Remote Sensing Based Modeling of Land Use Change on Ulayat Customary Land in Tilatang Kamang Sumatera Barat

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Abstract **– Ulayat land is traditional West Sumatra land frequently subject to competing demands from various stakeholders, including government agencies, private companies, and local communities. Those demands lead to the need to update geospatial data in the form of land use modeling for further land management purposes. This research used remote sensing technology to develop land use and land cover models based on cellular automata and socio-economic data. This research shows that there will be a significant increase in population in 2030, followed by changes in residential land use. The land use model shows that the use of customary land in most areas is not followed by a change in ownership which shows that tribe rules are still being followed and maintained correctly.**

Keywords **– Geographic information systems, land use change, remote sensing, Ulayat land.**

1. Introduction

Land use and land cover changes are phenomena heavily influenced by human activities that cause serious problems that impact the environment, society, and economy [1], [4], [12].

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Various factors frequently influence land use changes, including population growth, urbanization, deforestation, and agricultural expansion which caused the need for land to increase, especially for the fulfillment of human life needs and other activities [2], [17], [19]. Human needs were exponentially increased while the amount of land was still limited, causing the need for land to increase [20], [22]. Therefore, understanding the patterns and drivers of land use change is critical for long-term land use planning and management [3]. Remote sensing technology, particularly in large and complex areas, has been widely used to monitor land use change [8], [13]. There is, however, a research gap in the use of remote sensing for the phenomenon of land use change, particularly in customary land.

Land owned and managed according to traditional practices and customs is customary land [7], [18]. Customary land accounts for a significant proportion of land area in many developing countries and supports rural livelihoods and cultural practices [11]. Ulayat land is a customary land in Sumatera Barat that is a piece of land owned by a tribe that the tribe itself can only use, cannot be traded, and is also governed by the tribe itself. The existence of Ulayat land can provide an overview of a tribe that occupies an area. In contrast, Ulayat land that has changed ownership indicates that a tribe in that area no longer exists. Those became changing for local goverment where on the one side, there was a need for preserving the Ulayat land. On the other hand, the Ulayat land is frequently subject to competing demands from various stakeholders, including government agencies, private companies, and local communities [24].

The use of remote sensing technology for land use change analysis in Ulayat land is still limited. Those limitations were partly due to the challenges of working with Ulayat land, which often lacks formal land tenure and management systems, making it difficult to access and collect reliable data [21].

Additionally, the application of remote sensing technology requires technical expertise and resources [9] that may not be available in many customary land geospatial databases. Remote sensing technology has several advantages over traditional methods for analyzing land use change, especially in Customary land. Remote sensing enables collecting land use and land cover data over large areas at regular intervals [14]. This information can then be used to identify and track changes in land use and a model and predict future changes [9]. Remote sensing also integrates biophysical and socio-economic data, resulting in a complete understanding of the drivers and consequences of land use change [5].

Cellular automata (CA) have gained popularity recently as a tool for modelling land use change due to their ability to represent complex systems with simple rules [6]. The application of CA in land use modelling involves dividing the study area into cells or pixels and assigning land use categories to each cell. The cells then evolve based on transition rules determined by proximity to other land use types, accessibility, and socio-economic variables. Several studies have used CA to model land use change at different spatial and temporal scales, ranging from urban growth prediction to landscape pattern analysis [25]. Some studies have also incorporated machine learning techniques to improve the accuracy of CA-based models [23]. However, the use of CA-based models for mapping Ulayat land is still limited. It can be developed to solve stakeholder and government problems in managing Ulayat land. Therefore, further research is needed to address the critical importance of customary land in supporting rural livelihoods and cultural practices, and methods for monitoring and managing land use change in these areas are critical. By providing a systematic and objective approach to land use change analysis, remote sensing technology provides a powerful tool for achieving this goal. We can develop more effective land management policies that promote sustainable development and equitable outcomes for all stakeholders if we improve our understanding of the patterns and drivers of land use change in customary land.

2. Methodology

Land use change modeling on Ulayat land is carried out with remote sensing technology using the cellular automata method and analysis of population projections.

a. Materials

This study uses remote sensing data, specifically medium-resolution imagery obtained from the Landsat satellite, to help determine future models of land use change and cover. The Landsat image's coverage area includes the Tilatang Kamang sub-district, part of the Agam Regency Region. Landsat imagery is obtained temporally, namely in 2010, 2015, and 2020, as a modeling database because the development of land use and land cover models requires existing data on changes that have occurred. Furthermore, population data is required for future population projections. Table 1 contains the detailed data information that is required.

Table 1. Required Data

No	Data	Data source
1	landsat 7 imagery in 2010	USGS of 2010
2	landsat 7 imagery of 2015	USGS of 2015
3	landsat 8 OLI imagery in 2020	USGS of 2020
4	Population data for 2015 and 2021	Central Statistics Agency of Tilatang Kamang District in 2016 and 2021

b. Data Preparation and Analysis

1) Satellite image processing

Remote sensing data processing is essential in extracting useful information from satellite imagery. Landsat imagery used in this research was processed to correct geometric and atmospheric distortions. The image processing was done using ENVI Software. First, the image was corrected using Geometric correction to ensure that the data is accurately spatially aligned [10]. The process entails detecting and correcting distortions caused by changes in the position and orientation of the sensor platform, as well as terrain and atmospheric effects.

Geometric correction entails selecting a set of known geographic coordinates reference points known as ground control points (GCPs). The GCPs calculate the transformation that will align the image data with the desired coordinate system. This process was then followed by an atmospheric correction necessary to remove the effects of atmospheric scattering and absorption on the image data [16]. Atmospheric correction is essential for accurately interpreting the spectral information in the Landsat imagery, particularly for applications such as land cover classification and vegetation analysis.

Atmospheric correction was done using Fast Line-of-sight Atmospheric Analysis of Hypercubes (FLAASH) methods in ENVI. The corrected image can now be used for further analysis, specifically the land use and cover classification. This process begins with the selection of a set of training samples that represent the land use classes of interest, which include forests, dry land agriculture, mixed plantations, paddy fields, built up area, shrubs, open land, and bodies of water. These training samples are chosen based on field data or existing maps, and they should reflect the variability within each class. After collecting training samples, the next step is to train a classification algorithm. Maximum Likelihood was the algorithm used. These algorithms use the training samples to create statistical models that describe the spectral characteristics of each land use class. The algorithm then applies these models to the entire image to assign a land use class to each pixel.

2) Population projection

Population projections are needed in the analysis to produce information about the variables that determine the land use of space. Population projections are carried out by temporarily processing population data for 2016 and 2021 sourced from the central statistics agency. Data is processed using the following formula:

$$Pt = P_0(1+r)^t \tag{1}$$

$$r = \left(\frac{Pt}{P0}\right)^{\frac{1}{i}} \tag{2}$$

where in:
Pt = number of inhabitants year t
P0 = number of inhabitants of the base year
r = population growth rate
t = time period of the base year of the year t (in years)

3) Cellular automata land use modelling

Data analysis techniques to determine future land use and land cover changes are the Markov Chain Cellular Automata method.

The Markov Chain Cellular Automata method uses a transition matrix to determine the magnitude of future change based on spatial relationships and the probability of change [15]. The transition probabilities are derived from historical land use and land cover over observed time. The assumption built into this formulation is a future change in land use and land cover of Xt + 1 at that time (t + 1) depending on current conditions expressed by Xt. To determine the matrix of the probability of land use change and land cover used, the equation as follows;

$$X_t + 1 = X_t \text{ x } P \tag{3}$$

Where P is a matrix containing m x m pixels, e.g., the number of land use change classes and land cover P between a pair of land use change classes and land cover i and j, which can be formulated as follows;

$$\|Pij\| = \begin{bmatrix} p1,1 & p1,2 & p1,n \\ p2,1 & p2,2 & p2,n \\ p3,1 & p3,2 & p3,n \end{bmatrix} \tag{4}$$

where: $0 \leq P_{ij} \leq 1$

3. Result and Discussion

The results showed that Tilatang Kamang Subdistrict consists of three villages: Gadut, Koto Tangah and Kapau. The total population in 2015 in Gadut was 16.131 people; in Kapau, it was 3.072 people, and in Koto Tangah, it was 16.854 people. In 2020 the number of inhabitants in this area has increased, especially in Koto Tangah village, with a population of 18.531 people, followed by Gadut village, with a population of 16.718, and Kapau village, with a population of 3.394 people. This population is projected to increase significantly by 2030. The total population in Koto Tangah by 2030 is projected to be 27.055, Gadut village is projected to have a population of 24.408, and Kapau village is projected to have a population of 4.955. This increase in population will have an impact on changes in land use and land cover. More details can be seen in Table 2 show a change in population from 2015, 2020, 2025, and 2030. The increase in population in this area can be seen in Figure 1 below.

Table 2. Number and Population Projection of Tilatang Kamang District

No	Village	Year			
		2015	2020	2025	2030
1	Gadut	16.131	16.718	19.856	24.408
2	Kapau	3.072	3.394	4.031	4.955
3	Koto Tangah	16.854	18.531	22.009	27.055
	Total	36.057	38.644	47.921	58.448

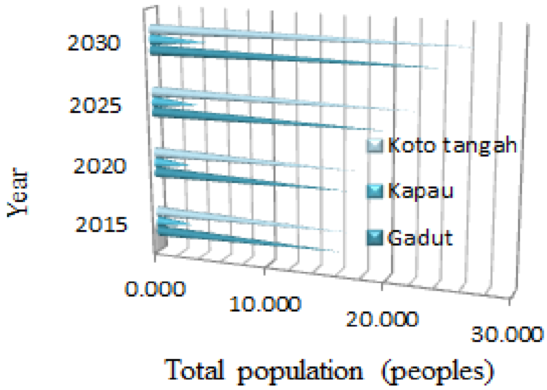

Figure 1. Population in 2015 and 2020 and the projected population in 2025 and 2030

Figure 2 above shows an increase in population in the study area. The total population in 2015 in the research area amounted to 36.057 people, in 2020, the number of residents in this area increased with a population of 38.643 people, while in 2025, the number of residents in this area is projected to be 42.665 people, and in 2030 the number of residents in the research area will continue to increase, amounting to 47.106 people. The increase in the number of people in this area is primarily due to migration and a high birth rate.

Koto Tangah village and Kapau village own Ulayat land that is regulated based on the tribes that occupy this area. Land use is regulated based on customary law, especially for children and nieces. Gadut village has ulayat land that is not so strict in land use that Gadut village has more migrants buying land in this area, while in Koto Tangah village and Kapau village, there is no change in land ownership. More details can be seen in Figure 2 and Figure 3 below;

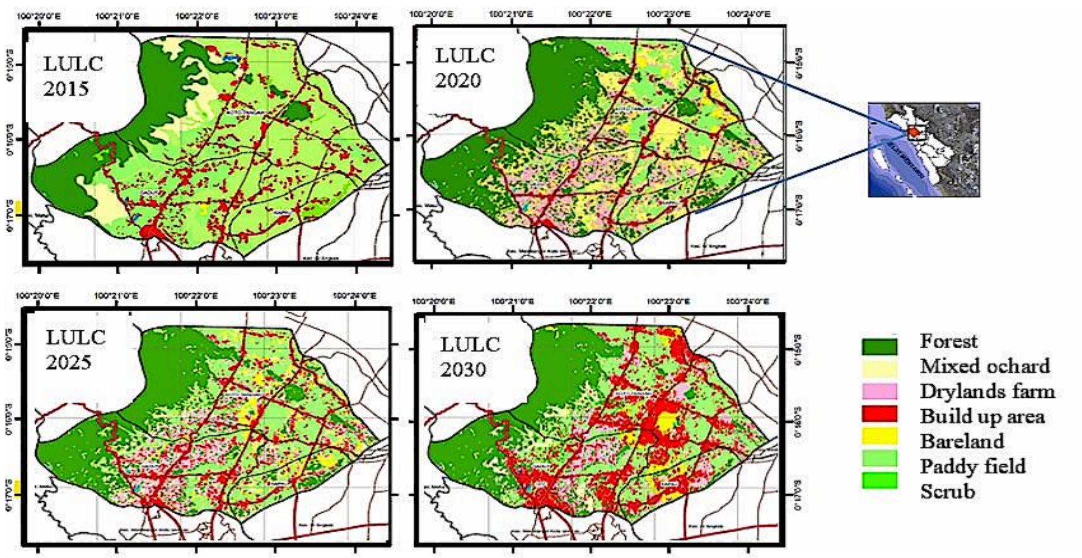

Figure 2. Land use and land cover change model from 2015 to 2030

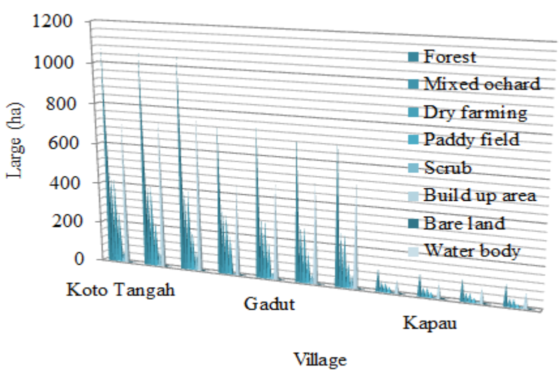

Figure 3. Graph of land use change and land cover from 2015 to 2030

Figure 3 depicts how the built-up area has increased significantly, from 1,193 ha in 2015 to 1,289.59 ha and 1,399.46 ha in 2030. The area of residential areas is predicted to increase in 2030 due to an increase in population which directly impacts the increasing demand for land for housing. This condition is linked to a decrease in forest land use of 20.32 ha from 2015-2020 and an expected decrease of 30 ha by 2030. Additionally, mixed orchards are projected to decrease by 100 ha in 2030, followed by a decrease of 131 ha in paddy fields. The trend of changes in customary land use is influenced by internal land use by local tribes, especially in Kapau and Koto Tangah villages. Changes in land ownership did not occur in this area, so land use changes were still entirely under control. However, this did not happen in Gadut Village, where land-use changes occurred out of control and was followed by land ownership changes. This condition is caused by the geographical position of Gadut Village, which borders the city of Bukittinggi, as an urban area with a very high need for residential land due to an increase in population, even though space availability is minimal. The ratio between land use and the predicted population from 2020 to 2030 can be seen in Figure 4 below;

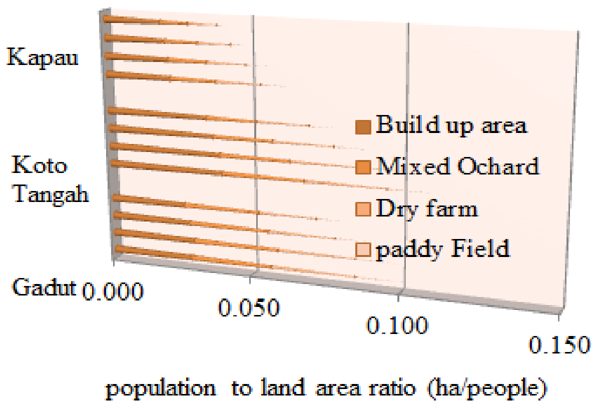

Figure 4. Comparison of land use area and population prediction

Figure 4 above shows that in Gadut village in 2020, the comparison of land use area for built up area with a population of 0.029 ha, in 2025, will decrease by 0,028ha, and in 2030 it will decrease to 0,026 ha. The use of paddy fields has a comparison between land area and the prediction of population. The paddy field and population ratio was 0,029ha in 2020, then predicted to decrease to 0,028 ha in 2025 and 0,026 in 2030. The ratio data shows that in Gadut village, from 2025 to 2030, residential or built-up land use has increased while paddy rice farmland has decreased. A change follows the land use development in Gadut village in ownership, where the Ulayat land rules that are not so strict in the village caused the land to be still traded to the village community.

In contrast, Koto Tangah village and Kapau have strict rules for the use of Ulayat land so that is not sold to migrant communities to people who are in the village who have tribal differences. In Koto Tangah, the ratio of built-up land to population was 0.039ha/people in 2020, 0.037ha/people in 2025, and 0.035 ha/people in 2030. The ratio of paddy fields with a projected population in 2020 was 0.014 ha/people, which is predicted to decrease to 0.011ha/people by 2025 and further to 0.009 ha/people by 2030.

This shows that the increasing population in this area has led to a reduction in paddy fields. Land conversion in the village generally occurs a lot of conversion of paddy fields into built up area. Kapau village has a comparison between the land use area and the predicted population for built-up land in 2020 of 0.022 ha. In 2025, it is predicted to be 0,021ha, and in 2030 it is predicted to be 0,020ha. Paddy fields have the smallest comparison, where in 2020 it will be 0,008 ha, in 2025 it is predicted to be 0,006ha, and in 2030 it is predicted to be 0,005ha. The increasing population in Kapau from 2025 to 2030 has led to a reduction in paddy fields. If not quickly anticipated, this can reduce rice yields in Kapau village, where rice that has been processed into rice is a staple food in this area. There need to be regulations governing the use of Ulayat land in the village, especially for built-up land. If left unchecked, it will cause a lack of rice yield in this area which, in the end, this area must bring rice from other regions to meet the basic needs of the people of this village Kapau.

4. Conclusion

An area's population increase can cause land use and land cover changes. Uncontrolled land use change can cause environmental damage.

The study examined land use changes and projected population growth in Kapau village from 2025 to 2030. The ratio of land use changes and the projected population in 2025 to 2030 shows that the most significant ratio was found in built-up land in 2020, which is 0,039ha, and the smallest in paddy fields, 0,005 ha in Kapau village in 2030. It is noted that the Ulayat land owned by a tribe or tribe does not limit land use development. However, it regulates land use, especially by children and nieces and nephews, for the sustainability of the tribe so that members of the tribe can only use Ulayat land without any change in land ownership. The change of ownership only occurs in Gadut village, which is land owned by individuals and not ulayat land. These findings highlight the need to consider different land ownership dynamics and regulations for effective land management. By understanding these dynamics, Kapau village can balance population growth, land use, and environmental conservation for the well-being of the tribe and its surroundings.

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