

Land Use Change Modelling Using Logistic Regression, Random Forest and Additive Logistic Regression in Kubu Raya Regency, West Kalimantan

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Abstract

Kubu Raya Regency is a regency in the province of West Kalimantan which has a wetland ecosystem including a high-density swamp or peatland ecosystem along with an extensive area of mangroves. The function of wetland ecosystems is essential for fauna, as a source of livelihood for the surrounding community and as storage reservoir for carbon stocks. Most of the land in Kubu Raya Regency is peatland. As a consequence, peat has long been used for agriculture and as a source of livelihood for the community. Along with the vast area of peat, the regency also has a potential high risk of peat fires. This study aims to predict land use changes in Kubu Raya Regency using three statistical machine learning models, specifically Logistic Regression (LR), Random Forest (RF) and Additive Logistic Regression (ALR). Land cover map data were acquired from the Ministry of Environment and Forestry and subsequently reclassified into six types of land cover at a resolution of 100 m. The land cover data were employed to classify land use or land cover class for the Kubu Raya regency, for the years 2009, 2015 and 2020. Based on model performance, RF provides greater accuracy and F1 score as opposed to LR and ALR. The outcome of this study is expected to provide knowledge and recommendations that may aid in developing future sustainable development planning and management for Kubu Raya Regency.

Keywords: land use change modelling, wetlands, logistic regression, random forest, additive logistic regression.

1. Introduction

Peat forest is an area that has the potential to store carbon stocks many times more than tropical rain forests or mineral forests (Adeolu *et al.*, 2018; Aditya *et al.*, 2020). The richness of biodiversity in peat forests also varies, interacting with each other to establish peat ecosystems. However, despite the potential benefits, peat forest is vulnerable to forest and land degradation (Abraham *et al.*, 2023). Land clearing is commonly followed by burning, while dry peatland is highly susceptible to fire. Fire on peatland cause the release of carbon into the atmosphere. The process of releasing greenhouse gases via the oxidation of peat into the atmosphere triggers a high level of greenhouse gas emissions (Abuhay *et al.*, 2023).

The amount of emissions resulting from degraded peatlands is greater than the emissions produced by other ecosystems. Based on the research conducted by Rahsia *et al.* (2021), the amount of CO² emissions on peatlands that burned in May-July 2019 in the city of Pontianak indicated that CO² flux during the measurement period ranged from 183-595 tons of CO². The research undertaken by Aguilera *et al.* (2023) maintains that the estimated calculation of carbon released by deforested and drained tropical peatlands is 31 Mg C per hectare, per annum. Emissions from peatlands have a significant impact on the surrounding biodiversity. The temperature of the Earth will increase due to heat trapped in the atmosphere. Preserving the earth from experiencing a temperature rise over 2 degrees Celsius in the future can be achieved by conserving peat ecosystem areas (Akbar *et al.*, 2023).

Peat ecosystem protection and management where attempts are made to preserve the function of the peat ecosystem and prevent loss to the peat ecosystem have been included in the Regulation of The Government of The Republic of Indonesia. The regulation also mandates stakeholders to prepare a Peat Ecosystem Protection and Management Plan document (RPPEG), that contains analysis and recommendations on peat ecosystem management (Beroho *et al.*, 2023). The document is summarised into a document for the protection and management of peat ecosystems at the provincial and regency levels. The RPPEG is expected to ensure the preservation of peat ecosystem functions in West Kalimantan, specifically in Kubu Raya Regency.

Kubu Raya Regency is a regency situated in West Kalimantan Province with somewhat extensive peat wetlands that support numerous economic activities. The most common activities that are carried out as a source of livelihood for people on peatland include farm management, fish farming, and other activities with high economic value (Wang, 2022). However, the utilisation of peatlands frequently fails to pay attention to the application of the principle of sustainable peatland



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use. One peatland exploitation activity that produces widespread damage is the draining of peatlands which causes drought resulting in peat fires, notably in the dry season. Therefore, the Indonesian government has focused on Kubu Raya Regency with the aim of restoring the peat. Based on these conditions, conducting land use change analysis is essential to support the government's goal of ensuring the preservation of peat ecosystem functions and to specifically assist in preparing the RPPEG documents, particularly in relation to Kubu Raya Regency.

Land use change analysis can be completed by building a model. The land use change model may facilitate the understanding of the process of land use change and its driving factors (Bohai *et al.*, 2023; Cao *et al.*, 2023; Danardono, *et al.*, 2021; Fikriyah, *et al.*, 2023). In addition, the model can be used to predict changes in land use and land cover by means of a simulation process based on a geographic information system using a statistical machine learning approach. The most common model in classification is Logistic Regression (LR), which is an example of Generalised Linear Models (GLM) (Chen *et al.*, 2022). In linear models, such as linear regression, the assumption that the response variables are normally distributed is required. In fact, response variables are repeatedly found in the form of binomial, Poisson, gamma and several exponential family distributions. Hence, the GLM has developed to overcome this problem.

GLM have three components: (i) the random component specifies the response variable and its probability distribution; (ii) linear predictors; and (iii) link function connects the random component with the linear predictors. In the context of the GLM, the distribution of a random component in LR is binomial and the link function is the natural log of the odds known as logit link function. Nonetheless, LR only captures the linear relationship between the logit link function and the explanatory variables (Tsiripidis, 2023). Nonlinear relationship patterns can be identified by replacing the linear predictors component in the GLM with the additive components. Hastie & Tibshirani (1985) developed and improved the component in GLM using the additive approach, as clearly explained in Subchapter 2.4. GAM employ a series of smoothing splines to express the nonlinear relationship between the expected mean of responses and a set of predictors. Similar to GLM, the adaptation of the logit link function in GAM is known as Additive Logistic Regression (ALR). ALR is able to model more complex relationships than those observed in GLM (Daba *et al.*, 2022).

Several previous studies of land use change modelling, namely land use change in the Western Highlands of Vietnam using LR, in a tropical mountain landscape of Northern Ecuador using GAM and in Waterloo, Ontario, Canada, compare the performance of Markov Chain, LR, ALR and survival analysis (Siddik *et al.*, 2022). However, the study area does not comprise peatlands, land change analysis is only undertaken in forest areas, together with agricultural and development areas. In general, peatlands are terrestrial wetland ecosystems. Thus, the study aims to develop a land use change model and predict the existing wetland in Kubu Raya Regency, West Kalimantan Province using LR from the GLM family, ALR as a component of GAM and Random Forest (RF), as a tree-based model that is also capable of identifying nonlinear relationships (Emmanuel *et al.*, 2023).

Based on the forest and land fire early warning and detection system, the largest changes ensued in West Kalimantan due to the fires that occurred between 2014-2019. Various factors contribute to the forest and land fires in West Kalimantan, although the large area of peatlands, particularly in Kubu Raya Regency are the main potential for fire disasters. These peatlands are prone to fire caused by human activities to clear and dry the peatland area and then develop it into plantation areas (Gao *et al.*, 2023). Numerous research has been carried out to prevent fire via a hydrological approach (Assidik *et al.*, 2021), forest and fire hazards modelling employing the Hybrid Fire Index and to provide awareness of community empowerment (Akbar *et al.*, 2023). Therefore, this study uses another approach through land use change modelling to prevent and overcome peatland fires. The years of observation were conducted in 2009, 2015 and 2020. This research predominantly focuses on the class of wetlands in land cover because peatland comes under this particular classification. The comparative study on the performance model aims to ascertain the potential changes in wetlands, enabling the development of valuable planning recommendations.

2. Research Methods

2.1. Study Area

The study area considered for this study was the regency of Kubu Raya. Kubu Raya is a regency resulting from the expansion of Pontianak Regency which was formed via Law No. 35 of 2007 with an area of 6,985.20 km². Kubu Raya is divided into nine sub-regencys, as shown in Figure 1. Kubu Raya is located on the west of West Kalimantan Province. The study area is located between longitudes 108°35' - 109°58' E and latitudes 0°44' N - 1°01' S. The physical character of

the regency consists of land areas and coastal islands that include seas. Kubu Raya is also composed of watersheds, namely Kapuas watershed in the downstream section, allowing many natural products from the upstream area of Kapuas River to flow into Kubu Raya. This allows the development of processing industries from various natural product commodities in Kubu Raya along the Kapuas River. Kubu Raya has 39 small islands situated in the marine coastal area. These islands are predominantly inhabited by the community who work as fishermen. The population has limited access to public services due to unequal development in remote areas.

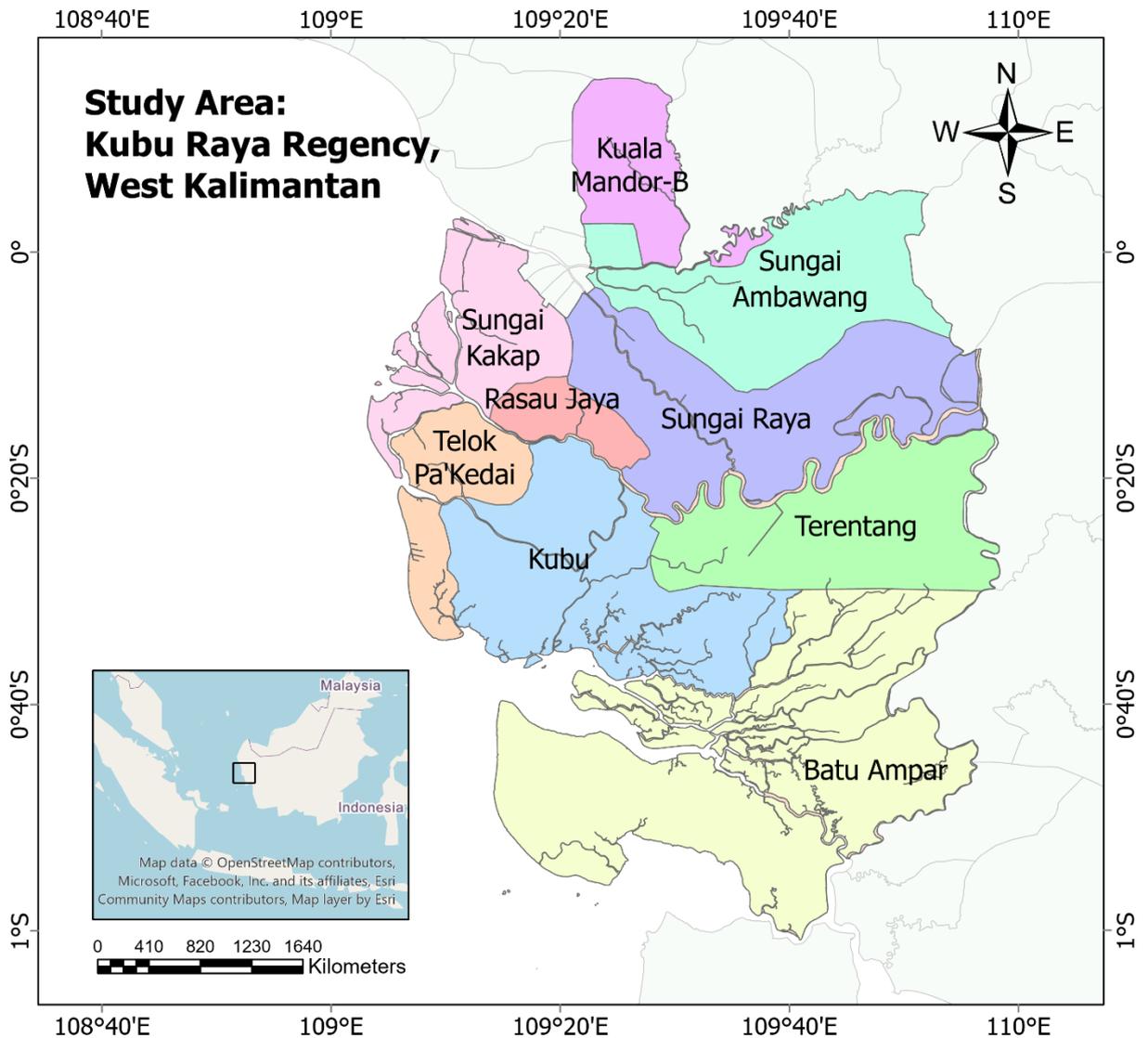


Figure 1. Map of Kubu Raya Regency, the Study Area.

2.2. Data

The original LC map covers the entire region of Indonesia. In this case, the national map has to be cut out of one dataset using an administrative area in the study area (see the illustration below). Observations during this period indicated numerous changes in land cover, predominantly due to fires and other land use change activities across the wetlands. The LC MoEF map has a resolution of 100 x 100 m with a one-pixel unit equivalent to an area of one hectare (Gaur, 2023). The response variables applied in the land cover classification based on the PPIC documents are forest land (F), cropland (C), grassland (G), wetlands (W), settlements (S), as well as other lands (O).

The occurrence of land use land cover change is caused by a combination of several driving factors triggering land change. The complexity, research site conditions and predetermined response variables are considered to establish the driving factors that are responsible for land use change or the explanatory variables determined based on the previous study listed in Table 1, along with the data sources used shown in Table 2.

Table 1. Explanatory Variables,

Variable	Description	Source
X1	Distance to road	(Ghosh, 2020; Baig, 2021)
X2	Distance to river	(Ghosh, 2020)
X3	Slope	(Baig, 2021)
X4	Elevation	(Baig, 2021)
X5	Distance to lost wetlands	(Ghosh, 2020)
X6	Population density	(Ghosh, 2020)
X7	Distance to city	(Ghosh, 2020)

Table 2. Data Used in This Research,

Data	Source
LC 2009, 2015, 2020	LC MoEF
Distance to road	Maps of the Earth’s Surface (RBI) from BIG
Distance to river	RBI from Geospatial Information Agency (BIG)
Slope	SRTM-DEM from United States Geological Survey (USGS)
Elevation	SRTM-DEM from USGS
Distance to lost wetlands	LC MoEF 2009 and 2015
Population density	Central Bureau of Statistics (BPS) Kubu Raya 2010
Distance to city	LC MoEF

2.3. Classification of Land Cover Classes

The MoEF data has 23 LC classes which are then regrouped into six LC classes as a response variable with reference to the definition provided by the Intergovernmental Panel on Climate Change (IPCC) (2003) document, specifically forest land (F), cropland (C), grassland (G), wetlands (W), settlements (S), and other lands (O). The reclassification step will assist in capturing changes in land cover by means of a more specific class with a focus on wetland cover as a class that is confirmed to have experienced significant changes. Table 3 presents the detail of the classification of the LC class.

Table 3. Classification of LC.

LC MoEF Code	LC MoEF Class	ID	LC IPCC
2001	Primary dryland forest	1	Forest land
2002	Secondary dryland forest	1	Forest land
2004	Primary mangrove forest	4	Wetlands
20041	Secondary mangrove forest	4	Wetlands
2005	Primary swamp forest	4	Wetlands
20051	Secondary swamp forest	4	Wetlands
2006	Plantation forest	1	Wetlands
2007	Dry shrub	3	Grassland
2010	Estate crop	2	Cropland
2012	Settlement areas	5	Settlements
2014	Bare ground	6	Other lands
2500	Cloud	6	Other lands
3000	Savanna and grasses	3	Grassland
5001	Open water	4	Wetlands
20071	Wet shrub	4	Wetlands
20091	Pure dry agriculture	2	Cropland
20092	Mixed dry agriculture	2	Cropland
20093	Paddy field	2	Cropland
20094	Fish pond/aquaculture	4	Wetlands
20121	Port and harbour	5	Settlements
20122	Transmigration areas	5	Settlements
20141	Mining areas	5	Settlements
50011	Open swamp	4	Wetlands

2.4. Logistic Regression

LR is a component of GLM. GLM consists of a random component, linear predictors and a link function relating two components. In the LR model, the response variable or the random component in the GLM, is assumed to have a binomial distribution. The natural parameter for the binomial distribution is the log odds of response outcome 1, the supposed logit of π_i . The logit is the link function for binary random components.

Logit link function provides the probability of land use land cover change; in this particular study the change in wetlands as a function of explanatory variables. The likelihood of land use change in every pixel is a function of the value of the explanatory variable at the same pixel. LR is employed to retrieve the variable conversion of wetlands in Kubu Raya Regency (Géant *et al.*, 2023). The LR model (Equation 1) was formulated to be written as follows:

$$\pi(x_i) = \frac{e^{\beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \beta_3 X_{3i} + \dots + \beta_n X_{ni}}}{1 + e^{\beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \beta_3 X_{3i} + \dots + \beta_n X_{ni}}} \quad (1)$$

where:

- n = number of explanatory variables
- $\pi(x_i)$ = probability of each pixel for the occurrence of land cover types
- X_1, X_2, \dots, X_n = explanatory variables corresponding to the driving factors
- $\beta_1, \beta_2, \dots, \beta_n$ = regression coefficients

The model can be transformed linearly where the link function f transforms x_i to the natural parameter known as the canonical link. $f(x_i)$ is the logit link function of $\pi(x_i)$, commonly termed logit transformation, as shown in Equation 2:

$$f(x_i) = \ln\left(\frac{\pi(x_i)}{1 - \pi(x_i)}\right) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \dots + \beta_n X_n \quad (2)$$

The probability of the occurrence of wetlands can be determined at each pixel using the *glm()* command with the argument *family='binomial'* in R that is available in the *lulcc* package as a function to execute LR analysis.

LR is a common method in predictive models used in land use change modelling. LR was initially applied in relation to deforested land in Massachusetts, land use change in Thailand by Buya (2020) and Vietnam by Huu *et al.*, (2022). Based on the simulation results obtained by those studies, LR is reasonably accurate at predicting the quantity of land use changes, nevertheless the model depended on the quantity and completeness of the driving factors.

2.5. Random Forest

Random Forest (RF) is a combined tree method in which the number of trees produced forms a forest enabling the analysis to be performed on a group of these trees. RF uses the majority vote mechanism of the various trees created to solve classification or prediction problems. Girma *et al.* (2022) described RF on a dataset of size n with a number of q explanatory variables in the following stages:

- i. Random sampling is performed by the bootstrap replacement of size n in each training dataset.
- ii. Trees are built up to their maximum size (without pruning). The tree's construction is conducted by randomly selecting variables where m explanatory variables are chosen with $m < q$. From the m explanatory variables, the best is selected as a divider and continues with separating into two new nodes. This process continues until the minimum size of observations in the node is reached.
- iii. Steps (i) and (ii) perform many L repetitions to obtain L decision trees.

Similar to LR, the model is ready to use in *lulcc* and can be performed using the *randomForest()* command with the default set parameter for the number of trees to grow to the equivalent of 500. The number of variables randomly sampled as candidates at each split is equal to two.

RF has been used in estimation and change in land cover under the urban area. The study compared the machine learning algorithms RF, K-Nearest Neighbour (KNN) and Support Vector Machine (SVM) with advanced deep learning algorithms DeepLabv3+, the variant of Deep Neural Network (DNN). Concerning the performance evaluation of all the algorithms, specifically in the case of urban targets, the DeepLabv3+ recorded the highest overall pixel accuracy and F1 score

followed by RF, KNN and SVM. Among the traditional machine learning algorithms, RF classifier exhibits a meaningful contribution from each of the classes but failed to map the river water accurately.

2.6. Additive Logistic Regression

The GAM (Generalised Additive Model) directly accommodates the existence of the non-linear effects of independent variables without having to explicitly understand the structure of these influences. GAM is the extension of GLM that replaces the linear predictors with an additive component. The ALR model is one of the families associated with GAM whose additive components are adapted to the LR model to become an additive logistic model as follows (Equation 3):

$$g(x_i) = \ln\left(\frac{\pi(x_i)}{1 - \pi(x_i)}\right) = s_0 + \sum_{j=1}^p s_j(x_{ij}); i = 1, 2, \dots, n \quad (3)$$

where $s_1(\cdot), s_2(\cdot), \dots, s_j(\cdot)$ are smooth functions. Based on the above function, all values in the additive component $G(x) = s_0 + \sum_{j=1}^p s_j(x) \in R$ have a logit link function $g(x_i)$. Not unlike the GLM, the probability to predict wetlands in the GAM is defined in Equation 4:

$$\pi(x_i) = \frac{e^{G(x_i)}}{1 + e^{G(x_i)}} \quad (4)$$

Applied the backfitting algorithm together with the local scoring method to obtain the fit model and estimate the smooth function in a nonparametric fashion. The study on land use change modelling using the GAM achieved a better performance than LR, Markov chain and survival analysis (Change *et al.*, 2018).

The ALR model is not supported in the current version of the *lulcc* package. In R, Huo *et al.*, (2022) developed the ALR algorithm into the *mgcv* package. Thus, the fitting and predicting command in *mgcv* is modified via the source code. The probability of the occurrence of wetlands using ALR in R could be executed using *gam()* command with the argument *family='binomial'*.

2.7. Data Analysis Procedure

Land use change modelling were conducted using the statistical program R using *lulcc* package that supports binary logistic regression and random forests (Jafarpour *et al.*, 2022). The model has been modified and combined with GAM in R using *mgcv* package (Kumar *et al.*, 2023). The procedure of analysis (Figure 2) in the study was as follows:

1. Collect LC maps of 2009, 2015 and 2020 and spatial parameters.
2. Produce land use change maps and transition probability matrices of land use changes to identify the largest dominant changes.
3. Combine all the maps.
4. Obtain 5% of the sample data using simple random sampling. The sample data will be compared with the overall data to identify the effect of the model for any type of data.
5. Split the sample data into two pieces, 80% is used for the training dataset, whilst the remainder as the test dataset.
6. Perform the LR, RF and ALR model using the training dataset.
7. Evaluate the model using the test dataset based on the accuracy, F1 score and AUC-ROC (Area Under Curve-Receiver Operator Characteristic) metrics (Pontius & Parmentier, 2014).
8. Repeat the process in steps 5 to 7 for the overall data 10 times to evaluate the overall performance of the model in order that the average goodness-of-fit value of each combination of variables is obtained.
9. Generate the prediction maps with the best model and validate by means of the actual map using the multi-label confusion matrix based on the performance value in step 7.

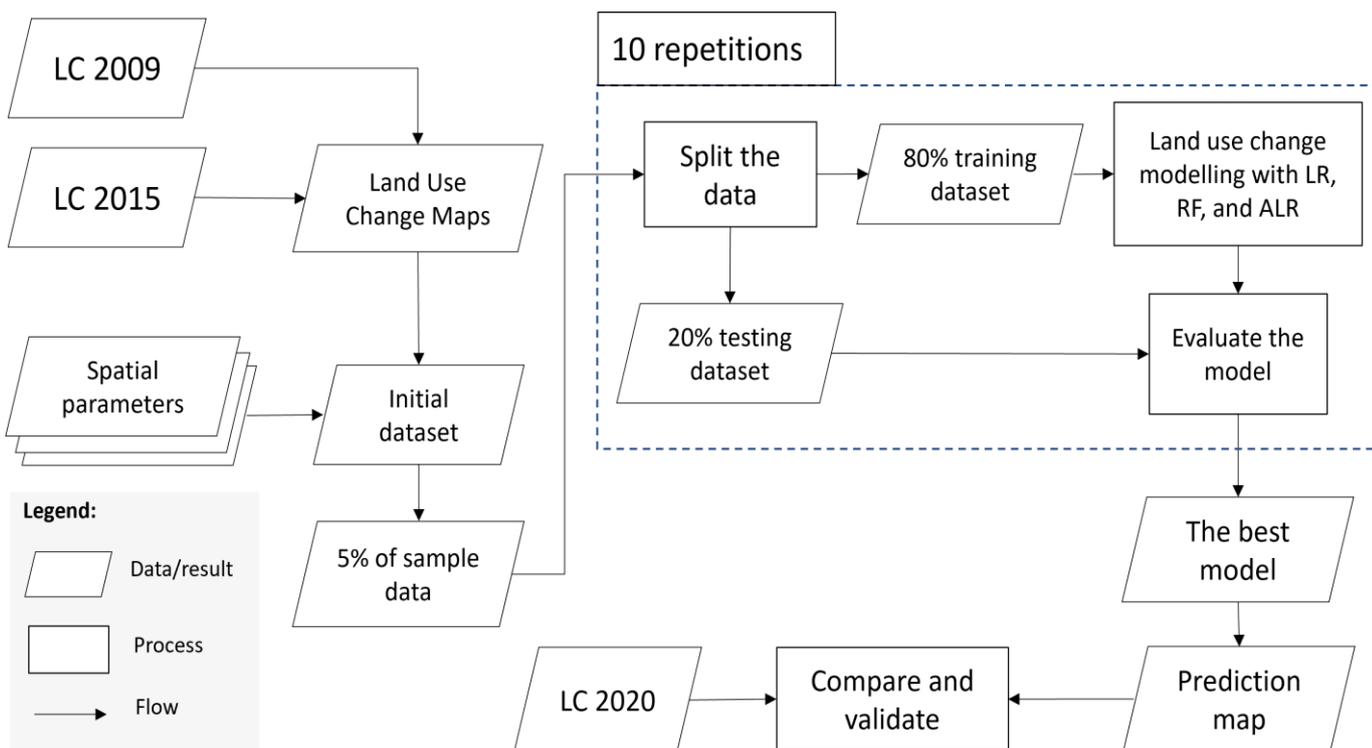


Figure 2. Analysis Process.

3. Results and Discussion

3.1. Land Cover Maps of Kubu Raya Regency

Figure 3 illustrates the map of Kubu Raya Regency with the six LC classes comprising a total area of 853,451 hectares (ha) with dimensions of 1,024 x 1,375 pixels. The details of the total area represented by those classes were considered by calculating the number of pixels multiplied by the area each cell represents. The process to calculate the total area for each class was obtained automatically using the terra package in R. Based on the area calculation of the LC maps from 2009–2020, wetlands and cropland dominated the regency of Kubu Raya. The area of LC in each observed year is presented in Table 4.

In 2009, wetlands comprised up to 556,561 ha or 65.2% of the total area of Kubu Raya Regency whereas cropland covered 32.35%. Six years later in 2015, wetlands decreased dramatically to approximately 425,489 ha or 49.86% of Kubu Raya Regency. Simultaneously, cropland increased by roughly 10.68% to occupy an area of roughly 367,212 (43.03%). The decline in the area of wetlands continued to occur in the following five years to 2020, covering 396,542 ha or 46.46% of the area. The area of cropland in 2020 dominated to become 46.58% of the total area of Kubu Raya Regency.

Forest land area increased appreciably between 2009–2020 owing to plantation forests in the LC MoEF being classified as forest land in the IPCC LC class. The development of settlements continued, rising to 10,524 ha in 2020, particularly in the area near Pontianak City. The land use category which changed dynamically comprised other lands. In 2009, it occupied approximately 0.99% of Kubu Raya Regency, although by 2015, it had increased to roughly 2.58%. Concerning grassland, only minimal changes were observed from 2009 to 2020.

Table 4. The Area of LC in Kubu Raya Regency.

No	LC	2009		2015		2020	
		ha	%	ha	%	ha	%
1	Forest land	6,691	0.78	33,280	3.90	37,754	4.42
2	Cropland	276,056	32.35	367,212	43.03	397,505	46.58
3	Grassland	1,975	0.23	1,404	0.16	1,489	0.17
4	Wetlands	556,461	65.20	425,489	49.86	396,542	46.46
5	Settlements	3,849	0.45	4,027	0.47	10,524	1.23
6	Other lands	8,419	0.99	22,039	2.58	9,637	1.13

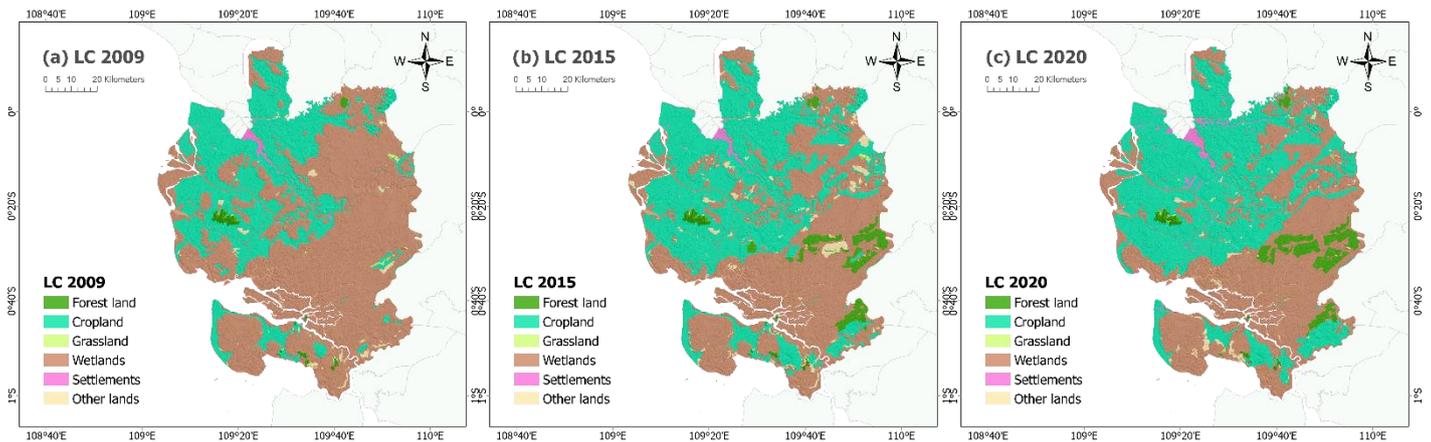


Figure 3. Land Cover Maps of Kubu Raya Regency in (a) 2009 (b) 2015 (c) 2020.

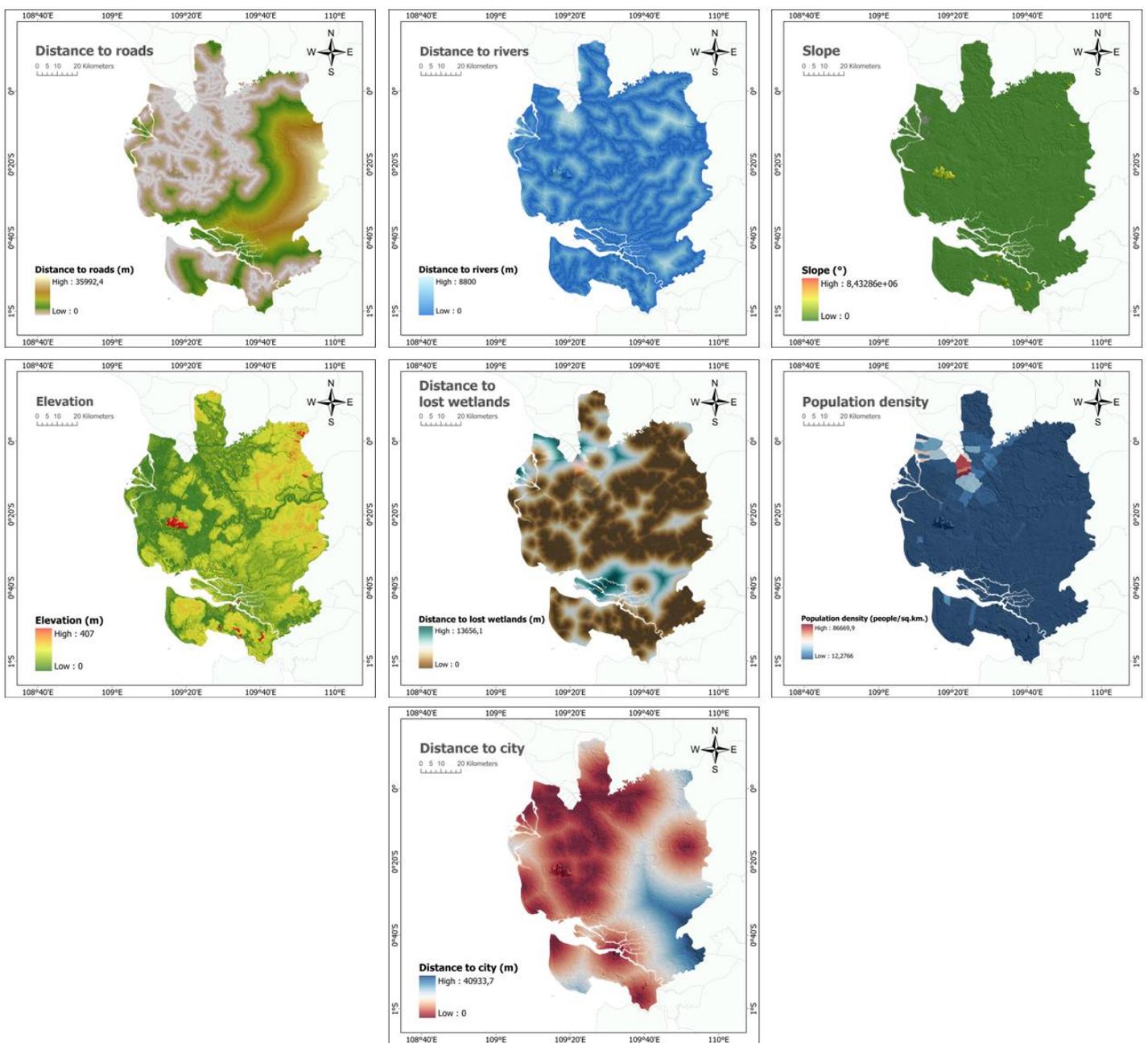


Figure 4. Explanatory Variable Maps. Distance to roads, distance to rivers, slope, elevation, distance to lost wetlands, population density and distance to city.

3.2. Spatial Data Layers of The Independent Variables

The explanatory variable map employs maps from several sources that have been clipped with the boundaries of Kubu Raya Regency and adjusted to the dimensions in the LC MoEF map. The distance to road variable is generated from arterial roads, local roads and collector roads which are used as driving factors to explain that the closer land use is to the road, the faster land use changes occurred. Distance to the river taken from the main river, population density and distance to the city also reveal something similar; that the closer the land use is to that aspect, the faster the land use changes occurred, considering the spatial proximity of roads and cities as important influencing factors (Ghosh *et al.*, 2020).

The slope and elevation from the Landsat DEM image are employed with the assumption that there is a strong relationship with land use land cover changes. Baig *et al.* (2021) included slope because the altitude dynamic is frequently associated with anthropogenic activity. The variable distance to the lost wetlands is obtained from the transition of reduced wetland area due to land use change activities in 2009-2015. Proximity to lost wetlands is essential for determining the vulnerable parts of a wetland area (Ghosh *et al.*, 2020). The explanatory variables maps are shown in Figure 4.

3.3. Land Use Change 2009-2015

Identification of land use change was conducted by constructing a transition matrix of land use change in the 2009-2015 period to observe the pattern of dominant changes that occurred at those two points of the year. Based on the land use change transition area matrix, 29 transitions occurred during this specific period (Table 5). This transition also confirms that the dominant change occurred from wetlands to other LC with significant changes observed in 91,545 ha of cropland, 23,595 ha of forest land, and 16,556 ha of other lands. The study conducted by Yang *et al.* (2023) identified that the land use change activities originated from human activities in an attempt at land use utilisation which is an essential factor in the occurrence of forest and land fires.

Table 5. Transition Area Matrix 2009-2015 (in hectares).

Land Cover	2015					
	F	C	G	W	S	O
2009						
Forest land (F)	6.230	126	70	242	0	23
Cropland (C)	2.188	272.110	34	192	356	1.176
Grassland (G)	392	125	1.149	287	0	22
Wetlands (W)	23.595	91.545	132	424.586	46	16.557
Settlements (S)	0	205	19	0	3.625	0
Other lands (O)	875	3.101	0	182	0	4.261

3.4. Land Use Change Modelling

Construction of the land use change model begins by taking a 5% sample point of 42,673 points from the entire area of 2009 LC data regularly for each land cover class to optimise the time spent in building the model compared to using all LC data as a whole, with the objective that the model does not tend to predict most of the LC class. Subsequently, the extraction of values on the LC map and each explanatory variable map is performed based on the coordinates of the sample points that have been previously distributed to form the dataset. The dataset is divided into training data comprising roughly 80% of the sample data or 34,140 points, with the remaining 8,533 points as test data.

The understanding of land use change models in relation to LR, RF, and ALR was conducted on training data and subsequently testing the results on each model with test data. The process is repeated 10 times to obtain 10 goodness-of-fit values. In addition to the sample data, all of the above steps are also applied to the entire observation dataset (Salmona *et al.*, 2023).

Table 6 presents the comparison of the accuracy and F1 scores of the LR, RF and ALR models in 5% of the sample data and the entire data. The RF model performed better than the LR and ALR models on the 5% sample data or when using all the data, on average. This is denoted by a high accuracy value of 0.950 for the sample data followed by 0.952 for all data and an F1 score of 0.962 followed by 0.954 for all data in the RF model compared to the other two models.

The accuracy and F1 scores between models are also displayed visually using the boxplot in Figure 5 and Figure 6. The goodness-of-fit model for the 5% sample data has a marginally broader interval than the overall data.

Table 6. Comparison of Goodness-of-fit Value for LR, RF and ALR.

Goodness-of-fit	LR		RF		ALR	
	5%	100%	5%	100%	5%	100%
Accuracy	0,856	0,854	0,950	0,952	0,880	0,878
F1	0,892	0,890	0,962	0,964	0,909	0,907
AUC	0,899	0,898	0,990	0,991	0,937	0,936

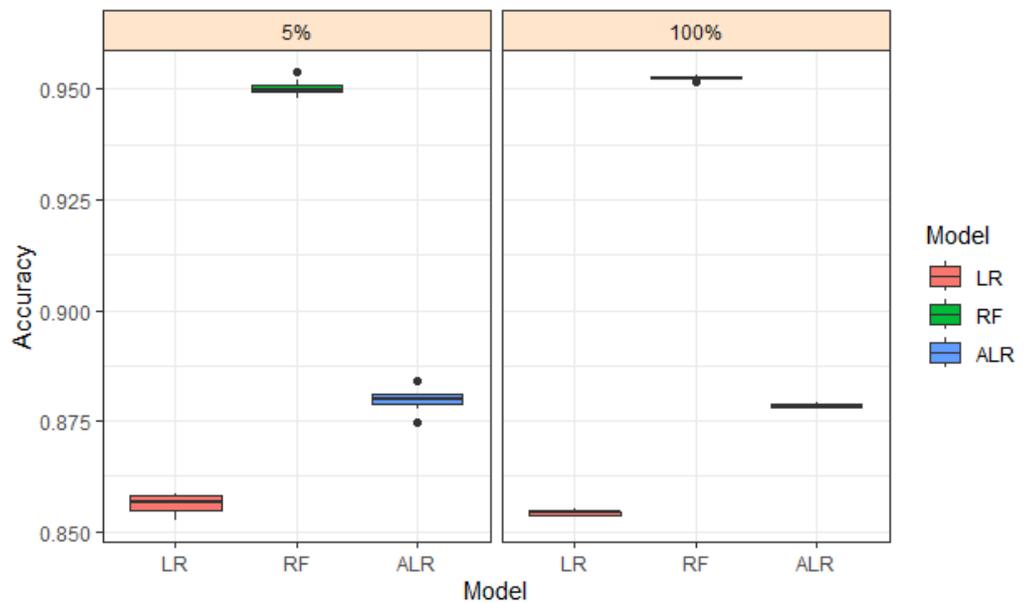


Figure 5. Accuracy between Models.

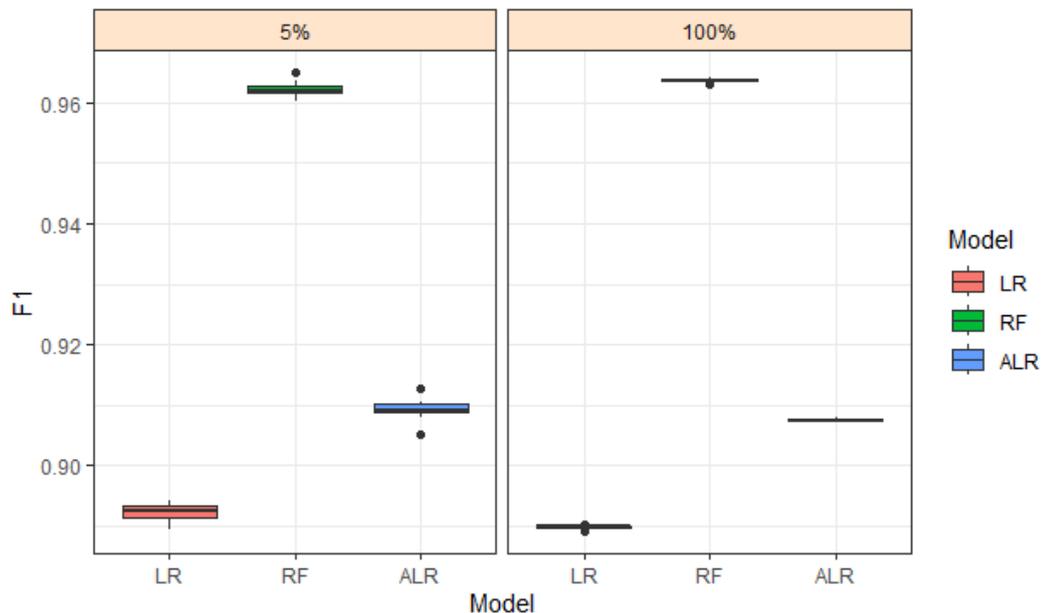


Figure 6. F1 Score between Models.

The classification capability of each model in determining wetland and non-wetland classes is also measured by the ROC curve, which is the curve between the true positive rate and the false positive rate. The model has good classification ability if the ROC curve line is above the diagonal line with the area under the curve (AUC) close to 1. In Figure 7, RF appears to deliver the best performance in both datasets with the curve line furthest from the diagonal line and AUC values of 0.990 and 0.991. Subsequently, ALR exhibited AUC values of 0.937 and 0.936 in both datasets, while LR, identified as the model with the lowest AUC values, recorded 0.899 and 0.989 in the respective datasets. The results of the ROC prove that the RF provided good prediction results in determining the changes of each pixels into wetland rather than non-wetland (Salako *et al.*, 2023).

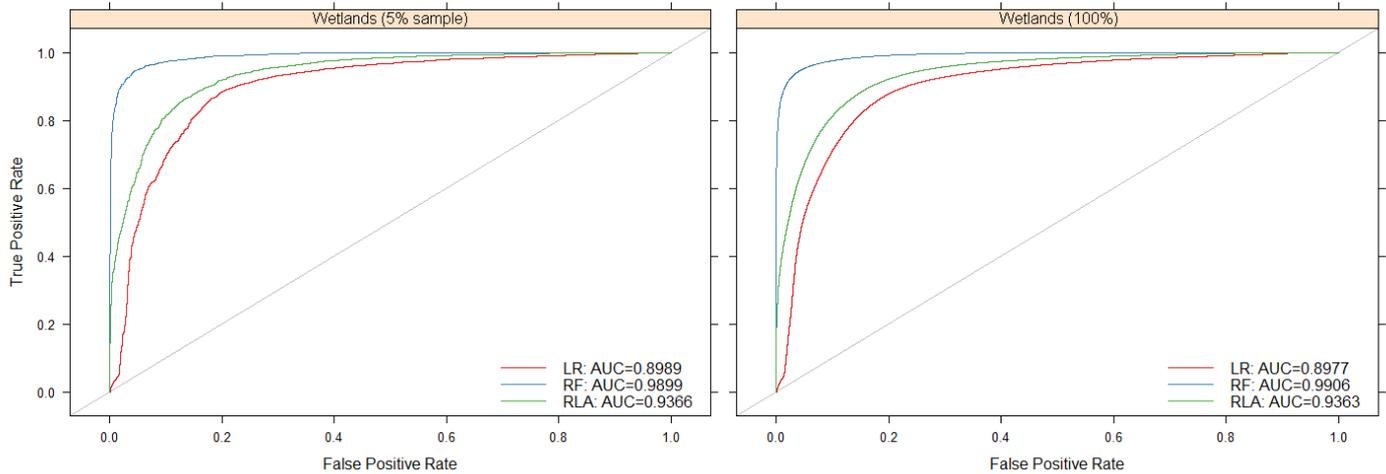


Figure 7. ROC curves between models for 5% and 100% data.

3.5. Probability Map

The probability map between models is a map where the probability value of a pixel develops into a class of wetlands marked with a lighter colour with a value close to 1. The probability of becoming a class of non-wetlands is darker in colour with a value close to 0. The actual wetland covered an area of 556,461 ha in 2009.

Based on the prediction results in the map, the total area of wetlands in the RF model is closer to its value with an actual total area of approximately 557,871 ha, while the ALR is 565,154 ha and the LR is 574,144 ha. All LC classes are predicted by inputting all 2020 datasets as test data into the RF model, as the model that produces the best performance. Figure 8, presents probability maps for the classes of forest land, cropland, grassland, wetlands, settlements and other lands, respectively.

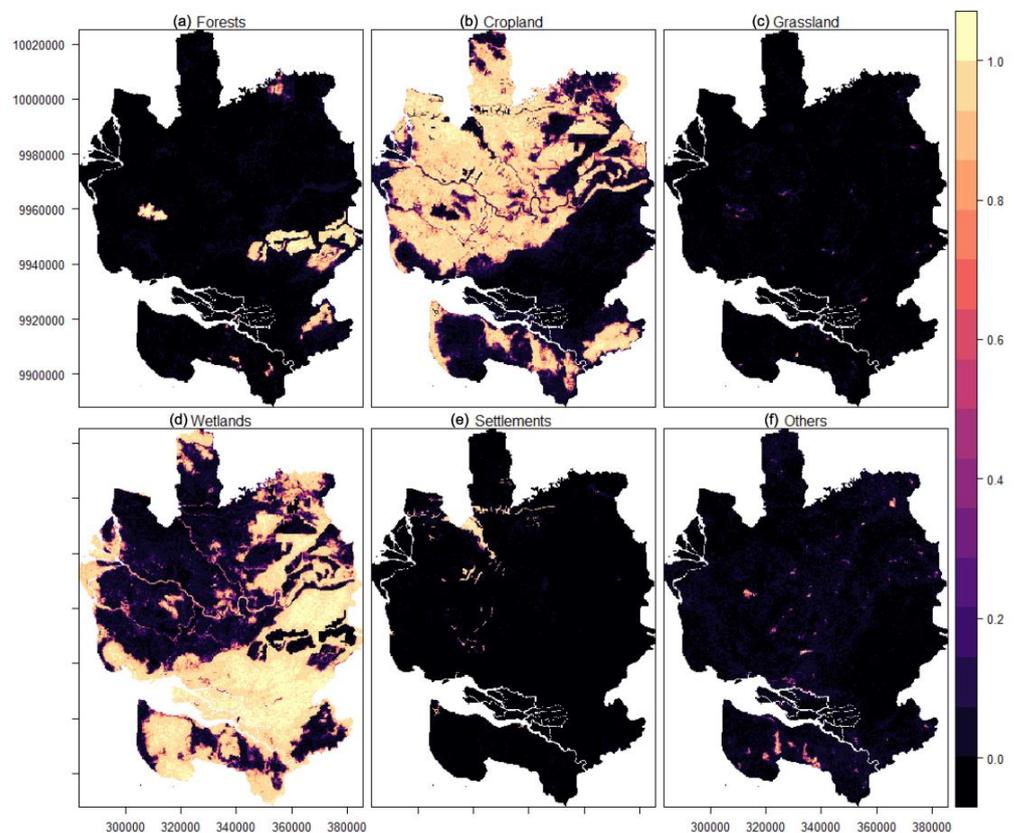


Figure 8. Probability Maps for All Land Cover Classes. (a) Forests, (b) Cropland, (c) Grassland, (d) Wetlands, (e) Settlements, and (f) Other lands.

Figure 9 illustrates the prediction map of the best model by overlaying all prediction maps for each LC. The predicted area of wetlands from the result in 2020 is 391,723 ha, a reduction in contrast to the actual wetland area of 396,542 ha.

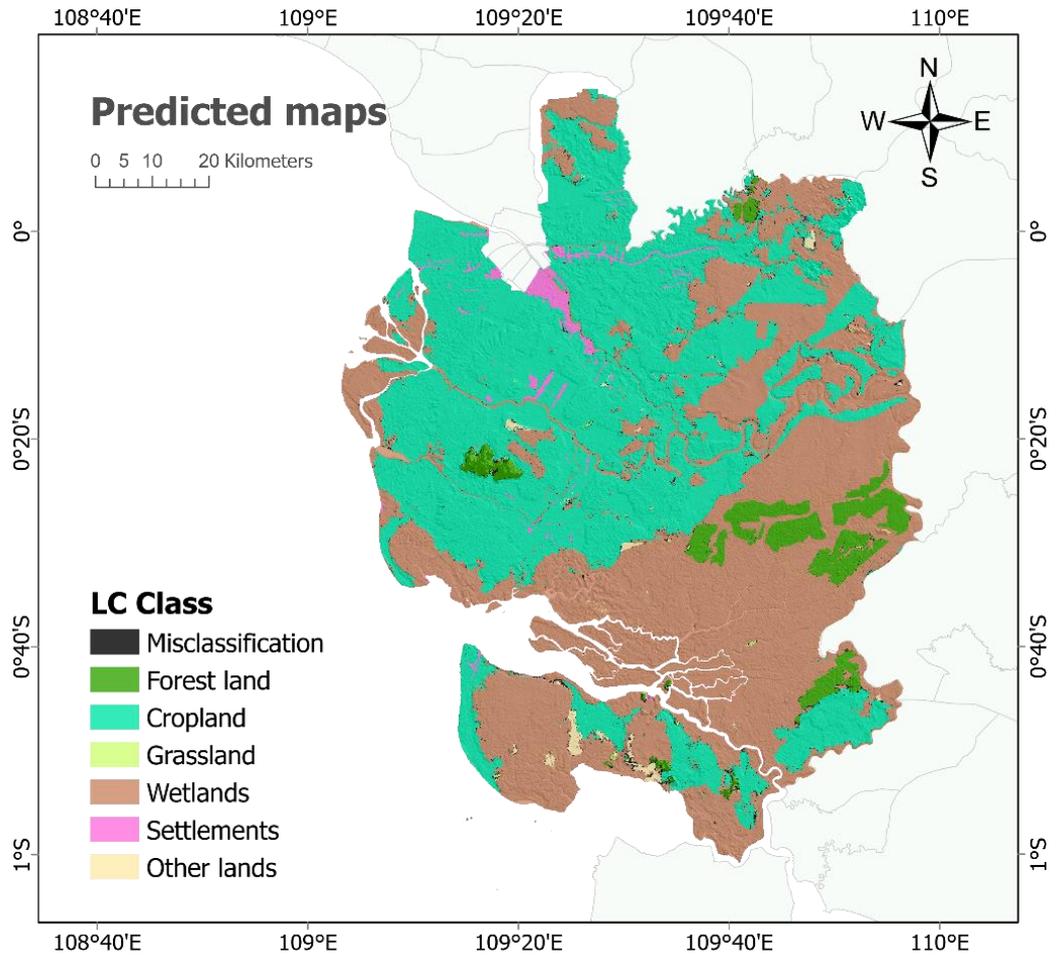


Figure 9. Prediction Map of the Best Model.

3.6. Discussion

The presented study seeks to answer the question: what is the overall accuracy of different statistical methods in predicting the potential changes from class wetlands to non-wetlands? (Zarandian *et al.*, 2023). To answer this question, three different conceptual approaches to modelling land use change, i.e., parametric model, tree-based model and nonparametric model as represented by Logistic Regression (LR), Random Forest (RF) and Additive Logistic Regression (ALR), are developed, quantified and compared for accuracy. These approaches were used to generate models of six different land cover classes and were tested using 2020 data for the Kubu Raya regency, West Kalimantan. The results demonstrate that overall accuracy was highest for RF followed by ALR and LR either with a small sample size or full data.

LR and ALR that are used to model land use change were designed to represent one-to-one land use change, with only two classes comprising wetlands to non-wetlands and non-wetlands to wetlands (Ren *et al.*, 2023). Although RF has the ability to address the multiclass classification problem, the execution performed remains the same as the binary classification. To develop the prediction map, all the combinations of two classes have been executed allowing the six probability maps to be established. Based on the ROC curves as a metric evaluation to the binary classification problem, yet again, RF outperformed the other modelling approaches (Penny *et al.*, 2023).

The utilisation of LR as a classification model presents several challenges because it does not require complex parameters and a specific model treatment. The execution time in LR is much faster than the other two models, with each iteration only lasting a few seconds. However, spatial autocorrelation in the error terms of the LR causes bias in the standard errors of the parameter estimates. Spatial autocorrelation in spatial analysis can affect the model for the reason that the pixel value can be predicted by its neighbours (Karasiak *et al.*, 2022). This phenomenon can also be found in several studies (Baig *et al.*, 2021; Buya, 2020; Gaur, 2023). A simple strategy to

reduce the impact of spatial autocorrelation is drawing a random sample size of the data to fit the predictive model (Liu *et al.*, 2023).

In contrast, the run time for the ALR and RF lasted half an hour for each iteration in the simulation class. In the study completed by Robinson (2018), the ALR took over eighty-five minutes to perform the simulation model due to the iteration in the back-fitting of smoothing functions. In R, smoothing functions have to be initialised for each selected explanatory variable which has been identified as a nonlinear relationship to perform the classification model using ALR (Aguilera *et al.*, 2023). The response variable also has to be set as a factor data type or categorical data. The smoothing parameters estimation in this research applied the default method, Generalised Cross Validation (GCV). Guarderas *et al.* (2022) employed beta regression to predict the model and Restricted Maximum Likelihood (REML) as an estimation method for smoothing parameters. The conservative results from the treatment of ALR based on the research explained between 21% to 42% of the variation of the distinct land cover transition in the study region. Moreover, the hyperparameter in RF was not considered in this study (Xia *et al.*, 2023). The number of trees to grow and variables as candidates at each split was set to default, 500 and 2, respectively. Nevertheless, the prediction result using the RF model was more accurate than LR and ALR. RF is the best recommendation for conducting land use change analysis, although it does not rule out the possibility that ALR can also be used by considering several parameters to improve the model (Ren *et al.*, 2023).

Between 2009 to 2015, it was observed that wetlands decreased dramatically in covered areas, as a result of cropland taking over wetlands. Due to this conversion, cropland witnessed substantial expansion, accompanied by significant changes in forest land. Sequestration, the process involving changes from the low carbon stocks area to the high carbon stocks area, is expected to reduce the emissions. However, forest cover used in this study includes the production forest, for instance, industrial plantation forest (Raihan *et al.*, 2023). A different finding is that the pattern of changes in wetlands tended to occur in the locations where the wetlands were close to the road. It indicated that distance to road is a significant variable in assessing the changes to non-wetlands. The second variable that plays an important role in this study was elevation. The relevant study incorporating wetlands as part of the analysis is the wetland conversion risk assessment of Kolkata Timur, India. This study determined that areas adjacent to megacities and other municipality areas and the highest population density were identified as high-risk zones concerning wetlands conversion (Seena *et al.*, 2023). The other land use simulation for Selangor, Malaysia (Baig *et al.*, 2021), concluded that land use changes are typically influenced by population and demand growth.

The performance of the model in detecting wetlands is a notable component of this study. However, it is essential to recognise and address certain limitations. Focusing only on the analysis of the response variable, without taking into account the effect of a set of predictive variables may cause misclassification. ALR is expected to perform better than LR and RF but the minimal design features and parameters may not maximise the ability of the model to classify. Future research will seek to determine the other related factors or covariates, such as weather, hydrological and socio-economic aspects (Verburg *et al.* 2019). Providing a more detailed classification of LC classes would offer a more accurate representation of the existing conditions in Kubu Raya. Notwithstanding that the one-to-one model or single transition can reveal the effects of predictors specifically, the performance of the many-to-one land use change model can enrich the output results and reduce the model's simulation time (Akbar *et al.*, 2023). It would be worth investigating and implementing a variety of statistical machine learning or deep learning approaches in the *lulcc* package in the future, such as the mixed effects model, ensemble learning or a variant of neural networks with several tuning hyperparameters to obtain the optimal performance. The final step is to validate the model using the Total Operating Characteristic (TOC) created by Liu *et al.* (2021) to substitute the popular ROC that claims to offer more information and a distinct interpretation.

4. Conclusion

From 2009 to 2020, Kubu Raya Regency was primarily characterised by wetlands and cropland, with wetlands occupying virtually half of Kubu Raya Regency. During that period, the largest transformation occurred in cropland with greater potential. The results of predictive land use change on the wetlands class in Kubu Raya Regency reveal that the Random Forest model provides the best average goodness-of-fit model compared to the Logistic Regression and Additive Logistic Regression models. The model with 5% sample point data does not produce a significantly different goodness-of-fit model compared to using all spatial data in Kubu Raya Regency. By considering the findings obtained by this research, RF is expected to be able to predict possible

changes in wetlands. Furthermore, synchronised spatial plans may prevent detrimental land use change and may support the sustainable peatland restoration and management in Kubu Raya ReGENCY.

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