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ASSESSING THE DRIVERS OF MANGROVE COVER CHANGE IN THE MEKONG DELTA REGION USING GIS AND LOGISTIC REGRESSION ANALYSIS

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Abstract

Mangroves are vital for preventing shoreline erosion, flooding, and carbon storage. However, land development for rice and aquaculture production in Southern Viet Nam is causing growing concerns for mangrove ecosystems. The aim of this study is to classify changes in mangrove cover by change type, and perform a logistic regression using various potential drivers of change to determine their significance. Spatial data collected from the Mangrove Forest Watch and GIS applications were used to create a classification map presenting how mangrove changes from 1996 to 2016. With the support of previous literature, patterns in mangrove cover changes were identified and the classifications are shown to be spatially correlated. We used GIS and RStudio to perform a logistic regression and spatially analyze the relationship of mangrove loss with potential drivers. Based on the Akaike Information Criterion, p-values, and an accuracy assessment, we determined the most significant drivers of mangrove loss. Using the regression coefficients, the probability of mangrove loss was determined with each model. Results showed that agriculture is the main driver of mangrove loss in the MDR. High population and road density were somewhat significant but inconclusive. Meanwhile, protected areas, aquaculture, and waterways were not found to be significant drivers. Aquaculture was expected to be important but showed insignificance likely due to the increase in mangrove-shrimp farms. The findings also indicate that different areas in the MDR have different drivers. These results are only applicable to the MDR and further analysis on a provincial scale is recommended.

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1. Introduction

1.1. Problem Context

Viet Nam has become one of the most rapidly developing economies in Southeast Asia (The World Bank, 2020). This growth can be attributed to the abundance of natural resources provided by the Mekong river (Liu *et* al., 2020). The Mekong river flows through Southeast Asia, spanning six countries and discharges via smaller rivers in the Mekong Delta Region (MDR) in Viet Nam. The Mekong Delta, one of the two deltas of Viet Nam, flows into the Pacific Ocean with a coastline dominated by mangroves and estuaries. Mangroves provide the region with freshwater, creating an ideal environment for agriculture and aquaculture development (The Ocean Portal Team, 2018). This region provides 55.9% of Viet Nam's rice production and 70.27% of the country's aquaculture production according to 2019 data (General Statistics Office of Viet Nam, 2020). Due to this economic potential, there has been an abundance of development, particularly of the MDR coastal provinces, where mangroves reside (Veettil *et* al., 2019).

Mangroves provide food and habitat for many species of insects, fish, birds, and monkeys. Mangroves help to protect freshwater from salinity intrusion and reduce erosion by helping to build up sand and silt with their complex root systems. They also help eliminate carbon from the atmosphere, where one acre of mangroves can store up to 1,450 pounds of carbon per year (The Ocean Portal Team, 2018). Due to the nutrient rich soil that mangroves create, they are able to store approximately 35 times more carbon than upland forests (Donato *et* al., 2011). Therefore, protecting and restoring mangrove ecosystems globally is vital to decreasing the amount of carbon in the atmosphere. In recognizing the importance of carbon storage, mangrove restoration projects have begun to be put into place in previously developed areas in the provinces of Ben Tre and Ca Mau (Dung *et* al., 2016). With an increasing emphasis being put on mangroves, drivers leading to their change have started to be studied more widely.

Previous studies have focused on land use drivers and its impacts on hydrological changes in the MDR. These findings suggest that land change causes increased flood risk and salinity intrusion (Liu *et* al., 2020). More recently, Adame *et* al. (2021) predicts that the highest mangrove deforestation emissions are likely to come from southern Asia, mostly due to agriculture and aquaculture land conversion. Liu *et* al. (2020) studied land cover dynamics in relation to human activity and economic development in the MDR. The results of their study found forest fragmentation caused by agriculture development led to mangrove cover loss between 1995-2015 (Lui *et* al., 2020). These mangrove changes are expected to be spatially dependent on close proximity to developed areas. Identifying potential causes of mangrove change can aid in land use management and suggest where policy interventions may be needed (Loc *et* al., 2021; Liu *et* al., 2020). The use of geographical information systems (GIS) is necessary to identify these spatial patterns and the proximity to potential drivers of changes. To assess the impact of those drivers, the distance to these variables as a function of loss was determined using logistic regression.

1.2. Research Purpose

The purpose of this research is to understand how the mangrove cover is changing in the MDR and to identify the main drivers of these changes through the use of GIS and logistic regression analysis.

1.3. Study Area

Our study area is the MDR, located in Southern Viet Nam. The MDR consists of twelve provinces and covers an area of 40,576.6 km^2 (Figure 1). The region is largely known for its extensive cover of mangroves, stretching 3260 km across the coastline (Veettil *et* al., 2019). In comparison to mangroves in the northern delta and the central coast of Viet Nam, the MDR provides ideal conditions for mangroves to thrive. The conditions include low lying topography, rich sediments carried by the Mekong river, a warmer climate, and less severe weather (Veettil *et* al., 2019). On the contrary, the low lying topography also presents concerns to the region such as rising sea levels and salinity intrusion. Due to these increasing concerns, studying mangrove change can assist the MDR not only ecologically but also economically.

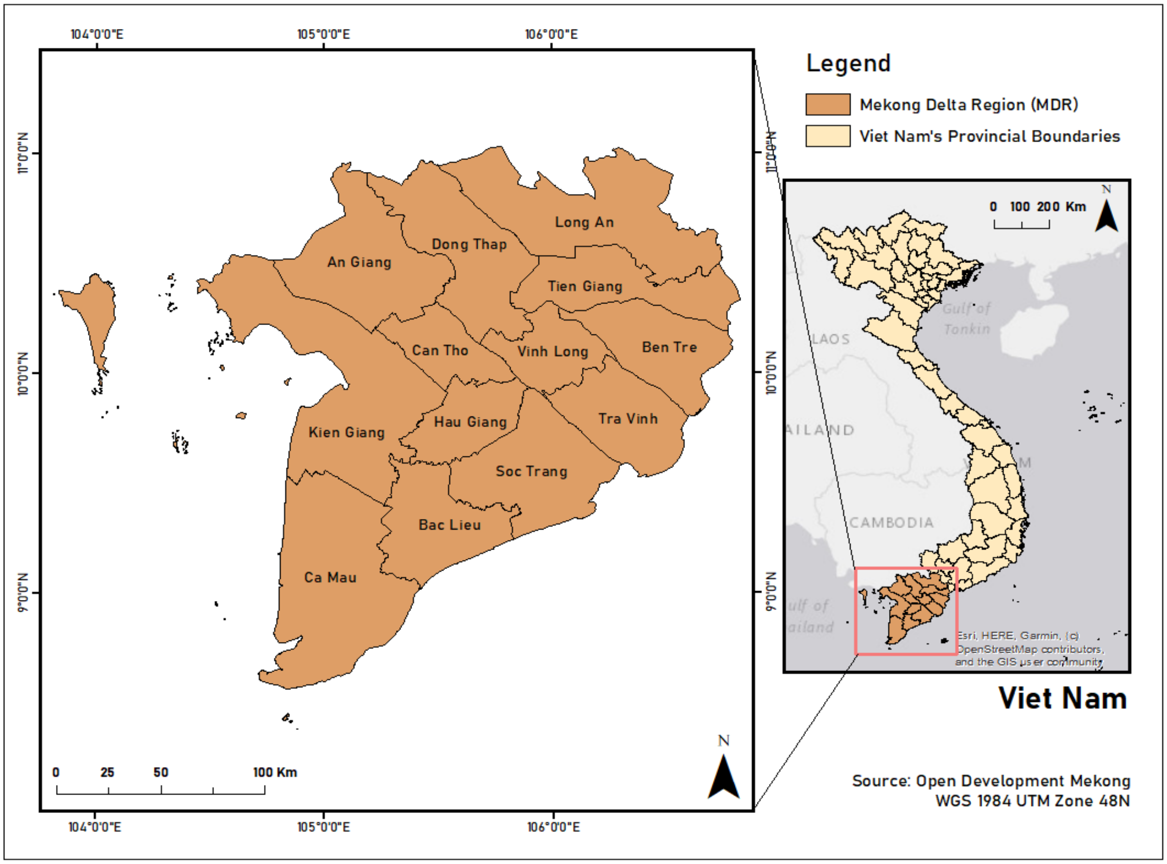

Figure 1: Location of our study area with labels of each province in the Mekong Delta Region.

In recent years, Viet Nam has seen an economic boom from industrialization and a large part of this has required expansion of urban development. Due to the availability of our mangrove dataset, we assessed mangrove cover over a period of twenty years from 1996 to 2016. This research mainly focuses on the coastal provinces which are Kien Giang, Ca Mau, Bac Lieu, Soc Trang, Tra Vinh, Ben Tre, and Tien Giang (Cosslett, 2013).

2. Research Approach

Research Objectives

1. Identify overall change and patterns in the changes of mangrove cover in the MDR between 1996-2007, and 2007-2016.
2. Identify potential drivers of mangrove cover change in the MDR.

3. Use logistic regression analysis to determine the significance of each potential driver and to create a probability model of mangrove loss in the region.
4. Assess the accuracy of the probability model by comparing the predicted probabilities of loss to the real loss.

2.1. Objective 1: Mangrove Change Pattern

Our project coordinate system is WGS 84/UTM zone 48N, which fits the Mekong Delta region with minimal distortion. The overall change between 1996, 2007, and 2016 was calculated by subtracting the mangrove rasters of each respective year from each other to show the amount of forest loss or gain for each cell. In addition to determining change, patterns in mangrove cover change were classified into seven categories (Table 1). In doing so, we recognize that change in forest cover each year may be due to error in the mangrove dataset and not due to actual mangrove loss or gain. The original dataset is at a 30 m resolution, per the recommendations of Bunting *et* al (2018), was resampled to 100 m resolution using nearest neighbour resampling. This resampling method changed the resolution while leaving it binary to help eliminate noise within the dataset. By identifying overall loss of mangrove cover, we can analyze how the proximity of the defined variables could be impacting these changes.

Table 1: *Seven mangrove change categories generated from mangrove cover raster datasets from 1996-2016.*

Mangrove Classes	**Years of Mangrove present**	**Raster Calculation Formula**
Constant cover	Present during all years 1996, 2007 and 2016	"GMW1996" = 1 AND "GMW2007" = 1 AND "GMW2016" = 1
Early loss	Present in 1996, not present in 2007 and 2016	"GMW1996"" = 1 AND "GMW2007" = 0 AND "GMW2016" = 0
Late loss	Present in 1996 and 2007, not present in 2016	"GMW1996"" = 1 AND "GMW2007" = 1 AND "GMW2016" = 0
Intermediate cover	Present in 2007, not present in 1996 and 2016	"GMW1996" = 0 AND "GMW2007" = 1 AND "GMW2016" = 0
Early gain	Not present in 1996, present in 2007 and 2016	"GMW1996" = 0 AND "GMW2007" = 1 AND "GMW2016" = 1
Late gain	Not present in 1996 and 2007, present in 2016	"GMW1996"" = 0 AND "GMW2007" = 0 AND "GMW2016" = 1
Regrowth	Not present in 2007, present in 1996, 2016	"GMW1996" = 1 AND "GMW2007" = 0 AND "GMW2016" = 1

2.2. Objective 2: Potential Drivers of Changes

Although natural drivers such as salinity level and elevation play a role in mangrove loss, these drivers do not vary significantly throughout the area of mangrove cover (Tuan *et* al., 2007; Minderhoud *et* al., 2019). Therefore, they are unlikely to affect the results and were not included in our model. Moreover, with the rapid economic development in the MDR, we are more interested in anthropogenic drivers. Our model was based on the proximity to each of the potential drivers (Figure 2). Table 2 presents the potential drivers that were used for the regression model in Objective 3, based on the availability of spatial data and recent studies.

Table 2: *Required data for the potential drivers, categorized by data type, resolution, year, and data source. All of the data are rasterized and resampled to fit our chosen resolution of 100 m.*

Required data	Data type	Resolution	Year	Source
Roads Networks	Vector (Line)	30 m	2018	Global Roads Inventory Project (GRIP)
Population density	Raster	100 m	2016	WorldPop - University of Southampton
Agriculture Lands	Raster	10 m	2017	Advanced Land Observation Satellite (ALOS-2)
Aquaculture Ponds	Raster	30 m	2014	Clark University- ClarkLabs
Protected Areas	Vector (Polygon)	N/A	2016	Open Development Vietnam
Waterways (canals, rivers, streams)	Vector (Line)	N/A	2021	Open Street Map

Road Networks

Road networks increase the accessibility of areas that would otherwise be cut off from development or transport of goods. For this reason, the proximity to areas of high road density was a variable in the regression model (FAO, 1986; Liu *et* al., 2020). Road density was calculated using a 1000 m radius, and any areas with density above the average density of the dataset were considered as high road density.

Population Density

Population is a factor that leads to increased development of land use over time (Liu *et* al., 2020). Areas of high population density are likely to expand and develop nearby land to support population growth, which create stress on the local ecosystem. For our model, high population density areas were considered as any area with a population density higher than the average population density of Viet Nam in 2016, which is 302 people per km^2 (Worldometers.info, 2021).

Agriculture and Aquaculture

With an increasing population, the demand for agriculture and aquaculture farms continues to grow. Previous research has suggested that agricultural development and runoff have been shown to lead to mangrove loss (Veettil *et* al., 2019). In addition to increased unsustainable rice and shrimp farming, the ongoing development requires the need for mangrove removal (Friess *et* al., 2016; Quoc *et* al., 2013). The economic dependence on aquaculture farming has been the primary cause of losing approximately 52.5% of mangrove in the province of Ben Tre between 1998 and 2015 (Veettil *et* al., 2019). Thus, the distance to aquaculture and agriculture farms are most likely to affect mangrove cover.

Protected Areas

Recognized worldwide heritage sites are used as a variable to assess how proximity to conserved land affects the mangrove loss. Protected areas can help in preserving the intact mangrove cover from being cut down. In particular, Ca Mau peninsula is one of the core zones of Mui Ca Mau Biosphere Reserve by UNESCO (RSIS, 2012). In this case, the government of Viet Nam only has investment plans in restoration but missing a management plan which potentially leads to illegal logging, and more agriculture and aquaculture development (RSIS, 2012).

Waterways

Aquaculture farms require consistent water quality, such as pH or salinity (FAO, 1986), and the flow of rivers can affect how and where these farms are being built. The MDR is a low lying region with complex rivers, canals, and stream networks, hence they can provide additional accessibility to dense mangrove forest areas.

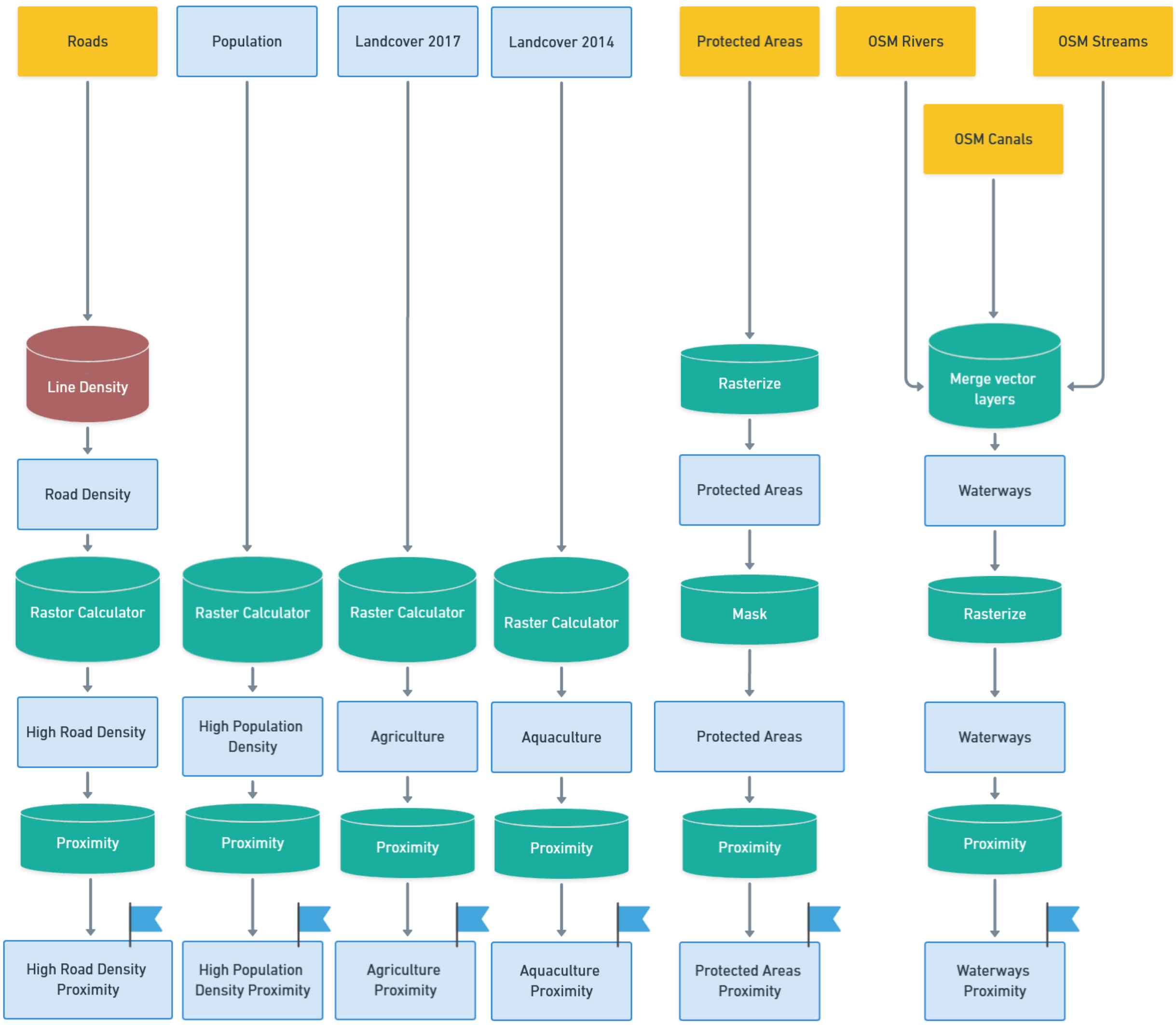

Figure 2: *Detailed workflow to obtain the proximity raster for all potential drivers.*

2.3. Objective 3: Logistic Regression Analysis

After we identified drivers of mangrove cover change, a logistic regression was performed to evaluate the relationship between each potential driver and mangrove loss.

Sampling

To avoid overrepresentation of mangrove loss in Ca Mau province and underrepresentation in provinces on the east coast, we used a stratified sampling method. The MDR was stratified into three subgroups: Kien Giang province, Ca Mau province, and the remaining provinces on the east coast (Figure 3). Then both the loss points and no-loss points were randomly sampled from each subgroup. We considered the loss area to be mangrove cover that was present in 1996 but was not present in 2016. We considered areas that had constant mangrove cover or mangrove gain over the study period as no-loss. The sample points of each subgroup were proportional to the sample size of the subgroup, for a total of 100 loss points (Table 3). While, the no-loss sample points were the same size as the loss sample. With this method of sampling, we could ensure that the sample sizes are representative of each subgroup.

About 84% of mangrove loss in the MDR is in the Ca Mau province, and within mangrove loss of Ca Mau there is roughly 32% of early mangrove loss (Figure 11). Prior to the establishment of Mui Ca Mau National Park in 2003, this area suffered from war chemical residuals, shrimp farm conversion, and timber exploitation (Tran & Fisher, 2017). Since the drivers of change in this protected area were previously identified they were not expected to affect other mangrove areas. For these reasons, we removed the 32% early loss of Ca Mau before sampling for loss points.

Table 3: *Sampling table of each subgroup with the total loss points. The sampled points of loss are roughly 2% of all loss, for a total of 100 points. The no-loss layer sampling size is the same as the mangrove loss sample size.*

	Total loss points	**Loss Sample**	**No-loss Sample**
Ca Mau	2601	78	78
Kien Giang	453	14	14
Remaining	276	8	8
Total (MDR)	**3330**	**100**	**100**

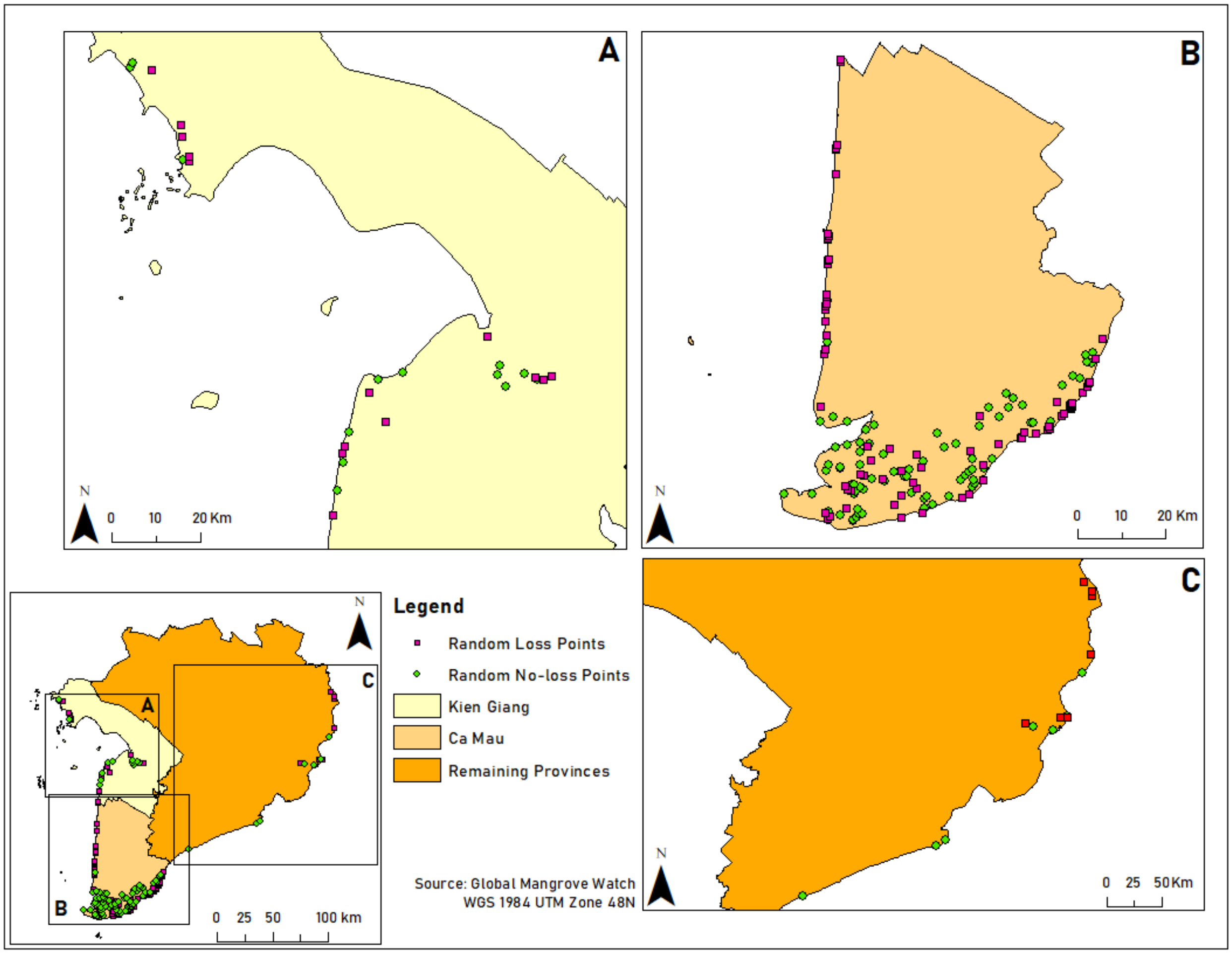

Figure 3*: The MDR is divided into three subgroups: (A) Kien Giang, (B) Ca Mau, and (C) Remaining provinces. Points are selected through the stratified sampling method after removing a large portion of loss points*

Logistic Regression Model

Logistic regression was applicable for our data because our response variable is binary (either loss or not loss). The results of the regression were used to determine probability of loss. From objective 2, we identified the six explanatory variables that can impact mangrove cover change in the MDR, and calculated the proximity of each. We then put our sampled points through RStudio to perform the regression (Figure 4). After the logistic regression, the beta coefficients for each driver were input into the raster calculator to generate log odds rasters. The log odds were then used to create a probability raster for each model through the raster calculator. We chose the model best fit for our data based on the *p*-value of the drivers ($p < 0.01$), Akaike Information Criterion (AIC) (Akaike, 1973) and an accuracy assessment.

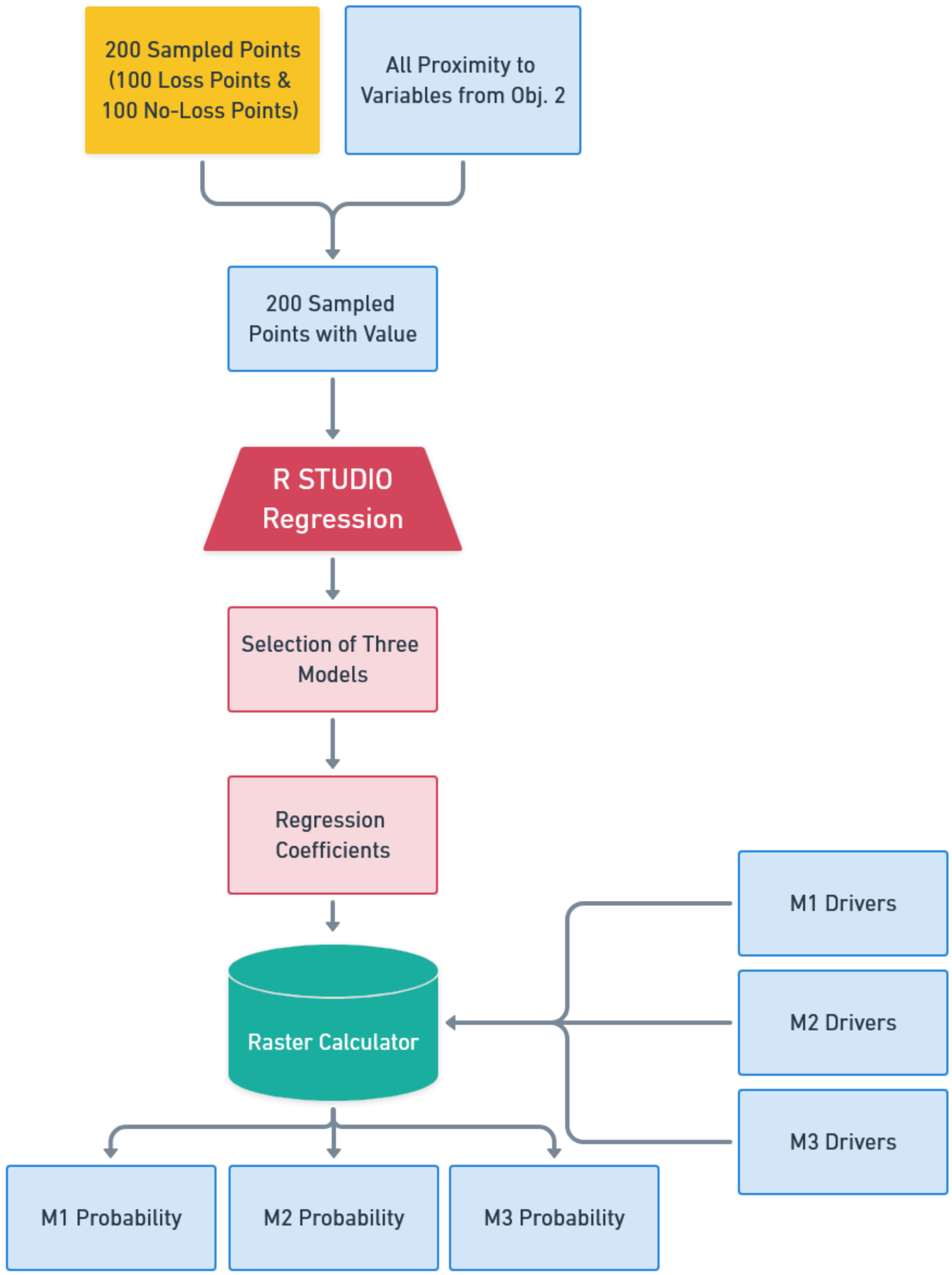

Figure 4: *Generalized workflow of logistic regression models in objective 3.*

2.4. Objective 4: Accuracy Assessment

To assess the accuracy of our three models, the probability of mangrove loss was compared with the sampled points and assessment points based on the result from objective 3. The number of assessment points were the remaining points of the mangrove layer that were not sampled, including both loss points and no loss points. By using the remaining unsampled points, the accuracy assessment was independent from the sample data. There were a total of 80,008 points used for our accuracy assessment.

3. Research Findings

Mangrove Cover Change

Based on our cover classifications in Table 1, several areas show a certain degree of spatial correlation, presented in Figure 5. Areas of early loss and late loss tend to occur near each other as highlighted in boxes A, B, and C. The same is true for areas of gain, where early gain and late gain tend to occur near each other, most prominently highlighted on the northern coasts in box D. These patterns suggest that loss and gain were not random, and were each affected by certain drivers.

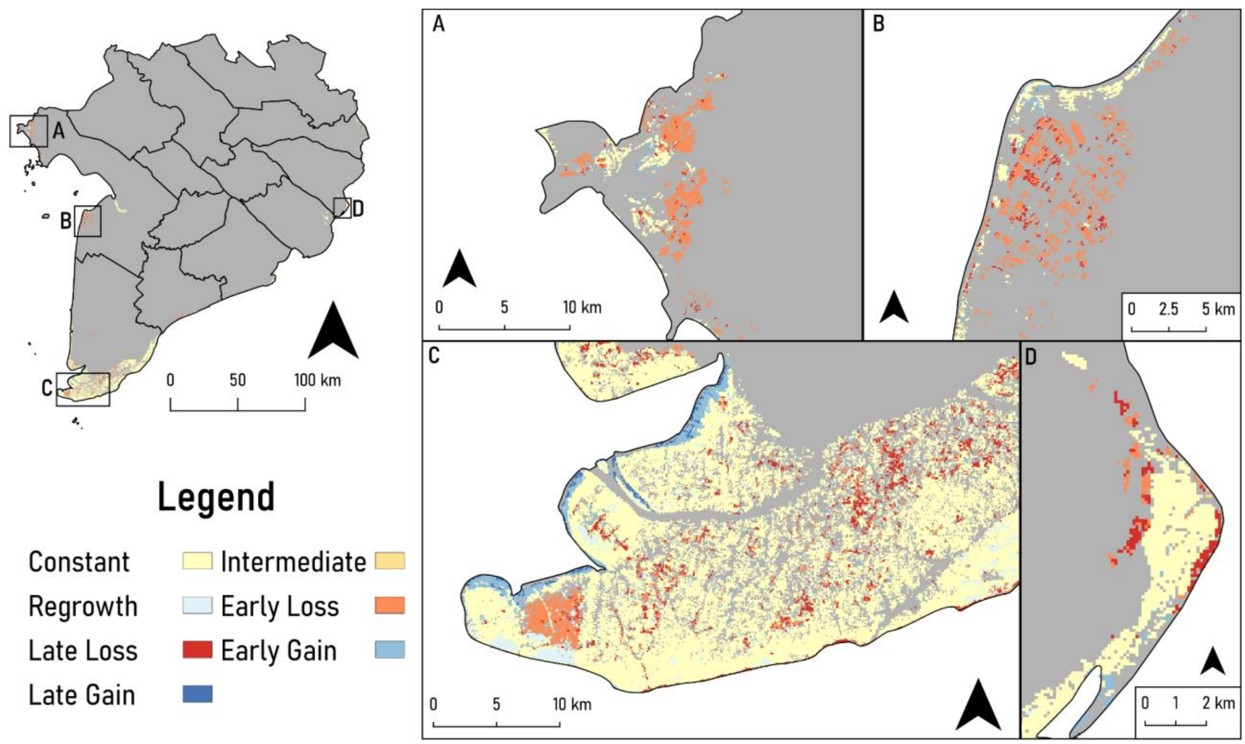

Figure 5: *Prominent areas of mangrove change in four areas along the coasts of Kien Giang (A & B), Ca Mau (C) and Ben Tre (D).*

According to Figure 5, the area overall has a lot more mangrove loss than gain. Areas of gain equal 35,200,000 m^2, with over 80% of total gain being early gain. Areas of loss total 143,550,000 m^2, and approximately 58% of that loss is early loss. The most significant loss, which includes early loss and late loss, is present on the coast of Kien Giang (Figure 5-A and B), in the peninsula area (Figure 5-C), and on the coast of Ben Tre (Figure 5-D). Ben Tre shows more late loss compared to other highlighted areas.

Drivers of Changes

In both model 1 and model 3, agriculture was shown to be statistically significant ($p<0.01$) with a p-value of 0.004 and p-value of 0.005 respectively, regardless of the other variables included in model 3. Whereas, high population density ($p=0.070$), waterways ($p=0.133$) and protected areas ($p=0.136$) were statistically insignificant in model 3. For model 2, we considered both high population density and high road density, as well as an interaction variable because of their high spatial correlation, with a p-value of 0.043. Model 2 demonstrated a positive relationship between high population density, high road density, and mangrove loss, but was not statistically significant ($p>0.01$). Visualized in Figure 6, mangrove loss increases as distance to aquaculture ponds increases. However, the aquaculture variable showed no significant impact on mangrove loss, with a p-value of 0.933.

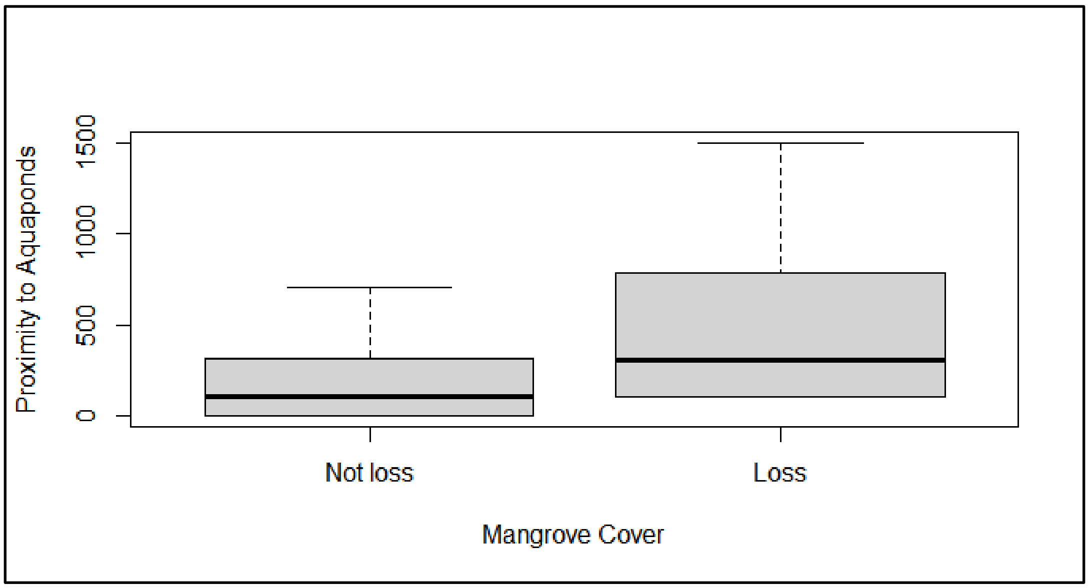

Figure 6*: Data variance of both types of mangrove cover is represented with relation to the aquaculture ponds variable. Aquaculture demonstrates an opposite pattern to mangrove loss than agriculture.*

We used the AIC scores to assess the fit of all three models; however the difference in AIC scores between the models was minimal (Table 4). Despite model 3 having the lowest AIC score, the p-values were not statistically significant.

Table 4: *AIC score of each model and its chosen explanatory variables. Variable combinations chosen based on z-scores of each individual variable. AIC value suggests model 3 to be the best fit for our data.*

Model	Variables	AIC
1	Agriculture	271.7160

Model	Variables	AIC
2	High population and roads density	270.7981
3	Agriculture, High Population Density, Waterways, Protected areas	269.6499

For the accuracy assessment, the predicted probabilities were compared to the real loss. We considered predicted values equal to or above 0.5 as a prediction of loss, and values below 0.5 are a prediction of not loss. The loss prediction of model 1 was the most precise of the three models, with most of the loss points above the threshold of 0.5 (Figure 7). Model 3 was the least precise of the three, with approximately even distribution of probability values for loss and no-loss. Probability raster maps were created to visually compare predicted loss with real loss (Figure 9 to 11).

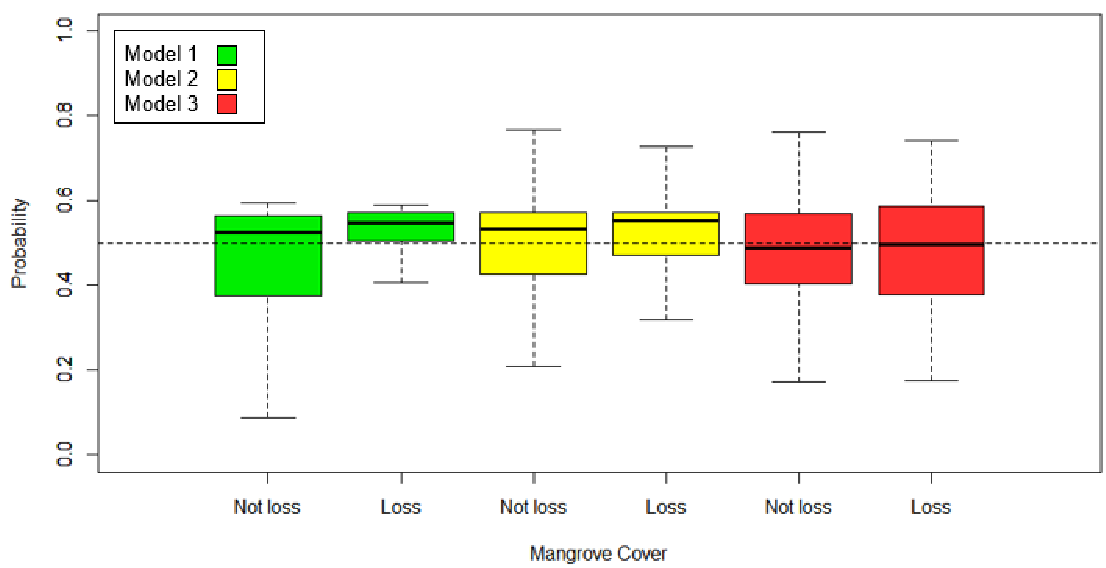

Figure 7: *Probability from remaining unsampled points from no-loss raster compared to sampled points from loss raster.*

4. Discussion

Patterns in mangrove change and its drivers could be explained by policy development and growing patterns in response to food demand. Early loss is the most prominent in the southern tip of Ca Mau, in the area of Dat Mui. This area also contains the Mui Ca Mau National Park. From the 1990s to the early

2000s, prior to its protection, there was a heavy push of shrimp monoculture. Following its protection, there was no longer loss seen at the southern tip of the Mekong Delta.

Early gain was most prominent along the western coast of Ca Mau (Figure 8). In the mid 1990s and into the 2000s, restoration projects began surrounding the Mui Ca Mau National Park. In addition, Ca Mau shows the most noticeable regrowth of mangrove cover (not present in 2007, present in 1996, 2016), near the Mui Ca Mau National Park and the eastern coast of Ca Mau (Figure 8). These regrowth patterns can be attributed to restoration projects. Although there is far more loss than gain, these results show that loss decreased by 15% over the latter half of the study period. With proper policy and management, the decreases in mangrove loss could continue well into the future, providing hope for the future of a healthy mangrove ecosystem in the MDR. However, since our analysis only focuses on mangrove loss, further research on main drivers leading to mangrove gain is necessary.

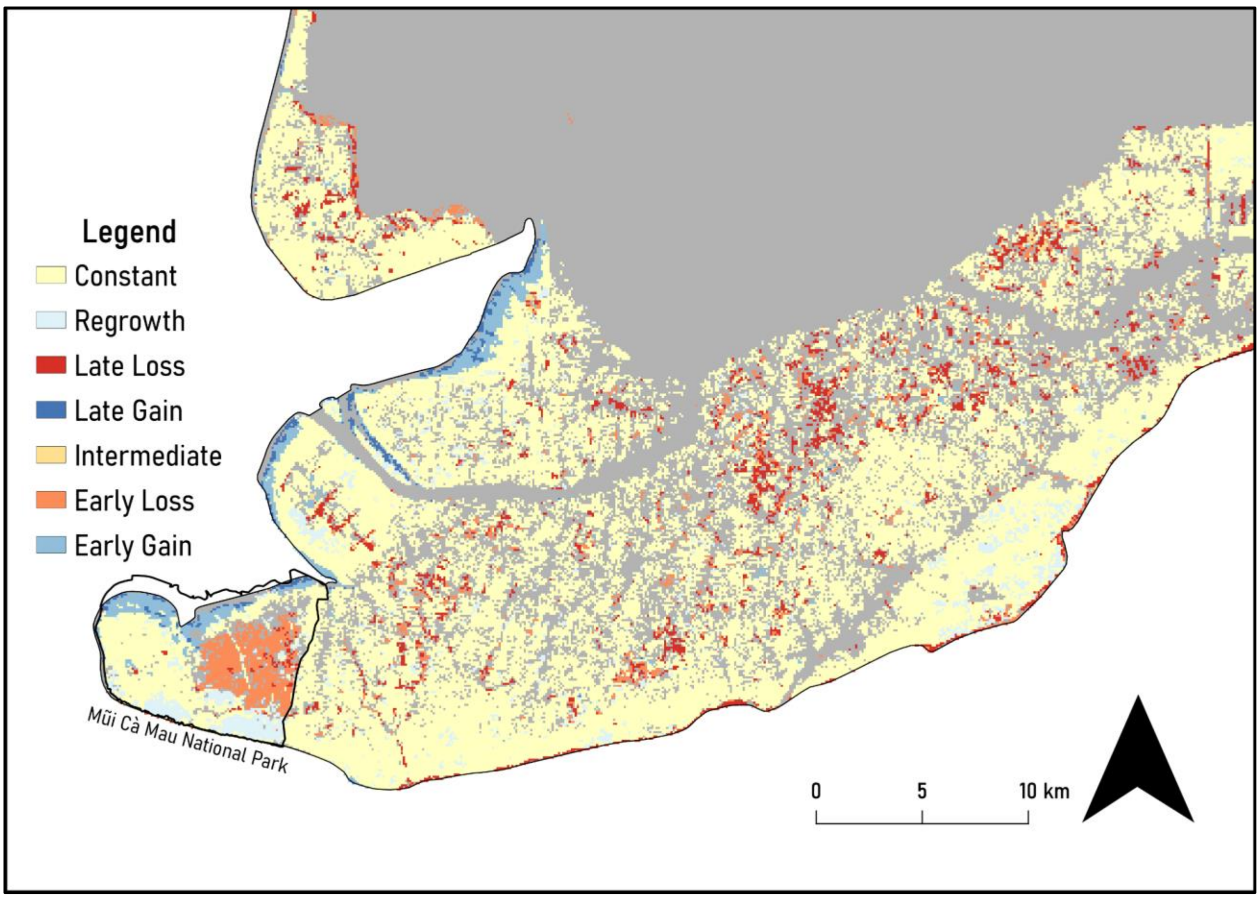

Figure 8: Different classification of mangrove change as indicated in Table 1 during 1996-2016 in the peninsula in Ca Mau.

The AIC scores and the p-values determined from the logistic regression contradicted each other. Model 1 showed to have statistically significant p-values despite having a higher AIC score, and vice versa for model 3. To determine which model is best fit for these results, we also needed to consider the accuracy of each model. In addition to the significant p-values, model 1 accuracy assessment showed the best result (Figure 7). This suggests that model 1 appears to be the best fit for our data and that agriculture is the main driver of mangrove loss in the MDR.

Predicted loss from model 1 shown in Figure 10 are mostly in agreement with the real loss of areas A and B in Figure 9. This suggests that agriculture is a driver of mangrove loss in these provinces. Predictions of loss were concentrated on the east coast of the peninsula (Box C of Figure 10), whereas the real loss in that area was sporadic. This could suggest that agriculture is not a driver of mangrove loss in the Ca Mau peninsula. Predicted loss for model 3 contradicted the real loss shown in Figure 9, highlighted in Box B and box C from Figure 11. This further supports that model 3 is not the best fit for our data, contrary to its AIC score.

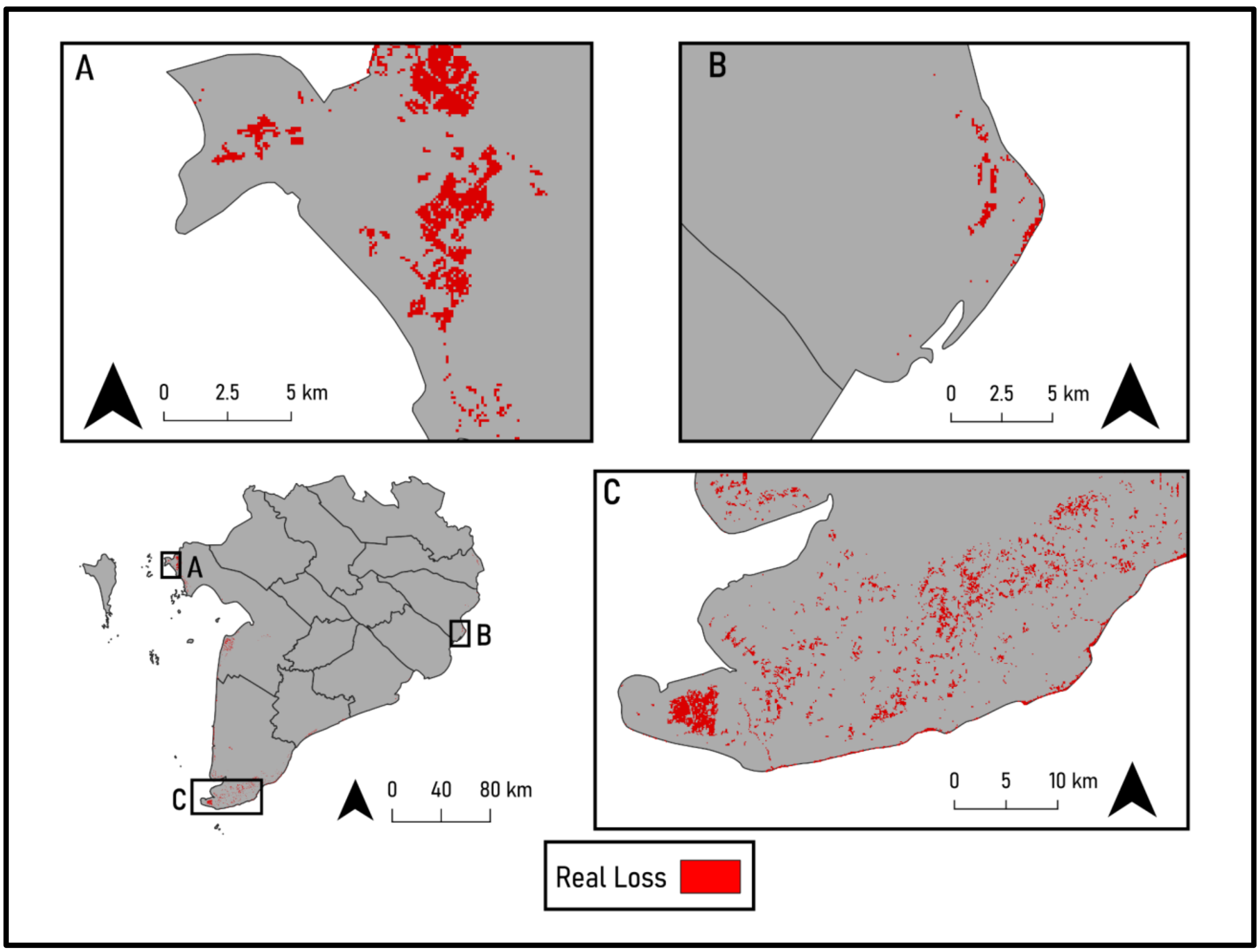

Figure 9: *Real loss between 1996-2016 in three areas Kien Giang (A), Ben Tre (B), and Ca Mau (C).*

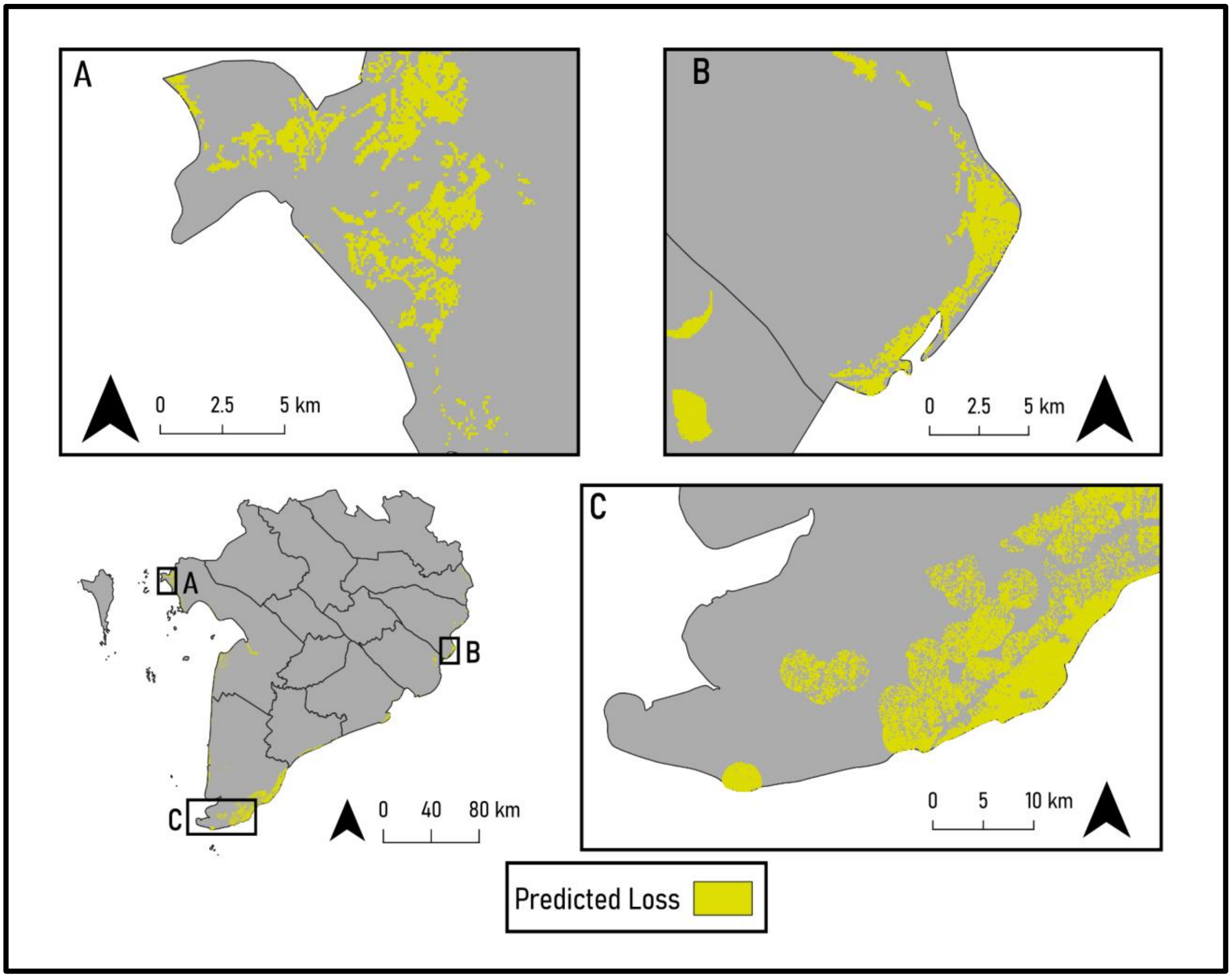

Figure 10: *Predicted loss of model 1 (agriculture) in three areas: Kien Giang (A), Ben Tre (B) and Ca Mau (C). The map was threshold to only display areas that are considered loss by the model, having a probability equal to or above 0.5.*

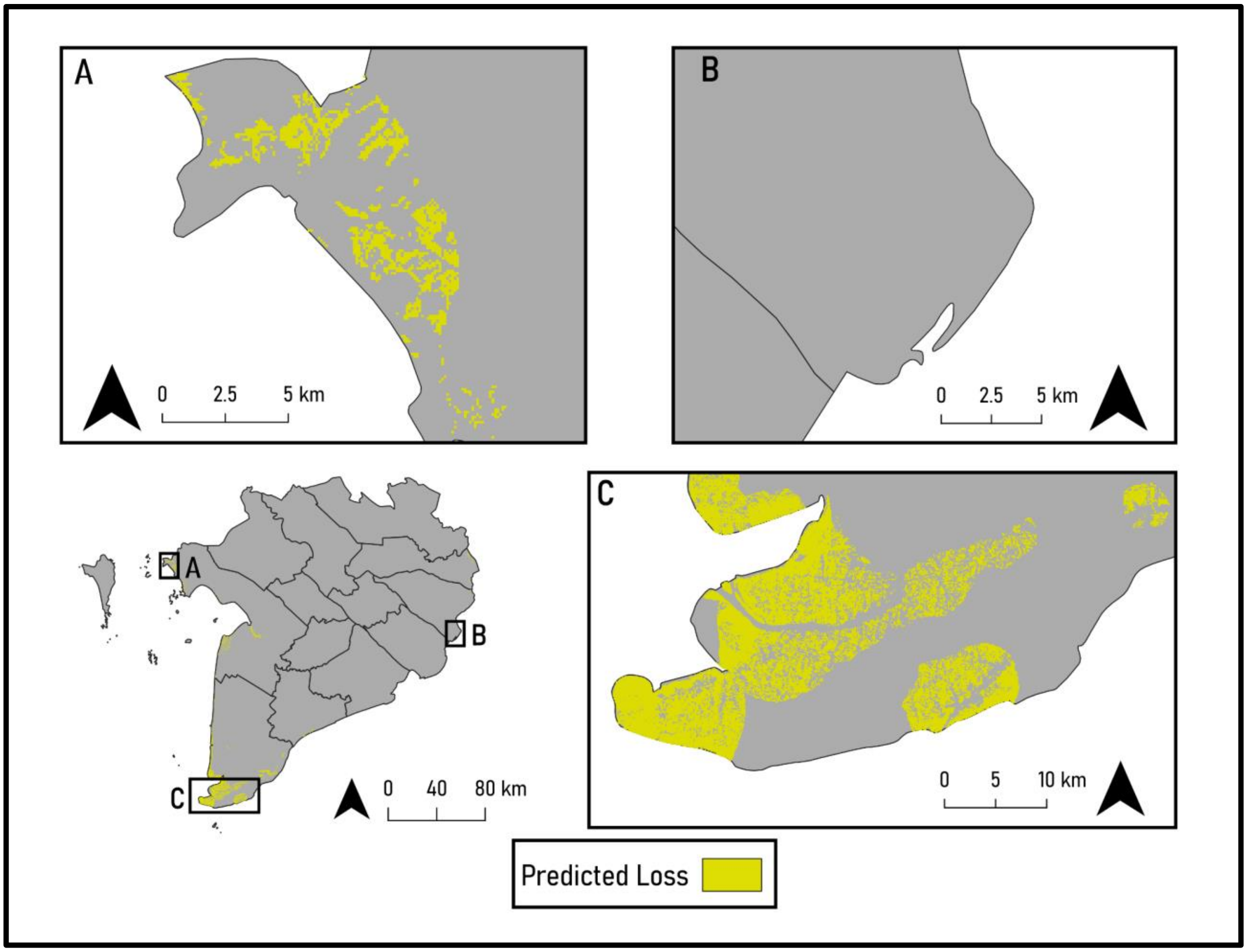

Figure 11: *Predicted loss of model 3 (agriculture, high population density, waterways, protected areas in three areas: Kien Giang (A), Ben Tre (B) and Ca Mau (C). The map was threshold to only display areas that are considered loss by the model, having a probability equal to or above 0.5.*

These results could be explained by shifts in land cover change during the study time period. In the late 2000s, the government increased the demand for rice production on the coast of Ca Mau (Van *et* al., 2015). This shift in demand could explain the model showing proximity to agriculture being a main driver in mangrove loss. The logistic regression analysis also suggests that aquaculture is not related to mangrove loss in the MDR between 1996 and 2016. Following the push away from monoculture in 1992, there was an increase in mangrove-shrimp forests. With this method, mangrove canopy is not lost and shrimp farming occurs underneath (Van *et* al., 2015). Although it is important to recognize that shrimp farming has been found to impact mangrove forests (Tran ; Liu *et* al., 2020), our model can not detect this relationship. This could explain the lack of a visible relationship between aquaculture and mangrove loss in our model.

Due to the complexity of socio-economics factors, we recognize our models are not fully conclusive for drivers of mangrove change to the entire study area. Our results suggest that further research at a provincial scale, with a closer look into the specific needs and challenges of each province, would better reveal the relationships between these drivers and mangrove loss. Although logistic regression was the best method of analysis for our study, it assumes that the explanatory variables are independent (Statistics Solutions, n.d.). Whereas our anthropogenic factors are likely to have a high degree of spatial correlation. For example, Appendix E shows how high road density tends to occur near high population density. Therefore, future studies of drivers of changes for this area is suggested to focus on the relationship between different drivers and perhaps apply a different analysis method.

5. Conclusion

The purpose of our study was to identify patterns of mangrove cover change in the Mekong Delta region of Viet Nam, and use logistic regression to study the relationship between mangrove loss and its potential drivers. Areas of mangrove loss occurred around other areas of loss, and areas of mangrove gain occurred near other areas of gain. This correlation suggests that mangrove cover change is not random, and the rest of our study was determining what the cause(s) of loss could be. Patterns of mangrove cover change were also consistent with the history of the area. For example, regrowth and gain occurred in areas where restoration projects were established. The results of our logistic regression suggested that agriculture is a significant driver of mangrove loss, while aquaculture is not. These results could be reflective of the shift toward mangrove-shrimp farms that do not require mangrove canopy removal. On the other hand, the accuracy assessment reveals the limitations of our model which were likely due to the scale of the study area. Model 1 predictions of loss generally line up with the real loss for most of our study area, but not on the Ca Mau peninsula. This suggests that Ca Mau has different drivers of mangrove loss than the rest of the region. As well, the complexity of the socioeconomic factors of Viet Nam makes it difficult to create a conclusive model. Despite the disagreement between the AIC scores and p-values, and limitation of the model itself, our study was successful in identifying patterns of mangrove cover change and determining agriculture as the most significant driver of mangrove loss. Further research of drivers at a provincial scale and the relationships between drivers is suggested to increase our understanding of mangrove cover change to assist with future local management and protection policy in Viet Nam.

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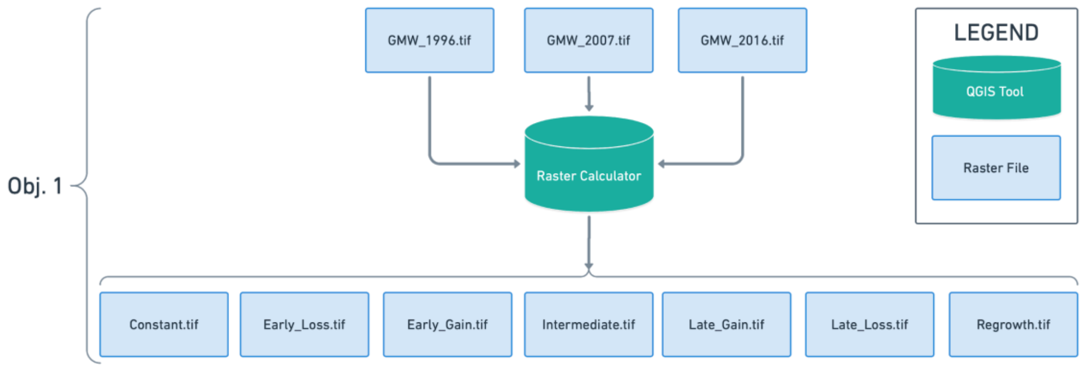
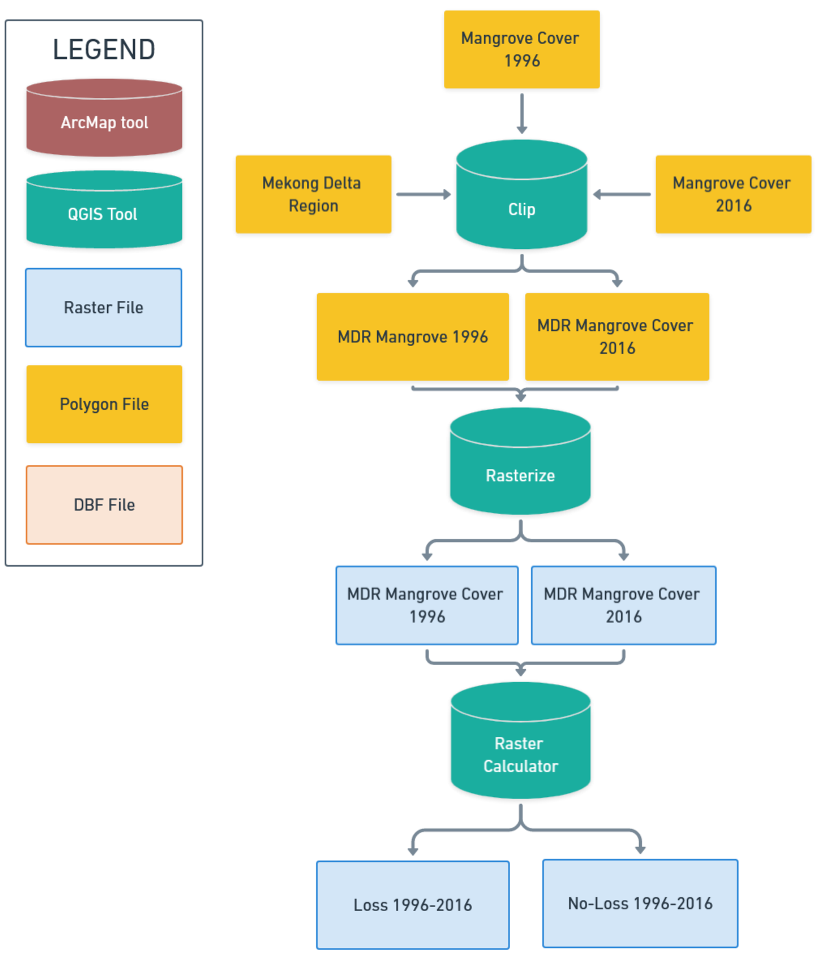
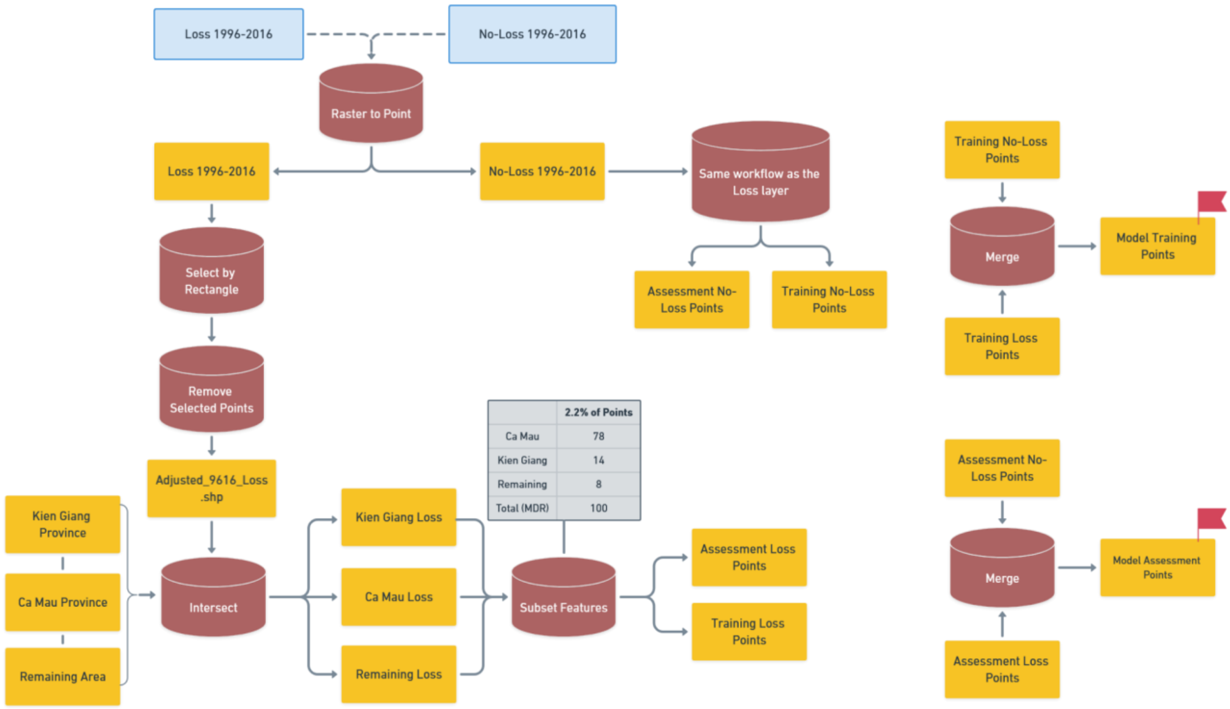
Appendix



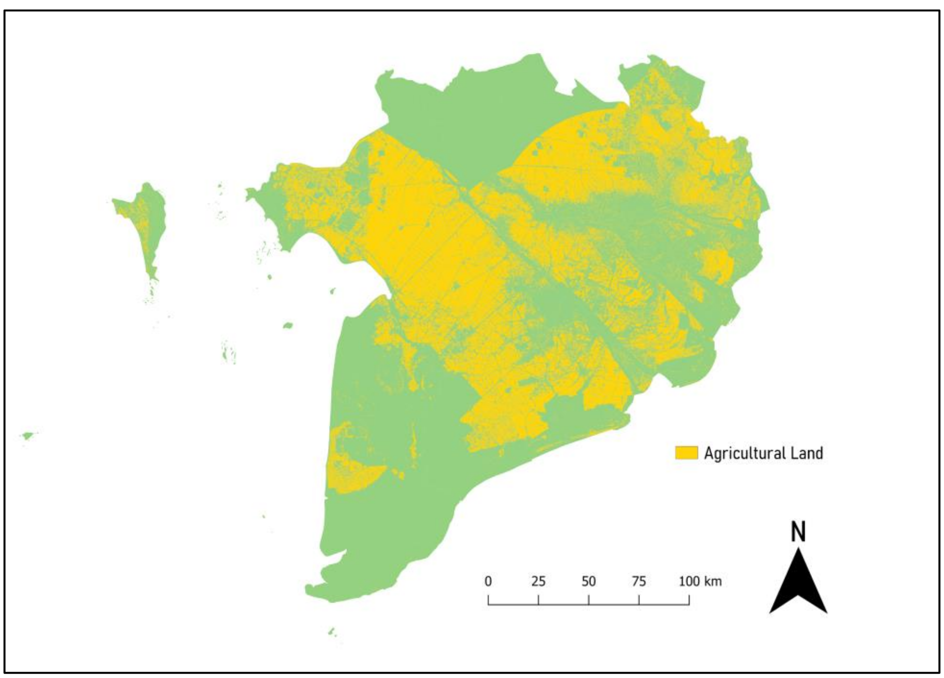
Appendix A: Process of mangrove cover changes classification for objective 1.



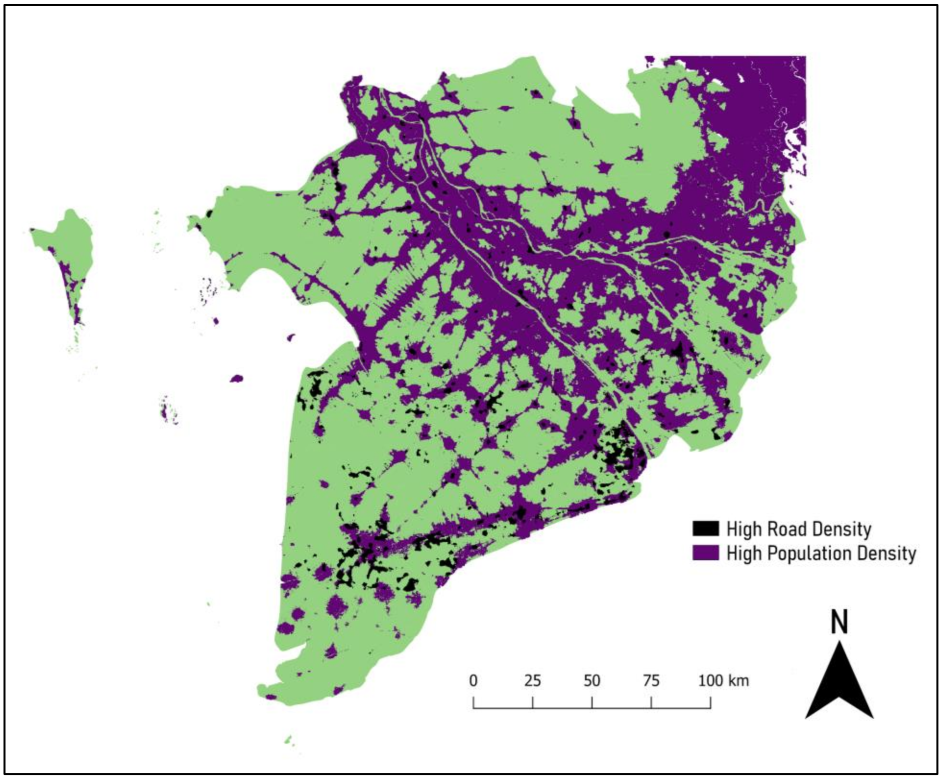
Appendix B: Workflow to generate mangrove loss and no loss rasters for sampling.



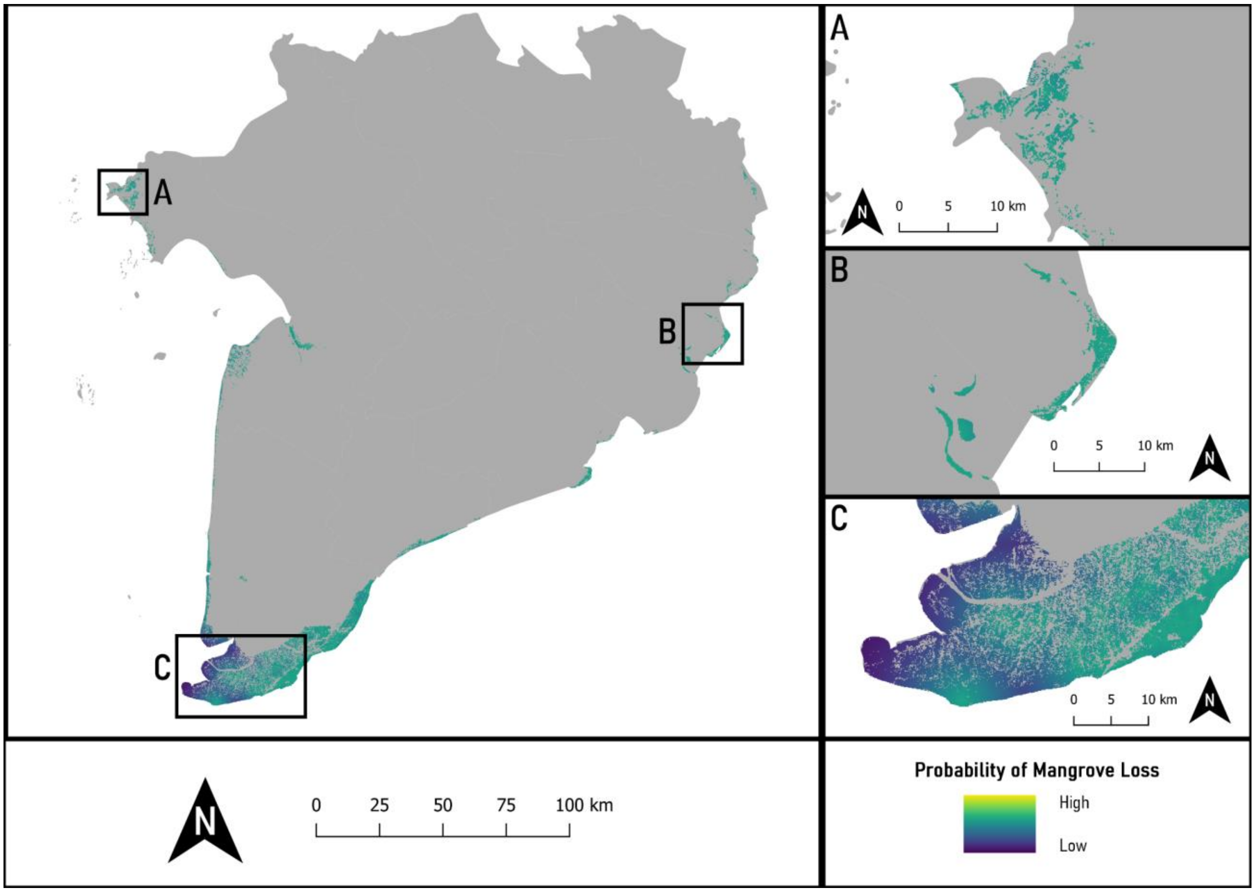
Appendix C: Workflow for sampling to generate training and assessment points.



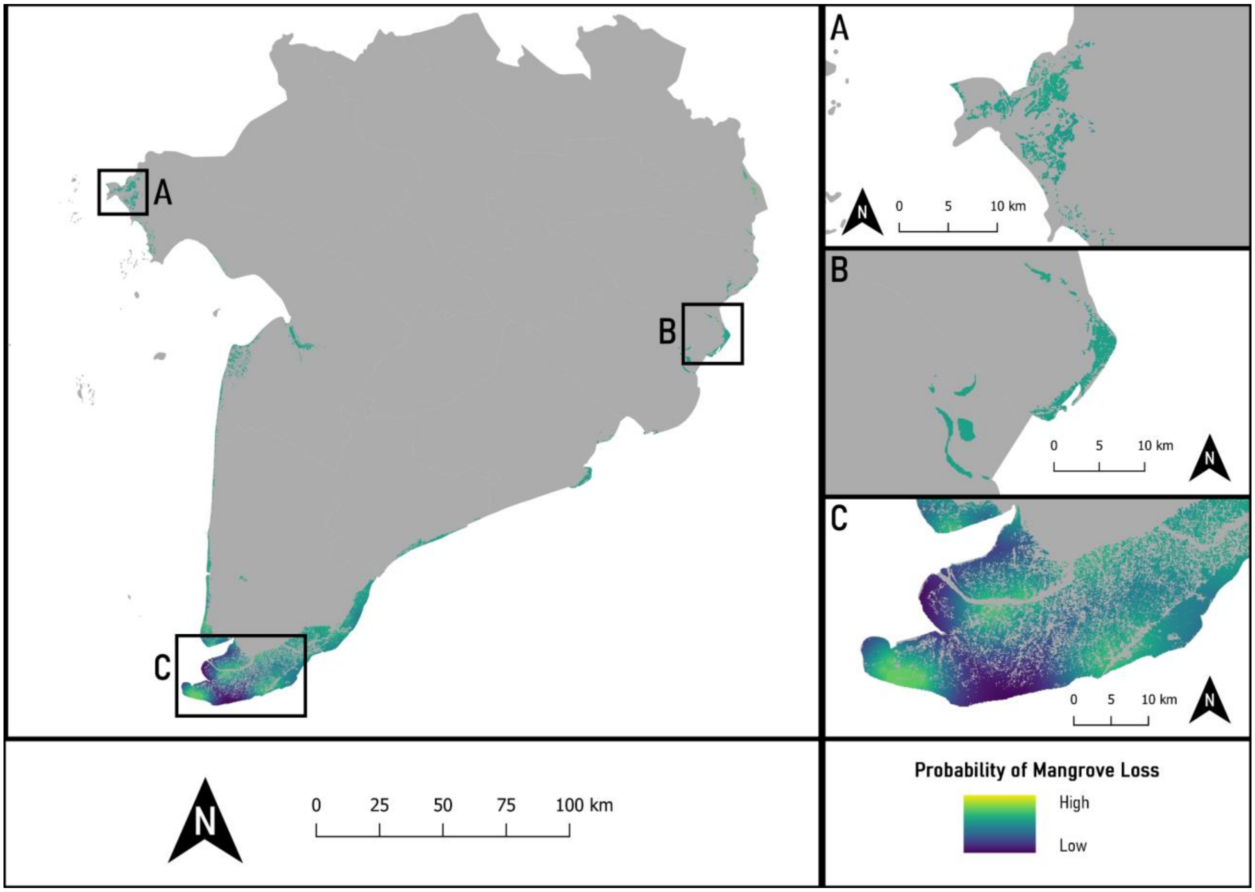
Appendix D : A map showing the distribution of agricultural farms across the region. Agricultural farms have very little presence in the southern Cau Mau peninsula.



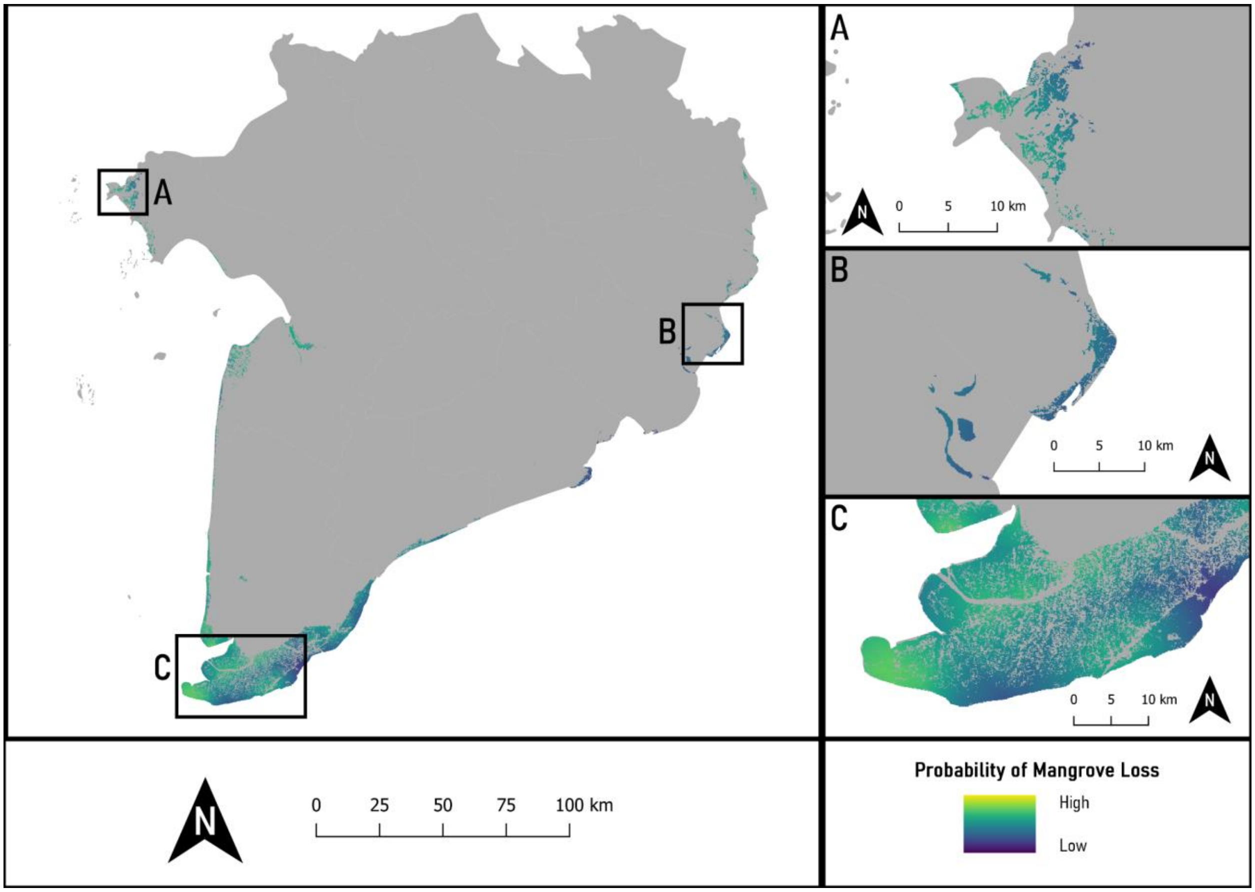
Appendix E: Showing the distribution of high road and population density areas across the study area. Notable lacking areas include the southern peninsula of Ca Mau and the northern coasts of Kien Giang.



Appendix F: Probability raster of model 1 which has agriculture as the only explanatory variable.



Appendix G: Probability raster of model 2 which has high population density and high road density as interactive explanatory variables.



Appendix H: Probability raster of model 3 which included agriculture, high population density, waterways, protected areas as explanatory variables.