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Sustainable Land Use and Land Cover Management Model for Flood Mitigation in Krueng Baro Watershed, Aceh, Indonesia

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ABSTRACT

Watershed management is a human effort to control the reciprocal relationship between natural resources and humans and all their activities to foster sustainability and harmony of ecosystems and increase natural resources for humans. Watershed damage results in various natural disasters related to land use and cover changes, such as flooding, erosion, and sedimentation. Krueng Baro watershed is one of the watersheds that has suffered severe damage. This research aims to find a sustainable spatial plan to mitigate natural disasters that arise in the study area. High-resolution satellite image data obtained from Google Earth Engine (GEE) for Sentinel 2A imagery as the great spatial resolution for land observation and change detection. Furthermore, land use and land cover (LULC) classification uses unsupervised classification. After identifying the LULC, the areas affected by flooding from year to year can be identified with a very well-processed analysis through the random forest (RF) principle, which was previously considered by analyzing several supporting variables so that the exact area affected by flooding other than the permanent water area is known. The supporting variables used in this research are the amount of rainfall, slope, river density, and soil type. At the same time, the discharge analysis uses a mock model to estimate the runoff discharge from rainfall and other variables that affect it. A scenario that will be used to overcome flooding in the Krueng Baro watershed will be recommended.

1. INTRODUCTION

Changes in land use and land cover (LULC) are among the key drivers of global environmental shifts, often leading to negative impacts due to population growth and socio-economic expansion [1]. Understanding LULC dynamics and their consequences is essential for planning future interventions in affected areas [2]. These transformations directly influence community well-being by altering environmental conditions, such as increasing land degradation risk and flooding [3].

Water resources management and hydrological risks are of significant concern in our society. A contributing part of hydrological hazards worldwide, floods, erosion and sedimentation are among the most frequent and environmentally damaging natural disasters. Globally, between 1994 and 2013, floods accounted for 43% of recorded natural disasters, claiming nearly 2.5 billion lives [4]. Flooding is considered the most devastating natural disaster in the world's major cities, resulting in ever-increasing economic losses to the community [5]. Flooding is a complex and dynamic process influenced by the interaction between watershed management and various hydro-meteorological, hydrogeological, and geomorphological factors [6, 7].

The Krueng Baro watershed in Pidie Regency is the longest of the six watersheds in Pidie Regency. Damage to the Krueng Baro watershed causes LULC to be increasingly vulnerable to water flow appropriately and quickly for the survival of the majority of the population of Pidie Regency. The Krueng Baro watershed is an area frequently affected by floods, occurring on average three times a year. Based on an analysis of land use, rainfall, land slope, and soil type, this area is highly susceptible to flooding [8]. It has led to several disastrous impacts on the community. The watershed is also vulnerable to changes in LULC, with the primary factor being deforestation [9].

It is necessary to address this damage by finding a treatment model suitable for the Krueng Baro watershed landscape. The development of logistic regression models to relate LULC to water resources and hydrological risks has yet to be used explicitly in solving the problems that occur, such as flooding, erosion, and sedimentation [10-12]. This model has been widely used in modelling urban and regional growth, though less so than the Cellular Automata (CA)-Markov model. CA-Markov does not use variable drivers, only temporally based on the probability of change from previous data [13, 14].

LULC change has the most significant effect on increasing the surface flow coefficient value, which impacts increasing peak discharge due to high runoff [15]. LULC changes in the Krueng Baro watershed indicate changes in the ecosystem that can threaten the function of the area. One way to do this is by utilizing remote sensing technology [16, 17].

The Sendai Framework for Disaster Risk Reduction 2015-2030 highlights the crucial role of land use planning and policy in addressing the root causes of disaster risk, such as rapid and unregulated urbanization, poor land management, and the lack of regulations and incentives for private investment in disaster risk reduction [18]. Although global efforts to integrate flood risk management into urban land use planning have increased, the practical implementation of these strategies still faces considerable challenges [19].

Properly designed land-use strategies can effectively reduce flood risks by restricting development in vulnerable areas, enforcing building regulations to minimize runoff, and allocating designated routes and open spaces to improve response and recovery efforts [20]. A best-fit model that spatially links LULC change to discharge and sedimentation for developing an area and appropriate management system has yet to be found. So, this research aims to build a LULC management model to mitigate flooding in the Krueng Baro watershed.

2. MATERIAL AND METHOD

2.1 Study location

The Krueng Baro watershed is situated in Pidie Regency, Aceh, Indonesia, covering an area of approximately 210.75 km². Geographically, it lies between 96°0'0" and 96°21'20" eastern longitude (EL) and 5°3'30" and 5°21'20" northern latitude (NL) (Figure 1). Based on the official boundaries defined by the Ministry of Home Affairs in 2022, the majority of the Krueng Baro watershed is located within Pidie Regency. However, a small section of its forested area extends into Aceh Besar Regency.

In the Krueng Baro watershed, there is the Krueng Baro River, which is 29.405 km long, up to the outlet of the Keumala Dam. The downstream section of the Krueng Baro river is situated in Blang Asan Village, within Sigli City, while the upstream originates in Geuni Village, located in Keumala District. The Krueng Baro River is the primary source of irrigation water needs in the Krueng Baro area and PDAM Tirta Mon Krueng Baro, so it is invaluable in meeting water needs, especially in Pidie Regency.

The degradation of the Krueng Baro River is generally caused by the massive extraction of excavation C for building materials, all of which come from within the river [8]. Based on data from the nearest rainfall stations to the Krueng Baro Watershed—namely Sarah Mane, Tangse, and Tiro—the average annual rainfall between 2012 and 2021 ranged from 1,586 to 1,907.3 mm/year at Sarah Mane station, 2,135.4 to 2,479.0 mm/year at Tangse station, and 2,908.4 mm/year at Tiro station.

2.2 Satellite imagery

The satellite imagery used in this study is from Sentinel-2A, which was launched in 2015 and provides the latest data for water area identification. Observations were conducted for the years 2016, 2020, and 2024. The use of time series or long-term analysis allows for detecting changes in LULC over time. With Sentinel-2's high spatial resolution—10 meters for multispectral bands and 60 meters for the panchromatic band—this study can capture finer details of the Earth's surface, enabling a more precise identification of LULC within the watershed area..

These classifications were determined based on the watershed's landscape characteristics, including: (1) forest, (2) cropland, (3) swamp, (4) rice fields, (5) built-up areas, (6) dry bare land, (7) wet bare land, and (8) water body.

This research has provided an overview of LULC in the Krueng Baro watershed from 2016 to 2024. To analyze landscape transformations, LULC mapping was conducted using Google Earth Engine (GEE). Sentinel-2A imagery, processed through GEE, can be used to detect LULC changes [21]. As part of machine learning techniques, the RF algorithm enables unsupervised LULC classification for more accurate analysis.

The RF model uses spectral features (e.g., bands B2, B4, B5, B6) and indices, e.g., Normalized Difference Vegetation Index (NDVI) and Normalized Difference Built-up Index (NDBI), to classify land use groups, including urban areas, farmland, forests, and water bodies. To train the RF model, pseudo-labels are constructed using clustering techniques for classified. With ensemble learning, which combines the predictions of several decision trees to enhance classification or regression accuracy principles, RF's strength is its capacity to handle high-dimensional data while minimizing overfitting and guaranteeing correct results. The workflow is useful for identifying land use without needing labelled datasets because it includes data preparation, feature extraction, model training, and validation.

Leo Breiman first introduced RF introduced 2001 as a method that can improve accuracy by randomly generating attributes for each node. RF consists of a collection of decision trees that classify data into specific classes [22]. Decision trees are created by defining a root node and ending with several leaf nodes to obtain the final result. The process of forming decision trees in the RF method is similar to the Classification and Regression Tree (CART) process [23], especially in detecting the unsupervised classification for LULC. However, RF does not perform pruning.

The first stage creates the decision tree with a randomly selected subset from the training sample and a random selection of features. This approach introduces correlation almost exclusively between individual decision trees at these two levels of randomization, which typically improve the accuracy of the model and lessen the risk of overfitting (assessed by the overall accuracy). To assess the classification errors resulting from this method in comparison to a purely random classification, the Kappa test is applied, as outlined in the following equation [24].

$$\text{Overall accuracy} = \frac{N_{AA} + N_{BB} + N_{CC}}{N} \times 100\% \tag{1}$$

$$\text{Kappa} = \frac{N\ \sum_{j=1}^{k} N_{jj} - \sum_{j=1}^{k} N_{jR} N_{Pj}}{N^2 - \sum_{j=1}^{k} N_{jR} N_{Pj}} \tag{2}$$

where, N is total points, k is number of classes, R is test classes, and P is classified class.

Figure 1. Research location

Source: https://www.nationsonline.org/oneworld/map/indonesia_map.htm

The key variables for analyzing LULC, particularly built-up areas, concerning flood disasters include population size, growth rate, rainfall, slope gradient, GDP, proximity to roads, rivers, and city centers, as well as existing LULC patterns. Due to Indonesia's susceptibility to natural catastrophes and various available data, this analysis could be further optimized to enhance the prediction accuracy per region [12].

2.3 Mock method

The Mock model is a popular rainfall-runoff model used to predict the hydrological response of a watershed. The rainfall data is then translated into river discharge using the model which is an essential sector for water availability analysis, water resources management and disaster mitigation, mostly for flood prevention. This model relies on rainfall data as its primary input and processes it using various parameters that represent watershed characteristics, including infiltration rate, evapotranspiration, and surface flow [25].

The calculation of discharge using the Mock Method involves preparing essential data, including average regional rainfall (P), potential evapotranspiration (Eto), number of rainy days (n), groundwater recession flow factor (k), and infiltration rate coefficient (i). Streamflow data is obtained using the empirical formula of the Mock Method. This method requires climatological data, as well as the area and land use of the catchment, to calculate streamflow. The method assumes that rainfall over the watershed is partially lost to evaporation, partially becomes direct runoff, and partially infiltrates the soil. When the soil's moisture capacity is exceeded, the water will flow downward due to gravity as percolation, reaching saturated aquifers and becoming groundwater, eventually discharging into rivers as base flow. The Mock Model is based on the concept of water balance (Figure 2) [25, 26].

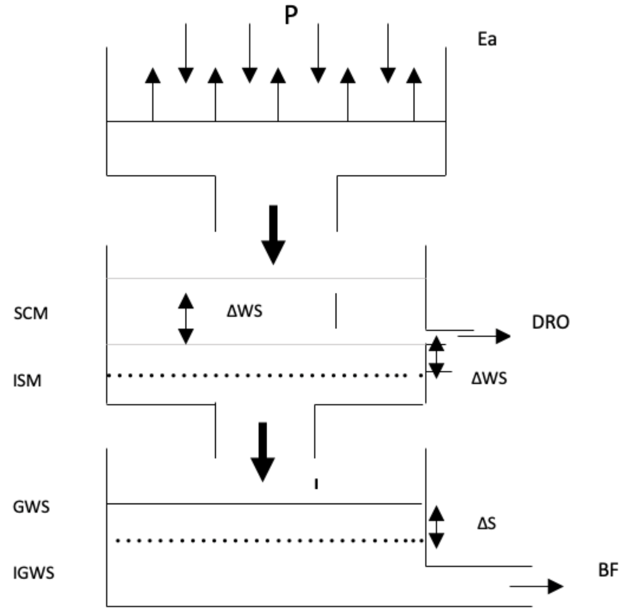


Figure 2. Calculation steps of the mock method

Water surplus (WS) influences infiltration rates and total runoff, which are components of streamflow.), water surplus (WS) affects infiltration and total runoff values.

$$WS = P - Ea \tag{3}$$

where, WS is water surplus, P is precipitation, and Ea is evapotranspiration

Two components influence the magnitude of total runoff (R): base flow (BF) and direct runoff (DRO). The magnitude of base flow depends on the extent of infiltration and changes in groundwater storage [25, 27].

$$BF = I - \Delta S \tag{4}$$

where, BF is base flow, I is infiltration, and ΔS is groundwater storage change.

$$DRO = WS - I \tag{5}$$

$$IGWS = GWS_{t-1} \tag{6}$$

$$\Delta S = GWS - IGWS \tag{7}$$

According to Mock, the total infiltration is [25]:

$$I = WS \times if \tag{8}$$

where,

I = infiltration
WS = excess water
If = infiltration coefficient

Infiltration is estimated by considering soil porosity and the slope of the drainage area. The calculation of groundwater storage (GWS) follows the formula:

$$GWS = [0.5 \times (1 + K) \times I] + [K \times IGWS] \tag{9}$$

where,
GWS = Groundwater volume in period-n
K = Monthly resistance factor

The accuracy of the Mock model is determined by examining the coefficient of determination (R^2). The classification criteria are as follows: *very good* ($0.86 < R^2 \leq 1$), *good* ($0.75 < R^2 \leq 0.86$), and *satisfactory* ($0.65 < R^2 \leq 0.75$). An R^2 value near 1 is the most favorable agreement between observed and simulated results. Meanwhile, the standard deviation of residuals is evaluated using the Root Mean Square Error (RMSE), with the following prediction categories: *highly accurate* (<0.009), good *accurate* (0.009 < RMSE < 0.09), and *satisfactory* (0.09 < RMSE < 0.5) [28].

$$\text{RMSE} = \frac{\sqrt{\sum_{i=1}^{N}(Y_i^{obs} - Y_i^{obs})^2}}{n} \tag{10}$$

$$R^2 = \frac{(\sum_{i=1}^{N}(Y_i^{obs} - Y^{-obs})\left(Y_i^{sim} - y^{-sim}\right)^2)}{(\sum_{i=1}^{N}(Y_i^{obs} - Y^{-obs})^2 \sum_{i=1}^{N}((Y_i^{sim} - y^{-sim})^2)))} \tag{11}$$

Notation:
Y^{obs} = measured value of each data point
Y^{sim} = estimated value of each data point
N = total number of samples

3. RESULTS AND DISCUSSION

3.1 LULC changes

The results of satellite image processing for land use from 2016 to 2024 can be seen in Table 1 and Figure 3. LULC is categorized into eight types using Sentinel-2A imagery. This study used eight classes to look specifically at land change. Changes can be identified by combining random forest (RF) and maximum likelihood models. RF—a widely used nonparametric, tree-based ensemble machine learning technique to generate high-quality inferences from input data, [21]—employs the principles of adaptive closest neighbour grouping and bagging. RF is among the most accurate supervised learning methods for classification and regression tasks, which is the primary reason this study adopts the RF model. An effective approach for handling missing data is using RF missing data algorithms. As an ensemble machine learning method, RF offers desirable properties such as scalability for large datasets, flexibility in capturing interactions and nonlinear relationships, and robustness in managing various types of missing data.

The RF model was parameterized and validated following dataset training. The performance was assessed using the median AUC, a useful statistic for comparing the performance of two different models, as long as the dataset was roughly balanced [29, 30]. The AUC idea states that if the model is given a randomly chosen positive and negative example, it is more likely to score the positive example higher than the negative. Prediction accuracy was highly influenced by parameterization when the case study trained the datasets, leading to high prediction accuracy.

For 2016, 2020, and 2024, the corresponding Kappa values were 0.817, 0.800, and 0.867, respectively. LULC data is vital in analyzing and monitoring environmental degradation as it provides information on spatial and temporal changes in land use. This technique is also useful for the evaluation of human action impacts on the ecosystems as in the case of deforestation, urbanization, and land transformation, leading to changes in sustainable environment [31].

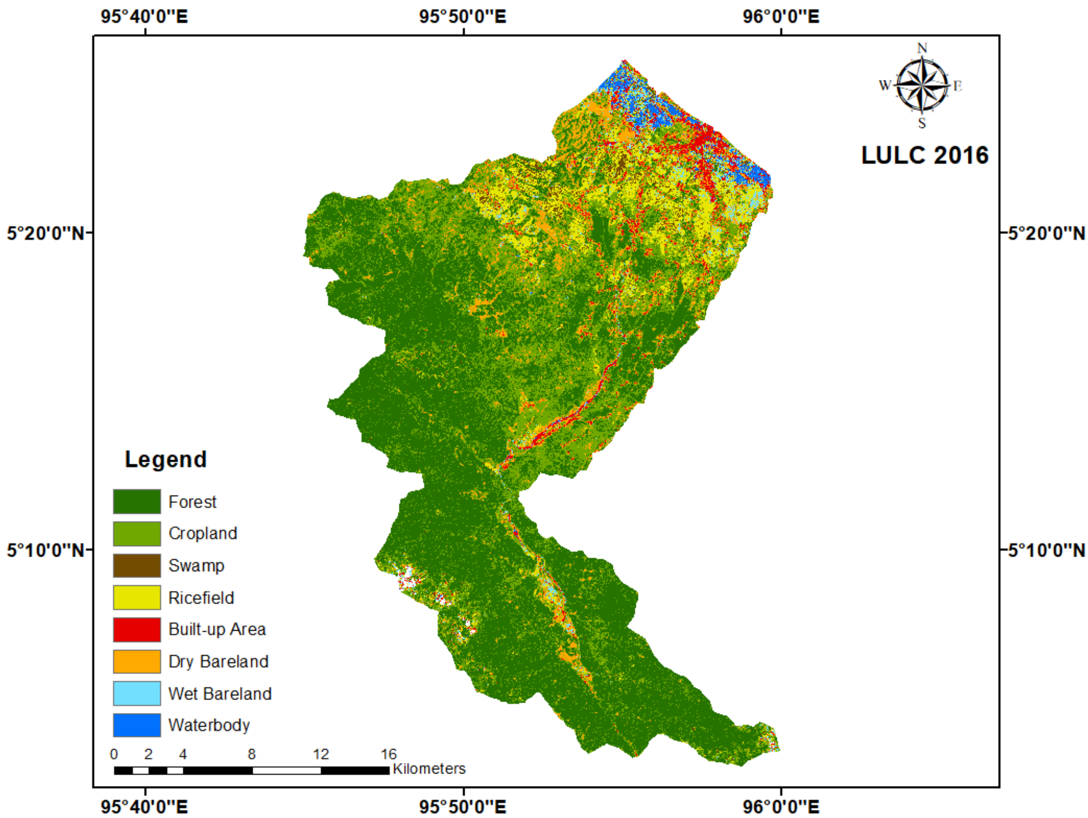
LULC analysis utilizing satellite imagery and remote sensing technology offers a comprehensive perspective on landscape change dynamics [17, 32]. This data is valuable for pinpointing regions susceptible to environmental degradation and developing efficient mitigation strategies. In addition, LULC analysis can also be used to evaluate the impacts of development policies, economic activities, or urban expansion on biodiversity and ecosystem functions. Thus, this approach is important in supporting sustainable natural resource management. The LULC change graph can be seen in Figure 3 and Table 1. The forest class shows an increase over time. In 2016, the area was 29,654.26 ha; in 2024, it will be 25,386.62 ha. LULC is one of several significant global change factors [33] and hurts the natural environment due to increasing population and socio-economic development [34-36].

A hydrological model describes the amount of flow or rainfall input that occurs in the Krueng Baro watershed. The Mock method is a hydrological model based on the concept of water balance, which assumes that some of the rainwater that falls on a watershed will flow directly and some will infiltrate the soil [25].

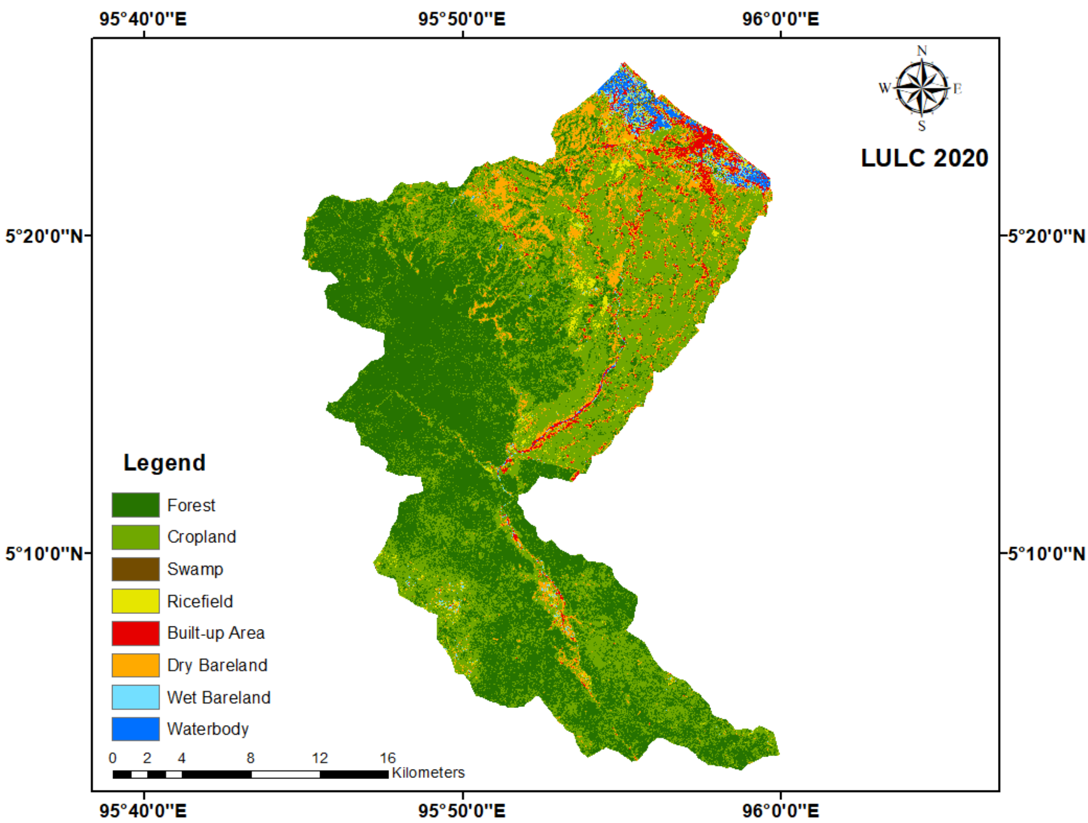
The Mock method was chosen to predict discharge because calculations using the model are accurate and take into account more natural conditions that affect river flow. Therefore, this method is relatively simple and allows the prediction of river discharge at monthly and annual time intervals. As shown in the Figure 4 and Figure 5, significant changes in LULC classes can be observed. The forest area, for example, has decreased significantly from 29,654.30 hectares in 2016 to 29,160.10 hectares in 2020, and further to 25,386.60 hectares in 2024. A notable increase, however, occurred in the cropland class, which expanded from 15,907.10 hectares in 2016 to 20,230.30 hectares in 2020, and further to 23,216.40 hectares in 2024. These two areas represent the most significant changes, with forest experiencing a substantial decrease and cropland a noticeable increase. In addition, the coastal urban areas show a clear expansion in built-up areas, with a total change of 941.48 hectares over the eight years, driven by the region's rapid economic and industrial development.

For other areas, such as rice fields, considerable changes occurred between 2016 and 2020, where rice fields were converted into cropland. Many residents have repurposed rice fields for cropland use. This trend aligns with the expansion of built-up areas due to the growing population. As the population increases, so does the demand for cropland, which serves as a source of livelihood and farmland as shown in figure, cropland areas are closely located and often adjacent to built-up areas.

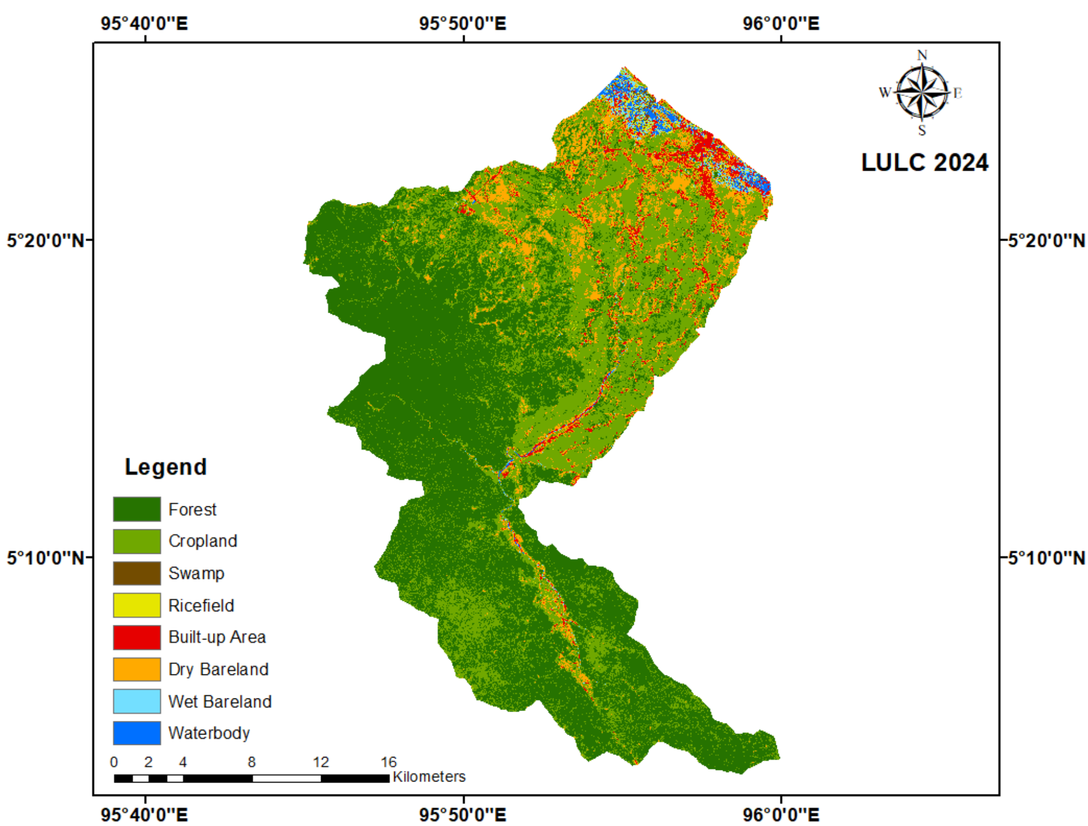
Based on the Figure 3 and Table 1, the forest, wet bareland, and swamp classes have shown a decline over eight years due to land clearing, which is predominantly converted into cropland and built-up areas, as well as the expansion of dry bareland around the Krueng Baro watershed. Furthermore, the rice field area near the watershed has also decreased, as evidenced in Table 1, which details the changes in area for each LULC class.



(a) LULC map 2016



(b) LULC map 2020



(c) LULC map 2024

Figure 3. LULC maps of Krueng Pase Watershed year 2016 (a), 2020 (b), and 2024 (c)

To analyse the persistence in each LULC change class, a land-use change test was conducted to determine the extent of transitions between one class and another, identifying interrelated and detectable changes. As shown in Figure 5 and Figure 6, there is minimal change in the waterbody area. However, the persistence of changes in cropland and forest remains the highest, with significant area coverage. In Figure 6, the map displays color-coded areas representing changes in each class.

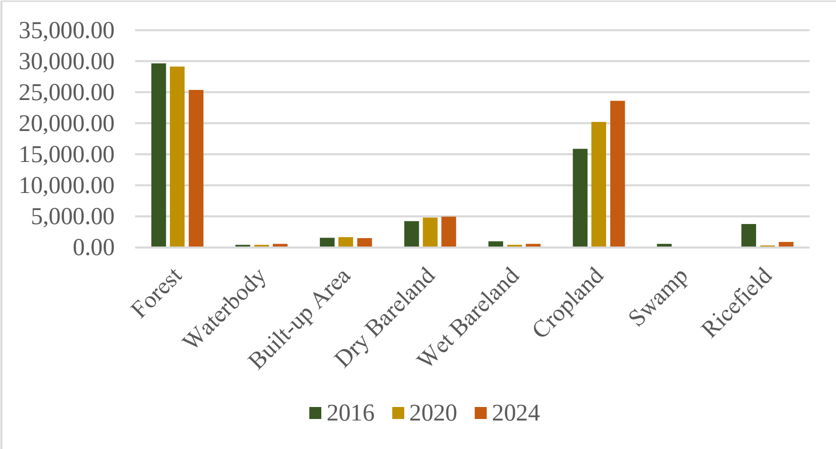


Figure 4. LULC changes 2016-2024

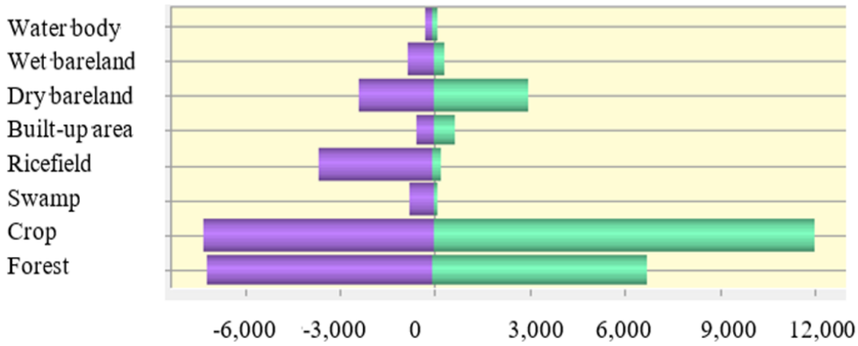


Figure 5. Gains and losses of LULC category between 2016-2024 (ha)

Table 1. Data overview of processed LULC data from Sentinel 2 imagery

2016	Count	Resolution (m)	m^2	ha
Forest	2,965,426	10	296,542,600	29,654.30
Waterbody	41,739	10	4,173,900	417.39
Built-up Area	158,359	10	15,835,900	583.59
Dry Bareland	426,456	10	42,645,600	4,264.56
Wet Bareland	100,906	10	10,090,600	1,009.06
Cropland	1,590,705	10	159,070,500	1,5907.10
Swamp	60,013	10	6,001,300	600.13
Ricefield	377,496	10	37,749,600	3,774,96
2020	**Count**	**Resolution (m)**	**m^2**	**ha**
Forest	2,916,012	10	291,601,200	29,160.10
Waterbody	45,062	10	4,506,200	450.62
Built-up Area	166,115	10	16,611,500	1661.15
Dry Bareland	482,948	10	48,294,800	4829.48
Wet Bareland	45,402	10	4,540,200	454.02
Cropland	2,023,025	10	202,302,500	20,230.30
Swamp	9,643	10	964,300	96.43
Ricefield	32,893	10	3,289,300	328.93
2024	**Count**	**Resolution (m)**	**m^2**	**ha**
Forest	2,538,662	10	253,866,200	25,386.60
Waterbody	57,228	10	5,722,800	572.28
Built-up Area	152,507	10	15,250,700	1,525.07
Dry Bareland	497,566	10	49,756,600	4,975.66
Wet Bareland	57,483	10	5,748,300	574.83
Cropland	2,321,642	10	23,2164,20	23,216.40
Swamp	7,632	10	763,200	76.32
Ricefield	88,380	10	8,838,000	883.80

3.2 Mock model calculated discharge

A hydrological model describes the amount of flow or rainfall input that occurs in the Krueng Baro watershed. The F.J. Mock method is a hydrological model based on the concept of water balance, which assumes that some of the rainwater that falls on a watershed will flow directly and some will infiltrate the soil [25]. The F. J. Mock method was chosen to predict discharge because calculations using the model are accurate and take into account more natural conditions that affect river flow. Therefore, this method is relatively simple and allows the prediction of river discharge at monthly and annual time intervals. Figure 7 shows the discharge data from 2016-2023. The correlation test yielded an R^2 value of 87.6%, indicating a *very good* level of accuracy, while the RMSE was measured at 0.0871, reflecting *good accuracy*.

The F. J. Mock Model's advantage lies in its simplicity and flexibility, which can be used even in watersheds with limited data. This model is often used to evaluate river discharge potential, analyze flood risk, or manage regional water resources [37, 38]. With its ability to predict hydrological responses, the Mock Model is an important tool to support watershed conservation planning and sustainable water management, especially in environmental degradation and climate change challenges [39].

Seven parameters are used to calculate simulated discharge in the Krueng Baro watershed, including evapotranspiration, water balance on the soil surface, excess water and soil moisture, infiltration, soil flow recession factor, soil water storage, and river flow [14, 40-43]. These seven parameters are calculated one by one, followed by calculating the simulated discharge by multiplying the catchment area by the total runoff, multiplied by 1,000, and then by the day's product multiplied by 24 and 3,600. The simulated discharge results obtained are in the form of debit calculation or, in other words, have been calculated from mm to m^3/s.

Discharge depends on rainfall and soil conditions, including soil texture, density, and moisture levels. Soils with porous and less dense structures allow water to infiltrate more easily (high infiltration), while dense or saturated soils tend to have low infiltration and can increase surface runoff [44]. The Krueng Baro watershed has various soil types depending on location and elevation. In the upper reaches, which are hillier and more mountainous, soils tend to have a coarser texture, such as sandy loam soils. In the lower reaches, which are flatter and closer to the coast, the soils usually have a finer texture, such as sandy clay [8]. Figures 7 and 8 show the trend of rainfall, observed discharge and simulated discharge using the Mock method.

3.3 Flood vulnerability

Determining flood-prone areas has been based on parameters such as rainfall intensity, slope gradient, and land use [8]. It was found through simulation that the area under impervious land cover will keep on increasing resulting in increased surface runoff leading to increased peak flood discharge as can be seen in the hydrograph. Flood depth calculations show the evolution of flooding affected area over time. Flood mitigation activities in this area require the correct spatial planning and land-use management. Proper spatial planning and land-use management are required for flood mitigation efforts in this location. These measures are essential in controlling LULC changes and minimizing the impact of flood disasters.

Based on Figure 9, it can be seen that in 2022, the area of inundation or flooding increases. This is based on the forest area development in 2024, which decreased by 13.72%, while use is one of the factors in increasing river flow. It can also be confirmed by the trend of discharge that occurs in 2022, although rainfall is still within standard capacity [45]. Watershed management involves human efforts to regulate the interaction between natural resources, human activities, and ecosystems to maintain sustainability and balance while enhancing resource availability for society [35]. Frequent flooding in the Krueng Baro watershed has led to community losses and infrastructure damage. To address this issue, this study proposes reorganizing LULC as a key solution [46, 47].

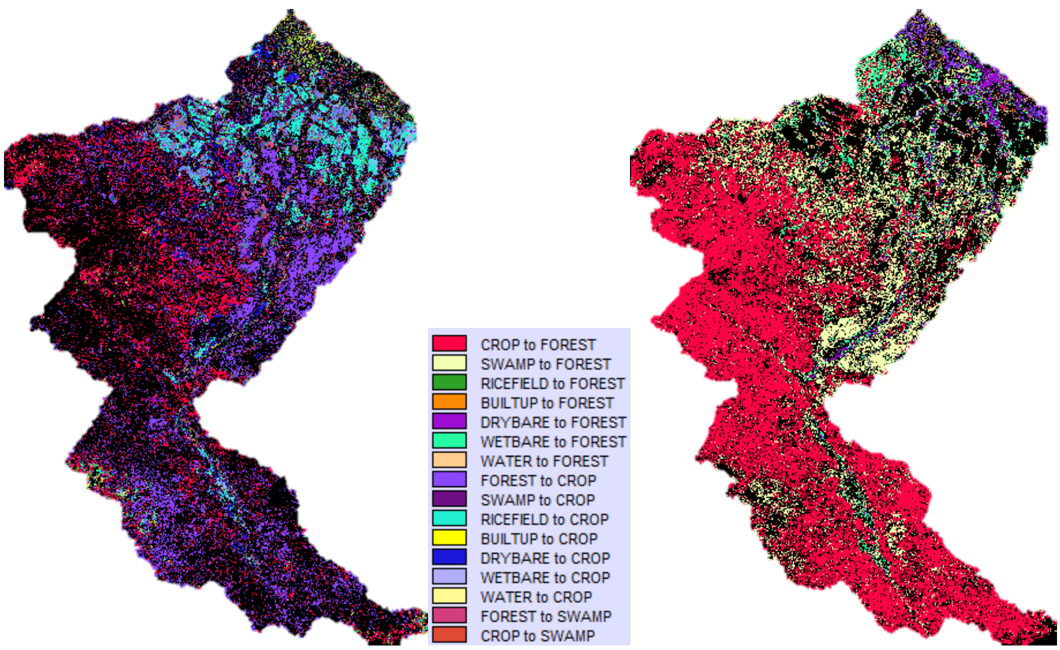


Figure 6. LULC and persistence maps for 2016-2024

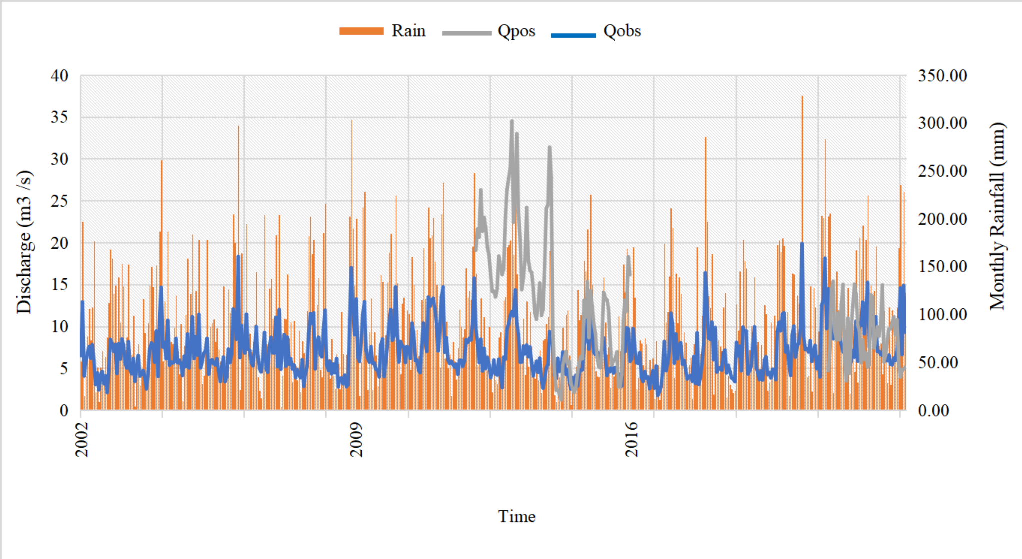


Figure 7. Discharge trends from 2002 to 2022

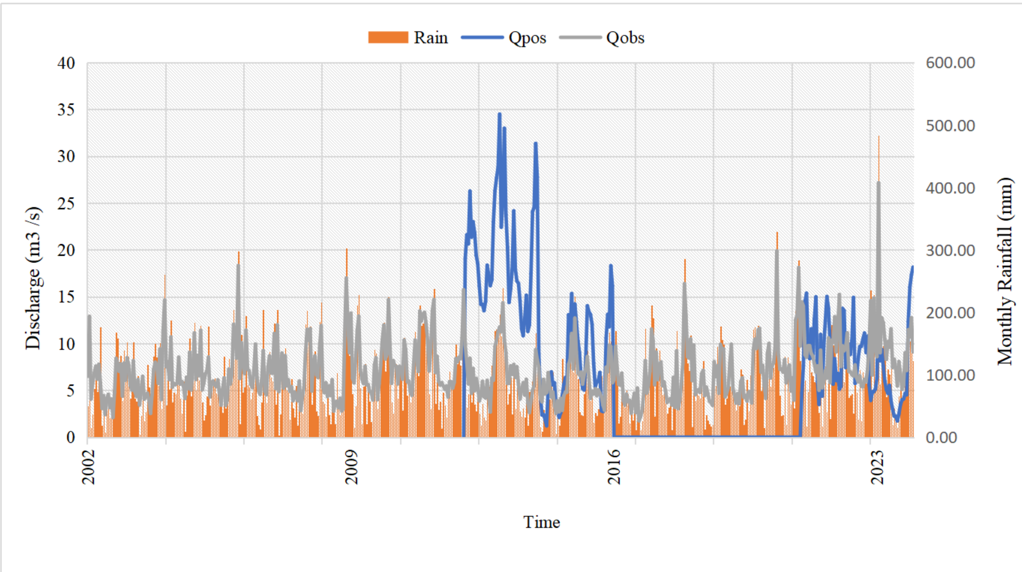


Figure 8. Simulated and observed discharge data (2002-2023)

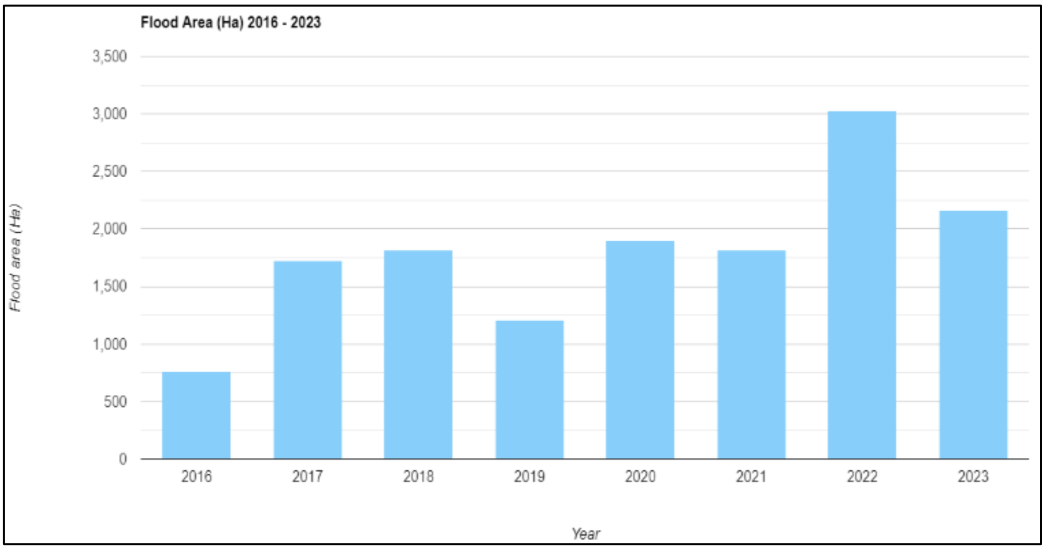


Figure 9. The extent of flooding in the Krueng Baro watershed (2016-2023)

Human activities such as urbanization, deforestation, infrastructure development, and other land management practices can significantly modify an area's hydrological response [48, 49]. For example, urbanization can create impermeable surfaces that accelerate water flow into rivers, increasing peak discharge and flood risk. Deforestation can also reduce the capacity of soil and vegetation to absorb water, increasing runoff. Distinguishing between 'land use,' which involves human activities like development and agriculture, and 'land cover,' which refers to natural features such as vegetation and water, helps assess both direct and indirect environmental impacts. To optimize LULC allocation for flood mitigation, goal programming constraints were applied, considering changes in LULC areas within the study region. Several key factors influencing LULC changes and location preferences for specific land cover types included elevation, slope, annual rainfall, average income per capita at the sub-district level, population density, proximity to road networks, distance to streams, and nearness to existing urban areas. Land use planning is crucial in regulating surface flow and water discharge as part of natural mitigation efforts [50].

These changes were analyzed using a combination of the RF, providing a clear and detailed view of spatial and temporal patterns. A combination of RF and maximum likelihood models were used to analyze these changes, providing a detailed spatial and temporal picture [51, 52]. Data generated from LULC analysis, such as the area covered by vegetation or the area that has been urbanized, can be integrated into the model parameters. Changes in LULC affect river water discharge, thus affecting water availability. The reduction in forest area impacts on ecosystem and climate service functions [53], so forest area management programs need to be improved [9].

Understanding the Earth's changing surface over time heavily depends on analyzing LULC. LULC describes how different land covers are utilized for human activities, such as agriculture, urban development, and conservation. In contrast, *land cover* refers to the physical features present on the Earth's surface, including vegetation, urban areas, water bodies, and soil. Using imagery and its applications in urban planning, environmental management, agricultural monitoring, and climate change mitigation strongly rely on LULC analysis.

Land use plays a crucial role in water storage and is directly associated with flooding. Its impact is quantified using the runoff coefficient, which differs depending on the type of land use [54]. Research has shown that land-use alterations significantly influence flood runoff and inundation more than climate changes [55]. The progressive conversion of natural landscapes into urbanized or agricultural areas influences the three key aspects of flood risk: hazard, vulnerability, and exposure. The expansion of human settlements and economic activities in flood-prone zones, combined with inadequate land-use planning, has amplified the threat of flooding in these areas. Furthermore, the adverse effects extend beyond physical hazards, intensifying economic, social, and environmental vulnerabilities within affected communities [47].

Flood susceptibility in a particular region is shaped by natural watershed characteristics—terrain, soil composition, and drainage capacity—and anthropogenic factors, including land management policies and economic sensitivity to flood damage [56]. The relationship between environmental degradation, land transformation, and flood risk is widely acknowledged, underscoring the necessity of sustainable land-use strategies.

Urban and regional planners play a pivotal role in synthesizing insights from multiple disciplines to guide land development decisions. Their responsibilities vary across different contexts, yet their primary function remains the same: to provide expert analysis and strategic recommendations that support responsible land utilization. Since land-use planning is integral to flood-risk mitigation—particularly in controlling development within flood-prone regions—it must be closely coordinated with flood management efforts. Comprehensive flood prevention measures should be incorporated at all planning levels, ensuring that hydrological data and land-use projections inform urban policies and infrastructure development. In practice, improved access to river flow data and its correlation with land use can empower decision-makers to devise effective strategies for minimizing present and future flood risks [57].

4. CONCLUSION

Sentinel-2A satellite images and RF analysis were used in LULC analysis from 2016 to 2024. The results showed strong performance, with an average kappa value of 0.828 and an overall accuracy of 88.467%. The dependability of the data was confirmed by the land use classification accuracy, which continuously surpassed 85% in 2016, 2020, and 2024. The Mock Model is used to assess how streamflow dynamics are affected by changes in the landscape. Data pertaining to runoff provides important information, especially when high water flow causes flooding because of the river's restricted capacity.

Data generated from LULC analysis, such as the area covered by vegetation or the area that has been urbanized, can be integrated into the model parameters. For example, a decrease in vegetation cover can increase surface runoff and reduce infiltration, thus affecting the calculated river discharge. Thus, the combination of LULC analysis and the Mock Model provides an integrated approach to evaluate flood risk, water resource sustainability and the impact of development policies. The combination of LULC analysis and the Mock Model provides excellent benefits in managing watersheds sustainably amidst climate change and environmental degradation challenges.

By using the results of the LULC analysis as input into the Mock Model discharge simulation, water resource managers can design more effective mitigation strategies, such as creating water catchment areas or forest rehabilitation in critical watersheds This approach supports flood risk management, improves water use efficiency, and designs data-driven policies supporting sustainability of watershed ecosystems. If look at the flood prediction modeling results detected using SRTM data processing results, it can be seen that flood conditions in 2022 will increase by an area of This proves that between 2016 and 2024, LULC will experience a decrease in vegetation of 4,267.7 hectares and an increase in built up area and bareland under development.

The limitation in this research is that the RF method can be used in conjunction with the supervised method. This is because much correct train data is needed for higher accuracy. However, the unsupervised RF in this research has a good application, but it needs to be collaborated with supervised methods to train visible objects better. This research was helped by the choice of Sentinel-2A imagery with a resolution of 10 m, making the image clearer.

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