EXPANDING COASTSAT SHORELINE DETECTION ALGORITHM TO TRACK COASTAL VEGETATION AND URBAN CHARACTERISTICS FROM SATELLITE DATA

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INTRODUCTION

Coastal erosion and flooding, exacerbated by climate change, threaten coastal communities and environments such as wetlands and beaches. Projects to mitigate these effects include sea walls, beach nourishments, dune planting, and sandbags [1]. Analyzing the longevity and effectiveness of these interventions requires monitoring with high spatiotemporal resolution over years to decades, which is challenging in situ given the spatial extent of these interventions (100s of meters to km).

Classical survey methods involve making in situ measurements of shoreline locations, which can never scale to the time spans and spatial extent necessary to cover large coastal areas. For 50 years now, satellites have provided images of the earth with reasonable resolution that can provide some insight into shoreline evolution over large timescales and wide areas [2]. One example of such a study indicates that 24% of the world's sandy beaches are eroding at rates exceeding 0.5 m/yr, while 28% are accreting and 48% are stable [3].

Determining shoreline location from satellite imagery involves a general pipeline of image pre-processing, segmentation of the image into water and beach, and then determination of the shoreline location [4]. One state-of-the-art software package that simplifies the process by handling the full process from obtaining publicly available satellite imagery to extracting shorelines is CoastSat. Users can easily obtain time-series data of satellite-observed shoreline positions anywhere in the world [5][6].

However, CoastSat, similar to previous research into shoreline evolution, focuses on sandy beaches, which are not necessarily representative of all shorelines [7]. The goal of the research here is to expand the capabilities of CoastSat to include identification of coastal vegetation and tracking of vegetated shoreline evolution. This may help us and other researchers answer questions such as: What is the large-scale relationship between vegetation and coastal erosion after a storm? How do restoration projects impact future coastal storm response? [8][9][10].

Accurate measurements of coastal vegetation extent and evolution from satellites may help our understanding of the health of shoreline ecosystems as sea levels rise and storms become more intense. Shoreline trends observed from satellite imagery will provide information to coastal communities that can be used for effective spatial planning, sustainable coastal development, coastal engineering projects, and mitigation of climate change impacts [3][11].

BACKGROUND

CoastSat works by first downloading publicly available satellite imagery. Once the imagery is downloaded, it is preprocessed to remove clouds and down-sample the image. After preprocessing, the image is classified into sand, water, and white water before the shoreline is extracted [6].

Shoreline extraction starts with calculating the Modified Normalized Difference Water Index (MNDWI) [6]. The MNDWI calculates a value for each data point of an image. The MNWDI is calculated using the equation below:

$$\text{MNDWI} = (\text{SWIR} - \text{GREEN})/(\text{SWIR} + \text{GREEN}) \quad [6]$$

SWIR and GREEN are specific satellite bands, each of which collects data on a specific wavelength of light reflected off the Earth. SWIR represents the Short-Wave Infrared band while GREEN represents the green band.

After a value is calculated for each pixel in the image, CoastSat uses Otsu's threshold, an image segmentation process, on the MNDWI image to create an array of 0's and 1's [6]. Otsu's threshold automatically calculates an appropriate threshold value based on the values found in the MNDWI image and goes through each data point in the MNDWI image. If a value is above the threshold, the data point is changed to a 1 and if a data point is below the threshold the data point is turned into a 0.

Then, a Marching Squares Algorithm is applied to map the contours of the shoreline [6]. The Marching Squares Algorithm generates contours for a rectangular array of individual numerical values. Every data point is treated as a grid vertex location. In each square grid cell, the algorithm looks at each vertex and determines which topological case (i.e. shoreline contour), should be applied based on the pattern of 0's and 1's found above using Otsu's threshold [12]. Since each grid cell has four vertices, there are 16 topological cases shown below in Figure 1. In the figure, data points marked with a "1" are shown as filled circles and data points marked with a "0" are shown as hollow circles [12]. This process continues for each grid cell until a contour of the image is created, which results in the shoreline [6].

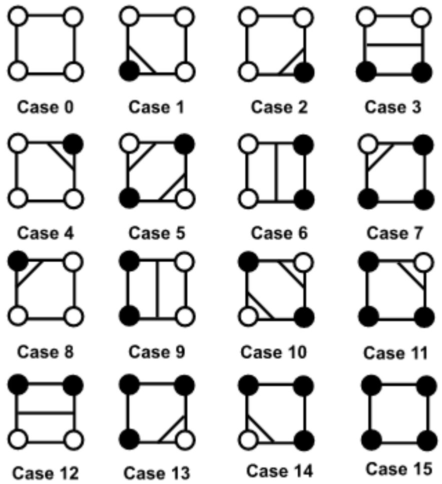

Figure 1 - The 16 topological cases of cells in the Marching Squares Algorithm. Filled circles represent 1's while hollow circles represent 0's, and 4 pixels are considered at a time. The algorithm goes through all the pixels in an image and at the end, the lines created from the 16 topological cases create the extracted shoreline [12].

METHODS

To find our shoreline we use K-Means Clustering, for image segmentation where pixels are grouped together based on similarity. We used K=2 clusters to separate the image into land and water. After dividing the image into land and water, we apply a Gaussian blur and use Canny Edge Detection to find our shoreline. Canny Edge Detection works by converting the image to grayscale and then detecting the edges based on the intensity of the pixels. In this application, the edge found is the shoreline. This processing pipeline is inspired by the one used in [13].

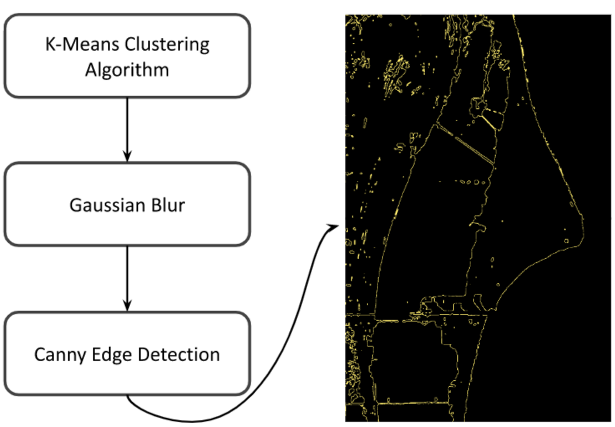

Figure 2 - Flow chart outlining the shoreline detection algorithm. We first separate the image into land and water using the K-Means algorithm. Then we apply a blur to the image before detecting the edge between the land and water clusters. The image to the right is the output.

Once the shoreline has been detected, the next step is to identify coastal features in the image. CoastSat already has a neural network that it uses to identify sand, water, and white-water, so we repurposed this neural network and used it to train the CoastSat model to also identify vegetation. First, we determine vegetation in our training satellite data by calculating the Normalized Difference Vegetation Index (NDVI) using the equation:

$$NDVI = (NIR - RED)/(NIR + RED) \quad [14]$$

Here, NIR represents the Near-Infrared band from satellite observations, while RED represents the red band. The NDVI value ranges from -1 to 1, with values above 0.3 indicating vegetation [14]. Figure 3 shows the NDVI image with our shoreline detection algorithm layered on top.

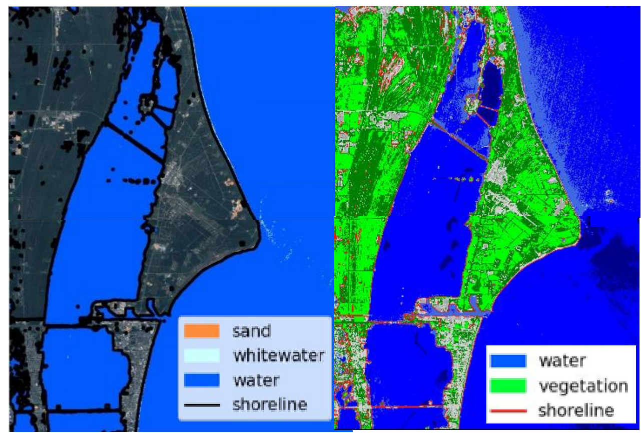

Figure 3 - Aerial image of Cape Canaveral, FL in two parts: Left is what CoastSat produced by default, where sand is represented in orange, whitewater in light blue, water in blue, and shoreline is the black line. Right includes our NDVI component of the CoastSat process, and shows the refined coastline algorithm (red line), the water (blue), and the vegetation density (green, with brighter green more vegetation).

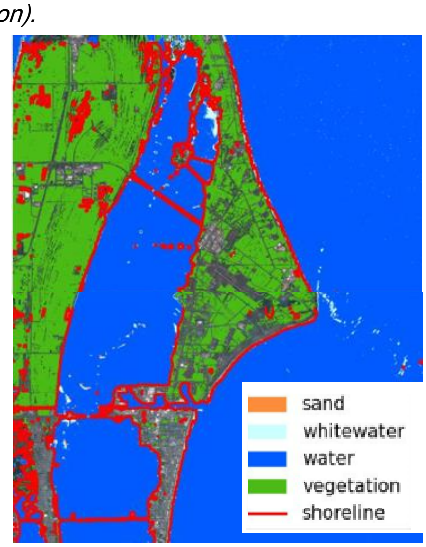

Figure 4 - Final output of CoastSat with the added Canny Edge Detection and vegetation index. The image shows a satellite view of the shoreline of Cape Canaveral, FL. Sand is represented in orange, whitewater in light blue, water in blue, vegetation in green, and shoreline is the red line.

Next steps for this process include identifying these features for a variety of shoreline locations such as Duck, North Carolina; Boston, Massachusetts; and Cape Canaveral, Florida in order to observe changes visible from satellites before and after beach nourishment, marsh restoration, and historical shoreline changes such as the building of seawalls and other coastal structures. We will specifically identify vegetation extent and health in response to these interventions, as well as shoreline extent and evolution in response to these interventions. The ultimate goal is to understand the utility of satellite observations in tracking and predicting the effects of these human interventions in a wide spatial area.

DISCUSSION

As stated above, there is an abundance of satellite imagery around the world over the past 50 years that has already been used to determine shoreline position of sandy beaches; we will be studying both vegetated beaches and the impact of vegetation on sandy beaches. We would also like to explore the effects of vegetation on shorelines for both intense short timescale events (storms) as well as over long timescales. A goal is to discover the large-scale relationship between vegetation and coastal erosion after storms, and to understand how restoration projects impact future coastal storm response. The data we collect could spur more research into coastal resilience against storms. If vegetation reduces coastal erosion, coastal communities around the world could use vegetative restoration techniques to prevent erosion. Research could also be done into vegetation types to see which types reduce coastal erosion the most efficiently while lasting long term.

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