9          |
| Non-Oil Palm Plantations  | 1,249,454    | 2,50         | 1,271,602    | 2,54         | 2,413,874    | 4,82         | 1,164,42 | 2,3          |

Figure 2. Penajam Subdistrict Land Use in 2009, 2014, and 2019
The Markov chain process generates a transition probability matrix to analyze the likelihood of a change in land use. The probability value of land-use change in Table 3 is based on changes in land use in 2009-2019. The probability value ranges from 0-1, where 0 indicates no chance of land-use change, while 1 indicates land-use change [2]. In the transition probability matrix, forest land shows a high probability value for each land use.

### Table 3. The Probability Matrix of Land Use Change in Penajam Subdistrict in 2009, 2014, and 2019

| Land Use             | Lake          | Forest        | Grass/Bare Land | Oil Palm Plantations | Non-Oil Palm Plantations | Built Up Area |
|----------------------|---------------|---------------|-----------------|----------------------|--------------------------|---------------|
| Lake                 | 0.0001        | 0.0004        | 0.0000          | 0.0000               | 0.0000                   | 0.0000        |
| Forest               | 0.0001        | 0.3454        | 0.0047          | 0.0038               | 0.0056                   | 0.0005        |
| Grass/Bare Land      | 0.0000        | 0.0051        | 0.0024          | 0.0001               | 0.0001                   | 0.0000        |
| Oil Palm Plantations | 0.0000        | 0.025         | 0.0010          | 0.0429               | 0.0038                   | 0.0000        |
| Non-Oil Palm Plantations | 0.0000   | 0.0173        | 0.0000          | 0.0030               | 0.0021                   | 0.0000        |
| Built Up Area        | 0.0000        | 0.0019        | 0.0000          | 0.0000               | 0.0000                   | 0.0015        |

4.2. Analysis of The Drivers of Land Use Change

The driving factors around it influence changes in oil palm land. These driving factors consist of distance from roads, distance from rivers, distance from forests, elevations, and slopes (Figure 3). Push factors are added to the model where each aspect is tested with Cramer's V value to see the driving factors' association. The range of Cramer's V values ranges from 0-1, where 0 indicates a disconnect, and a value of 1 indicates a relationship to the model [2, 14].

### Table 4. The Weight of Cramer's V Test Results Driving Factors of Land Use in Penajam Subdistrict

| No. | Driving Factors          | Test Cramer's V |
|-----|--------------------------|-----------------|
| 1   | Distance From The Forest | 0.0986          |
| 2   | Distance From The Road   | 0.1173          |
| 3   | Distance From The River  | 0.1754          |
| 4   | Elevation                | 0.1386          |
| 5   | Slope                    | 0.0085          |

Table 4 shows Cramer's V test results, where the five driving factors can be used in predictive models of land-use change. Distance from the road, distance from the river, and height have the most significant weight, which means that the three driving factors influence land-use changes in Penajam Subdistrict. Oil palm land changes occur in areas with good elevation, accessibility, and irrigation.
4.3. Prediction of Land Use Change in Penajam District in 2031

The modeling results produced a land-use projection map in 2031, which can be seen in Figure 4. In determining the land use projection map for 2019, this study used an accuracy test with actual land use in 2019 using a validation test with the Kappa Index of Agreement (KIA). The Kappa test results show
a Kstandart value of 0.88 or 88%, which indicates that the projected land use in 2019 has a perfect level of accuracy. So, it can be continued to launch land use in 2031.

In Table 5, we can see the results of the prediction of land use in 2031. Forecasts of land use that have decreased significantly in the area are forest and grass / bare land, while land uses that have increased in the area are oil palm plantations and developed land. The results of the prediction of land use in 2031 indicate a decrease in forest land area, which has been converted into land for oil palm plantations and developed land. These changes can be seen in Figure 4. Based on these predictions, it is necessary to have government policies governing land use, so that forest land does not always experience a decrease in the area every year.

| Land Use            | Year          | LULC 2019-2031 |
|---------------------|---------------|----------------|
|                     | Area (Ha)     | Percent (%)    | Area (Ha)     | Percent (%)  | Area (Ha)     | Percent (%)  |
| Lake                | 51,75428      | 0,10           | 50,31427      | 0,10          | -1,44001      | -0,0029      |
| Forest              | 38.586.79     | 77,1           | 34.860,92     | 69,7          | -3.725,87     | -7,44        |
| Grass/Bare Land     | 820,5035      | 1,64           | 649,3077      | 1,30          | -171,1958     | -0,34        |
| Oil Palm Plantations| 7.804.364     | 15,6           | 11.542,57     | 23,1          | 3.738,210     | 7,47         |
| Non-Oil Palm Plantations | 2.413,874 | 4,82           | 2.371,228     | 4,74          | -42,6462      | -0,09        |
| Built Up Area       | 378,9271      | 0,76           | 565,8295      | 1,13          | 186,9024      | 0,37         |

5. Conclusion
Changes in oil palm land use in 2009-2019 in Penajam Subdistrict showed a significant increase in the area of 2,459.41 ha, an increase in oil palm plantations followed by a decrease in forest land area of 3,761.23 ha. The driving factors for land-use change in Penajam Subdistrict are the distance from the road, distance from the river, and altitude. Oil palm land changes occur in areas with good elevation, accessibility, and irrigation. Prediction of land-use change in 2031 is carried out using the Cellular Automata (CA) Markov Chain prediction model, with a Kappa value of 0.88 or 88%, which means it has a perfect level of accuracy. The prediction result of oil palm plantation land in 2031 is estimated to reach 11,542.57 ha or 23.1% of the total area of Penajam Subdistrict, Penajam Paser Utara Regency. Based on these predictions, it is necessary to have government policies regulating land use, so that forest land does not always experience a decrease in the area every year.

6. References
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