ASSESSING LAND COVER CHANGE AROUND BAYOU PEROT-LITTLE LAKE, NEW ORLEANS USING SENTINEL 2 SATELLITE IMAGERY

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ABSTRACT

Global climate change has affected the rate of rising sea level, the frequency, intensity, timing, and distribution of hurricanes and tropical storms which threatens coastal ecosystems such as Bayou Perot, Little Lake in New Orleans along the Gulf of Mexico. The impact of hurricanes could include wetland and coastal land loss. This paper compared the land cover changes around Bayou-Perot- Little Lake, New Orleans, USA following Hurricanes Ida (August 26, 2021 to August 28, 2021). Two high-resolution Sentinel 2 imagery dated before and after Hurricane Ida was compared to assess the impacts of the hurricane on the land cover around Bayou Perot. A Random Forest classification (RF) algorithm in Google Earth Engine was used to produce maps and identify areas that have experienced conversions in land use or land cover change after the hurricane. This method of classification has the advantages of high classification accuracy and the ability to measure variable importance in land-cover mapping. In addition to random classification algorithm, other analysis such as the Normalized Difference Vegetation Index (NDVI) was be used to gain a better perspective of the overall changes in vegetation across the landscape. Five main classes were considered after the classification which included water, vegetation, bare soil, built up and marsh area. The results of the land cover change showed exposed old coastal marsh, valuable dune habitat providing storm protection to estuaries, wetlands, and the coastal population destroyed.

1.0 INTRODUCTION

Increasing global temperatures has resulted in high-intensity of hurricanes. The Gulf of Mexico region in the United States is a region subject to frequent hurricane strikes. With the threat of global climate change, landfall of more intensive hurricanes along the Gulf of Mexico coast should result in stronger winds and greater storm surges. The sea level in the south east region of the United States keeps increasing. Besides the changes in hurricanes climatology, coastal flooding will also likely increase due to future sea-level rise (Ferreira et al., 2014). Coastal areas with lower elevations such as those found around Bayou Perot are particularly vulnerable to impacts of climate and land cover change. According to (Bay et al., 2011), the effects of storm surges may extend further inland, potentially affecting more landward communities than gradual sea level rise. The accurate assessment and prediction of damages from and subsequent responses by coastal ecosystems to intense hurricanes will be critically important to forecasting effects of climate change in the Gulf Coast region (Bay et al., 2011). Information derived from such studies will be useful to the planning and management of the region. Several studies have incorporated the use of satellite data in assessing and monitoring the impacts of hurricanes on coastal ecosystems.

Towards this goal, this research project integrates remote sensing, to study the land cover changes around Bayou Perot, Little Lake following Hurricane Ida, a category 4 storm which affected the area from August 26, 2021 to August 28,2021. The specific aims of the project were to: (1) assess the land cover changes around Bayou Perot, Little Lake following the Hurricane Ida impact (2) detect post-storm vegetation changes by remote sensing techniques. Specifically, this paper reports the results from detecting the land cover change in this coastal area following the hurricane strike using high-resolution Sentinel 2 imagery with a 10-m pixel resolution. Sentinel-2 is an Earth observation mission of the European Space Agency (ESA) designed for land and coastal applications, and it includes the identical Sentinel-2 A and Sentinel-2 B temporal resolution with temporal resolution of 10 days and 13 multi-spectral bands. Also, it has increased great consideration in research due to its free access and global coverage.

2.0 STUDY AREA AND DATA

2.1 Study Area.

Bayou Perot is an anchorage located in Lake Salvador in the Jefferson Province of New Orleans, Louisiana. It lies between the geographical coordinates Latitudes 29°41.006′N and Longitudes 090°11.283′W with a depth of 8 feet. The area is remote and is well-known for its fishing prowess. Much of the shoreline in this area is characterized by fresh to brackish salinity marshes (Henry et al., n.d.). This area has shown substantial land loss due to subsidence and erosion, and most marshy areas are fragmented. The shoreline of Bayou Perot is mostly freshwater marsh, but there is a change in salinity within the watershed to the south toward the Barataría Bay. Like much of Louisiana, this area has exhibited significant land loss due to subsidence and erosion, and many of the marsh areas are fragmented (Henry et al., n.d.). The study area was greatly affected by Hurricane Ida which hit the coastal areas of

Louisiana from August 26th to September 3rd, 2021 bringing with it high winds of a maximum sustained wind speed of 150mph (240 km/h) and heavy rainfall to the region. We compared the land cover changes around Bayou Perot – Little Lake, following Hurricane Ida. Two sentinel 2A Surface Reflectance images dated November 13th, 2020 (before hurricane Ida made landfall) and September 24th 2021 (after hurricane Ida made landfall).
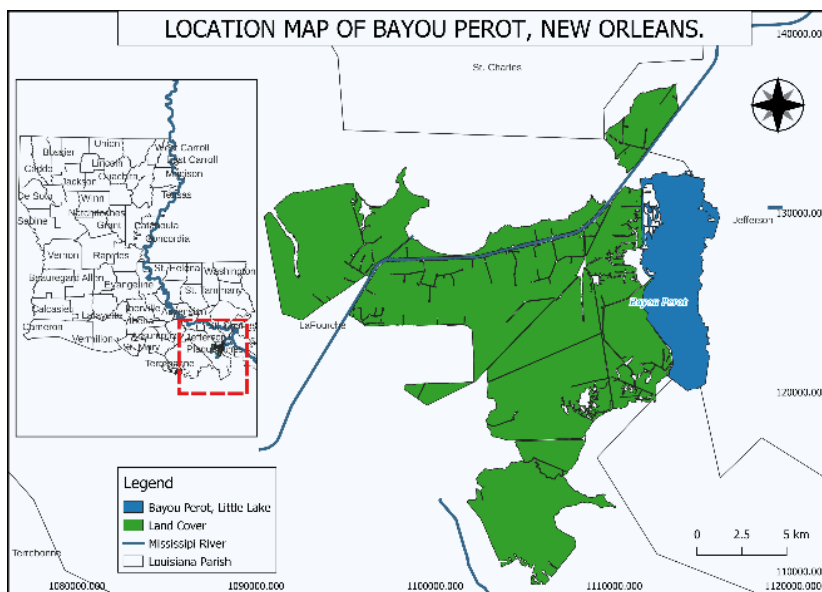

Figure 1. Bayou Perot – Little Lake, New Orleans

2.2 Data

We used Sentinel-2 imagery, because its bands are considered more suitable for vegetation and land cover analysis, thanks to its finer spatial resolution compared to other satellite images and its wavelength sensitivity to chlorophyll content and phenological states (Praticò et al., 2021).

Table 1. Sentinel 2 bands wavelengths

Sentinel 2A			
Band	Bandwidth (nm)	Central Wavelength (nm)	GSD (m)
1	21	442.7	60
2	66	492.4	10
3	36	559.8	10
4	31	664.6	10
5	15	704.1	20
6	15	740.5	20
7	20	782.8	20
8	106	832.8	10
8A	21	864.7	20
9	20	945.1	60
10	31	1373.5	60
11	91	1613.7	20
12	175	2202.4	20

3.0 METHODS

Our methodology, overviewed in Figure 2 and applied in the Bayou Perot – Little Lake area, was based entirely on the use of the Google Earth Engine (GEE) cloud platform environment. GEE is a big geo data processing platform developed for planetary scale geospatial analysis (Gorelick et al., 2017). The existing capabilities within GEE, such as a consolidated library of free satellite images, have opened the door to continually monitor the Earth's surface through reasonable spatial and temporal resolutions (Zurqani et al., 2018). GEE provides rapid and easy prototyping, analysis, and visualization of largescale geospatial data through parallel processing with its web-based integrated development environment(Ghorbanian et al.,2020).
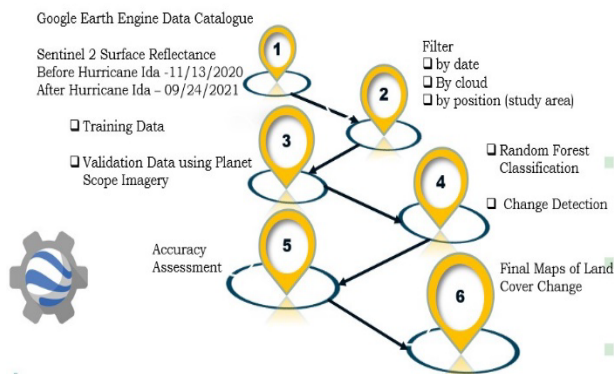
Figure 2. Research methods

3.1 Image Processing

In Google Earth Engine, Sentinel-2 data are available in two different levels, based on the atmospherically corrected status of the images: Level 1C for top-of-atmosphere (TOA) images, and Level 2A for bottom-of-atmosphere (BOA) reflectance. The former need to be atmospherically corrected, in order to obtain useful reflectance values. To adhere to the research objectives, we used level 2A images, which are already atmospherically corrected. In the GEE code editor environment, we imported Sentinel-2 level 2A images as an image collection for both before and after hurricane Ida. (i.e., a set of Google Earth engine images).

3.2 Image Filtering

In this work, we filtered the image collection using three variables: covered location, time interval, and cloud percentage. The location of the images was given by the shapefile of the study area that was imported into GEE environment. The time period was fixed, starting from November 2020 to September 2021, thus covering the before and after the hurricane impact. We used the cloudy pixel percentage value, stored as metadata for each image, to select and extract only those images with a cloud cover less than 10% in the study area.

3.3 Normalized Difference Vegetation Index (NDVI)

The Normalized Difference Vegetation Index (NDVI) is calculated based on the normalized ratio of Near Infrared (NIR) and red bands. This is a well-known and widely used Vegetation Index, which allows for the identification of photosynthesizing vegetation by investigating the bands of higher absorption and chlorophyll reflectance. The NDVI is a useful indicator of vegetation abundance and it is computed by

$$NDVI = \frac{NIR-RED}{NIR+RED} \qquad (1)$$

Where   NDVI = Normalized Difference Vegetation Index

NIR = Near Infrared Band

RED = Red band

NDVI assume values between -1 and 1.

3.4 Random Forest Classification

Random Forest Classification is a popular machine learning algorithm that belongs to the supervised learning technique. The classification can be performed either by pixel- or object-based approaches. In this study, considering the resolution of the images used to carry out the supervised classification of land covers, we adopted a pixel-based approach which is considered as the best GEE approach and has been most adopted by the scientific community. Considering the characteristics of the area and previous research works, we chose five classes to perform the classification: water, vegetation, bare soil, built-up and marsh areas.

3.5 Determination and Training of Validation Points

To improve the quality of the final classification results, the choice of training and validation points is one of the most critical steps in the whole process. The classification method used was pixel-based; therefore, training and validation points represented the defined land cover classes to which they belonged, avoiding mixed pixel issues. For each land cover class, a set of 100 points (500 in total) was collected in the GEE map area environment using different reference layers. Each set was formed of 25 training points (25% of the total) and 75 validation points (75% of the total), for each class; thus, with a total number of 175 training points and 525 validation points. All training points were collected through a visual approach, while the validation points were collected, on one hand, using a visual approach justified by a detailed knowledge of the area.

3.6 Accuracy Assessment

For each performed classification test, a measure of accuracy was performed, considering, as indicators, the Overall Accuracy (OA), the User's Accuracy (UA), Error of Commission. The OA is the total percentage of classification, given by the ratio between the number of correctly classified units and their total number, while UA refer to single class classification accuracies. The UA is the ratio between correctly classified and all classified units in a given class. Validation samples were collected from Planet Scope imagery which has spatial resolution of 5m to perform the accuracy assessment.

4.0 RESULTS AND DISCUSSIONS

From figure 3 (a) (b), the 2021 image had a higher mean NDVI value than the 2020 image. The increased vegetation index shows the increased in forest cover, agriculture activities or shrubs at the Bayou Perot upland. The 2021 NDVI map shown Figure 3. (b) displays fragmented vegetation as a result of the hurricane. However, (Bay et al., 2011) mentioned that interpretation based on NDVI values alone is not valid, thus accurate land cover classification and mapping of their spatial pattern is necessary for valid interpretation. Land cover changes between the two images are presented in Table 2. "Bare soil" had the largest relative percent increase in acreage, to "water" with a value of 14.41%." vegetation" and "marsh areas" also show a relative percent decrease in area to "water" between the two dates (14.41% and 3.55% respectively). The

other category that experienced a slight decline was "built-up" areas. Table 3 shows how land cover changed from one category to another. The increased water level inundated the other classes causing a reduction in the acreages of the bare soil, vegetation and marshy areas as shown in the histogram in figure 5 (a) and (b).
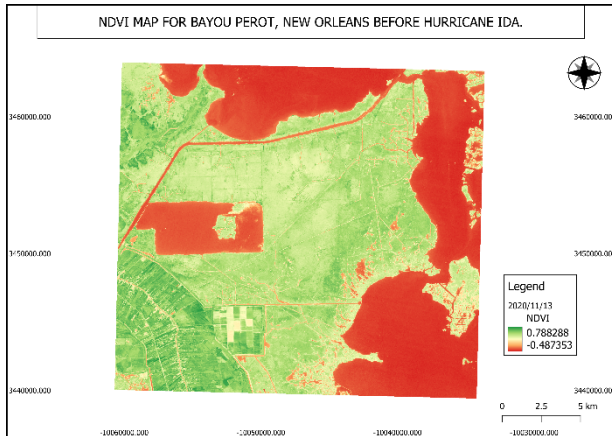

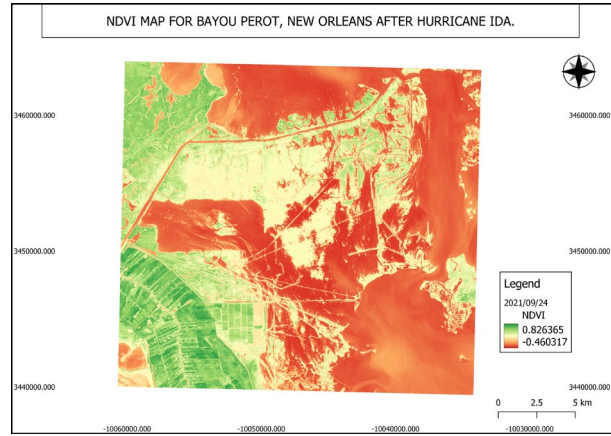**Figure 3 (a) 2020 NDVI map before Hurricane Ida**

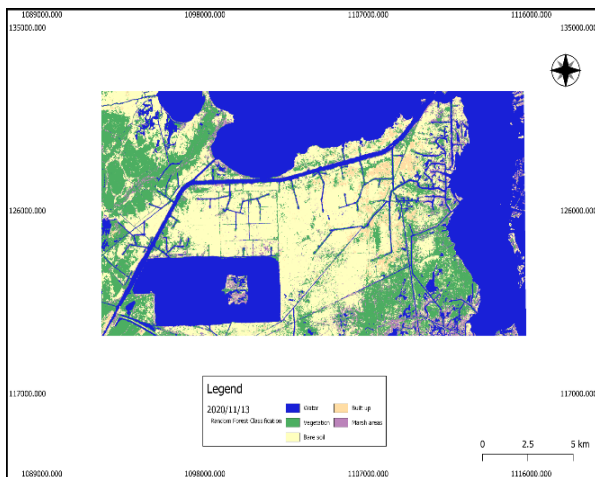

Figure 3 (b) 2021 NDVI map for after Hurricane Ida

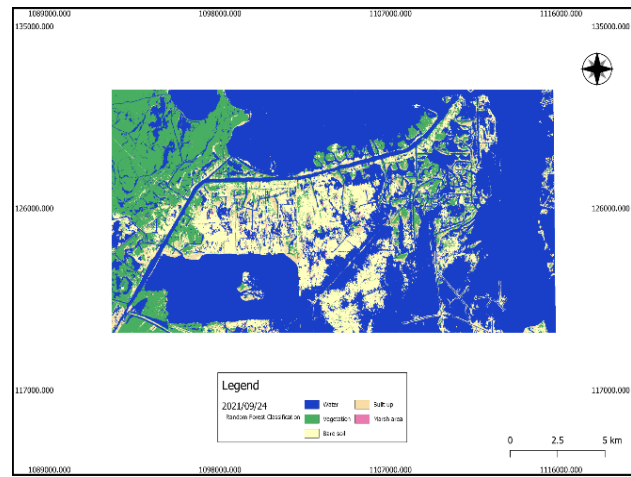**Figure 4 (a)2020 Random Forest classified map**

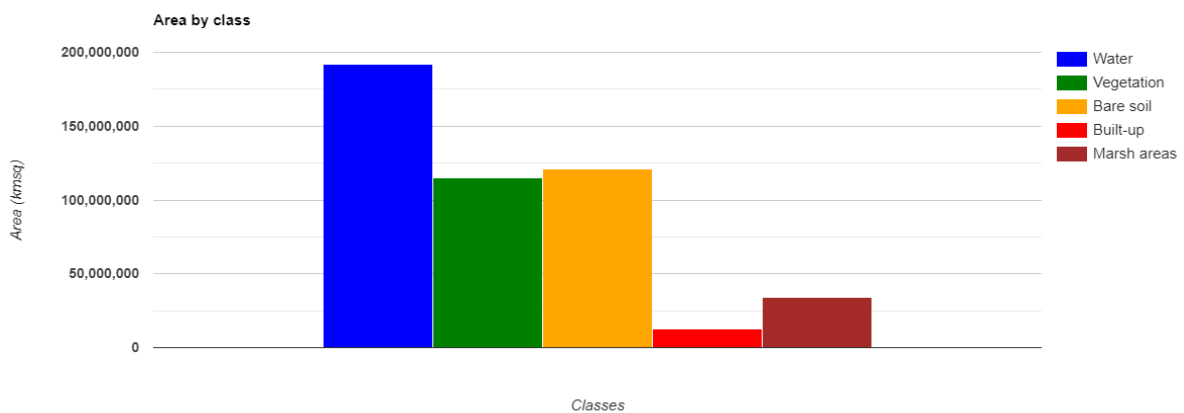**Figure 4 (b) 2021 Random Forest classified map**

Figure 5 (a) Spatio-Temporal Land Cover Classes Variation for before the Hurricane Ida Impact (2020).
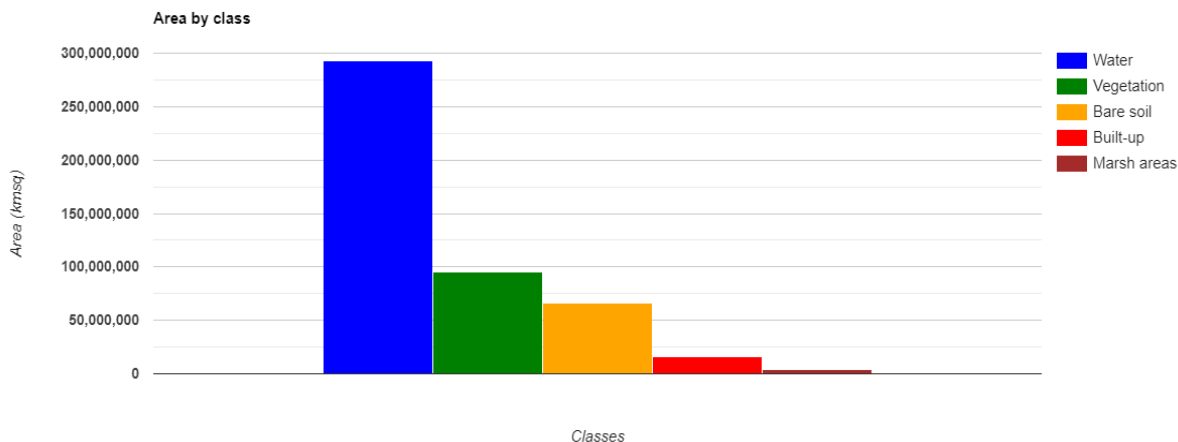
Figure 5 (b) Spatio-Temporal Land Cover Classes Variation for after the Hurricane Ida Impact (2021).

Table 2. Over-all land cover change statistics for before and after the Hurricane Ida Landfall.

Area Covered Percentage (%)	No change	Water	Vegetation	Bare Soil	Built up	Marsh Areas
No change	100	0	0	0	0	0
Water	0	64.94	2.33	4	9.51	7.71
Vegetation	0	14.41	48.83	12.4	18.19	19.29
Bare soil	0	14.83	37.55	73.14	54.4	54.73
Built up	0	2.27	2.29	1.17	7.67	1.94
Marsh areas	0	3.55	9	9.3	10.23	16.33
Total	100	100	100	100	100	100

Table 3. Accuracy Assessment statistics

Class	Users Accuracy	Error of Commission
Water	93.33	6.667
Vegetation	86.67	13.333
Bare soil	73.33	26.667
Built up	75.79	24.210
Marsh Area	88.12	11.880
Overall Accuracy	**0.9995729647890058 (99.95%)**	

Table 4. Confusion matrix

		Ground Truth Values (G)					
		Water	Vegetation	Bare Soil	Built-up	Marsh Area	Total
Predicted Values	Water	**48299**	0	1	1	1	48302
	Vegetation	8	**1644**	2	0	0	1654
	Bare Soil	0	0	**1471**	0	0	1471
	Built up	2	0	0	**9**	0	11
	Marsh Area	0	4	3	0	**73**	80
	Total	48309	1648	1477	10	74	**51518**

5.0 CONCLUSION

We note that there are limitations of this study, and caution is needed for interpretation. First of all, although the classification accuracy of the images is considered acceptable, there are misclassifications that might affect our interpretations. Secondly, a few remote sensing studies of the effects of hurricanes on this study area have been conducted. The assessment of land cover changes around Bayou Perot- Little Lake, Louisiana using sentinel images dated before and after the hurricane suggest that the sea level rise during that period increased the water level, thus inundating the marsh areas, vegetation and bare soil in the region. The results of the land cover change showed exposed old coastal marsh, 14.43% of bare soil (valuable dune habitat) providing storm protection to estuaries, wetlands, and the coastal population destroyed. Marsh areas/ swamp areas which could include fresh marsh or brackish marsh decreased in acreage as 3.5% of the marsh land cover class was inundated with water. The differential rates of land cover change documented in this study provide useful baseline information for future studies to compare with. Also, the rates of loss and gain in land cover, after repeated verification can be used in future predictive modelling and will be valuable in assessing changes produced by hurricanes.

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