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RESEARCH ARTICLE

CA-Markov Chain Model-based Predictions of Land Cover: A Case Study of Banjarmasin City

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Abstract. Changes in land cover are widespread in Indonesia. This tendency frequently causes annual deforestation rates to increase, which might lead to numerous natural calamities. This study will examine land cover changes, develop land cover prediction models, and examine the link between land cover changes and the Banjarmasin City and surrounding area flood disaster. Annual variations in land cover are determined using images from the GlobeLand30 satellite and a remote sensing method. Using the Cellular Automata – Markov Chain approach, satellite imagery is analyzed to estimate land cover. The results indicate that built-up land and forests will have the most remarkable change in land cover from 2000 to 2020, whereas forests are expected to face deforestation of 356 km2 from 2020 to 2030. In 2021, deforestation produced catastrophic floods, with 111 flood locations in the plantation zone. The water has reached areas with low predicted flood risk.

1. Introduction

Indonesia is one of the countries with the largest forest area in the world. Indonesia's forest monitoring results in 2019 were 94.1 million hectares, which is 50.1% of Indonesia's total land area (KLHK 2020). However, forests in Indonesia have undergone deforestation since 1990, as FAO research shows that the forest cover has decreased from 74% to 56% in 30-40 years (FAO 1990). Deforestation occurs due to changes in the forest to non-forest, such as agriculture and road construction (Chiteculo et al. 2018). South Kalimantan is one of the Indonesian provinces experiencing severe deforestation and the increased number of mining locations and oil palm plantations.

Land cover change is a significant contributor to global climate change and environmental issues for global consideration (Guan et al. 2011; Li et al. 2020; McCarl et al. 2014; Sterling, Ducharne, and Polcher 2013; Zhang et al. 2016). Vegetation cover and its spatial distribution significantly affect the framework and function of the ecosystem (Hao, Zhu, and Cui 2021). South Kalimantan has approximately 3.7 million hectares, of which 1.8 million hectares are forest, and 0.1 million hectares are peatlands (INCAS 2015). The forest area in South Kalimantan is almost half of the total area, so South Kalimantan has a severe problem in deforestation. Deforestation can cause soil erosion and flooding (de la Paix et al. 2011). In January 2021, there was a flood in South Kalimantan, which caused 11 sub-districts to flood. Banjar Regency is the most affected district by this disaster. Around 120,226 people became flood victims (Syaarawie 2021). According to President Joko Widodo, this flood is the biggest in South Kalimantan in the last 50 years (Widadio 2021).

Land changes that occur continuously will lead to other disasters. Regular monitoring of land-use change is critical in observing coastal changes (Kaliraj et al. 2017; Misra and Balaji 2015), city expansion (Zanganeh Shahraki et al. 2011), mine land change (Erthalia, Supriatna, and Damayanti 2018), change of planting area (Abd EL-kawy et al. 2019; Pramudya et al. 2016), deforestation (Brovelli, Sun, and Yordanov 2020; Negassa, Mallie, and Gemeda 2020; Ramdhoni, Fitriani, and Afif 2019), and any other. To better understand the patterns and impacts of ever-changing landscapes, one must obtain information that captures anthropogenic changes to the Earth's surface systematically and measurably (Wulder et al. 2019). Recent advances in remote sensing tools and techniques allow researchers to detect and synthesize these changes (Hemati, Hasanlou, and Mahdianpari 2021). The use of remote sensing technology is an efficient way to see changes in land use in the desired period because it has a continuous data record (Andualem, Belay, and Guadie 2018).

By knowing land changes in a place, we can predict how the land cover will be in the future. Predictive models are the right tools for analyzing dynamic land cover changes and evaluating land-use policies (Khawaldah, Farhan, and Alzboun 2020). Cellular Automata, coupled with Markov Chain, is a viable technique for producing land cover prediction models (Akbar & Supriatna, 2019; S. Supriatna et al., 2020; Khawaldah et al., 2020; Kusratmoko et al., 2017,). Cellular Automata and Markov Chain (CA-MC) analysis is the most universal and effective model for predicting short and long-term Land Use – Land Cover (LULC) dynamics in various scenarios. It produced better spatial patterns in each category than other models (e.g., Clue- S, GeoMoD, and Markov Chain) (Gidey et al. 2017). The CA-MC approach is utilized in forestry to forecast forest cover change and forest degradation (Hasan et al. 2020), detect and project forest change (Malhi et al. 2020; Sun and Li 2010; Vázquez-Quintero et al. 2016; Vick and Bacani 2019), and project deforestation (Fuller, Hardiono, and Meijaard 2011), among other applications. This study will look at changes in land cover, make land cover prediction models, and see the relationship between land cover changes and the flood disaster that occurred in Banjarmasin City and its surroundings.

2. Methods

The study location is in Banjarmasin City and its surroundings. The surroundings include the Banjarbaru City and Banjar Regency, South Kalimantan Province, Indonesia (Figure 1). Lowland areas in South Kalimantan are mostly peatlands to swamps, and in the highlands, some are still natural tropical forests protected by the government (Sosilawati et al. 2020). In addition, there are state plantations and various mining potentials (Sosilawati et al. 2020).

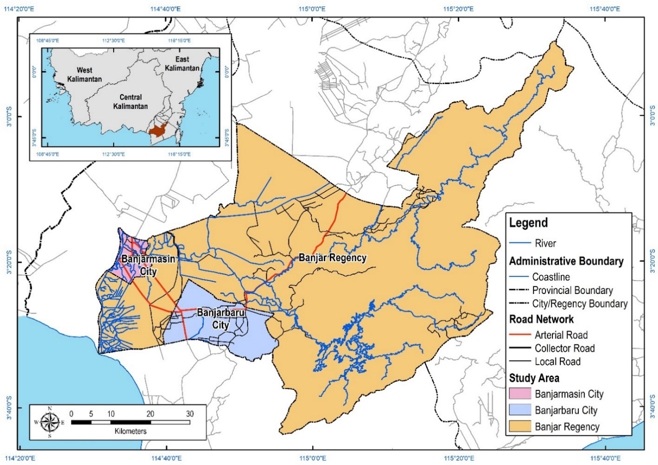

Figure 1. Research sites.

The use of remote sensing for mapping is beneficial in mapping large areas. This study used The Global Land Cover (GlobeLand30) satellite imagery. It is a product issued by the Ministry of Science and Technology of China that combines multispectral satellite imagery from LANDSAT and the Chinese Environmental Disaster Alleviation Satellite (HJ-1) to produce a land cover map with a spatial resolution of 30 meters (NGCC 2014). GlobeLand30 adopt "Pixel-Object-Knowledge" (POK) method. This method includes three steps, namely pixel classification which uses several methods such as Maximum Likelihood Classifier (MLC), Support Vector Machine (SVM), threshold value, etc.; object filter which operates the threshold value method and counts the pixel number ratio of the segmented object; and human-computer interactive check and verification to check the classification result of object filter, eliminating error mapping units and supplementing neglected mapping units. Over 150,000 test samples are assessed for GlobeLand30's accuracy; the overall accuracy of GlobeLand30 2010 is 83.51 percent, and the Kappa indicator is 0.78. This satellite imagery data is beneficial in detecting land cover in Indonesia, but not many studies have used this data in Indonesia. Therefore, this study uses land cover data for the Banjarmasin City and its surroundings in 2000, 2010, and 2020 based on GlobeLand30.

The land-cover data were processed using the Cellular Automata-Markov Chain (CA-MC) method in IDRISI software to obtain land cover in Banjarmasin City and its surroundings in 2030. The separate Markov model has no spatial knowledge and does not consider the spatial distribution of geographic factors and land use types. In contrast, the CA-Markov model adds spatial features to the Markov model, uses Cellular Automata filters to create weight factors with spatial characters, and changes the state of cells according to the state of adjacent cells and transition rules (Halmy et al. 2015). The CA-MC model is integrated with spatial-temporal analysis to analyze dynamic land-use events in space-time patterns and simulate future scenarios (Vázquez-Quintero et al. 2016). The modelling can provide accurate and reliable results in a study with spatial and geographic domains (Ghosh et al. 2017).

IDRISI runs CA-MC processing that uses a Markov chain matrix to determine the amount of change and generates suitability maps from two different land cover data, and the Cellular Automata allocates these changes spatially (Gallardo and Martínez-Vega 2016; Mas et al. 2014). Cellular Automata works with the concept of proximity analysis, which checks or assesses the value of the nearest pixel to determine the possibility of a pixel being changed to another (Malhi et al. 2020).

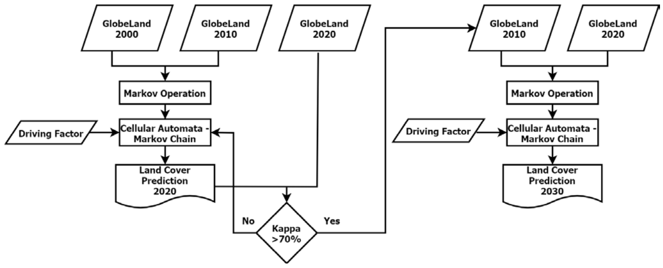

Figure 2. Flow works of land cover prediction.

The prediction process begins with the Markov operation, which will obtain a transition probability matrix using land cover data in 2000 and 2010 for 2020 predictions and 2010 and 2020 land cover data used for 2030 predictions (Figure 2). To assess the likelihood of a pixel's change, driving factor factors such as distance from rivers, distance from the road, distance from the settlement, and slope were utilized. All those driving factors variables data are collected from Peta Rupa Bumi Indonesia issued by Geospatial Information Agency of Indonesia. The classification of each driving factor variable is determined by weighting each variable (Table 1), then fuzzy membership is performed on each variable and combines all variables with a fuzzy overlay.

The results of the fuzzy overlay with a range of 0-1 will be utilized to estimate land cover using CA-MC (Figure 3). The

Table 1. Driving factors score.

Variable	Range	Score	Reference
Distance from road (m)	0-100	5	(Akbar and Supriatna 2019)
	100-200	4	
	200-500	3	
	500-1000	2	
	>1000	1	
Distance from river (m)	0-25	1	(Akbar and Supriatna 2019)
	25-50	2	
	>50	3	
Distance from settlement (m)	0-100	4	(Yudarwati 2016)
	100-500	3	
	500-1000	2	
	>1000	1	
Slope (%)	0-2	4	(Akbar and Supriatna 2019)
	3-15	3	
	16-40	2	
	>40	1	

Source: (Akbar and Supriatna 2019; Yudarwati 2016)

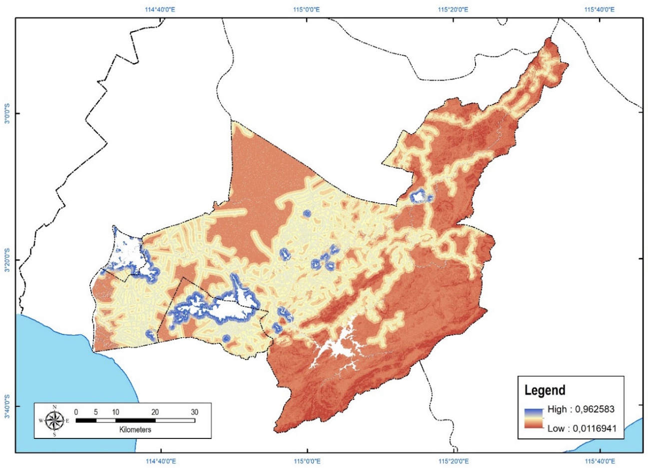

Figure 3. Fuzzy overlay of all driving factors.

prediction model must then be validated to see how accurate the model is with the actual data. If the Kappa value is > 70%, then the resulting model is highly accurate (Guo, Zhang, and Hao 2020).

3. Result and Discussion

Land Cover Changes in Banjarmasin City

Land-cover changes on the Kalimantan island dominated by changes in forest function to oil palm plantations (Gunarso et al. 2013; Verstegen et al. 2019) and mining (Kartikasari, Rachmansyah, and Leksono 2019; Kiswanto et al. 2018). Therefore, this study will discuss on forest land cover, planting land, and built-up land (artificial surface). GlobeLand30 satellite image data shows land cover maps for 2000, 2010, and 2020 (Figure 4).

Built-up land increased by 83 km2 between 2000 and 2020, which was the most critical change (Table 2). The population of Banjarmasin City, Banjar Regency, and Banjarbaru City increased from 1,066,383 in 2000 to 1,581,723 by 2020. (BPS 2020). South Kalimantan's most populous city is Banjarmasin, which can be attributed to the city's comparatively high urbanization (Hassan and Pitoyo 2017). With a decline of 57 km2, woodland was the second-largest land cover type to suffer change (Table 2). Continual forest function changes are incompatible with the sustainability of an ecosystem. It is well-recognized that large-scale agriculture and plantations in Indonesia are the primary causes of deforestation (Austin et al. 2019). Additionally, the planted area has shrunk by 41 km2 (Table 2). Because rural regions have lower earnings than urban areas, the decline in the planted area may be attributable to individuals leaving the countryside and moving to the city (Hamad, Balzter, and Kolo 2018).

The land cover forecast model for 2030 is derived from land cover data from 2010 and 2020. (Figure 4). The validation findings indicate that the Kstandard (Kappa) value of this model's accuracy test is 0.906 or 90.6% (Figure 5), meaning that the agreement value between the prediction model and the actual land use in 2020 is relatively high, allowing this model to be utilized for predictions in 2030. Predictions based on prior research with a Kstandard value greater than 70% are trustworthy (Darmawan et al. 2020; Khwarahm 2021; Munthali et al. 2020).

The results of the land cover prediction model for 2030 result in several forest land cover changes. 2020 is anticipated to mark a decline of 356 km2 in forest cover (Table 2). The prediction results for built-up land (artificial surface) also increased significantly by 187 km2 beginning in 2020. (Table 2). The land cover of the cultivated area has experienced a tremendous transformation, with an anticipated increase of 13 km2 by 2020. (Table 2). These data show that forest management is lacking. Future environmental difficulties and

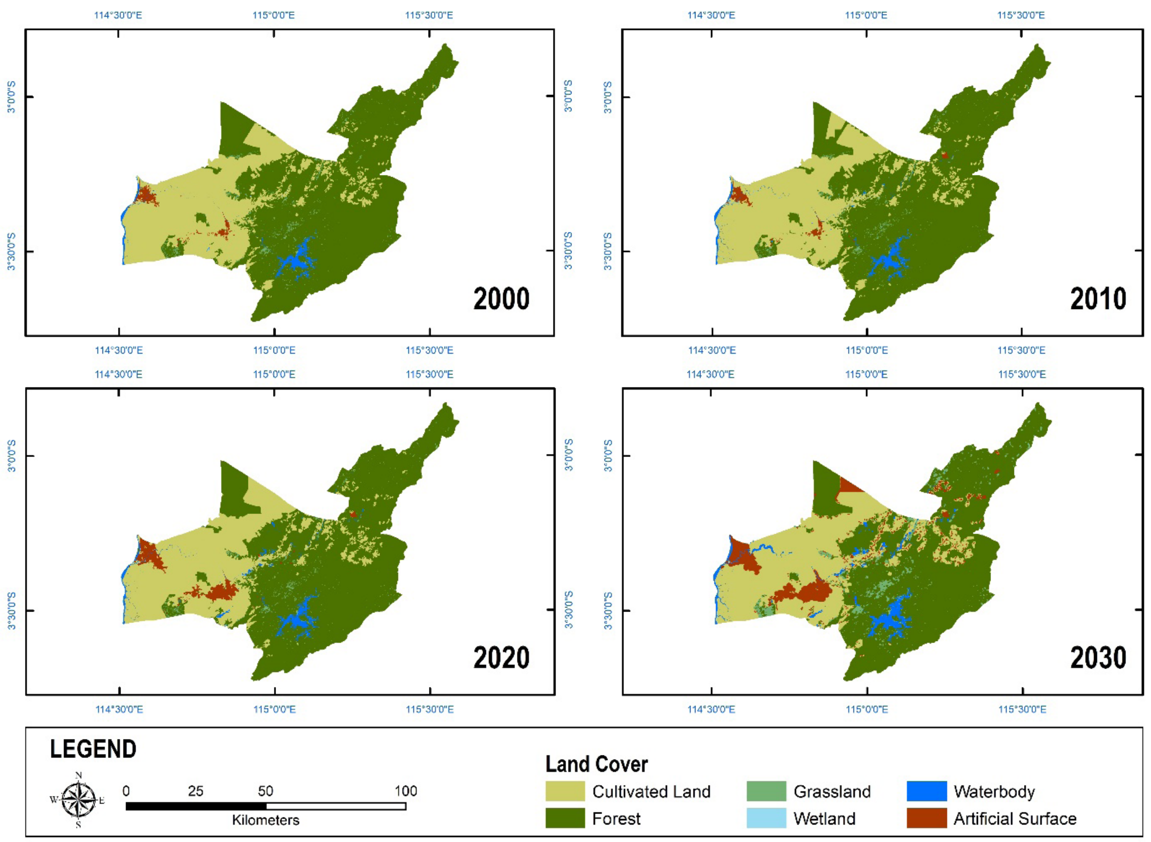

Figure 4. Land cover of Banjarmasin City, Banjarbaru City, and Banjar Regency in 2000, 2010, 2020, and prediction in 2030.

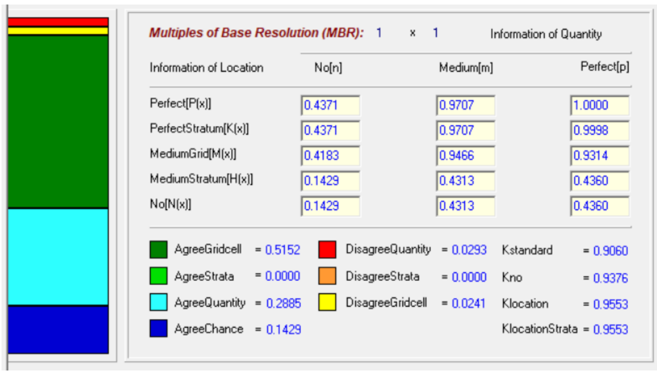

Figure 5. Kappa value of land cover prediction based on CA-Markov chain model.

Table 2. Land cover area.

Class	Area per Year (sq.km)			
	2030	2020	2010	2000
Cultivated Land	1550	1537	1621	1578
Forest	2681	3037	3042	3094
Grassland	160	61	67	69
Wetland	0.31	0.33	0.29	0.23
Waterbody	158	101	89	77
Artificial Surface	314	127	43	44

natural calamities will arise if woods continue to be converted into developed areas.

This study's findings show the relevance of the Markov chain model for predicting the future of the land. The Markov process is used to determine the value of the transition probability matrix, which is used to examine changes in land use. The row of the probability matrix depicts the genesis of the land use, while the column shows any modifications to the initial land use (Table 3). There is a strong probability that cultivated land will become developed land, but it will not become forest, grassland, or wetland. The likelihood of forest conversion to plantation land is high, while the forest has a low probability of transforming into grasslands, water bodies, or developed land. Grasslands have a high possibility of converting into agricultural land and a low chance of transforming into water bodies and built land. The likelihood of wetland transforming into water bodies is increased. This is because wetland habitats are located around the water's edge. No chance that developed land will become farmland, forest, grassland, or wetland.

On the basis of the 2020 and 2030 forecast maps, it is evident that the land cover in each class will vary (Figure 6). A rise in population, regional growth, and the economy can increase the demand for land to build settlements, office areas, and industrial districts. This can result in the conversion

Table 3. Probability matrix of land cover changes.

	Cultivated Land	Forest	Grassland	Wetland	Waterbody	Artificial Surface
Cultivated Land	0.872	0	0	0	0.012	0.116
Forest	0.069	0.883	0.033	0	0.012	0.003
Grassland	0.015	0	0.983	0	0.001	0.001
Wetland	0.019	0.006	0	0.948	0.028	0
Waterbody	0.002	0	0	0	0.998	0
Artificial Surface	0	0	0	0	0.016	0.984

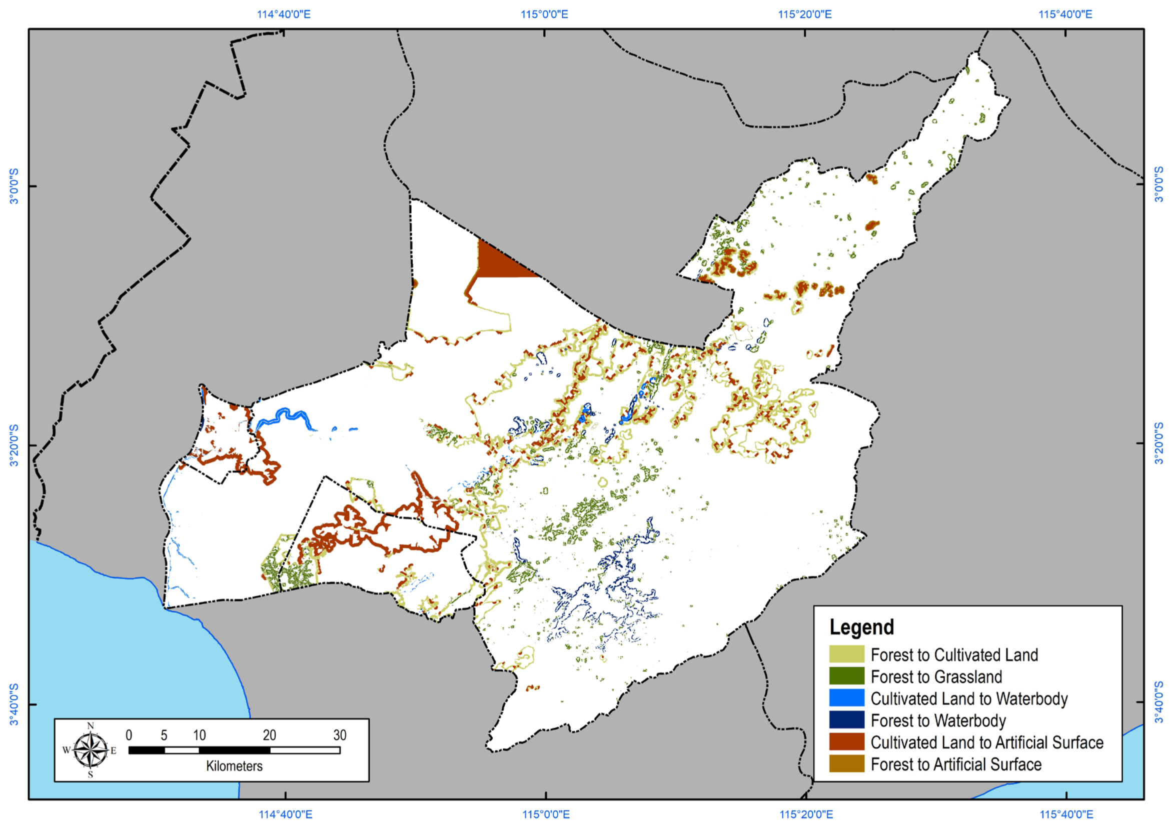

Figure 6. Land cover changes prediction from 2020 to 2030.

of undeveloped land into built-up land. With an anticipated land change of 179 km2 and a predicted forest conversion to built-up land of 10 km2, it has been determined that cultivated land is highly likely to become built-up land. With a forecast shift of 210 km2, forests also have a significant likelihood of transforming into agricultural land. According to WALHI, half of South Kalimantan's land area consists of oil palm plantations and mining (Jong, 2021); this indicates that the planted area for oil palm plantations would increase if the appropriate government did not take action. An estimated 100 km2 of forest conversion to grassland is one of the primary causes of deforestation, contributing to an increase in fires during the dry season (Austin et al. 2019).

Floods and Its Relation to Land Cover Changes

Floods are connected to land use through alterations in hydrological processes and river morphology that influence the timing and quantity of water flows, as well as modifications in human vulnerability based on settlement distribution and societal capability for flood prevention or adaptation (Wells et al. 2013). South Kalimantan was inundated in the start of 2021. During a visit to the catastrophe-stricken Banjar area, President Joko Widodo ascribed the calamity to persistently heavy rains. However, environmentalists assert that forest degradation in the region has contributed to flooding in recent decades (Jong 2021).

The flood hazard index map (BPBD 2021) shows a high hazard area of 1278 km^2 which is 26% of the total area (Figure 7). The flood hazard index is estimated based on the slope and distance from the river in the flood-prone area using the fuzzy logic method (Amri et al. 2016). The result is a flood hazard level in 0-1, where >0.6 is a high hazard. Compiled from the South Kalimantan Geoportal website (BPBD 2021), the flood point in the study area until 20th January 2021 is 213 points (Figure 7). It is interesting to find that only 83 points are in the high flood hazard area. The other 130 points are in the area, which tends to have a low flood hazard and indicates that the flood has spread to areas not estimated to have a high flood hazard.

One hundred and eleven points out of 213 flood points when viewed based on land cover in 2020 are in planted areas, 67 points are in forest areas, 29 points are on built-up land, 5 points are in water bodies, and 1 point is in grasslands (Figure 8). One hundred and eleven flood points are known to be on planting land, this shows that due to the proliferation of planting land, water cannot seep properly, causing inundation. Forested watersheds and forest cover or severely damaged oil palm plantations are essential predictors of flooding (Wells et al. 2013). In particular, the development of oil palm plantations on peatlands will result in long-term greenhouse gas emissions, hydrological problems associated with flooding and salinization of freshwater resources, and a higher risk of peat fires (Hooijer et al. 2010, 2012; Page et al. 2011; Wösten et al. 2006).

Damage and losses due to the flood disaster are a signal that disasters can hinder the sustainability of development in an area. The Sustainable Development Goals (SDGs) are an international agenda drawn up by the United Nations by involving 194 countries, civil society, and various economic actors worldwide and produce 17 goals (PBB 2015). Several SDGs were hampered by flooding, especially SDG 15, namely protecting, restoring, and supporting sustainable use of terrestrial ecosystems, managing forests sustainably, combating desertification, and preventing and reversing land degradation and halting biodiversity loss (PBB 2015).

The community, researchers, government, private firms, and other stakeholders must work together to prevent land alterations that are detrimental to the environment. It is

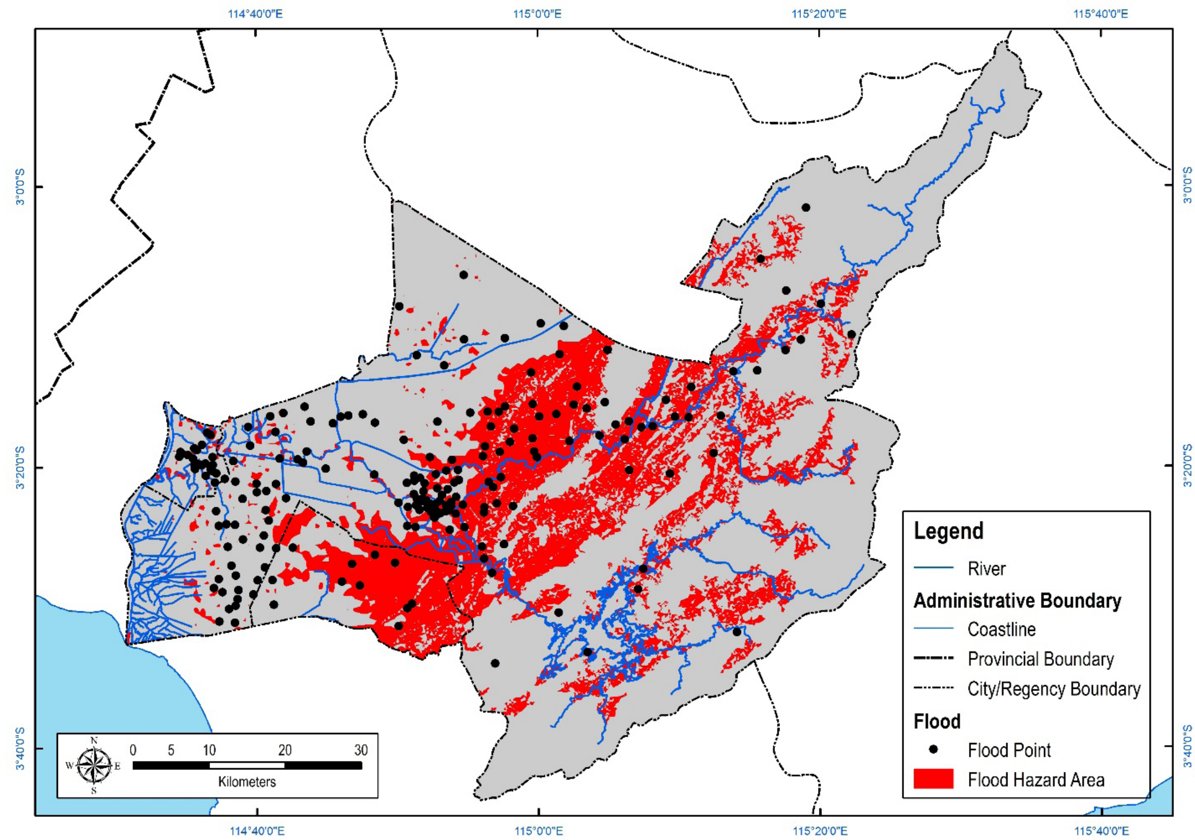

Figure 7. Distribution of flood points and flood prone area.
(Source: Modified from BPBD South Kalimantan, 2021)

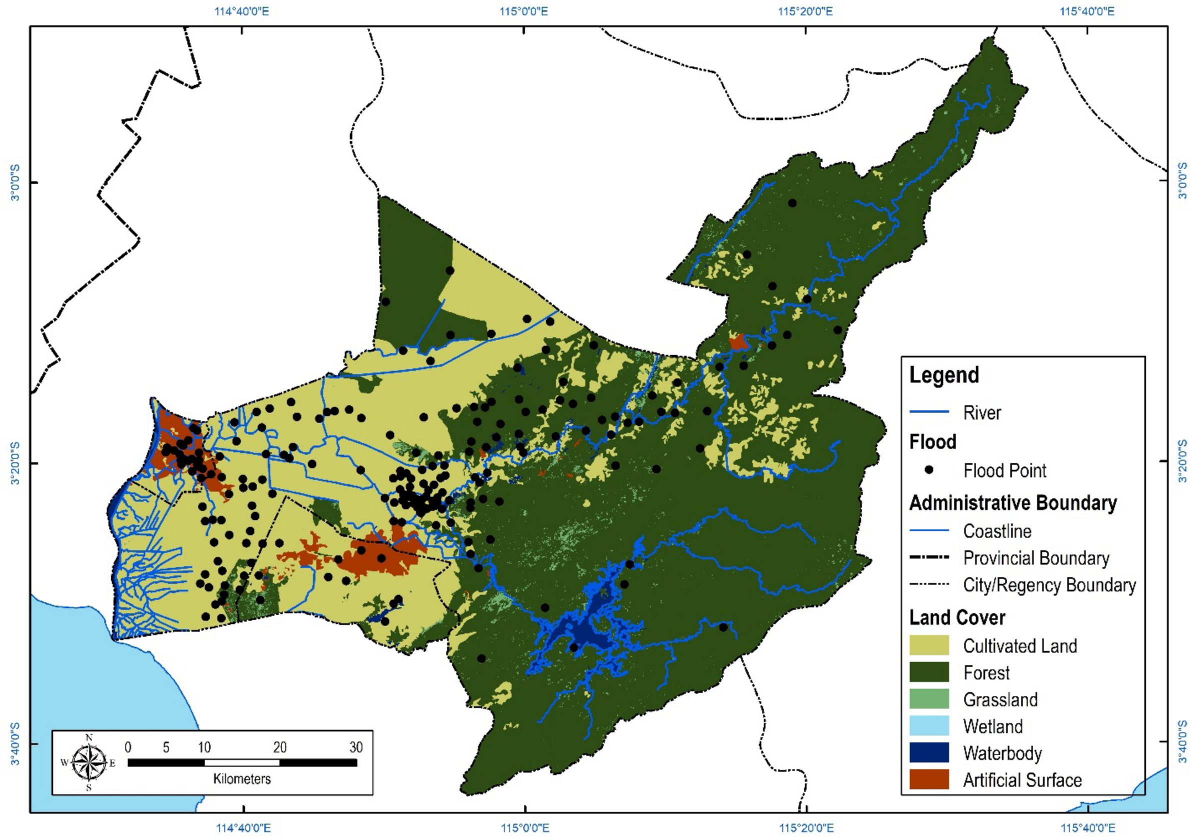

Figure 8. Distribution of flood points and land cover of 2020.
(Source: Modified from BPBD South Kalimantan, 2021)

necessary to strengthen regulations on land clearance licenses for plantations and mining so that they do not continue to consume forest areas. In order to evaluate hazards, vulnerabilities, and dangers, it is necessary to continually update data on soil types, precipitation, rivers, land cover, and other supporting data. With an emphasis on ecological values, this data may be utilized in regional and spatial development planning. Combining manual (recording) and automated (remote sensing) techniques is necessary for watershed monitoring to minimize environmental degradation. Community members can participate in monitoring so that they are also aware of the need to protect the river.

4. Conclusion

Built-up land saw the most significant change in land cover from 2000 to 2020, with an annual rise, while the forest is anticipated to endure 356 km2 of deforestation by 2030. Abnormalities in the hydrological cycle will be caused by deforestation as a result of forest conversion to agricultural and urban areas. Early in 2021, the flood reached places that were not anticipated to be at high risk for flooding, although as many as 111 flood spots were in the planted area. Forests have a higher water-absorption capacity than agricultural land. All stakeholders must collaborate to prevent future natural disasters to avoid land transformation. In a prospective investigation, we recommend using satellite images with a more excellent resolution and a broader range of time series to observe land cover changes.

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