MAXIMUM LIKELIHOOD ALGORITHM DETECTS COASTAL WETLAND CHANGES IN TWO CONTRASTING COASTAL WETLANDS IN LOUISIANA

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ABSTRACT

Louisiana coastal wetlands contain about 37 percent of the estuarine herbaceous marshes in the conterminous United States. However, the combined effect of sea level rise and other anthropogenic factors have altered land use land cover over the last few years. This is true for two wetlands in coastal Louisiana, Barataria bay and Wax Lake delta. Barataria Bay, Louisiana, USA has experienced significant land loss. Updated information on the dynamics of change in these wetlands is limited and poorly documented. This information is necessary to develop strategies that will contribute to reversing and halting degradation. Thus, this study employed the Maximum Likelihood classifier on Landsat satellite imagery to assess land use and land cover changes in Barataria Bay and Wax Lake Delta, southeastern Louisiana, USA. The analysis revealed notable alterations in the land cover patterns over the study period. In Barataria Bay, there was a decrease in salt marsh areas with a corresponding increase in open water and Built-up area. In contrast, Wax Lake Delta demonstrated substantial land/wetland growth, with significant expansion of vegetation cover. The Maximum Likelihood classifier demonstrated high accuracy in classifying the land cover types, with an overall accuracy of 86% for Barataria Bay and 92% for Wax Lake Delta. These results highlight the effectiveness of the classifier in accurately identifying and mapping land cover changes in coastal environments. The findings contribute valuable insights for understanding the dynamics of coastal ecosystems and can inform decision-making processes for coastal management and conservation efforts.

1.0 INTRODUCTION

1.1 Coastal Wetlands and Coastal Louisiana

Coastal wetlands include saltwater and freshwater wetlands located within coastal watersheds. They are characterized by hydricsoils, hydrophytic vegetation, and wetland hydrology(Andrew *et al*., 2012). They are one of the most productive, highly biological diverse ecosystems in nature.

Coastal wetlands in Louisiana make up the seventh largest delta on Earth. They contain about 37 percent of the estuarine herbaceous marshes in the conterminous United States and support the largest commercial fishery in the lower 48 States (Glick *et al*., 2013; Couvillion *et al*., 2011). Two of the Mississippi river deltas, Wax Lake delta and Barataria Bay delta in Coastal Louisiana however have been undergoing changes to their land use and land cover. While Barataria bay is experiencing widespread degradation and submergence of its coastal wetlands and losing land because of complex interactions, the other, Wax Lake delta is pro-grading and constantly accreting sediments. It has been determined that total land loss in Louisiana's coastal zone is at least 4,300 ha/ year (Day *et al*., 2021). Also, projected wetland loss over the next 20 and 50 years within Barataria Basin (in which Barataria Bay lies) without actions, have been estimated to be another fifth of the basin's wetlands (Day *et al*., 2021). The disappearance of wetlands throughout Barataria Basin would mean the loss of critical breeding, nesting, nursery, foraging, or overwintering habitat for economically important fish, shellfish, furbearers, migratory waterfowl, alligator, and several endangered species. Loss of wetland freshwater habitat and the accompanying trend toward higher salinities would lead to lower biodiversity and productivity.

On the other hand, the Wax Lake Delta (WLD) is actively pro-grading and actively accumulating mineral and organic sediment that increases soil surface elevation. These create succession and development of emergent wetland communities.

1.2 Remote sensing and Geographic Information System

In recent years, Remote sensing and Geographic information systems (GIS) have emerged as powerful tools for monitoring and analyzing changes in coastal wetlands. These technologies provide a cost-effective means of collecting and analyzing spatial data, making it possible to assess changes in land use, vegetation health, biomass, and carbon stocks at high spatial and temporal resolutions (Hussain *et al*., 2013; Tewkesbury *et al*., 2015). Remote sensing data can provide a wealth of information about land cover, land use, vegetation health, biomass, topography, and many other environmental parameters that can be used to track changes over time (Jensen *et al*., 2016; Jensen *et al*., 2021). This technology has revolutionized our ability to monitor and understand changes in the Earth's environment at local, regional, and global scales (Chughtai *et al*., 2021; Lawley *et al*., 2016; LeBlanc, 2019). Previous studies have used remote sensing and GIS techniques to monitor changes in these wetlands. For example, data acquired from Lidar, Radar, hyperspectral images, high-resolution images, medium-resolution images, coarse-resolution images, and aerial photographs have been used to study dynamics of wetland ecosystems using different techniques. Kayastha (2012) used Landsat 8 data to map land use and land cover in the two wetlands and found that they were dominated by marsh vegetation, with a small percentage of open water, and agricultural and urban areas. Gao *et al*. (2014) used MODIS data to analyze the spatial and temporal patterns of vegetation greenness and found that the wetlands were experiencing a decline in vegetation health over time due to a combination of natural and human factors. Wang *et al*. (2018) used Landsat 8 and Sentinel-2 data to estimate aboveground carbon stocks and found that the wetlands had high carbon stocks, with the highest stocks found in areas with high biomass densities. Despite these studies, there is still a need for continued monitoring and assessment of changes in these wetlands, especially in regions that are susceptible to climate change due to the ongoing threats they face.

1.3 Remote Sensing Image classification

Remote sensing image classification is a crucial task in various applications, including land cover mapping and environmental monitoring. Among the different classification techniques, the Maximum Likelihood (ML) algorithm stands out as a reliable and effective method, particularly in the context of classifying coastal wetlands. Coastal wetlands are ecologically important and sensitive areas that require accurate classification for their management and conservation. The ML algorithm, with its statistical approach, can effectively handle the complex spectral characteristics and mixed pixel problems commonly encountered in coastal wetland imagery. It utilizes the probability distributions of different classes, considering both spectral and spatial information, to assign pixels to their most likely classes. Studies have shown the success of the ML algorithm in accurately classifying coastal wetlands, achieving high classification accuracies, and supporting informed decision-making processes (Carle *et al*., 2014). Therefore, the ML algorithm proves to be a valuable tool for remote sensing image classification in coastal wetland environments.

1.4 Objectives

Thus, the study aims to assess the changes in land use land cover in Barataria Bay and Wax Lake Delta between 2010 and 2022 using Maximum Likelihood classification, as well as compare changes in land cover between two study sites from 2010 to 2022.
It will build on previous research by providing updated information on the changes in land use-land cover in Barataria Bay and Wax Lake Delta between 2010 and 2022. The results will provide valuable information for researchers, policymakers, land managers, and conservationists working to protect and manage these wetlands. It will also contribute to the broader understanding of the application of remote sensing, GIS, and data science in monitoring and assessing changes in coastal wetlands.

2.0 STUDY AREA DESCRIPTION

2.1 Barataria Bay

The Barataria Bay is in the lower Northeast side of the Barataria basin, southeastern Louisiana USA, located between Jefferson, Plaquemine, and Lafourche Parish (Figure 1). The coordinates are 29.5783° N, 89.8897° W. It is an inlet of the Gulf of Mexico and surrounded by Salt Marshes. It is about 15 miles (24 km) long and 12 miles (19 km) wide.

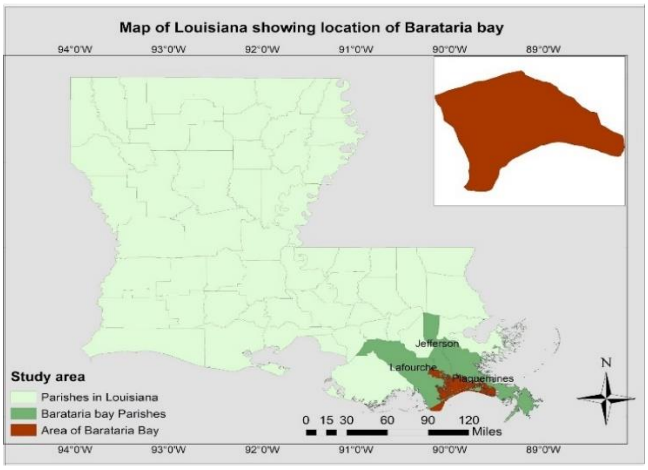

Figure 1: Map showing location of Barataria bay in Jefferson Parish, Louisiana

2.2 Wax Lake Delta

The Wax Lake delta (WLD) is located at the mouth of the Wax Lake Outlet in St Mary Parish, Louisiana. The coordinates are 29.5910° N, 91.4200° W (Majors, 2020). Wax lake delta is an artificial diversion of the Atchafalaya River that was built in 1941 by the Army Corps of Engineers to protect the city of Morgan City, Louisiana from flooding (Carle, 2013). Wax Lake outlet diverts water from the Atchafalaya River to the Gulf of Mexico.

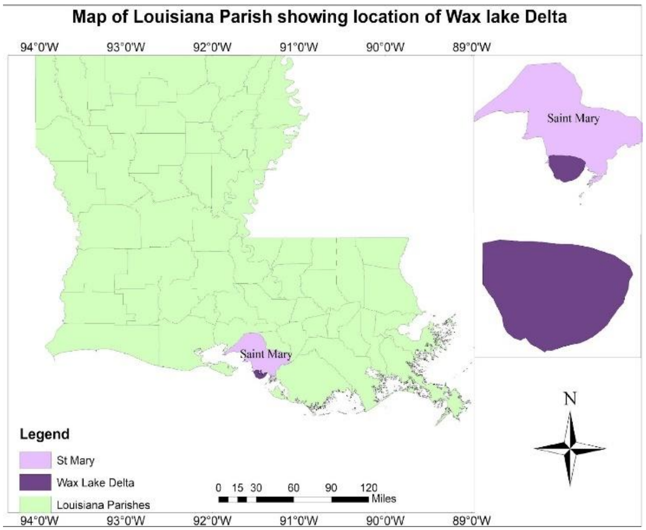

Figure 2: Map showing location of Wax-lake Delta in Saint Mary Parish, Louisiana

The WLD is a real-world example of the potential land/wetland growth possible via sediment diversion project and one report claims that it is a field model for investigating the geomorphology, ecology, carbon dynamics, and carbon storage capacity in young prograding deltas. The Wax Lake Delta first emerged from Atchafalaya Bay following record flooding on the lower Mississippi River in 1973 and 1975. Since that time, it has continued to accrete both vertically and horizontally.

3.0 METHOD OF DATA COLLECTION

3.1 Data Acquisition

Landsat images covering 2010 and 2022 which are freely available for download at USGS earth explorer were used to compute analysis of Land use Land cover change in the study area to assess changes (Table 1).
These satellite images were taken between April and August (except for March 2022) of these years because during these months the sky will be free from the hindrance of cloud, and it is the lushest season for plant growth, hence the satellite image will show a distinct feature among the land-use system clearly. The downloaded satellite images were in a tiff format.

Satellite	Date Launched	Data Acquired	Resolution	Source
Landsat 5	2010	07-17-10	29.98 m TM	https://earthexplorer.usgs.gov
Landsat 8	2013	04-19-13	29.98 m OLI/TIRS	
Landsat 8	2016	05-06-19	29.98 m OLI/TIRS	
Landsat 8	2019	05-13-13	29.98 m OLI/TIRS	
Landsat 9	2022	04-09-22	29.98 m OLI-2	

Table 1: Satellite Data Characteristics and Source for Barataria and Wax Lake.

3.2 Satellite Image Processing

The Landsat satellite images of 2010 Thematic Mapper (TM), 2013, 2016, 2019 Operational Land Image I (OLI-1) and 2022 Operational Land Imager II (OLI-2) obtained, were subjected to the basic pre-processing enhancements. This preprocessing is necessary to adjust the data for use in quantitative analysis and it consists of geometric and radiometric corrections. Radiometric and geometric errors of the Landsat satellite images were removed to ensure data quality using ERDAS imagine software. The images used in this study were first converted to Top of Atmosphere (TOA) radiance using the equation below (Giannini *et al*., 2015).

$$L\lambda = LMAX\lambda\text{-}LMINQCALQCAL+LMIN \qquad (1)$$

Where:
$L\lambda$ =Spectral radiance at the sensor's aperture [W/(m^2 sr µm)]
Q_{CAL} = Quantized calibrated pixel value [DN]
$Q_{CAL}MIN$ = Minimum quantized calibrated pixel value corresponding to L_{MIN} [DN]
$Q_{CAL}MAX$ = Maximum quantized calibrated pixel value corresponding to $L_{MAX}\boldsymbol{\lambda}$) [DN]
$L_{MIN}\ \lambda$ = Spectral at-sensor radiance that is scaled to $Q_{CAL}MIN$ [W/(m^2 sr µm)]
LMAX, = Spectral at-sensor radiance that is scaled to Qcalmax [W/(m 2 sr µm)].

The above expression does not consider the atmospheric effects, therefore there is a need to convert images from radiance to reflectance measures, using the equation below (Giannini *et al*, 2015).

$$P\lambda = \frac{\pi * (L\lambda - Lp) * d\text{^}2}{(ESUN\lambda * \cos(\theta z))} \qquad (2)$$

Where:
$\rho\lambda$ represents the reflectance at a specific wavelength (λ).
$L\lambda$ is the TOA radiance value at the same wavelength.
Lp is the path radiance value, which represents the radiance from the atmosphere and surrounding environment.
d is the Earth-Sun distance in astronomical units (AU).
ESUNλ is the mean solar exoatmospheric irradiance for the specific Landsat sensor and spectral band.
θz is the solar zenith angle, which is the angle between the zenith (vertical) and the direction to the sun.

3.3 Image Classification

Maximum Likelihood classification Algorithm and spectral values based on Vegetation indices and band ratios were used as integral part of the classification processes. The results of these operations make classification of the study area in pixels into different land cover types.

3.4 Accuracy Assessment

One of the most important final steps in the classification process is the accuracy assessment. The accuracy assessment aims to quantitatively determine how well the pixels were sampled in the appropriate land cover categories. In addition, locations that could be easily identified on the high-resolution. Google Earth and Google Map were used for selecting pixels for the accuracy assessment. In the classified image of the research area, a total of 200 and 100 points were used for Barataria and Wax Lake respectively.
The Overall accuracy, Producer accuracy, User accuracy and Kappa coefficient were obtained using the reference data from the established points.
The accuracy assessment was determined using a confusion matrix.
To evaluate how the classification has performed the Kappa Coefficient was generated using (Eq.4) from the confusion matrix. Also, the overall accuracy, users, and producer’s accuracy will be calculated using Eq.5,6, and Eq.7 respectively.

$$\text{Kappa Coefficient} = \frac{\text{total} * \text{sum of correct} - (\text{sum of all (row total} * \text{column total)}}{\text{Total squared} - [\text{sum of all(row total} * \text{column total)}]} \qquad (3)$$

$$\text{User accuracy} = \frac{\text{Correctly Classified Pixels for a Class} \quad \text{x 100}}{\text{Total Classified Pixels for that Class}} \qquad (4)$$

$$\text{Producer accuracy} = \frac{\text{Correctly Classified Pixels for a Class} \quad \text{x 100}}{\text{Total Reference Pixels for that Class}} \qquad (5)$$

$$\text{Overall accuracy} = \frac{\text{Total Correctly Classified Pixels} \quad \text{x 100}}{\text{Total Number of Pixels}} \qquad (6)$$

4.0 RESULTS

4.1 Land use Land cover change for Barataria Bay

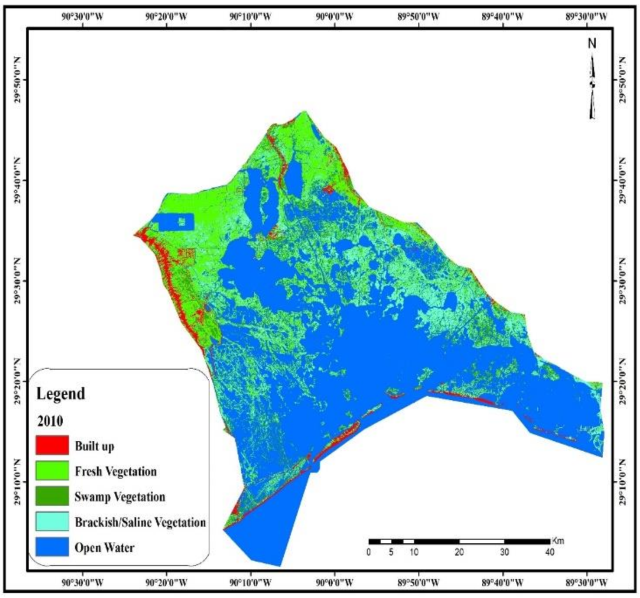

Figure 3: Map of Land use land cover change of Barataria Bay for 2010

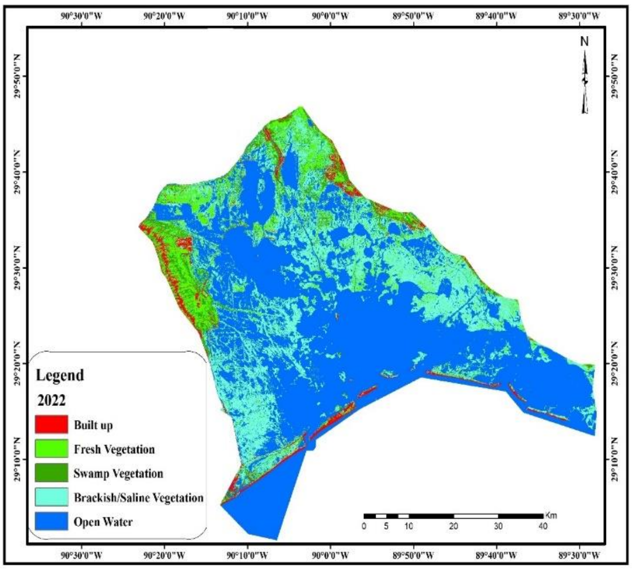

Figure 4: Map of Land use land cover change of Barataria Bay for 2022

4.1.2 Land use land cover Classification Statistics for Barataria Bay

Table 2. presents the classification statistics for five land cover categories for Barataria bay for the years 2010 and 2022. The numbers in the table represent the area in hectares.
The area of built-up land increased from 12125.19 hectares in 2010 to 12462.76 hectares in 2022. The area covered by fresh vegetation decreased from 72236.60 hectares in 2010 to 53388.31 hectares in 2022. The area covered by Brackish/Saline vegetation type increased from 56333.50 hectares in 2010 to 59737.92 hectares in 2022. The area covered by open water increased from 140948.51 hectares in 2010 to 156686.46 hectares in 2022.
The dominant category through the years was open water.

Land cover class	2010	2022
Built up	12125.19	12462.76
Fresh Vegetation	72236.60	53388.31
Swamp Vegetation	29680.60	29048.92
Brackish/Saline Vegetation	56333.50	59737.92
Open Water	140948.51	156686.46
Total	311324.40	311324.40

Table 2. Tabular Illustration of Land use Land cover change statistics for Barataria Bay(hectare)

4.1.3 Accuracy assessment

Land cover	Producer Accuracy (%)		User Accuracy (%)		Overall Accuracy (%)		Kappa Coefficient (%)	
	2010	2022	2010	2022	2010	2022	2010	2022
B	93	97	96	94	89	92	86	89
FV	93	97	70	76				
SV	83	83	94	98				
BSV	80	83	77	86				
OP	96	83	98	98				

Table 3. Tabular illustration of Accuracy assessment for Barataria Bay (2010 and 2022)

**B,FV,SV,BSV,OP represent Built-up, Fresh marshes, Swamp vegetation, Brackish or saline vegetation, Open water vegetation respectively.

The accuracy assessment report presents the results of land use land cover change (LULC) mapping in Barataria Bay for the years 2010 and 2022.
The overall accuracy of the LULC maps varied across the different years, with the highest being 92% in 2022 (Table 4) and the lowest being 89% in 2010 (Table 3). The user accuracy was variable across the different land cover classes, with the built-up area and open water categories showing the highest accuracy across both years. The producer accuracy was high for most categories, except for the brackish/saline vegetation and swamp vegetation categories in some years.
The kappa coefficient ranged from 86% to 92%, indicating a substantial agreement between the maps and the actual land cover. This suggests that the classified maps are reliable and can be used for further analyses and decision-making processes related to land use management and conservation.

4.2 Land use Land cover change for Wax Lake Delta

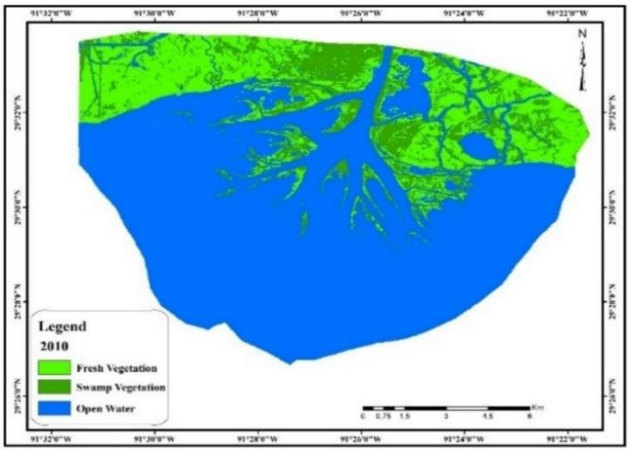

Figure 5: Map of Land use Land cover change for Wax Lake for 2010

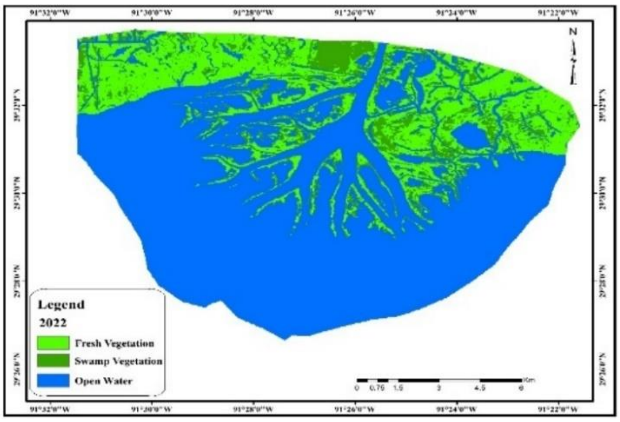

Figure 6: Map of Land use Land cover change for Wax Lake for 2022

Table 5 shows the land use and land cover classification statistics for the Wax Lake Delta for the years 2010, and 2022.
The data shows that the area covered by Swamp Vegetation has decreased over the years from 1,973.61 hectares in 2010 to 1,660.68 hectares in 2022. The area covered by Fresh Vegetation increased from 2,732.4 hectares in 2010 to 3,153.24 hectares in 2022 (Table 5, figure 5 and 6). The area covered by open water, an area of 10,700.3 hectares in 2010 decreased to 10,592.4 hectares in 2022. Overall, the table suggests Wax Lake Delta has changed over the years, with decrease in Swamp Vegetation and open water and increase in fresh vegetation land cover class (Fig. 5and 6).

4.2.2 Land use Land cover Statistics for Wax Lake Delta

Category	2010	2022
Swamp Vegetation	1973.61	1660.68
Fresh Vegetation	2732.4	3153.24
Open Water	10700.3	10592.4
Total	15406.3	15406.3

Table 5: Tabular illustration of land use land cover classification statistics for Wax Lake Delta (2010-2022)

4.2.3 Accuracy assessment for Wax Lake Delta

Land cover	Producer Accuracy (%)		User Accuracy (%)		Overall accuracy(%)		Kappa coefficient	
	2010	2022	2010	2022	2010	2022	2010	2022
SV	87	77	90	92	93	90	89	85
FV	90	90	90	79				
OP	100	100	98	98				

Table 6: Tabular illustration of land use land cover classification accuracy assessment for Wax Lake Delta 2010 and 2022

**FV,SV, OP represent Fresh vegetation, Swamp vegetation, and Open water land cover class respectively.

Table 6 shows the accuracy assessment report for 2010 and 2022 land cover classification. The land cover in 2010 shows that most of the land was covered by open water. The user accuracy for this class was 98%, indicating a high degree of confidence in the classification. The overall accuracy of the classification was 93%, with a Kappa coefficient of 0.89.
In 2022, the user accuracy for the swamp vegetation and open water classes was 92% and 98%, respectively, while the user accuracy for the fresh vegetation class was 79% (Table 7). The overall accuracy of the classification was 90%, with a Kappa coefficient of 0.85, indicating a high degree of accuracy.
Overall, the results suggest that the classification results were generally accurate, with high user accuracy and overall accuracy. The 2022 classification, however, had a slightly lower overall accuracy compared to 2010.

5.0 DISCUSSION

5.1 Land use Land cover Classification

The classification statistics presented suggest that the land cover/ land use composition of Barataria bay ecosystem has undergone some changes over the years.

The increase in the built-up area from 2010 to 2022 suggests that the development of infrastructure and urbanization has continued in the region. This trend is consistent with the overall growth in population and economic activities in the area, which was reported by the world population review.

The increase in the open water area from 2010 to 2022 is likely due to a combination of natural and human factors. Sea-level rise, subsidence, and erosion can cause the loss of land and the conversion of wetlands to open water. Additionally, natural disasters such as hurricanes can cause significant changes in the landscape. Human activities such as oil and gas exploration and navigation can also cause the conversion of wetlands to open water (Barras *et al.*, 2003). The 2010 Deepwater Horizon oil spill, 2011 Mississippi River floods, 2012 Hurricane Isaac are some of the natural and manmade disasters that may have contributed to loss of land and increase in open water within this time. Couvillion *et al.*(2011), Mendelssohn *et al.(*2012) and Turner *et al.* (2019) all reported that after the deep-water spill in 2010, there were observed changes in the vegetation community, structure, and land areas in coastal wetlands of Louisiana.

The decrease in the freshwater vegetation area from 2010 to 2022 is concerning as freshwater vegetation are part of critical wetlands that plays an important role in protecting the shoreline from erosion, reducing storm surge impacts, and providing habitat for many species. Wetlands also act as a carbon sink, helping to mitigate the effects of climate change. The loss of wetlands is a significant environmental concern, and efforts are being made to restore and protect wetlands in these region (Lane *et al.,* 2021; Li *et al*.,2020; Liu *et al*., 2020; Keim *et al*., 2019)

Overall, it is evident that Barataria Bay has increased in the open water and built-up areas land cover category but decreased in the forest and marsh categories.

There have been several similar studies conducted in Louisiana to assess changes in coastal ecosystem composition over time. One such study conducted in the whole of Barataria Basin found that between 1932 and 2010, there was a net loss of approximately 287,000 hectares of wetlands and an increase in open water areas due to natural and human-caused factors such as sea-level rise, subsidence, erosion, and oil and gas extraction (Turner *et al*., 2018). Another study conducted in the Mississippi River delta region found that between 1984 and 2016, there was a net loss of approximately 490,000 hectares of wetlands and an increase in open water areas due to factors such as sea-level rise, subsidence, sediment diversion, and dredging (Melancon *et al*., 2020). This studies have similar share similar trends with our findings. The difference observed may be due to the size of the area under study and number of years of observation.

Also, similar studies have been conducted in other coastal regions to assess changes in ecosystem composition over time. One such study conducted in the Florida Everglades found that between 1995 and 2005, there was a net loss of approximately 33,000 hectares of wetlands and an increase in open water areas due to human activities such as agriculture, urbanization, and water management practices. This area of about 600,000 hectares is larger than the area under study but has same year of observation (10years). However, the loss observed is about the same ratio as the loss observed in the study area.

Another study conducted in the Chesapeake Bay found that between 1984 and 2010, there was a net loss of approximately 84,000 hectares of wetlands and an increase in open water areas due to factors such as sea-level rise, shoreline erosion, and human activities such as development and navigation (Chesapeake Bay Program, 2016).

These studies, including the one presented in the table for Barataria Bay, highlight the significant changes in ecosystem composition that are occurring in coastal regions around the world. The loss of wetlands and the conversion of these areas to open water are of particular concern due to the important ecological functions that wetlands provide, including water filtration, carbon storage, and habitat provision for many species. Efforts are being made to restore and protect wetlands in Louisiana through initiatives such as the Coastal Wetlands Planning, Protection, and Restoration Act and the Louisiana Coastal Master Plan. These initiatives involve the collaboration of government agencies, non-governmental organizations, and local communities to address the complex issues surrounding wetland loss and ecosystem restoration in Louisiana.

5.2 Accuracy Assessment

Based on the results of the accuracy assessment for land use land cover changes in Barataria Bay from 2010 to 2022, there were slight changes in the classification accuracy of the different land cover categories over time. Overall, the accuracy of the classification was high, with an overall accuracy ranging from 89% to 93% and a Kappa coefficient ranging from 86% to 92%.

One possible reason for the high classification accuracy is the use of high-resolution satellite imagery and advanced image classification techniques. The availability of high-resolution imagery allows for more detailed analysis and mapping of land cover changes, while advanced classification techniques such as maximum likelihood classification and object-based classification can improve the accuracy of the results by accounting for spectral, spatial, and contextual information (Jensen *et al.,* 2019)

Other studies have also reported high classification accuracy using similar methods. For example, in a study of land use and land cover changes in the Pearl River Delta region of China using Landsat imagery, Zhang *et al*. (2017) reported an overall accuracy of 90.1% using maximum likelihood classification. Similarly, Ahmed and Ouegan. (2012) reported an overall accuracy of 92% using object-based classification.

In addition, the high classification accuracy in Barataria Bay may be attributed to the use of ground truth data for accuracy assessment. Ground truth data collected through field surveys and ground-based instruments can provide accurate and reliable information about land cover types and conditions, which can be used to validate and improve the accuracy of remote sensing data. These findings are consistent with other studies that have reported high classification accuracy using similar methods.

6.0 CONCLUSION AND RECOMMENDATION

Coastal wetlands are a critical but highly vulnerable ecosystem. It is important to continue to find better ways to manage coastal wetlands. Managing wetlands requires constant monitoring, to track changes that may become detrimental to the overall health of wetlands. Monitoring also helps proffer solutions that can reverse degradation to wetlands.

For this study, remote sensing and GIS were used to assess land use land cover, it was found that these two wetlands Barataria Bay and Wax Lake Delta have both changed tremendously in the past twelve years. While it is correct to say that Wax Lake delta is actively pro-grading, it is important to note that our studies have shown that it is not totally immune to Land loss as well. To keep the current trends and possibly make the current situation in Wax Lake delta better, it is very important to continue to monitor, constantly.

Maximum likelihood algorithm continues to be a highly effective approach for change detection in land use land cover studies for coastal areas. The moderately high accuracy result in these studies is evidence of that.

Overall, findings from these study prove the importance of monitoring changes in coastal wetlands, with land cover showing different dynamics. The changes observed in the two wetlands can be attributed to a varying range of socioecological factors including

storm surge and hurricanes. Future changes to land cover will mean a further loss of biomass, biodiversity, and carbon stock vis-a vis social, economic loss at regional and global scale. Thus, it is critical to continue to monitor and track changes in these sentinel wetlands to better mitigate against future anthropogenic and natural disasters.
Future research needs to look at important areas like assessing sequestration capacity and carbon content of the remaining wetlands in Louisiana.

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