Forecast of Land Cover Change as a Sustainable Flood Prevention Strategy using Cellular Automata Model in Lampoko Watershed, South Sulawesi, Indonesia

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Abstract
The Lampoko watershed is the biggest watershed in South Sulawesi's Barru Regency. Flooding is a common occurrence in this area, particularly tidal flooding. To get around this, this research uses a geographic information system to estimate land cover and reveal how an organization will grow in the future. This forecast is meant to help plan preventive measures in organizational regions where flooding is anticipated. The CA-Markov model was used to analyze satellite imagery data (Landsat 8 OLI TIRS Year 2015-2021).

The findings revealed an increasing pattern of land cover change in several land cover classes that were hubs of communal activity including villages, fisheries (ponds) and agricultural (rice fields). Balusu, Lampoko and Ajakkang are areas that need to be prepared for since they are part of regions with a high likelihood of flooding in the future.

Keywords: Flood Mitigation, Land Cover, Geographic Information System (GIS), CA-Markov.

Introduction
Indonesia is regarded as a nation with numerous disasters because of its characteristics as a group of islands and a country traversed by the Ring of Fire. It is hardly unexpected that natural disasters dominate the disaster occurrences that occur in Indonesia each year. Indonesia experiences earthquakes, floods, volcanic eruptions and other hydro-meteorological calamities as natural disasters. Indonesia is currently experiencing an ecological calamity and a space emergency. The Covid-19 outbreak, which began in Indonesia in 2019, has had a significant influence on the country's economy and social activities.

Additionally, the majority of Indonesia was also affected by natural calamities. This caused numerous casualties and the destruction of numerous homes and buildings. Disaster-affected communities invariably must leave their homes in search of safety.

Natural occurrences that endanger and disturb human life and inflict losses, including economic and social losses, are known as natural disasters. Natural disasters are not always caused by natural causes alone; non-natural causes can often hasten the occurrence of disasters. Disasters cannot be completely prevented by humans because they are a little part of nature.

Only by varied tactics or alternative ways of thinking, humans can lessen the effects that natural disasters have on their environment. Therefore, one way to lessen the effects of disasters is through mitigation activities. The Government and regional governments are responsible for implementing disaster management, which includes reducing the risk of catastrophe and integrating disaster risk reduction into development initiatives, in accordance with the Law of the Republic of Indonesia concerning Disaster Management from 2007. The type of mitigation used in each impacted area relies on how the local population views catastrophic events.

According to ISDR, a disaster is a significant disruption to a community or society's ability to function that causes significant human, material, economic, or environmental losses and is greater than the capacity of the affected community or society to cope with using its own resources. Disaster is the result of a combination of capabilities, threats and vulnerabilities that are brought about by an occurrence. Human activities are very important in dealing with and handling disaster situations[9,10,12,15,34]. Disaster is an occurrence, or a sequence of occurrences, that causes human suffering and can affect a community's way of life. Disasters are essentially inescapable, but people can only prevent them and get ready for them in advance of when they occur[37].

According to the BNPB infographic on the issue of flood catastrophes in Indonesia, hydrometeorological disasters have happened often during the past three years. According to the infographic of BNPB catastrophe occurrences, there were 1,518, 1,794 and 1,531 flood disaster incidents in 2020, 2021 and 2022 respectively. South Sulawesi Province is one place with a high number of people exposed and a disaster risk index. Based on the kind of catastrophe, specifically floods, the results of the national disaster risk research for South Sulawesi Province indicate that all regencies and cities are in the high category.

As a result, there is a chance that the entire South Sulawesi region might experience floods with inundation heights greater than 1.5 meters. The Barru Regency's Balusu District is one of the affected locations. Geographically, the Balusu sub-district is made up of three sizable watersheds:

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Lampoko, Takalassi and Padange. The area of the watershed has a lot of potential to cause disastrous floods.

Pressure is being put on land use and land cover (LULC) due to the rising population. The fast increase in population altered the LULC pattern. Urban regions' social and physical environments are negatively impacted by the unsystematic land use changes. Negative effects are experienced by the slope, forest, soil and river ecosystems. The social climate, access to food and water, the expansion of slums, unemployment, undernourishment, access to healthcare and housing are prevalent issues in Indian cities. Numerous health issues arise in cities because of traffic congestion, air pollution, land pollution, the solid waste problem and sewage issues. Unsystematic land use patterns that are changing make people more vulnerable to the effects of earthquakes, floods, landslides, soil erosion and urban heat[21].

There are many ways to avert flood tragedies, one of them is by providing information on flood-prone locations. A region is a flood danger if it is likely to flood, typically as a result of its location near water bodies, specific physical characteristics, or insufficient drainage systems[26]. When it rains heavily or when the water level rises, these places are more likely to experience flooding. Floods can disrupt infrastructure, result in major property damage and endanger human safety[1,33].

By mapping the growth of settlements along with probable flood disaster zones, it is possible to determine the significance of measures to cope with flood catastrophes. We decided to choose one of the watershed areas, specifically the Lampoko watershed, because it is thought that this watershed area contributes the most to the likelihood of floods[5,17]. As a proactive measure to reduce flooding, we are attempting to forecast land changes, particularly for settlements, using the Cellular Automata model. These driving factors include DEM, Slope, Roads, Rivers, Education Service Centers, Health Service Centers and Government Service Centers.

The outcomes of this prediction will then be overlaid with a map of flood-prone areas, allowing for the recommendation of sustainable flood disaster mitigation efforts and the development of community resilience forces, particularly in future disaster-prone areas, for the Government.

Study Area

One of the longest rivers in the Barru Regency of South Sulawesi is the Lampoko Watershed. The community continuously uses the Lampoko River's flow for a variety of purposes, particularly in agriculture and fishing. Several parts of the Lampoko watershed have frequently experienced flooding during the past three years.

Given its coordinates, the Lampoko watershed is located at 119.62º E – 119.76º E dan 4.255º S - 4.366º S ranging from 0 to 1152 meters above sea level in their respective regions (Figure 1). The watershed's administrative area is divided into 6 regions: Paccekke, Ajakkang, Lampoko, Balusu and Kamiri. In this area, there are 13856 people living.

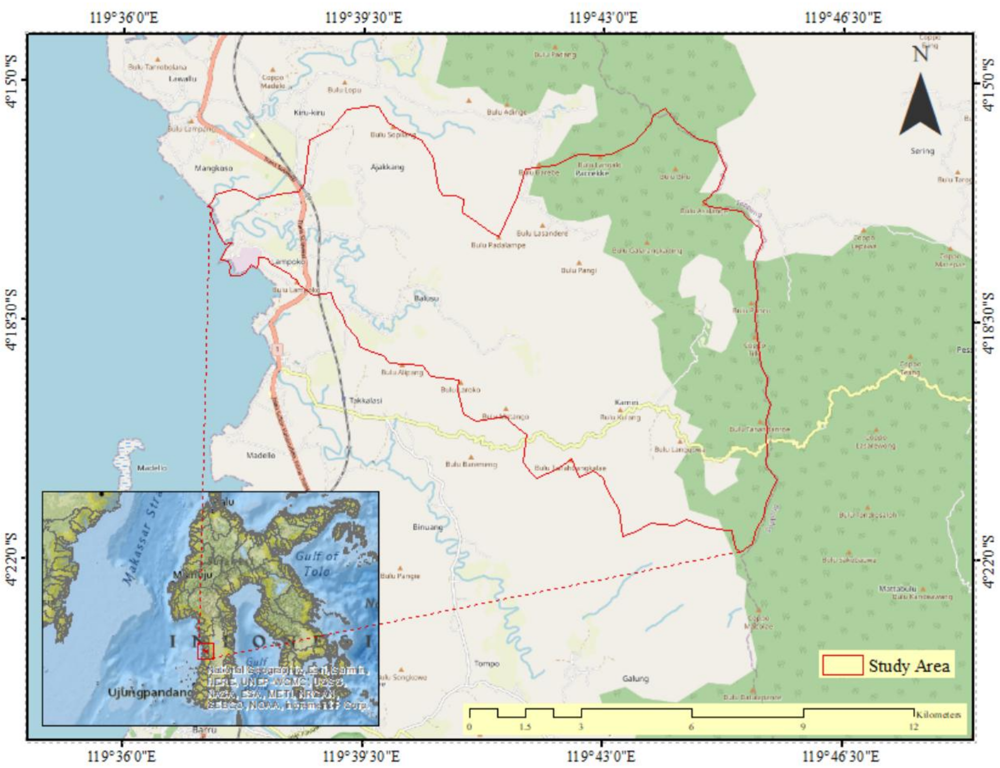

Figure 1: Study Area of Lampoko Watershed

Material and Methods

LANDSAT 8 satellite imagery with a spatial resolution of 30 meters was used to determine the patterns and changes in land cover in the study area. The USGS Earth Explorer supplied the open-source satellite picture data for use in research and other sectors. The most modern addition to the 42-year-old LANDSAT project, which was launched in 1972 with the goal of delivering worldwide, moderate-resolution, multispectral data of the earth's surface, is LANDSAT 8[25]. A land cover time series is required to get changes in land cover in the study area, hence three LANDSAT 8 satellite photos from distinct time periods namely 2015, 2018 and 2021 are employed in this case. Each image has first undergone geofencing.

Through supervised analysis (maximum likelihood classification) that used training samples for its classification, changes in land cover in the study area were discovered. The land cover types under concern are forest, paddy fields, ponds, water bodies, built-up land, grass/shrubs and open land. The accuracy of the calculated findings of assessed land cover changes is then verified using the Kappa method to derive the Kappa coefficient as a foundation for predicting land change[6]. The confusion matrix found in each classification is used to calculate the user accuracy, producer accuracy and Kappa Coefficient for each land cover[7]. The suitability of categorization data, accuracy and the suitability of two nominal data kinds are assessed using this method.

The differences between the adequacy of the classification result data and the likelihood of a random classification match in comparison to the reference data may also be measured using the Kappa coefficient[36]. Kappa can also be used to gauge how well a model's predictions match reality. The following equation can be used to calculate the accuracy of land cover.

$$User's Accuracy = \frac{n_{ii}}{n_{i+}} \quad (1)$$

$$Producer's Accuracy = \frac{n_{ii}}{n_{+i}} \quad (2)$$

$$Percentage\ Correct = \frac{\sum_{k=1}^{q} n_{kk}}{n}\ x\ 100 \quad (3)$$

$$Kappa\ Coefficient = \frac{n\sum_{k=1}^{q} n_{kk} - n\sum_{k=1}^{q} n_{k+}n_{+k}}{n^2 - \sum_{k=1}^{q} n_{k+}n_{+k}} \quad (4)$$

Six categories make up the interpretation of the Kappa accuracy value[16] which can be seen in table 1.

A discrete dynamical system called a cellular automaton (CA) divides space into spatially ordered cells and has time processing at various stages. In this system, each cell has a single condition that is constantly updated based on local laws, the current time, its own state and the states of its neighbors at a prior time[35]. Later, using the Cellular Automata model, the outcomes of land cover maps that have been interpreted and evaluated based on accuracy values that match good criteria, will be investigated for land cover prediction[3].

The following chart illustrates how the research methods used in this study flowed (Fig. 2).

Table 1
Kappa Coefficient and Its Interpretation

Kappa Coefficient	Interpretation of Kappa Value
< 0	Poor
0.01 – 0.20	Inadequate
0.21 – 0.40	Fair
0.41 – 0.60	Moderate
0.61 – 0.80	Good
0.81 – 0.99	Very Good

Results and Discussion

Land Cover Class Analysis: A generic phrase used to describe Earth's surface cover, whether it is natural or artificial, is land use and land cover (LULC) study[4,20]. Based on the data in the database and the findings of field observations in the study region, land cover classes are grouped. Green cover, water bodies, settlements, ponds, shrubs, bare land and paddy fields are among the areas that are classified as land cover.

Land Cover Change Analysis: The science and applications of remote sensing are during a vibrant and transformational time. Opportunities for computing and data storage have emerged[14,41], while the quantity and variety of free and open imagery have also grown at the same time[39]. While the ability to produce information outcomes, like land cover maps, is growing, there is still a pressing need to guarantee and measure the quality of the resulting map products[30,38]. Key components of the land cover categorization process include calibration and validation[13]. The Maximum likelihood classification method was used to examine changes in land cover in the Lampoko watershed[19,29].

LANDSAT 8 satellite imaging data from the study area from 2015, 2018 and 2021 is needed as an input for the data. Each land cover class will be sampled using a training sample, which will then be used in the analysis to produce the results of the land cover interpretation. The outcomes of the interpretation can be seen in figure 3 and table 2.

According to land cover classes, changes in the Lampoko watershed region demonstrate that all land cover classes went through intriguing dynamics between 2015 and 2021. There was a loss of 283.03 Ha of land area in the Green Cover land cover class. Shrubs land cover class shrank by 1.56 Ha as well. Ponds and paddy field land cover classes increased in the settlements, increasing by 122.5 Ha, 61.58

Ha and 100.51 Ha respectively. However, there were variations in the Bareland cover class; from 2015 to 2018, there was an increase of 3.69 Ha, while from 2018 to 2021, there was a decline of 5.07 Ha.

Analysis of Land Cover Change Forecast using the Cellular Automata Model: The Cellular Automata Model is used in this analysis to forecast changes in land cover utilizing a variety of supporting variables including DEM, slope, roads, rivers, education service centers, health service centers and government service centers. Euclidean Distance will be used in proximity analysis to determine the distance to the closest source in each cell for each supporting component[40]. The following equation can be used to determine Euclidean Distance:

$$d_{Euclidean} = |x - y^2| = \sqrt{\sum_i^n = (x_i - y_i)^2} \tag{5}$$

Figure 4 shows the outcomes of the proximity analysis of each driving element.

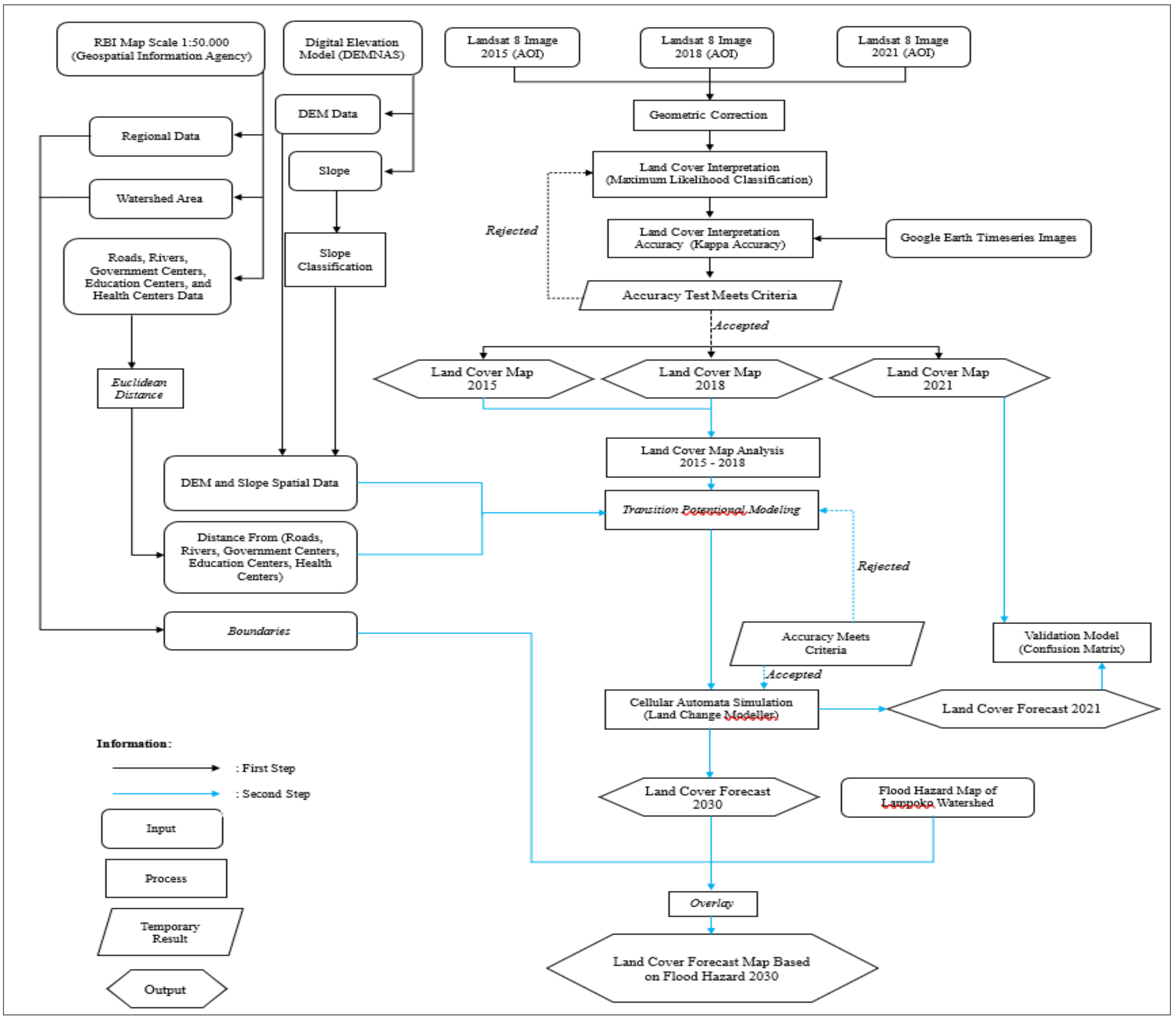

Figure 2: Research Methodology

Table 2
Land Cover Change Classification of 2015, 2018 and 2021

S.N.	Land Cover Classifications	Years (Ha)		
		2015	2018	2021
1	Green Cover	6675.62	6488.63	6392.59
2	Water Bodies	283.53	283.53	283.53
3	Settlements	750.87	825.96	873.37
4	Ponds	567.18	627.04	628.76
5	Shrubs	115.53	114.41	113.97
6	Bare Land	58.69	62.39	57.32
7	Paddy Fields	1435.84	1485.30	1536.35
Total		9887.26	9887.26	9887.26

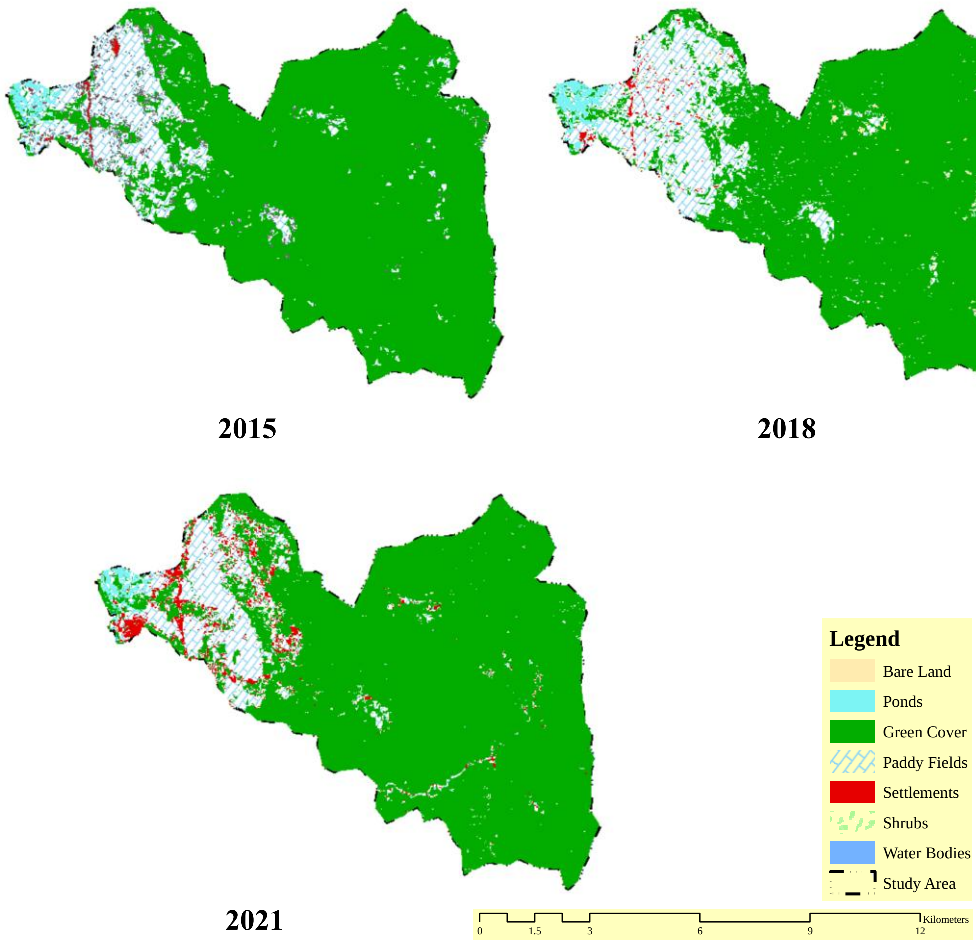

Figure 3: Land Cover Interpretation of Lampoko Watershed

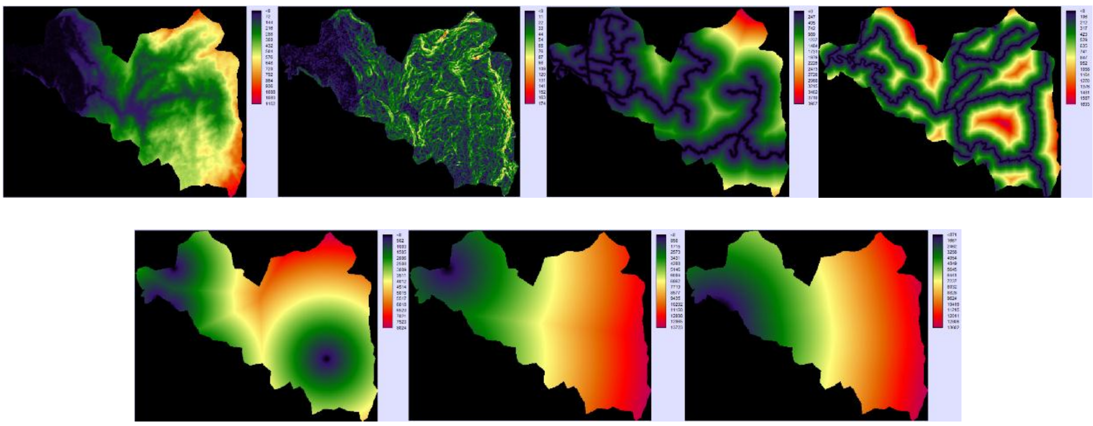

Figure 4: Driving Factors for Land Cover Forecast

Driving Factors for Land Cover Forecast: The land cover forecast study will consider every driving component. External factors are typically thought of as being outside the land-use system. This assumption, however, occasionally prevents the appropriate description of the land-use system[23]. DEM, Slope, Roads, Rivers, Education Service Centers, Health Service Centers and Government Service Centers are the driving variables that are entered in figure 4 in order. The analysis's findings will result in a transition map for the studied time.

In this instance, we utilize a 3-year time frame so that the transition's outcomes are map predictions for 2021. Following the validation of the transition map results for 2021, predictions will be made utilizing the Cellular Automata model. The transition map, validation map (2021),

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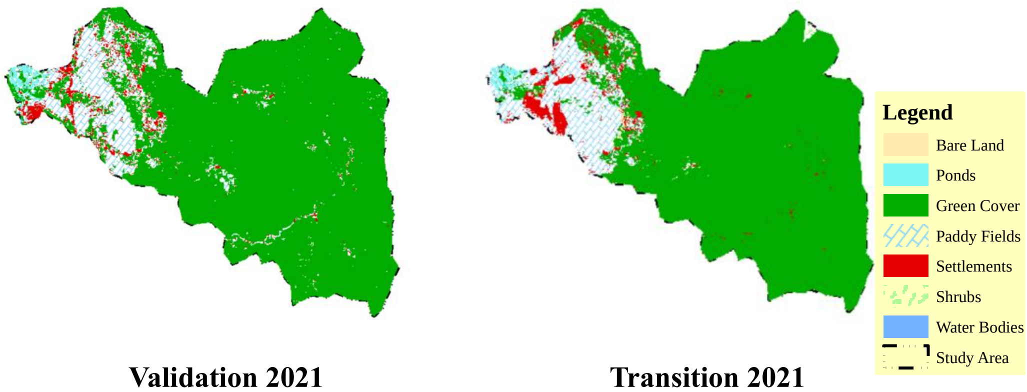
prognosis map for 2030 and the changes that have taken place are all summarized in figure 5.

Transition and Validation for Cellular Automata Predict: Land use and land change models can be effective tools for predicting future patterns of landscape change and assisting in decision-making[11,22,24,27,31]. They are computational in nature and allow for experiments at various spatial scales to study how changes in land cover can occur under various circumstances and the ecological effects of those changes[32]. A wide range of methodological approaches can be created by incorporating social, environmental, institutional and economic dynamics in land transformation models. Land change models might infer underlying processes from observed patterns of land change (pattern-based), explicitly define processes (deductive), use statistical correlations (inductive), or mimic individual decision-makers (agent-based)[18].

The expected transition map, which is impacted by several prior driving forces, is used in this step as a validation tool along with the land cover of 2021. The potential changes that could occur in each category of land change because of this method, can be utilized to forecast land change that will take place in 2030. The accompanying graphic (Figure 6) shows the potential changes that are predicted to occur in 2030.

Analysis of Flood Prone Land Cover Change Forecast: Due to the unjustified and harmful rise of urbanization, floods are susceptible. According to earlier studies, the flood is the major natural disaster with the greatest potential for destruction[2,28]. An overlay procedure will be used to compare the flood danger map and the 2030 prediction map after the 2030 Land Cover Forecast has successfully been processed[2,8]. To show the changes as well as the potential for future flood hazard in the Lampoko Watershed, we also present change data from the map for the years 2021 to 2030. The likelihood of places that could flood is depicted in the following picture. As can be seen from the map's color, which is going darker and indicates a higher level of probability than areas with a hue that is moving toward light, these locations are more likely to experience flooding than those with a hue that is getting lighter.

Land Cover Forecast for Sustainable Flood Prevention: The comparison of land change between 2021 and 2030 based on figure 7 reveals a decrease in green cover and shrubs with respective areas of 117.45 ha and 3.95 ha. There is a high likelihood of flooding in the land cover class in the Lampoko watershed area, as depicted in the image, particularly in the settlements, ponds and paddy field areas. There is no doubt that the area will influence local economic activity.



Validation 2021 **Transition 2021**

Figure 5: Validation and Transition Map for Land Cover Forecast

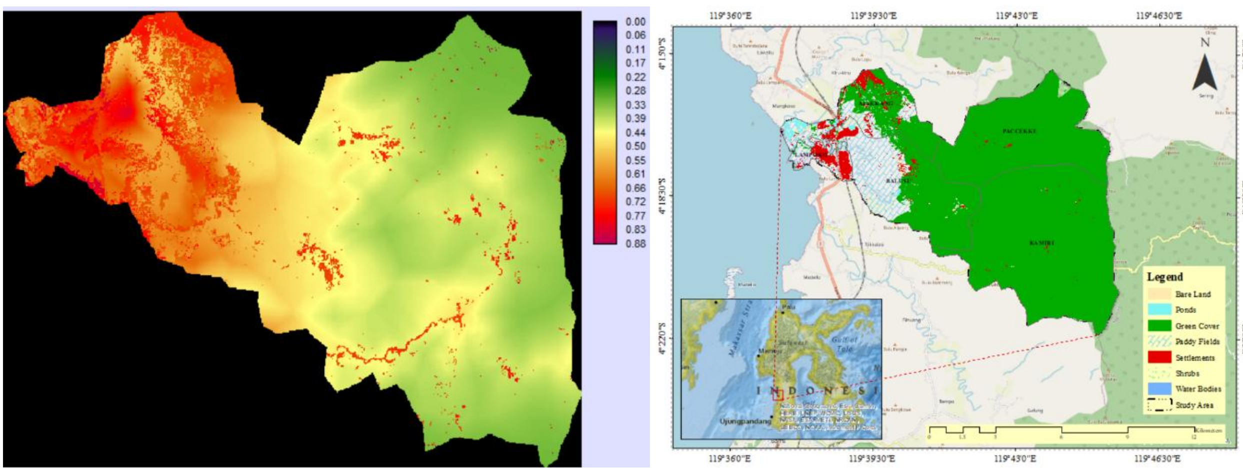


Figure 6: Projected Potential for Transition and Land Cover Forecast 2030

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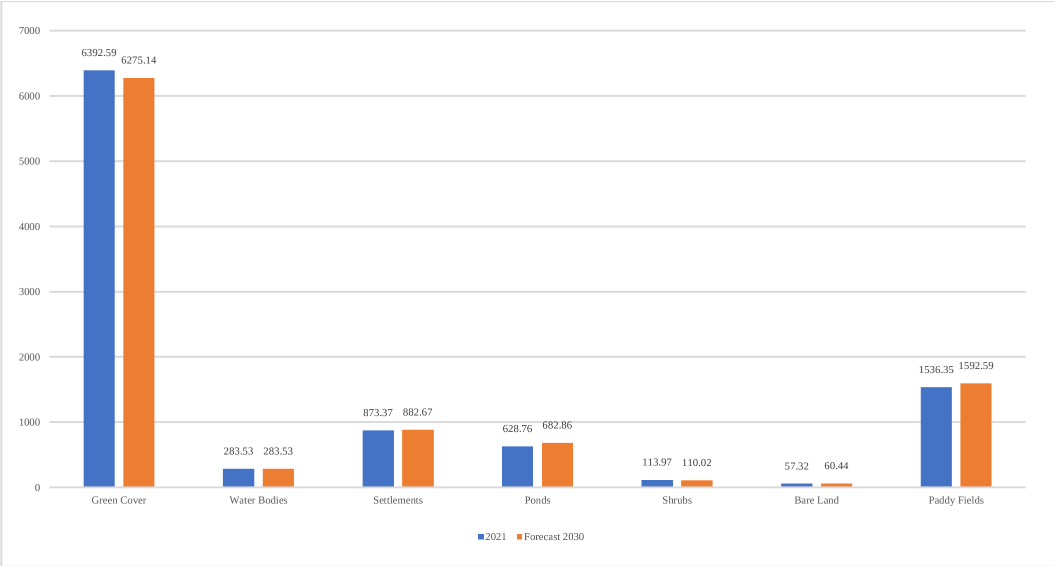

Figure 7: Land Cover Change of 2021 to 2030

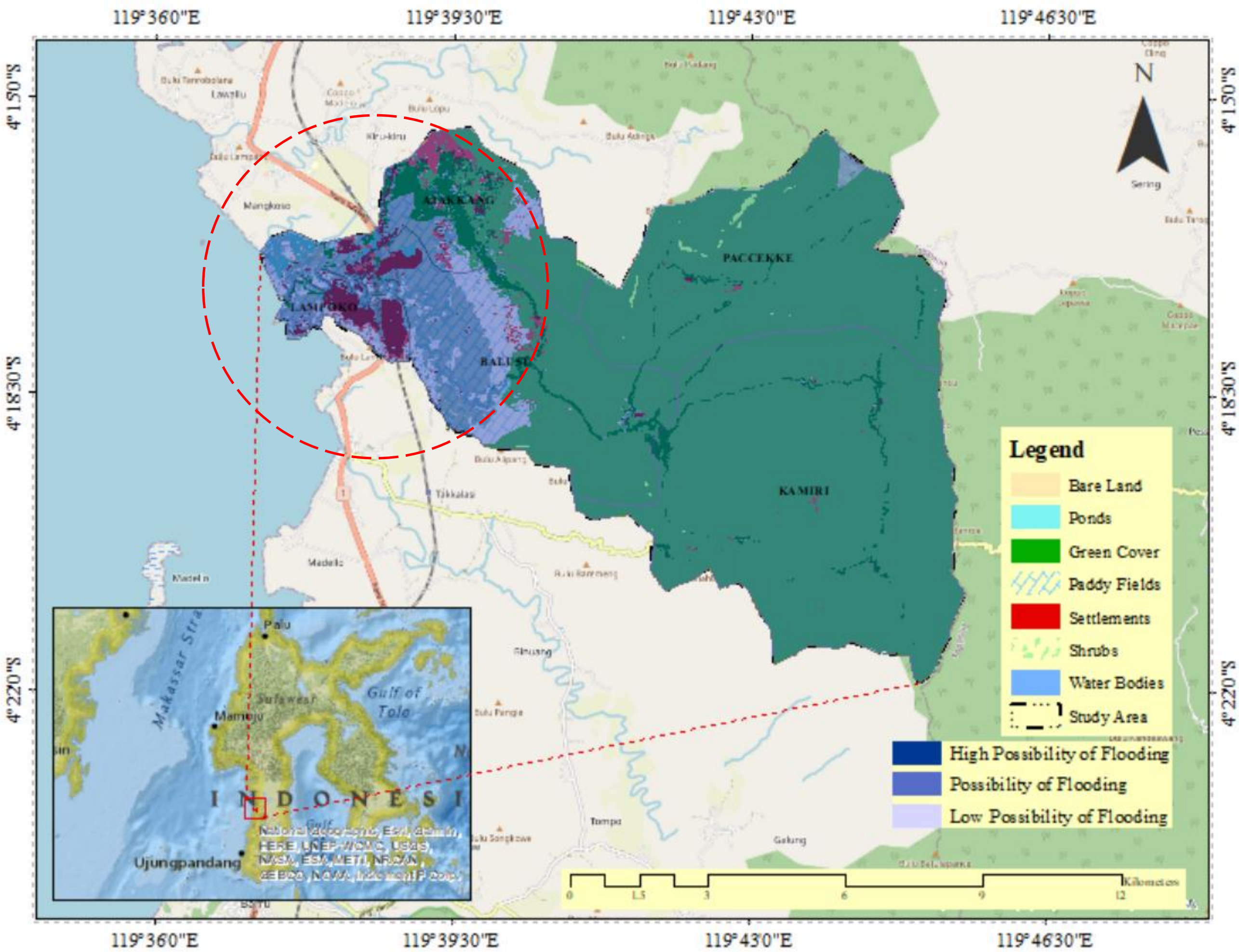

Figure 8: Land Cover Forecast of 2030 Based Flood Vulrenability

Balusu and Lampoko are two administrative areas that require high levels of attention because most of their areas fall under the category of high likelihood of flooding. Settlements, agriculture (paddy fields) and fisheries (ponds) are examples of land cover changes that will quickly develop and may be seen in the figure 8.

Conclusion

The likelihood of a catastrophic flood in the Lampoko watershed area in 2030 is considerable. Lampoko, Balusu and Ajakkang are several locations that need to be considered concerning and treated to. This region will see a rise in villages, paddy fields and ponds for fisheries in the future. As a result of the area's inclusion in the category of high flood probability and the growth of settlements there, it needs a great deal of attention, particularly in the Lampoko administrative area.

To lessen the risk of disasters brought on by floods in communities and to lessen economic losses in ponds and farmland (paddy fields), settlements of the Lampoko watershed area urgently need to work collaboratively. This land cover forecast can be used as a guide to help local governments to create community capability and resilience to deal with catastrophes. It can be used to manage the physical environment and increase public awareness of flood disaster management.

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