GIS Project to Categorize and Map Smalltooth Sawfish (*Pristis pectinata*) Shoreline and Nearshore Habitat Features in Southwest Florida

by

Rabiya Dar
Dr. Patrick Halpin, Advisor
NOAA Fisheries, Client
May 2022

Master's project submitted in partial fulfillment of the requirements for the Master of Environmental Management degree in the Nicholas School of the Environment of Duke University

Executive Summary

This project was done in cooperation with NOAA Fisheries to support management of endangered smalltooth sawfish (*Pristis pectinata*) in Charlotte Harbor, Florida. Smalltooth sawfish have experienced a serious decline in their range due to commercial and recreational fishing, entanglement, illegal trade, and coastal development. In the United States, they once ranged from Texas to North Carolina, but are now only found in parts of southern Florida. NOAA Fisheries has designated Charlotte Harbor and the Ten Thousand Islands/Everglades as critical habitat units for sawfish in Florida due to their abundance in mangroves in shallow, euryhaline water which is prime nursery habitat for juvenile sawfish. This project focuses on the Charlotte Harbor unit of critical habitat and utilizes ArcGIS to categorize the shoreline with emphasis on locating and analyzing mangroves to identify priority sawfish habitat.

All imagery was acquired from USGS Earth Explorer and is owned by the National Agriculture Imagery Program. Imagery was generated in 2019 and has a spatial resolution of 0.6 meters. A supervised classification using the maximum likelihood classification method was used to categorize imagery into three classes: mangrove, other vegetation, and non-vegetation. Once a suitable classification was developed and shoreline and nearshore mangroves were identified, analysis was conducted to identify contiguous mangrove patches, mangrove distance to shoreline, and mangrove neighborhood density.

Contiguous mangrove patches were defined as mangrove pixels that have orthogonal or diagonal connectivity and have an area greater than or equal to 25.2 square meters. Mangrove distance to shore was calculated by measuring the distance from the center of each mangrove cell to the shoreline. In this project, shoreline can generally be defined as the boundary between water and any other structure, natural or human-made, from an aerial perspective. Mangroves that were closer to shore were considered higher priority habitat as sawfish are not likely to travel deep into mangrove forests as they are harder to access. Mangrove neighborhood density was calculated by summing all mangroves within each mangrove cell's 8 by 8 cell neighborhood (23.04 square meters). Mangroves with a higher mangrove neighborhood density were considered higher priority habitat as sawfish are more likely to inhabit mangroves surrounded by lots of other mangroves.

Priority sawfish habitat was identified by developing indices that rate mangroves that are close to shore with a high mangrove neighborhood density as high priority habitat and mangroves that are far from shore with a low mangrove neighborhood density as low priority habitat. The first index developed was modeled after the equation used to calculate the Normalized Difference Vegetation Index (NDVI). Mangrove distance to shore was subtracted from mangrove neighborhood density and then divided by their sum to produce an index ranging from -1 to 1 where 1 represents high priority habitat and -1 represents low priority habitat. An inherent flaw of this index was that mangroves touching the shoreline (i.e. where distance to shore equals zero) were automatically assigned a value of 1, regardless of their mangrove neighborhood density.

To address this issue, an additional index was developed based on a general suitability modeling workflow. Mangrove distance to shore and mangrove neighborhood density were reclassified into 10 classes each and then summed to produce an index ranging from 2 to 20,

where 20 represents the highest priority habitat (i.e. close to shore with high mangrove neighborhood density) and 2 represents the lowest priority habitat (i.e. far from shore with low mangrove neighborhood density).

The products from this project will be used by NOAA Fisheries in combination with other datasets to develop a sawfish distribution model. Such a model could be useful in predicting sawfish abundance across seascapes to promote better management of this endangered species. Additional areas of research could include:

- conducting a sea level rise threat assessment to identify high priority habitat that is at risk of flooding due to climate change;
- conducting a land ownership threat assessment to identify high priority habitat that is at risk of being removed due to development;
- and utilizing unoccupied aerial systems (UAS) to collect higher resolution imagery to enable more detailed analyses and more frequent habitat monitoring.

TABLE OF CONTENTS

I. INTRODUCTION AND BACKGROUND

A. Project Overview

The clients for this project, hereon referred to as "the client", are based in NOAA Fisheries' Southeast Regional Office and include Species Conservation Branch Chief Dr. Nicholas Farmer, Sawfish Recovery Coordinator Adam Brame, and GIS Coordinator Amanda Frick. The primary objective of this project is to identify and characterize smalltooth sawfish (*Pristis pectinata*) shoreline and nearshore habitat in Charlotte Harbor, Florida to promote sustainable management of the species. This was accomplished by identifying contiguous mangrove patches, calculating mangrove distance to shoreline, and conducting a nearest neighbor analysis to identify mangroves with a high mangrove neighborhood density. Development of a baseline map showing the current shoreline and nearshore habitats could be used to compare with historical and future maps for tracking changes in the environment. This may be especially important in developing models to track climate change impacts to species protected by the Endangered Species Act (ESA) and critical habitats, as well as essential fish habitat. The client is particularly interested in using products from this project to develop a species distribution model of sawfish in south and southwest Florida that can be used by agency biologists to better manage this species.

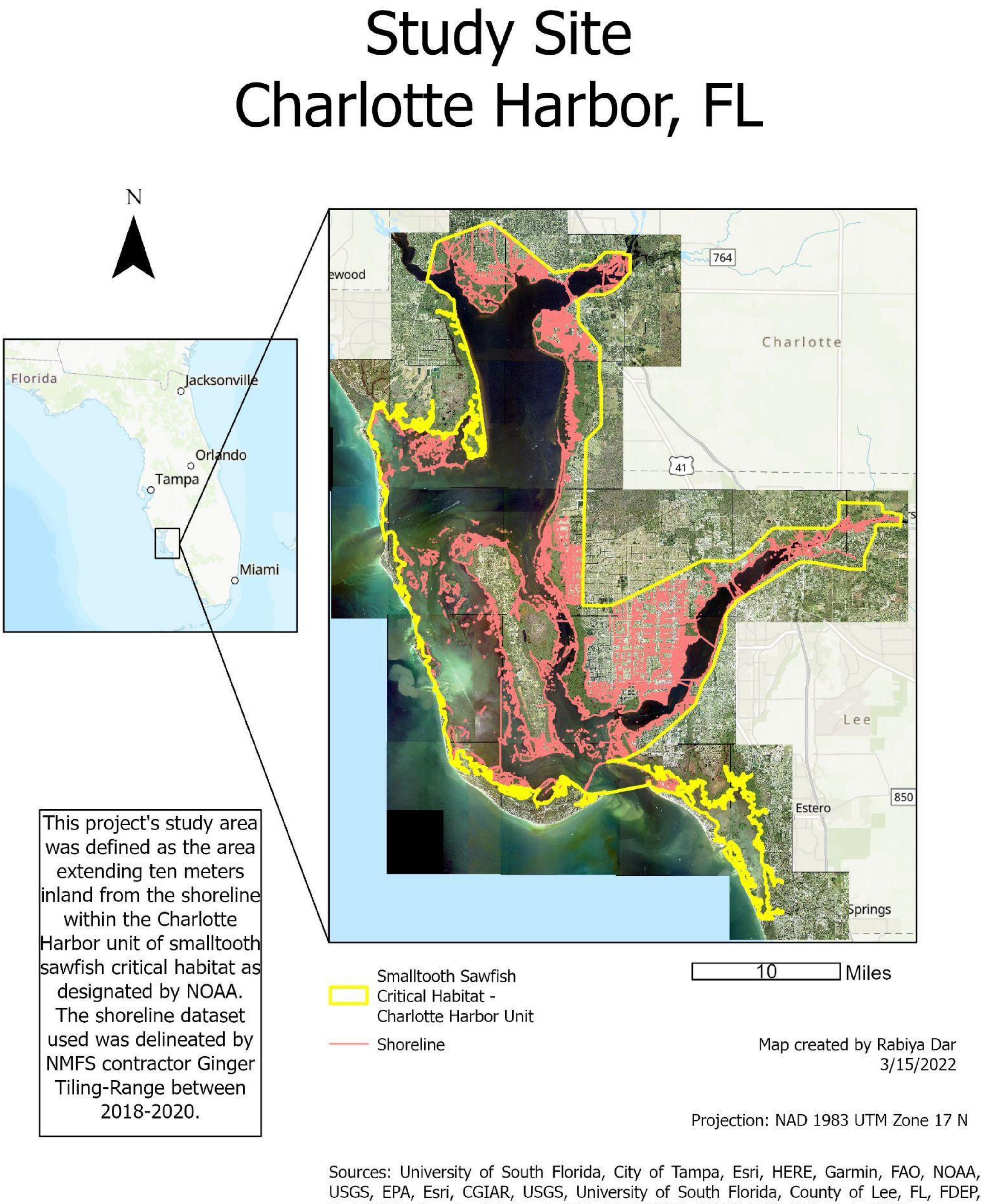
B. Smalltooth Sawfish (*Pristis pectinata*)

The smalltooth sawfish is an elasmobranch, named for its saw-like rostrum used to feed on smaller fish. They reproduce sexually and have a gestation period of 12 months. Females are able to produce young every other year and give live birth to brood sizes between 7 and 14 pups. These slow-growing rays take between 7 and 11 years to mature and have a relatively long lifespan of about 30 years. Once mature, they are approximately 12 feet in length, but can reach lengths of 16 feet (5 meters) at their full size. Historically found in Brazil, throughout the Caribbean, and the United States from North Carolina to Texas, the species is now only regularly found in the Bahamas and south and southwest Florida. Commercial and recreational fishing, illegal trade, coastal development, and entanglement are responsible for their decline warranting a series of governmental protections. In 1992, the State of Florida prohibited all harvest of smalltooth sawfish. Florida also passed a ban on the use of gill nets in 1994 which went into effect in 1995. Although this measure was not taken to expressly protect sawfish, it greatly benefitted their population along with many other species. In 2003, the U.S. distinct population segment of smalltooth sawfish were listed as endangered under the ESA. Since their listing, NOAA Fisheries has been responsible for managing smalltooth sawfish under the purview of the ESA.

On September 2, 2009, NOAA Fisheries designated two units of critical habitat, the Charlotte Harbor unit and Ten Thousand Islands and Everglades unit, to protect important sawfish nursery grounds. Critical habitats are defined as geographic areas that are important to the conservation of a particular species.[1] These two areas were selected as they have an abundance of red mangroves and euryhaline water (<3ft at MLLW) that are necessary for juvenile sawfish survival. Coastal development in southwest Florida overlaps with these nursery grounds and NOAA Fisheries is tasked with consulting with federal action agencies on proposed activities and tracking impacts to sawfish and their habitats.[2]

C. Study Extent

This project focuses on the Charlotte Harbor critical habitat unit. Charlotte Harbor, a natural estuary and Florida’s second largest bay, is located within Charlotte and Lee counties in southwest Florida. It has more than 165 miles of human-made waterways, many of which connect to the Gulf of Mexico. There are also miles of natural shoreline bordering Charlotte Harbor and the Peace and Myakka rivers which flow into the upper Harbor.[3] The Caloosahatchee River, connected to the southeast side of the Harbor, has a highly developed shoreline with cities such as Cape Coral and Fort Myers on its banks. This project relies on a shoreline delineation conducted by Ginger Tiling-Range, a contractor with Jamison Professional Service, Inc. and the National Marine Fisheries Service between 2018 and 2020. Although all analyses were conducted for the full extent of the Charlotte Harbor critical habitat unit, the client is most interested in the area extending 10 meters inland from the shoreline dataset (see Figure 1). Shoreline is defined as the boundary between water and any other structure, natural or human-made, from an aerial perspective. This includes where Charlotte Harbor estuary meets the edge of a mangrove forest, even though the forest may be inundated with water which would only be visible from the ground. Shoreline also includes where water meets development, such as the many canals built throughout Cape Coral, FL.



Study Site
Charlotte Harbor, FL
N
Florida
Jacksonville
Orlando
Tampa
Miami
ewood
764
Charlotte
41
Lee
Estero
850
Springs
This project's study area was defined as the area extending ten meters inland from the shoreline within the Charlotte Harbor unit of smalltooth sawfish critical habitat as designated by NOAA. The shoreline dataset used was delineated by NMFS contractor Ginger Tiling-Range between 2018-2020.
Smalltooth Sawfish Critical Habitat - Charlotte Harbor Unit
Shoreline
10 Miles
Map created by Rabiya Dar 3/15/2022
Projection: NAD 1983 UTM Zone 17 N
Sources: University of South Florida, City of Tampa, Esri, HERE, Garmin, FAO, NOAA, USGS, EPA, Esri, CGIAR, USGS, University of South Florida, County of Lee, FL, FDEP, Esri, HERE, Garmin, SafeGraph, FAO, METI/NASA, USGS, EPA, NPS, Esri, USGS

Figure 1.

II. CURRENT PROGRESS

A. Preparing for Analysis

To prepare the study area in ArcGIS Pro, I downloaded a shapefile of smalltooth sawfish critical habitat as designated by NOAA. The critical habitat for this species includes two units in Florida: 1) the Charlotte Harbor Estuary unit, and 2) the Ten Thousand Islands and Everglades unit. This project focuses solely on the Charlotte Harbor unit, so I constrained the study extent to this critical habitat unit and also clipped the shoreline dataset to only include segments that are within this critical habitat polygon. To conduct the supervised classification, I required a dataset with high enough resolution to allow for accurate identification of mangroves and other features of interest. I began with a data exploration to find a suitable dataset for this purpose. I looked at imagery collected by Sentinel-2, a satellite with a global 5-day revisit frequency and equipped with a multispectral sensor capable of collecting 13 different spectral bands: visible and NIR at 10 meters, red edge and short-wave infrared (SWIR) at 20 meters, and atmospheric bands at 60 meters spatial resolution. Although useful for assessing the state and change of vegetation, soil, and water cover, it did not have a fine enough resolution for this project as the client was interested in 1- or sub-meter resolution.

At the time I started this project in spring 2021, the most recent data available for my study site in USGS Earth Explorer was generated in 2019. I downloaded imagery with a 0.6 meter resolution owned by the National Agriculture Imagery Program (NAIP) and generated on 11/21/2019 for my full study extent in Charlotte Harbor. This imagery was then mosaiced within ArcGIS to seamlessly stitch together individual rasters that had overlapping cells and to enable easier viewing at different scales.

B. Normalized Difference Vegetation Index (NDVI)

After all of the necessary imagery was downloaded and mosaiced for the study extent, I began my analysis by calculating the NDVI for the Harbor. The NDVI is a useful tool for visualizing vegetation density. This is achieved by measuring the difference between near-infrared (NIR) and red light. This takes advantage of the fact that chlorophyll reflects high amounts of near-infrared light and absorbs high amounts of red light. The value for NDVI ranges from -1 to 1, where -1 is most likely water, 1 is likely dense vegetation, and 0 indicates an absence of green and may represent urban development.[4] The NAIP imagery used for this project is multispectral and includes four bands: red, green, blue, and near-infrared. This enabled me to calculate the NDVI in Arc's Raster Calculator tool using the following standard NDVI equation:

$$NDVI = (NIR - Red)/(NIR + Red)$$

I calculated NDVI separately for each individual mosaic rather than combining the whole harbor's imagery into one mosaic and calculating a single NDVI as that can reduce the tool's accuracy. The resulting rasters provided a good preview of vegetation density throughout Charlotte Harbor, however, NDVI does not make vegetation species apparent without further analysis. To identify mangroves and other shoreline and nearshore features, I conducted a series of supervised classifications in ArcGIS.

C. Supervised Classification of Shoreline Habitat

For this project, there was particular interest in characterizing habitat features within 10 meters of the shoreline. I used the Buffer tool in ArcGIS to further constrain my study extent from the whole Charlotte Harbor critical habitat unit to just the area extending 10 meters inland from the shoreline dataset. I chose to calculate the buffer distance using the planar method instead of the geodesic method as I am not looking at a geographically large area for this project. I also specified for the tool to use rounded edges for the buffer output instead of flat edges.

I conducted a series of eight total supervised classifications, hereon simplified as "SupClass". Each successive classification was executed to increase accuracy and utility from previous iterations. The process of conducting a supervised classification in ArcGIS can be simplified into three steps: 1) collect the training samples, 2) create a signature file, and 3) run the maximum likelihood classifier. Collecting training samples involves defining what classes you are interested in classifying in your imagery. The user hand selects pixels of known identity for each desired class. These training samples are used as the input, along with the imagery of your study extent, for the Create Signatures tool which takes the information from the training samples to produce an ASCII signature file with information on the classes including how many cells were classified under that class and covariances across all raster bands (RGB, NIR, etc.). The final step is running the Maximum Likelihood Classification tool which, at a minimum, requires the input signature file, and input imagery (raster bands) to be classified. This tool then proceeds to classify each pixel within your input imagery into the classes defined in the signature file.

SupClass I

In this first classification attempt, I collected training samples for six classes of interest: mangrove, other vegetation, natural shoreline, hardened shoreline, water, and developed. "Mangrove" included any species of mangrove (red, black, or white) although it should be noted that the majority of the mangroves analyzed were most likely red mangroves. White and black mangroves tend to be found further upland, most likely outside of the 10-meter study extent.[5] Red mangroves are also the most relevant to sawfish nursery habitat. "Other vegetation" included any species of vegetation that was not a mangrove. “Natural shoreline” was defined as any unaltered shoreline. “Hardened shoreline” was defined as any altered shoreline or shoreline constructed by humans such as seawalls and bulkheads. “Water” included any water body, natural or human-made. “Developed” was classified as any pixels within developed areas such as residential and commercial zones. Training samples were selected without the guidance of ground truth data and were based on my best assessment of what I saw depicted in the imagery. I collected 20 training samples for each class for a total of 120 training samples. This initial classification had several flaws, the primary one being that training samples were collected without ground truth data to confirm the accuracy of my selections. Another issue was that pixels that should have been classified as “other vegetation” were often incorrectly classified as “mangrove”. In order to run the maximum likelihood classifier in one step, I mosaiced all imagery into a single mosaic of the harbor. After running the classifier and reviewing the result of SupClass I with the client, I decided to reduce the number of classes from six to three: mangrove, other vegetation, and non-vegetation. This decision was made in an effort to reduce the amount of incorrectly classified pixels. I believe this limitation was due in large part to the resolution of the imagery used. At a 0.6 meter resolution, it was difficult to distinguish between different shoreline types. Access to higher resolution imagery in the future could potentially enable a classification that includes more detailed classes.

SupClass II

The primary differences between SupClass I and II are the simplification of the classes from six to three, and the incorporation of ground truth data to improve the accuracy of training samples. Ground truth data was provided by Adam Brame who obtained the data from partners at the Florida Fish and Wildlife Conservation Commission (FWC) and Fisheries-Independent

Monitoring (FIM). There was a lot of information associated with each data point, however, not all of it was relevant to this project. The attributes I retained were “Reference”, “Date”, “Latitude”, “Longitude”, “ShoreType[Code]”, and “ShoreTypeRatio/%Cover”. Each data point was given a unique identifier listed in the “Reference” attribute. The cover type observed on the ground was listed under “ShoreType” and “ShoreTypeRatio/%Cover” indicated what percentage of the shoreline was occupied by the specified cover type. The FWC and FIM data points are from two different surveys with different objectives, but they contain equivalent information for the purposes of this project. To simplify my analysis, I extracted the relevant attributes from each dataset and merged them into a single file. I then uploaded these data points into Arc using their latitude and longitude to plot them in the geographically correct place on my map of Charlotte Harbor in ArcGIS. Points were uploaded using WGS 1984 geographic coordinate system and NAD 1983 UTM Zone 17N projected coordinate system.

There were 34 different shore types represented among the ground truth points within the 10-meter buffer study extent. To simplify these shore types into the three classes of interest (mangrove, other vegetation, and non-vegetation), I calculated a new field in the ground truth points dataset. All mangrove shore types (“white mangrove”, “red mangrove”, “black mangrove”, and “mangrove”) were reclassified as “Mangrove”. All other vegetation shore types were designated as “Other vegetation”. Any other shore types not considered vegetation (e.g. rip rap, oysters, sea wall, dock, and rock) were labeled as “Non vegetation”.

Using the combined FWC and FIM ground truth point datasets, I collected new training samples, 10 for each class, that overlapped with the points to confirm that my training samples accurately characterized the pixels that they contain. Note that I only sampled data points that fell within the 10-meter study extent. There were several thousand points outside of the buffer which I omitted from sampling in favor of getting the most accurate representation of my study extent.

Like SupClass I, one of the primary issues with SupClass II was that the Maximum Likelihood Classification tool consistently misclassified pixels that should have been classified as “other vegetation” as “mangrove”, especially grass lawns in residential areas. There were also very limited ground truth points within the 10-meter buffer which limited the variation of the training samples I could collect. One of the clients, Adam Brame, noted that there were a lot of points georeferenced to the water adjacent to the shoreline and informed me that they likely georeference the vessel that was used to collect the data and not the actual shoreline being characterized in the survey. With this information, I was advised to include all ground truth points in the subsequent classification, regardless of its presence within the actual buffer.

SupClass III

For this classification, I wanted to incorporate residential parcel data to address the issue of lawns being classified as mangroves. Using the Florida Geospatial Open Data Portal, I downloaded South Florida Water Management District’s (SFWMD) Land Cover Land Use data for 2014-2016. This dataset included a cover type called “Urban and Built Up” which matched the residential areas in the NAIP imagery used in this project. I subset this SFWMD Land Cover Land Use data to only include the “Urban and Built Up” polygons that intersected with the study extent. This dataset only included data for the southern part of Charlotte Harbor. For this reason, SupClass III was used as a proof of concept for incorporating residential data to improve classification accuracy. Subsequent classifications to categorize the full study extent were necessary.

I modified the eligibility of ground truth points from only including points within the shoreline buffer to also include points up to 20 meters away from the buffer. Points also had to be within 20 meters of the SFWMD "Urban and Built Up" data. 30 points were randomly chosen from among the "mangrove", "other vegetation" and "non-vegetation" ground truth points that met the aforementioned eligibility criteria for this classification. Using these 90 ground truth points as a guide, I collected 90 total training samples (30 for each class) to be used for the supervised classification. Instead of using the entire Charlotte Harbor NAIP imagery as the input raster band as was done in SupClass II, I clipped the imagery to the 10-meter shoreline buffer to reduce processing burden.

SupClass III saw the introduction of a priori probability weighting to the Maximum Likelihood Classification tool. This is an optional input for the tool and allows the user to modify the probability of pixels being classified into any given class. I adjusted the probability of being classified as a mangrove to 0.05 (5%) in "Urban and Built Up" regions to explore if this would reduce the misclassification of residential lawns as "mangrove". The probability of "other vegetation" and "non-vegetation" were kept equal, making up the remaining 95% probability (~47.55% each). A priori weighting was kept equal for the three classes for all areas within the study extent not overlapping with the SFWMD "Urban and Built Up" dataset. This required two runs of the Maximum Likelihood Classification tool: once for urban areas and again for nonurban areas. The results of the classifications revealed that utilizing a priori probability weighting had successfully reduced the amount of pixels categorized as "mangrove" within residential areas. Collecting the training samples was difficult, however, as the FWC and FIM ground truth points' accuracy was questionable. There were many cases where a point was nearest to what visually appeared to be mangrove in the NAIP imagery, but was instead labeled as another vegetation type.

SupClass IV

In SupClass IV, I replaced the SFWMD “Urban and Built Up” data with Florida Department of Environmental Protection’s (FDEP) Statewide Land Use Land Cover (LULC) data from 2012-2019. This dataset had very useful LULC information for the entire state of Florida, including the “Urban and Built Up” information for all of Charlotte Harbor. I also relied on this dataset to ground truth training samples instead of using the original FWC and FIM ground truth points which had questionable accuracy for this project’s purposes.

I collected 10 training samples for each class, only selecting points within upper Charlotte Harbor as this was the extent missing from SupClass III. Combining these 30 new ground truth points with the previous 90 points from the lower harbor, I had 120 ground truth points total. I added 30 new training samples that corresponded to the new points and also added these to the previous set of training samples for a grand total of 120 training samples, 40 for each class. Note that I replaced nine inaccurate training samples labeled “other veg” with guidance from the FDEP LULC dataset.

The classification was, again, done in two parts to allow for different a priori probability weighting of mangroves between urban and nonurban areas. I increased the weight of “mangrove” from 0.05 in SupClass III to 0.10 in SupClass IV. By default, this set “other vegetation” and “non-vegetation” to 0.45 each to account for the remaining 90% probability. The nonurban classification was run with equal a priori probability weighting for all classes. There was an abundance of cells within urban areas that were incorrectly identified as mangrove indicating that a probability weighting of 0.10 for mangroves may be too high for the urban areas within the study extent.

SupClass V

SupClass V maintained all parameters from SupClass IV except a priori probability weighting for mangroves was reduced from 0.10 back to 0.05 for urban areas. A repeat classification with a priori weighting set below 0.05 for assessment was necessary to determine the final weighting to be used that is most appropriate for mangroves in urban areas of Charlotte Harbor. Note that the nonurban classification remained unchanged from SupClass IV.

SupClass VI

SupClass VI maintained all parameters from SupClass V except a priori probability weighting for mangroves was reduced from 0.05 to 0.02 for urban areas. This set "other vegetation" and "non-vegetation" to 0.49 each to account for the remaining 98% probability. Note that the nonurban classification remained unchanged and was identical to the nonurban classifications from SupClass IV and V.

SupClass VII

The main purpose of this classification was to generate confidence rasters in addition to the classification rasters. In all of the previous classifications, I had selected for the Maximum Likelihood Classification tool to not calculate confidence rasters in favor of lightening the processing load of Arc. The client later expressed interest in this product, so I ran the classification tool again for urban and nonurban areas with all of the same parameters as SupClass VI, but made sure to include an output for confidence rasters. The 0.02 a priori probability weighting for mangroves in urban areas was maintained, as well as the equal weighting for all classes in nonurban areas. Rerunning the Maximum Likelihood Classification tool was necessary as there is no way to retroactively create confidence rasters. This parameter must be specified prior to running the tool. Cells in confidence rasters are assigned a value between 1 and 14 with 1 being the highest confidence in a cell being classified correctly and 14 indicating the least amount of confidence that the cell was accurately classified.

SupClass VIII

SupClass VIII was conducted to include all pixels within the Charlotte Harbor unit of smalltooth sawfish critical habitat, not just pixels within the 10-meter shoreline buffer. This was done to facilitate full harbor analyses and also to get accurate mangrove nearest neighbor values for pixels at the edge of the buffer. Without a full harbor classification of mangroves, mangrove cells at the farthest edge of the shoreline buffer could receive a falsely low value for mangrove neighborhood density simply because Arc is unaware of any mangroves beyond the buffer. SupClass VIII addresses this issue by classifying all pixels within the critical habitat unit. Urban and nonurban masks were created from the FDEP LULC shapefile. The urban mask was created by selecting all polygons labeled as “Urban and Built Up” and clipping to the critical habitat extent. The nonurban mask was created by erasing all “Urban and Built Up” polygons from the FDEP LULC shapefile and clipping to the critical habitat extent. The same signature file from SupClass VII was input into the Maximum Likelihood Classification tool and a 0.02 a priori probability weighting was, again, used for the “mangrove” class in urban areas and an equal weighting was used for all classes in nonurban areas (see Figure 2).

Supervised Classification 8 (SupClass 8)

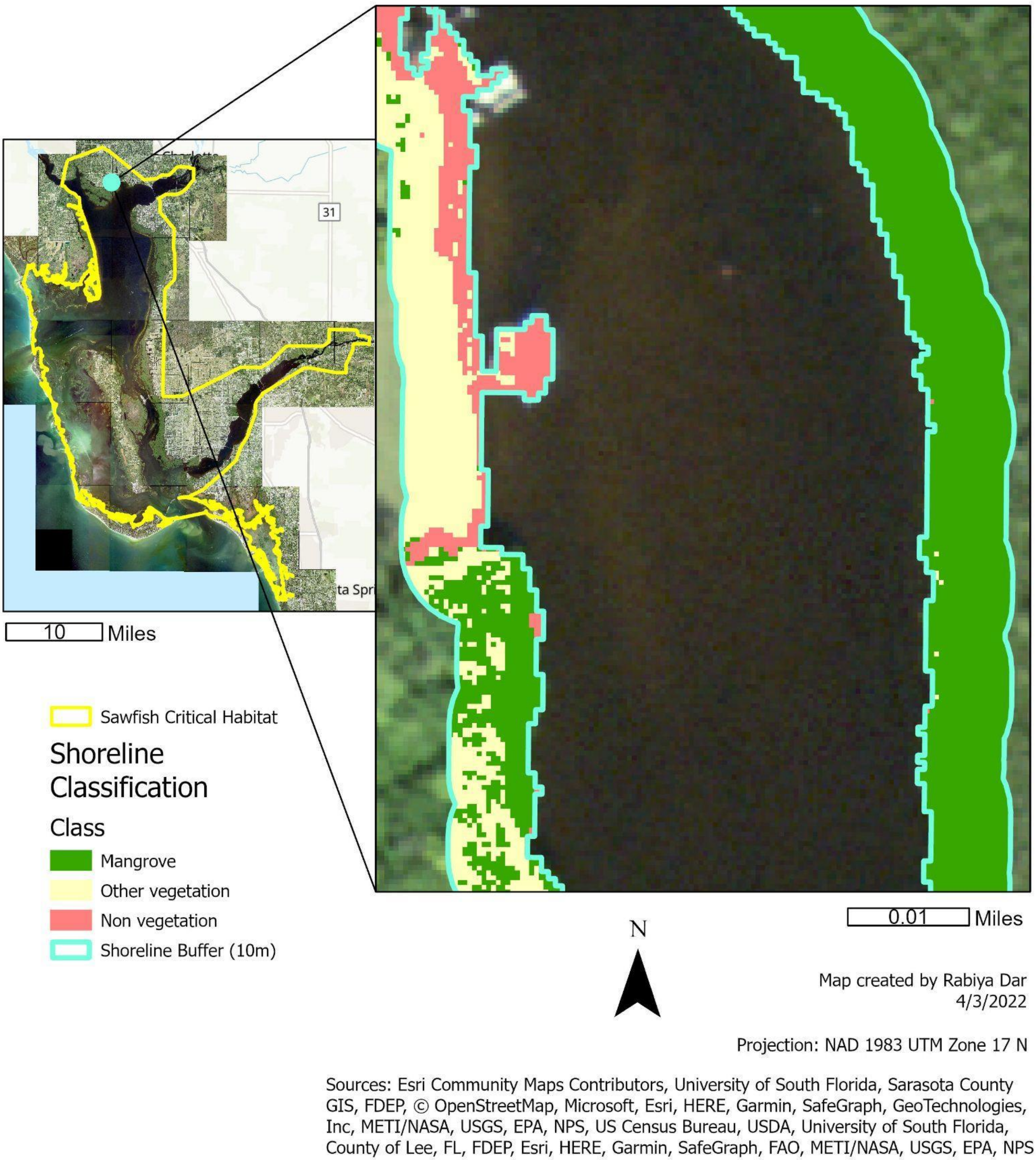


Figure 2.

D. Mangrove Region Grouping

After finalizing the classification, I used Arc's Set Null tool to isolate all mangrove pixels by setting all pixels not classified as mangrove to null. I then used the Region Group tool to identify contiguous mangrove patches. The Region Group tool assigns a unique number to each region of pixels, including individual pixels. I specified eight as the number of neighbors to use for determining connectivity. This means that connectivity is evaluated for the eight nearest neighbors, both orthogonal and diagonal, of each input cell. Cells with the same value, in this case, those classified as mangrove, that are connected either along a common edge or corner to each other constitute an individual region.[6]

The client expressed interest in mangrove patches that were 25 square meters or larger. This size was determined to be higher priority sawfish habitat compared to patches smaller than this size. One pixel in the NAIP imagery, as previously mentioned, is 0.6 by 0.6 meters in area, or 0.36 square meters. Based on this pixel size, I used the Set Null tool on the output of the Region Group tool to select for mangrove patches that were greater than or equal to 70 pixels, or 25.2 square meters. This tool assigned all other pixels to be null, producing a raster of mangrove patches meeting the size criteria. I converted the output raster to a polygon dataset for easier analysis and manipulation. I did not opt to simplify polygons, so the polygon dataset is an exact match of the original raster dataset of mangrove patches. A total of 147,123 patches meeting the size criteria were identified within the Charlotte Harbor critical habitat unit (see Figure 3). This number decreases to 18,435 patches when the mangrove dataset is clipped to the 10-meter study extent buffer (see Figure 4).

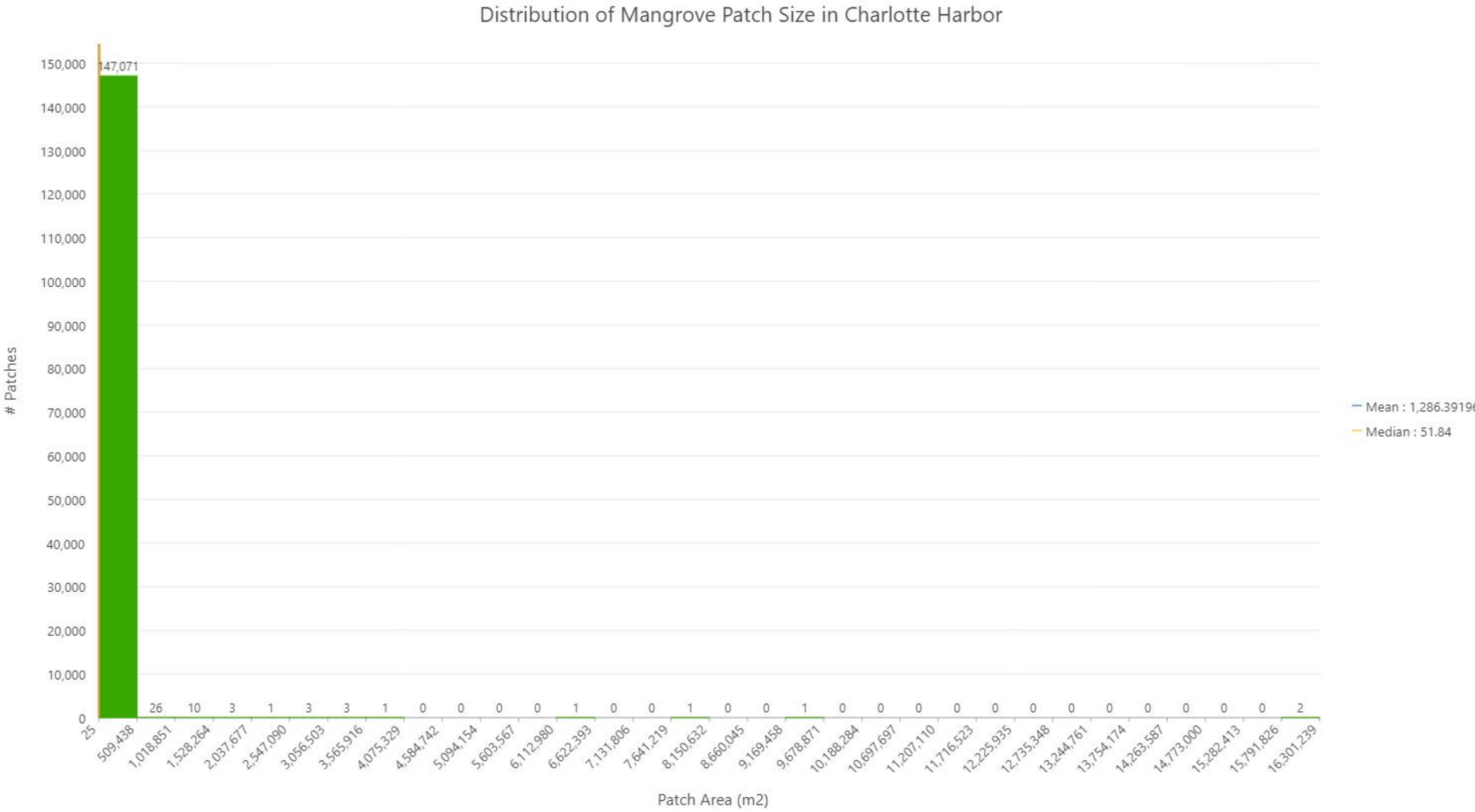


Figure 3. Distribution of mangrove patch size within the Charlotte Harbor sawfish critical habitat unit.

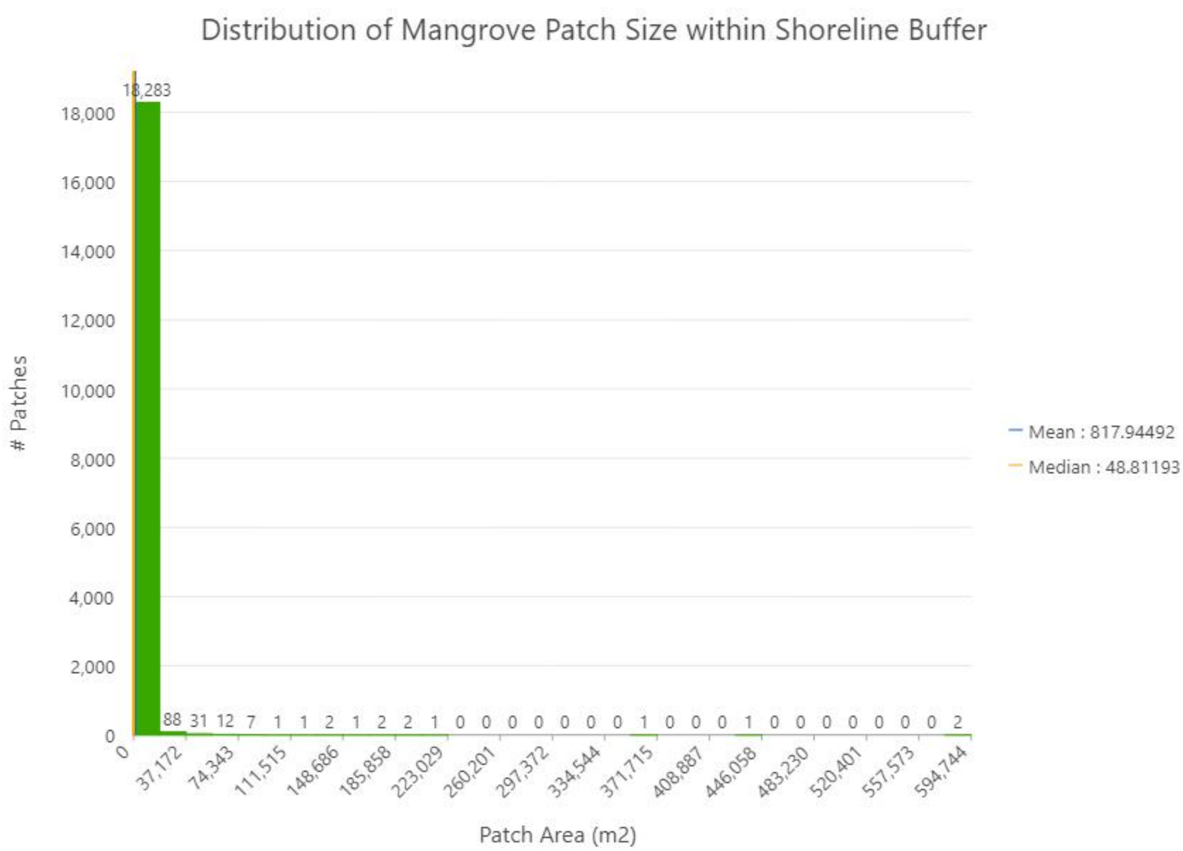
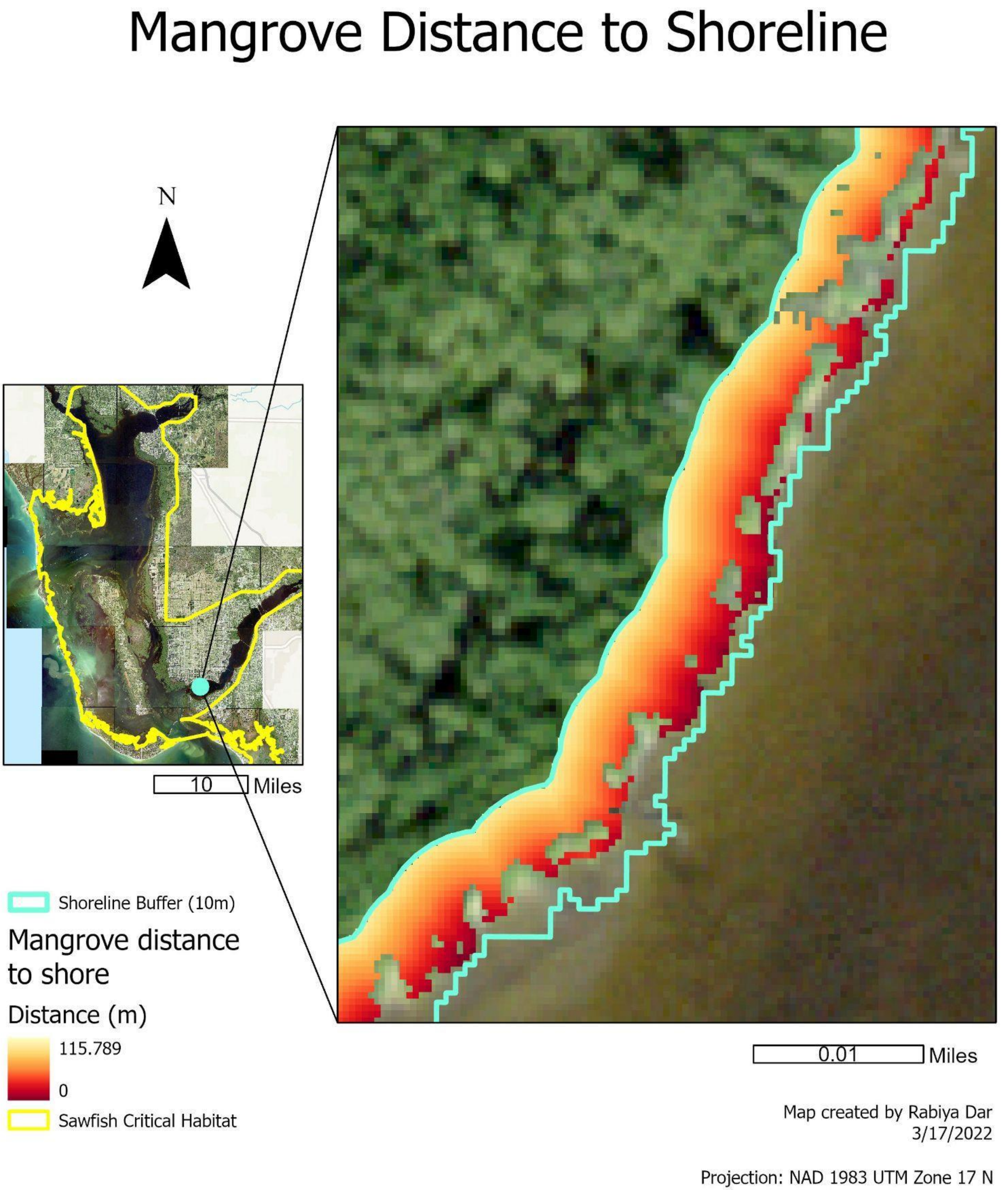


Figure 4. Distribution of mangrove patch size within the 10-meter shoreline buffer study extent.

E. Mangrove Distance to Shoreline

The client was interested in knowing the distance to shoreline from each mangrove cell. This information is important in determining the quality of habitat and the likelihood that sawfish may be occupying that space. We predict that there is a higher likelihood for sawfish to be present in mangroves that are closer to the shoreline and, thus, open water. The distance to shoreline was calculated for all cells classified as mangrove within the study extent, regardless of their inclusion in mangrove patches 25 square meters or larger. To create this dataset, I used the Euclidean Distance tool and input the shoreline dataset I began the project with. The output was a raster of all cells within Charlotte Harbor assigned with a distance to the closest shoreline segment. Distances were calculated from the center of raster cells. To subset this data to only include mangrove cells within the 10-meter shoreline buffer, I used the Raster Calculator tool and multiplied this raster with a raster mask of mangroves which used “1” as the value for all mangroves and had a background of “No Data”. The result of this multiplication was a raster of mangrove cells within the 10-meter study extent assigned with their respective distances to the nearest shoreline segment (see Figure 5).



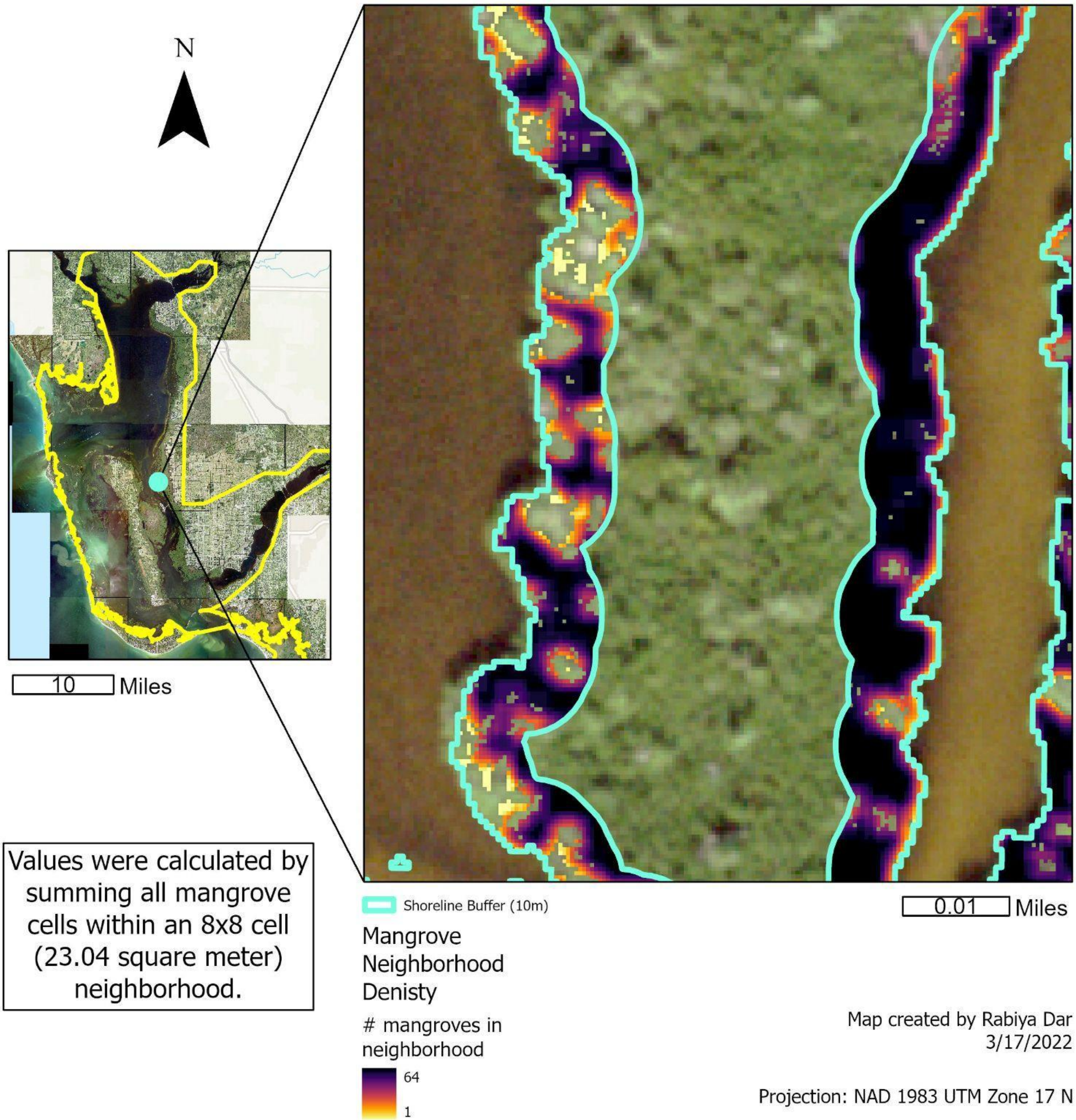
Sources: Esri Community Maps Contributors, University of South Florida, County of Lee, FL, FDEP, © OpenStreetMap, Microsoft, Esri, HERE, Garmin, SafeGraph, GeoTechnologies, Inc, METI/NASA, USGS, EPA, NPS, US Census Bureau, USDA, University of South Florida, County of Lee, FL, FDEP, Esri, HERE, Garmin, SafeGraph, FAO, METI/NASA, USGS, EPA, NPS, Esri, USGS

Figure 5.

F. Mangrove Nearest Neighbor Analysis

Conducting a nearest neighbor analysis of all mangrove cells can provide insight into the surroundings of each mangrove cell. Mangroves that have a higher mangrove neighborhood density (i.e. have more mangroves within the specified neighborhood window) are considered higher priority mangroves than those that have less mangroves within their neighborhood. Using the Focal Statistics tool, I summed all mangrove cells within an 8 by 8 cell neighborhood (23.04 square meters) for each classified mangrove cell. The result was a raster of mangrove cells with values from 1 to 64 where 1 indicates that the only mangrove within the neighborhood is the one at the center and 64 indicates that all cells within the neighborhood are classified as mangroves (see Figure 6). The client expressed specific interest in identifying mangrove cells on or near the shoreline that had a high amount of mangroves behind them. Although the nearest neighbor analysis conducted here summed mangroves in all directions, not just "behind" (i.e. inland direction), it still provides useful insight into the surroundings of each mangrove cell which can be used to predict sawfish presence when combined with other datasets.

Mangrove Nearest Neighbor Analysis



Sources: Esri Community Maps Contributors, University of South Florida, County of Lee, FL, FDEP, © OpenStreetMap, Microsoft, Esri, HERE, Garmin, SafeGraph, GeoTechnologies, Inc, METI/NASA, USGS, EPA, NPS, US Census Bureau, USDA, Esri, CGIAR, USGS, University of South Florida, County of Lee, FL, FDEP, Esri, HERE, Garmin, SafeGraph, FAO, METI/NASA, USGS, EPA, NPS

Figure 6.

G. Identifying Priority Habitat

As a final product for this project, I combined the mangrove distance to shore and mangrove neighborhood density rasters to create a raster that identifies priority sawfish habitat. Priority habitat, for the purposes of this project, are cells classified as mangrove that are close to shore and have a high mangrove neighborhood density. This is not an exhaustive list of criteria that are important for determining priority sawfish habitat, rather they are the criteria that I explored in this project as agreed upon with the client. I calculated priority habitat using two different methods. The Normalized Difference Index method was modeled after the NDVI, while the Reclass method was modeled after a general suitability modeling workflow.

Normalized Difference Index Method

To create this product, I input the following equation in the Raster Calculator tool:

(Neighborhood Density - Distance to Shore)/(Neighborhood Density + Distance to Shore)

The output of this equation was a raster with values from -1 to 1 where 1 represents the ideal combination of distance to shore and neighborhood density and equates to the highest priority habitat (i.e. close to shore and high mangrove neighborhood density). A value of -1 indicates the least desirable combination of distance to shore and mangrove neighborhood density and represents the lowest priority habitat (i.e. far from shore and low mangrove neighborhood density). One issue with this method of identifying priority habitat is that all mangrove pixels touching the shoreline (distance to shore = 0) were automatically assigned a value of 1, regardless of their mangrove neighborhood density. This is an inherent flaw with the equation used to calculate the output. To address this issue, I recalculated priority habitat using the Reclass method.

Reclass Method

This method of identifying priority sawfish habitat was modeled after a general suitability modeling workflow. This type of workflow includes four steps: 1) determine and prepare the criteria, 2) transform the values of each criterion to a common suitability scale, 3) weight criteria and combine them to create a suitability map, and 4) locate the areas for the siting or to preserve.[7] The criteria have already been defined, distance to shore and mangrove neighborhood density, so I proceeded to reclassify these criteria into 10 classes each, where a rank of 10 represents the highest priority habitat and a rank of 1 represents the lowest priority habitat. The mangrove neighborhood density raster was reclassified using the equal interval method which divides the dataset's values into equal-sized ranges (see Table 1).[8]

Table 1. Mangrove neighborhood density reclass table calculated using the equal interval data classification method. "Start" and "End" values define the range of values to be reclassified. "New" indicates what the range of values was reclassified as.

Start (# of mangroves in neighborhood)	End (# of mangroves in neighborhood)	New
57.7	64.0	10
51.4	57.7	9
45.1	51.4	8
38.8	45.1	7
32.5	38.8	6
26.2	32.5	5
19.9	26.2	4
13.6	19.9	3

7.3	13.6	2
1.0	7.3	1

The distance to shore raster was reclassified using the manual interval method which allows the user to define the ranges for the new classes.[8] I set the top 8 classes ("New" values 3-10) to have an equal interval of one meter, class 2 ("New" value 2) to have a 2 meter interval, and the lowest priority class ("New" value 1) to have a range that included all values greater than 10 meters. This assigns an automatic rank of 1 to all mangroves outside of the 10-meter study extent (see Table 2).

Table 2. Distance to shore reclass table calculated using the manual interval data classification method. "Start" and "End" values define the range of values to be reclassified. "New" indicates what the range of values was reclassified as.

Start (distance from shore, m)	End (distance from shore, m)	New
0	1	10
1	2	9
2	3	8
3	4	7
4	5	6
5	6	5
6	7	4
7	8	3
8	10	2
10	8264.099	1

After reclassifying the input rasters, I used Arc's Raster Calculator tool to sum the reclassified distance to shore and mangrove neighborhood density rasters producing an index from 2 to 20, where 20 represents the highest priority habitat and 2 represents the lowest priority habitat (see Figure 7). The criteria were weighted equally.

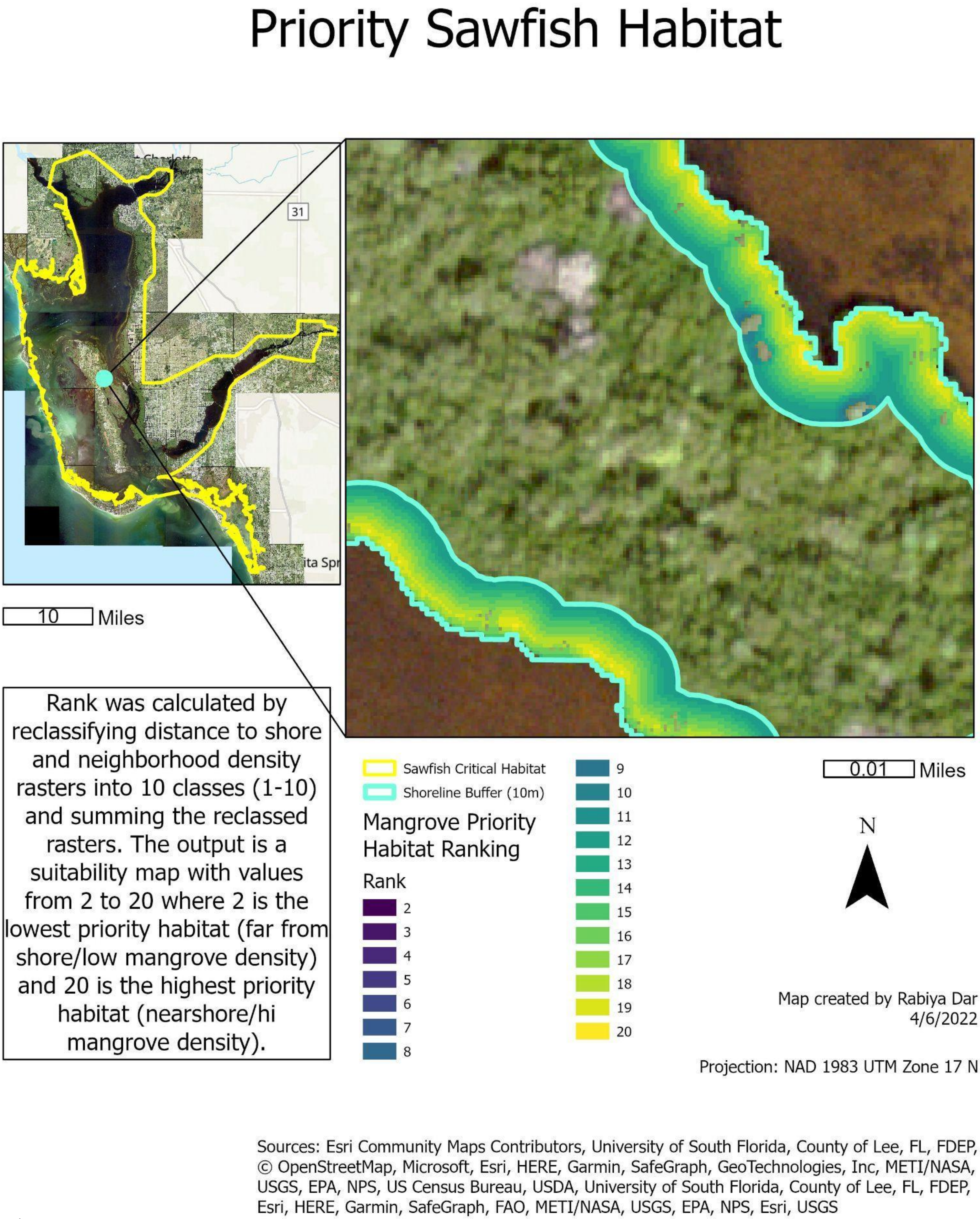

Priority Sawfish Habitat
31
10 Miles
Rank was calculated by reclassifying distance to shore and neighborhood density rasters into 10 classes (1-10) and summing the reclassed rasters. The output is a suitability map with values from 2 to 20 where 2 is the lowest priority habitat (far from shore/low mangrove density) and 20 is the highest priority habitat (nearshore/hi mangrove density).
Sawfish Critical Habitat
Shoreline Buffer (10m)
Mangrove Priority Habitat Ranking
Rank
2
3
4
5
6
7
8
9
10
11
12
13
14
15
16
17
18
19
20
0.01 Miles
N
Map created by Rabiya Dar 4/6/2022
Projection: NAD 1983 UTM Zone 17 N
Sources: Esri Community Maps Contributors, University of South Florida, County of Lee, FL, FDEP, © OpenStreetMap, Microsoft, Esri, HERE, Garmin, SafeGraph, GeoTechnologies, Inc, METI/NASA, USGS, EPA, NPS, US Census Bureau, USDA, University of South Florida, County of Lee, FL, FDEP, Esri, HERE, Garmin, SafeGraph, FAO, METI/NASA, USGS, EPA, NPS, Esri, USGS

Figure 7.

III. NEXT STEPS

A. Sawfish Distribution Model

The client is interested in using the products from this project to contribute to a sawfish distribution model. Species distribution models combine observed species occurrences with environmental estimates to predict distributions across landscapes.[9] This model would incorporate data such as neighborhood mangrove density, proximity to shoreline, depth, salinity, sea surface temperature, position in harbor, among other factors.

B. Sea Level Rise Threat Assessment

Further research could look into the threat of sea level rise to high priority smalltooth sawfish habitat. This could be done using LiDAR (light detection and ranging) data to identify lower-lying mangrove patches which may be at higher risk for flooding as sea level continues to rise due to anthropogenic climate change.

C. Land Ownership Threat Assessment

Another area of research could be to examine land ownership rights of high priority sawfish habitat. This would be done to assess which areas are more vulnerable to being developed or have less protection or less certainty of being maintained as high quality mangrove habitat.

D. Unoccupied Aerial Systems (UAS) Data Collection

I recommend NOAA Fisheries expands its UAS program to include the Sawfish Recovery Program as an eligible program for data collection with drones. A limitation of this project was the inability to fully characterize the shoreline to the level of detail that the client desired. This issue could potentially be resolved if I had access to higher resolution imagery such as the kind that can be obtained with a UAS. Possible imagery resolutions obtained from a UAS could range from 1-5 centimeters, a twelve- to sixty-fold increase in resolution from the 0.6 meter resolution imagery I selected for the project. This level of detail could enable higher quality classifications that include more classes than the three I examined ("mangrove", "other vegetation", and "non-vegetation"). Using the UAS-collected imagery, I could rerun the supervised classification to include classes such as "developed" and "natural shoreline" which I was not able to successfully classify with the current imagery. Although the NAIP imagery used for this project is suitable for identifying mangroves, higher resolution imagery could enable identification of distinct species of mangrove, as well as other features of interest that are relevant to sawfish management.

IV. REFERENCES

1. Critical Habitat. (2022). Retrieved 24 March 2022, from https://www.fisheries.noaa.gov/national/endangered-species-conservation/critical-habitat

2. Brame, A. (2022). *A Brief Overview of Sawfish in the United States*. Presentation, NOAA Fisheries Southeast Region.

3. Charlotte Harbor Florida - Things to Do & Attractions in Charlotte Harbor FL. (2022). Retrieved 24 March 2022, from https://www.visitflorida.com/places-to-go/southwest/charlotte-harbor/

4. What is NDVI (Normalized Difference Vegetation Index)? - GIS Geography. (2022). Retrieved 24 March 2022, from https://gisgeography.com/ndvi-normalized-difference-vegetation-index/

5. Mangrove Species Profiles. (2022). Retrieved 22 April 2022, from https://www.floridamuseum.ufl.edu/southflorida/habitats/mangroves/species/

6. Region Group (Spatial Analyst)—ArcGIS Pro | Documentation. (2022). Retrieved 24 March 2022, from https://pro.arcgis.com/en/pro-app/latest/tool-reference/spatial-analyst/region-group.htm

7. The general suitability modeling workflow—ArcGIS Pro | Documentation. (2022). Retrieved 22 April 2022, from https://pro.arcgis.com/en/pro-app/latest/help/analysis/spatial-analyst/suitability-modeler/the-general-suitability-modeling-workflow.htm

8. Data classification methods—ArcGIS Pro | Documentation. (2022). Retrieved 22 April 2022, from https://pro.arcgis.com/en/pro-app/2.8/help/mapping/layer-properties/data-classification-methods.htm

9. Elith, J., & Leathwick, J. (2009). Species Distribution Models: Ecological Explanation and Prediction Across Space and Time. *Annual Review Of Ecology, Evolution, And Systematics*, *40*, 677-697. doi: https://doi.org/10.1146/annurev.ecolsys.110308.120159