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Using NASA Earth Observations to Monitor Historical Changes in the Extension of Seagrass Meadows in the Breton National Wildlife Refuge in Louisiana

DEVELOPTechnical Report

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1. Abstract

The barrier islands of Louisiana's Breton National Wildlife Refuge (BNWR) are disappearing due to sea level rise, extreme hurricanes, sediment starvation, and the Deepwater Horizon oil spill. This decline in land area has damaged important bird habitat and reduced the islands' ability to protect coastal Louisiana from storm surges. The persistence of the islands is synergetic to that of the surrounding seagrass beds; seagrass binds together land, protecting the islands from erosion, and the loss of land exposes the seagrass and accelerates its decline. Furthermore, seagrass is independently important, absorbing excess nutrients and providing habitat for marine ecosystems. Here we present the Tool for Coastal Remote Ecological Observations in Louisiana (Tool CREOL), a Google Earth Engine Tool built to easily access data from Landsat 5 TM, Landsat 7 ETM+, Landsat 8 OLI, and Aqua and Terra MODIS. We show, using time series and maps generated using the tool, how land area and seagrass have responded to destructive events from the past 36 years (1984-2021). In only 7 years, Hurricane Georges (1998), Ivan (2004), and Katrina (2005) reduced land area by approximately 85%, accompanied by a major decline in seagrass extent. Tool CREOL will have strategic utility in planning upcoming restoration and revegetation efforts planned by Louisiana's Coastal Protection and Restoration Authority in the Breton National Wildlife Refuge and will provide up-to-date monitoring of the results of that project. The tool serves as a basic model which can be adapted to study similar coastal regions in the world.

Key Terms

remote sensing, seagrass, Landsat, MODIS, turbidity, hurricanes, restoration, salinity, Google Earth Engine

2. Introduction

2.1 Background Information

The persistence of submerged aquatic vegetation (SAV) is essential to the restoration and maintenance of a healthy ecosystem in the Breton National Wildlife Refuge in southeastern Louisiana. SAV refers to rooted underwater vegetation, such as seagrasses, that primarily grows in shallow waters (Kentworthy et al., 2017). Louisiana's seagrass meadows are located approximately 50 miles off the coast of the Mississippi River's St. Bernard Delta, primarily along the Breton and Chandeleur Islands (Figure 1). The Chandeleur Islands, which stretch for approximately 72 miles, separate the Chandeleur Sound from the Gulf of Mexico and provide storm surge protection to Louisiana's coastal communities (Poirrier & Handley, 2006). At a maximum depth of 20 feet, the Chandeleur Sound provides the ideal shallow habitat for native seagrass beds which thrive in natural shoals behind the Breton and Chandeleur Islands (Poirrier & Handley, 2007). The seagrass beds are known to support fisheries and biodiversity by providing aquatic habitat and absorbing excess concentrations of nitrogen and phosphorus, which cause harmful algal blooms and oxygen deficits. Seagrass beds also help protect coastal communities such as New Orleans by reducing storm surges, slowing barrier island erosion, and trapping suspended sediment.

Despite the numerous ecological and economic benefits, SAV populations are currently in a global decline due to a combination of natural and anthropogenic forces. The Chandeleur Islands are facing increased land loss, reducing habitat and exposing fragile SAV to harsher and deeper waters. Devastating events such as Hurricane Katrina in 2005 (Fearnley, 2009) and the Deepwater Horizon Oil Spill in 2010 (Kentworthy et al, 2017) increased the vulnerability of existing populations. Impending threats of rising sea levels, increasing temperatures, and changes in water quality and turbidity are expected to further reduce the extent of seagrass meadows (Poirrier & Handley, 2006). Increased monitoring, revegetation, and restoration of the Breton and Chandeleur Islands are thus needed to understand shifts in SAV populations and prepare for both climate-induced and anthropogenic changes in the ecosystem. Current *in situ* sampling methods are insufficient in visualizing changes in SAV extent over large periods of time due to human error, temporal limitations, and sample processing time (Rowan and Kalacska, 2021). Passive satellite remote sensing and aerial photography may be able to provide a highly reliable and low-cost method to monitor SAV changes and advise restoration efforts.

Data from Landsat satellites have been previously used to study global SAV populations. Misbari and Hashim (2016) used NASA's Landsat 5 Thematic Mapper and Landsat 8 Operational Land Imager data to measure changes in SAV extent in Johor, Malaysia. While the Landsat satellites provide reliable 30-meter spatial resolution, data analysis is limited by cloud cover and coarse temporal resolution (16-day return time). NASA's MODIS, launched in 2002, is commonly used to determine surface water temperature, a key component of SAV persistence (Carlson et al, 2014). While MODIS has a coarse spatial resolution, its 1 to 2-day return time provides an ideal temporal resolution for monitoring SAV changes. For the purposes of this project, we adopted a study period of 1984-2021 to encompass historical SAV extents and better advise revegetation efforts around the Chandeleur Islands. We compiled data to analyze seagrass meadows in the Chandeleur and Breton Islands via the development of a graphical user interface (GUI) to measure turbidity, chlorophyll-a, land area, sea surface temperature and NDAVI/seagrass extent.

Figure 1. Study area of Louisiana's Chandeleur Sound and Islands

2.2 Project Partners & Objectives

Our team collaborated with Louisiana's Coastal Protection and Restoration Authority (CPRA) and the Louisiana Department of Natural Resources (LDNR), Office of Coastal Management. The CPRA is required to submit an annual report on the state's effort to preserve coastal wetlands that details short-term and long-term results citizens can expect to see. Currently, the LDNR is implementing the Louisiana Coastal Resources Program (LCRP) to promote the restoration and revegetation of Louisiana's seagrass beds. Partners will utilize project results to identify primary areas for restoration and understand ideal areas for seagrass habitat. The CPRA and LDNR will then implement restoration and revegetation efforts.

One of the key objectives for this project was to develop a user-friendly interface in Google Earth Engine (GEE) to allow for seagrass monitoring via satellite remote sensing. Key variables include turbidity , salinity and NDVI. Results of the GEE tool will aid users in identifying current and historical seagrass beds as well as ideal areas to focus restoration efforts.

3. Methodology

3.1 Data Acquisition

The team accessed Landsat and MODIS data through GEE (Table 1). We used Landsat 5 Surface Reflectance (SR) Tier 1, Landsat 7 Surface Reflectance Tier 1, and Landsat 8 Surface Reflectance Tier 1 optical imagery for January 1984 to January 2000, January 2000 to April 2013, and April 2013 to June 2021, respectively. In addition, the team used data from the Aqua MODIS and Terra

MODIS temperature bands from July 2002 to April 2021 and February 2000 to April 2021, respectively.

We also used the Joint Research Centre (JRC) Global Surface Water Dataset, which is a data product derived from Landsat data (Pekel et al., 2016). We used two ancillary datasets to analyze environmental conditions that we could not derive from the remote sensing data. To track runoff from the Mississippi river we used a USGS dataset of monthly nutrient flux and streamflow (Aulenbach et al. 2007). The USGS generated these data with the intention to track sources of major nutrients that lead to hypoxia in the Gulf of Mexico. We supplemented this with an ocean sea surface salinity model made by combining data from the SMOS and SMAP satellites (Droghei et al. 2016, Droghei et al., 2018). Ideally, these datasets provide independent constraints on Mississippi River runoff we can use to test output from our tool against.

3.2 Data Processing

We processed all data in GEE. Our team used the pixel QA band to mask both cloud and land pixels from the Landsat SR imagery, retaining only pixels with the value 68 for Landsat 5 and 7 imagery and 324 for Landsat 8 imagery. These values represent pixels where water is present and clouds are absent. Our tool presents multiple options for viewing the data. One option is a least cloudy perspective,

which layers images over three-month periods in order of least cloudiness and mosaics them. Another option is to get a median composite image, which takes the median of all non-cloudy pixels at a given position.

3.2.1 Seagrass bed extent

We used the normalized difference aquatic vegetation index (NDAVI) to classify seagrass bed extent throughout the study area. This unitless index was adapted from the normalized difference vegetation index (NDVI) by Villa, Mousivand, and Bresciani (2014). NDAVI efficiently identifies aquatic vegetation rather than terrestrial. NDVI, which has typically been used to identify the extent and health of terrestrial vegetation, is the normalized difference of the near infrared and red bands. NDAVI differs from NDVI by using the blue band in place of the red band, accounting for the difference in vegetation substratum between aquatic and terrestrial vegetation (Equation 1).

$$
NDAVI = \frac{(NIR - \lambda)}{(NIR + \lambda)}\tag{1}
$$

3.2.2 Turbidity

We mapped turbidity using the normalized difference turbidity index (NDTI). NDTI is calculated by comparing the intensity of red light to green light. Red light is reflected by suspended sediment, organic matter, and other solids, while green light is reflected by clearer water. The index uses the normalized difference of the red and green band reflectance values in order to account for uncertainties (Equation 2).

$$
NDTI = \frac{(\dot{\mathbf{i}} - \dot{\mathbf{i}})}{(\dot{\mathbf{i}} + \dot{\mathbf{i}})}
$$
 (2)

3.2.3. Salinity

Surface salinity and surface ocean density data was sourced from the Multi-Observation Global Ocean Sea Surface Salinity and Sea Surface Density dataset and downloaded from the Copernicus Environmental and Marine Ecosystem Services website. Data were processed with Python using the geospatial data analysis package, x-array. We selected a location landward of the Chandeleur Islands, in the Chandeleur Sound, and generated a time series across the timespan dataset (1993-2019). There were no sea surface salinity datasets with adequate time or spatial resolution available on GEE natively, so this functionality is not available in the Tool CREOL, only in the results presented in this technical report.

3.2.4. Land and Water

Our land water classification system is derived from the Joint-Research Center's Global Water History dataset, loaded into the Tool CREOL using the Google Earth Engine. The raster has values of 0 for pixels with no data, 1 for pixels with land, and 2 for pixels with water. Within the Tool CREOL, there is a function that drops pixels with no data and transforms the raster values to binary, 0 where there is land, and 1 where there is water.

3.3 Data Analysis

All of the Chandeleur Island data for this study was processed using the Tool CREOL and Google Earth Engine. While Google Earth Engine has its limitations regarding data analysis and the application of rigorous statistical models, its advantage is that it is very user friendly. Our study is designed to highlight the utility and simplicity of the Tool CREOL, and using the data processed by the tool maximizes reproducibility.

Interpretation of NDAVI, the index we used to monitor SAV, was limited by a lack of *in situ* data. We have images of the field area with presence/absence data for SAV, generated by the USGS in a study assessing the response of seagrass to the BP Oil spill, from 2010 and 2011 (Consentio-Manning et al., 2015). We georeferenced these field images and the seagrass extent was compared to Tool CREOL's SAV outputs. We did not perform a quantitative classification identifying presence/absence of SAV per pixel using NDAVI. Instead, we adjusted the color scale of the NDAVI images to provide the best visual match to the USGS image.

4. Results & Discussion

4.1 Tool for Coastal Remote Ecological Observations in Louisiana

We developed the Tool for Coastal Remote Ecological Observations in Louisiana (CREOL) on the GEE JavaScript API to analyze water quality parameters within coastal Louisiana. Tool CREOL consists of an interactive graphical user interface (GUI) that allows users to analyze historical trends in seagrass extent (represented by NDAVI), turbidity (represented by NDTI), SST, and land area. Within the GUI, users can select a predefined area of interest, upload their own asset, or draw an asset for analysis. Users then input a year and season ranging from January 1984 to the present and select a set of water quality parameters for analysis. Tool CREOL reads the specified user inputs and creates a filtered and masked image collection of the selected water quality parameters using imagery from Landsat 5 TM, Landsat 7 ETM+, Landsat 8 OLI, and Aqua and Terra MODIS. Within Tool CREOL's GUI, users also can also compare parameters through a split screen comparator, generate time series analyses through a specified point change inspector, and export GeoTIFFs to Google Drive.

4.2 Analysis of Tool CREOL Results

4.2.1 Hurricane Impacts to the Islands

We used the imagery and time series generated by Tool CREOL to assess the impact of major hurricanes on the Chandeleur Islands and seagrass there across the duration of our study interval (1984-2021). The left and right panels of figure 2 show true color images of the Chandeleur Islands in 1984 and 2021, respectively. The middle panel includes time series of NDAVI for 5 points in a latitudinal transect across the islands, as well as a time series of total land area throughout the Chandeleur Islands. Vertical dotted lines represent major hurricanes that impacted the region during our study interval.

Figure 2. Spring 1984 true color image of the Chandeleur Islands. Red dots represent the locations NDAVI time series were extracted using the Point Inspector Tool (left panel), NDAVI and land area time-series graphs taken with the Point Inspector tool and Time Series Chart Generator tool. Vertical lines and bars represent major events in the islands across the past 36 years, including hurricanes, and the BP Oil Spill. (center panel), and spring 2021 true color image of Chandeleur Islands (right panel).

The NDAVI and land area time series demonstrate the ability of Tool CREOL to reconstruct past environmental change and measure the impact that hurricanes have had on the islands (Figure 2). Between 1984 and 1999, the NDAVI index and land area appears to be in an equilibrium state, with a relatively consistent seasonal cycle within a flat long-term trend. Short-term variability in land area is evident across this time interval, with rapid response and recovery to storm systems Andrew and Josephine. Long-term variation in this period is minor, with only a gradual increase in land occurring in the first 5 years of the record.

The passage of a few major storms, Georges (1999), Ivan (2004), and Katrina (2005), eroded a huge fraction of the land in the Chandeleur Islands. Land area dropped from approximately 16 km² in 1998 to approximately 2 km² in 2006. The NDAVI remained stable until Hurricane Katrina in 2005, after which followed the most severe declines in the NDAVI records. According to the NDAVI, seagrass in the northern part of the island declined immediately, while seagrass in the southern part of the island suffers a more gradual decline. The down trending NDAVI in many cases stabilized by around 2010. Following 2010, and land area stabilized or even increased in some areas. Seasonal variability in the NDAVI also increased markedly after this interval.

Our long-term time series analyses of NDAVI and land cover allow for a nuanced analysis of how various events have impacted the Chandeleur Islands over both space and time. The time series reflect the tremendous land loss caused by hurricanes over the past several decades. The impacts of hurricanes on the islands are highly variable since it's dependent upon the path, intensity, and duration of

the storm (Fearnley et al., 2009). However, our analysis shows that some particularly catastrophic hurricanes, such as Hurricane Katrina, caused lasting land loss as well as long-term impact on seagrass extent and health. Finally, the time series demonstrate the impacts of restoration efforts and natural rebound on land area recovery. The increase in land area after a sand berm was constructed in 2010 to protect the islands from the BP Oil Spill was likely due to a combination of the berm itself and natural recovery.

4.2.2 Mississippi River Discharge and Seagrasses

We compared a time series of NDAVI integrated across the Chandeleur islands, generated with the Tool CREOL, to discharge from the Mississippi River (Figure 3) to get a sense of how the seagrass responds to changing salinity conditions, sediment discharge, and concentrations of important nutrients. We supplemented the Mississippi discharge data with a global salinity model, sampled behind the Chandeleur Islands in the Chandeleur Sound between 1993-2019 (Figure 3) to get independent constraints on river discharge, as the Mississippi is the main source of fresh water regionally. A qualitative comparison of trends in the data shows a possible positive long-term relationship between freshwater input from the Mississippi River and a NDAVI. Seagrass growth could be directly related to the salinity of the environment (Hillmann & Peyre, 2019), but could also be enhanced by the increased availability of macro-nutrients delivered by the river during high discharge periods (Darnell et al, 2017). Regardless, our results have positive implications for the health of seagrass beds in southern Louisiana as the CPRA plans new diversions for sediment and fresh water out of the lower Mississippi River (Bradberry et al., 2017).

Figure 3. Seagrass (NDAVI), salinity, and freshwater discharge in the coastal Louisiana region from 1984 – 2021

4.3 Errors and Uncertainties

Limitations of our data included cloud cover, limited access to *in situ* data, inconsistencies between satellites, and the lack of assessing chlorophyll-a in our analysis. In remote sensing research, clouds are a typical source of error and can result in skewed data values and calculations. The Chandeleur Sound region is an exceptionally cloudy area which contributes to cloud cover as a potential error in our tool's imagery. For years such as 2020, cloud cover results in scattered data which can be misinterpreted and misrepresented as exceptionally high or low values for any of our parameters. Secondly, limited access to in situ data prevented proper data calibration and validation which may result in uncertainties in output values. Lack of ground truthing particularly produced uncertainties in our SAV model outputs generated via the NDAVI index. Our only source of *in situ* data came from two georeferenced site images depicting seagrass extent which were then utilized to calibrate our model as accurately as possible. Calibration of NDAVI had limited success across the 36-year study period, some of which can be attributed to differences between the Landsat 5 TM, Landsat 7 ETM+, and Landsat 8 OLI satellites and sensors. Differences in bandwidths between each of the satellites may result in differing values for our parameters and affect trends seen in time series analyses.

4.4 Future Work

Future work includes the incorporation of *in situ* data, calibration of our indices and improvement of our SAV model. Firstly, our project had limited access to *in situ* data which reduced our ability to calibrate our parameters and validate our results. The addition of more *in situ* data would allow for us to better understand what values our study area typically sees for chlorophyll, turbidity, SST and SAV. In the future, *in situ* data can be incorporated into our parameters to help produce stronger results and improve confidence in Tool CREOL's outputs for our partners. Additionally, we would like to improve our SAV model to provide accurate visualizations of historical seagrass trends. We currently use the NDAVI index to determine seagrass extent. This can be improved in the future by utilizing *in situ* data and Tool CREOL outputs to develop a binary seagrass model. This future model would aid the CPRA and LNDR in the identification of ideal areas for seagrass revegetation and island restoration. This would directly assist the Breton National Wildlife Refuge in the ongoing 2020 restoration effort.

There are also opportunities for future additions to Tool CREOL. Firstly, added statistical capabilities within the tool would be beneficial. For example, the ability to add trend lines to time series charts in the tool would help our partners to better understand historical trends in seagrass and water quality. Another potential addition is a GIF generator, which would allow users to create and export a GIF of images spanning a given time range. This would be useful in creating communication and public outreach materials.

5. Conclusions

The Louisiana Water Resources Team developed the Tool for Coastal Remote Ecological Observations in Louisiana Coastal within GEE which assesses how the distribution of seagrass meadows in the coastal Louisiana region have shifted from 1984 to 2021, and also monitors how the barrier islands in the region have

changed over time. This tool, also known as "Tool CREOL," allows the users to conduct different kinds of data analyses within the tool's GUI that aid identifying historical trends and spatio-temporal variation in both seagrass extent and water quality around the selected regions of interest. The tool is programmed to automatically utilize the most up-to-date available imagery and enables more frequent monitoring than can be obtained from *in situ* data collection of the coastal region and various water quality parameters which include: true color, NDAVI, NDTI, SST and land/water. Tool CREOL allows the user to select their preferred area of interest out of the provided options, or allows them to draw their own asset instead, which will be used as a parameter to guide the amount of imagery being generated. This selection opens more of the tools' functionalities such as: splitscreen comparisons, a point change inspector, and time series generator. The tool also allows users to export the generated time-series graphs, and export imagery as batch or single image files.

Using remote sensing analytical techniques, our team used Tool CREOL to identify various trends and correlations between different parameters in the region. We observed that the islands' land area has greatly declined in response to hurricanes since 1984, and that the extent of surrounding seagrass bed has decreased as well. We also found that the health of seagrass beds in the region may be related to the amount of freshwater discharge from the Mississippi River, either through changes to the salinity of the environment, or through the influx of nutrients from the river. Further analyses with additional satellite (Sentinel 2) and in situ corresponding data are suggested to validate these results.

Our partners will be able to utilize Tool CREOL to not only analyze the results we have drawn from various parameters in the region, but also to consistently study the coastal Louisiana region moving forward. The many functionalities available in the tool will help our partners with restoration and revegetation efforts in our study region and enable real-time monitoring of the Chandeleur Islands and Breton National Wildlife Refuge.

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This material contains modified Landsat data (1984-2021), processed by JRC.

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7. Glossary

API – Application programming interface **BNWR** – Breton National Wildlife Refuge **CPRA** – Coastal Protection and Restoration Authority **Earth observations** – Satellites and sensors that collect information about the Earth's physical, chemical, and biological systems over space and time **ETM+** – Enhanced Thematic Mapper Plus **GEE** – Google Earth Engine **GeoTIFF** – An image file with georeferenced metadata **GUI** – Graphical User Interface **JRC** – Joint Research Centre **LCRP** – Louisiana Coastal Resources Program **LDNR** – Louisiana Department of Natural Resources **MODIS** – MODerate resolution Imaging Spectroradiometer **NDAVI** – Normalized Difference Aquatic Vegetation Index **NDTI** – Normalized Difference Turbidity Index **NDVI** – Normalized Difference Vegetation Index **OLI** – Operational Land Imager **SAV** – Submerged Aquatic Vegetation **SR** – Surface Reflectance **SST** – Sea Surface Temperature **TM** – Thematic Mapper **Tool CREOL** – Tool for Coastal Remote Ecological Observations in Louisiana

USGS – United States Geological Survey

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