Monitoring Shorelines via High-Resolution Satellite Imagery and Deep Learning

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1 Rising Sea Level and the Coastal Impact

Twentieth century has seen an overall sea-level rise of 0.5m [7, 11] and the studies for the twenty-first century [22, 10] project the overall increment within a range of 0.5m to 2m, considering high emission scenarios and rapid melting of major Antarctic glaciers. Naturally this has a severe impact on a major percentage of the population inhabiting coastal land zones [18], with a recent study [12] placing 110 million people living below the local high tide line. Of all the different coastline types, sandy shores, forming 31% of the world's beaches [14], undergo major erosion and accretion changes and hence are of special focus in this paper. Because of these reasons, it is paramount to regularly monitor the coastline changes across the world for better understanding, and to create necessary preparation and mitigation strategies.

1.1 Status Quo: Coastline Monitoring via Satellite Imaging

Majority of remote-sensing datasets created in the past have been sourced from Sentinel and Landsat satellites (10m and 30m resolution respectively), across a timespan of many decades. As an example Luijendijk *et al.* [14] uses images from 32 years of capture since 1988. On top of this, when traditional image processing techniques are applied over single images to estimate shorelines it results in errors due to misalignment and time of capture. To address this issue, a moving average based composite image approach presented by Hagenaars *et al.* [4] reduces the error margin to a half-pixel precision value. Few other factors promoting the usage of remote sensing data are the ever-improving sources of data both in terms of resolution and frequency of capture, and in-situ approaches like land surveys being very difficult and expensive to achieve.

A recent review paper by Toure *et al.* [20] categorizes the shoreline detection algorithms into:

- Segmentation based approach: Using index like NDWI (Normalized Difference Water Index) or SWI (Superfine Water Index), followed by supervised and unsupervised approaches for pixel-based classification. A recent work by Yang *et al.* [23] has utilized deep learning architecture for sea-land segmentation on Landsat images within a single geography.

- Edge Detection based approach: These approaches work at a finer level to discern the precise shoreline. Heene *et al.* [5] have utilized Canny edge detector followed by post-processing to get the final shorelines, whereas Kass *et al.* [9] have proposed an active contour approach, named Snake, to obtain initial set of edges that are further post-processed.

- Band Thresholding methods: Aedla *et al.* [1] have proposed adaptive thresholding and its variants, while Jishuang *et al.* [8] have used a threshold based morphological approach. However, due to the availability of better modeling approaches, these are running out of favor.

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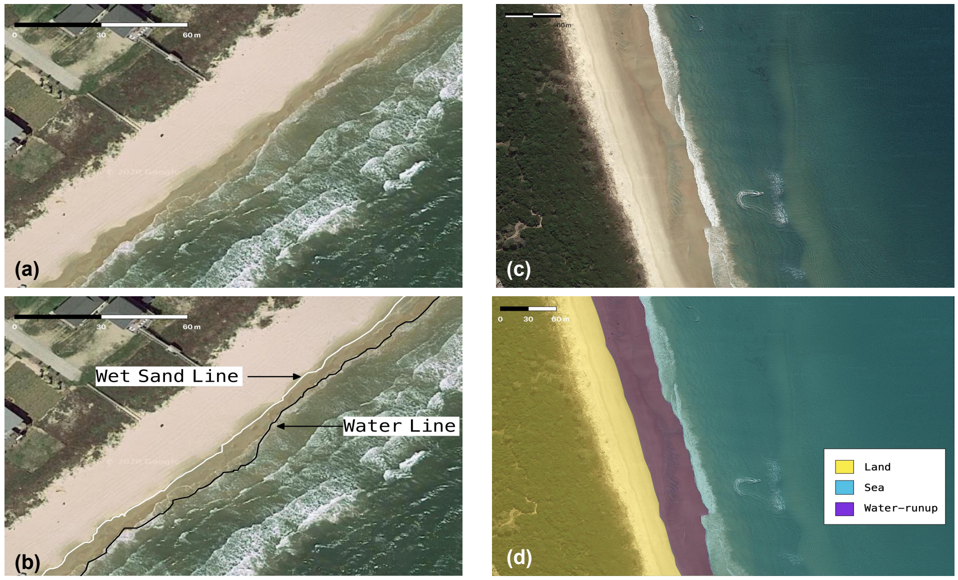

Figure 1: (a) Surfside Beach, TX, USA (b) Shows the two lines (i) Wet Sand Line which is the upper wetting limit of the foreshore visible as dark sand in the image. and (ii) Water Line where the body of water hits the slope of beach creating white foam. Delineated between the two of them is the water-runup class. (c) Letitia Beach, NSW, AUS. (d) Shows the sample annotations. It consists of three classes, Land, Sea and Water-runup which have been colour coded.(best viewed in colour) Source: Google Earth, 2020.

1.2 Our Goal

In order to estimate accurate shorelines, we use high-resolution (HR) Airbus SPOT imagery (1.5-2.5m resolution), this enables us to focus on the visible key indicators like the white foam created by waves hitting the shore and wet dark sand suggesting the maximum runup of the waves. For our dataset, we create a separate water-runup class, in addition to the usual sea and land classes. We convert the problem of shoreline detection to fine-grained segmentation along the coast. We employ state-of-art deep learning algorithms to model this problem. Training and validation is conducted on individual images and further tested on few hotspot shoreline regions to showcase the observed change in a time-wise fashion. By doing so, we present a case for automated systems using HR satellite imagery to monitor shoreline trends for high impact regions of the world.

2 Dataset

The dataset is created using high-resolution (HR) satellite imagery sourced from Airbus SPOT 5, 6 and 7 satellite constellation capturing the globe since 2003 with the panchromatic resolution of 1.5m and 2.5m. As already mentioned in section 1, sandy beaches are of high importance because of high population density, and loose soil texture resulting into heavy erosion and accretion phenomena. Another criteria taken into consideration for selection of regions is to diversify in order to accommodate variations incorporated by change in geographies. The current picked area list includes Chennai (India), Nubel Island (Denmark), Coolangatta Bay (Australia), Freeport Texas (USA) and Byron Bay (Australia), with more areas being explored.

All the previous approaches using semantic segmentation formulation have made it a two-class segmentation problem *i.e* land v/s sea segmentation, this has aligned with the resolution of imagery used previously (10m to 30m) because the points at shoreline where the waves are hitting the beach are inconspicuous. Since in our work we are using HR imagery, we can delineate various indicators with much more clarity like the water line [3, 15], where the body of water hits the slope of beach creating white foam, and the wet sand line [16, 6] which is the upper wetting limit of the foreshore visible as dark sand in the image. Hence, we create mask segments with 3 classes: Land, Sea and

Water-runup. The beach area between the water line (foam) and the wet sand line is marked as water-runup, the central region shown in Figure 1. The length of shoreline covered in the dataset we've currently procured and processed is around 60 kilometers and more being added. We are ensuring high quality annotations via strict quality check. For few of the hotspot regions, multiple images will be used across a longer time-frame to automatically track the shoreline change trend as a demonstration. Note that in the final version of the dataset, more areas will be added to make the dataset exhaustive. As of the date of writing, this is the first comprehensive dataset for estimating shorelines using HR satellite imagery with special focus given to shorelines by introducing a specific class.

3 Method

We are posing this problem as a three-class semantic segmentation task and posit to use state-of-art deep learning (DL) algorithms for modeling purposes. To the best of our knowledge, only Yang *et al.* [23] have employed DL algorithms for binary sea-land segmentation using 30m resolution Landsat imagery for restricted regions in China. Our goal is to create a general model which can be robustly applied to any sandy shoreline across the globe achieving high accuracy. We propose to:

1. Split the dataset into two sets of geographies. In the first set, we'll split the data for training and validation purposes and the second set will be used purely for testing purposes. The second set of geographies will be tested on multiple images from a larger time-span to demonstrate the efficacy of developed models for shoreline monitoring.
2. We will explore and compare the performance of different semantic segmentation architectures varying from UNet [17], DeeplabV3 [2], HR-Net [21] *etc.*
3. To push the optimization towards a better minima, we will try out loss functions like cross-entropy, dice loss [19], focal loss [13] etc; also thorough hyper-parameter search for learning rate, loss multipliers, class balancing and batch size will be done.

We will be publicly releasing the codebase, weights for the baseline models as well as the curated dataset to further research development in this direction.

4 Discussion

With increasing amount of emissions leading to changing climate, in terms of rising temperature and melting glaciers, has led to a continuous rise in the sea-level. This is directly resulting into changing shorelines, and coastal zones being heavily populated makes it crucial to continuously monitor the changes. The recent upheaval of remote sensing technologies along-with the advent deep learning provide a great set of tools to establish automatic trigger systems and further enabling prevention and mitigation strategies in a timely manner. In the final version of this work, we will be releasing the curated HR satellite imagery dataset as well as the code. We will also demonstrate the applicability of developed models on new hotspot regions across a larger time-frame of imagery while delineating the observed shift in shorelines. Finally, we hope that this work helps in the advancement of shoreline monitoring algorithms and system developments to create positive climate impact for the overall good of our planet.

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