Spatio-temporal monitoring and analysis of Nigerian Bonny Island coastline dynamics and the physical impacts

A Master Thesis by

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Abstract :

This thesis intends to develop a method for spatio-temporal monitoring and analysis of coastline dynamics and its physical impact from 1984 to 2018.

The experiment is conducted with Landsat data from Bonny Island, Nigeria and its interest is to design a fast track process and of low cost.

The preparation of the time series classification is reported along with the theoretical aspects concerning the methods and concepts used in order to conduct Random Forest and Otsu’s thresholding to classify land and water. After the classification, the coastline is extracted by the boundary of the classes, and transects are deployed with DSAS tool. The transects are deployed and produce erosion and accretion rates that upon them, the analysis takes place.

The results show that about in 75,5% of the Island, accretion is dominant with a gain of 6.81m per year. The statistic outcomes of the transects rates show a strong agreement between the results of Otsu and Random forest respectively. A validation applied, calculated the area under erosion and accretion for 1984 to 2003, showed that the Otsu’s method has the highest accuracy. The measurements of the thesis are presented extensively in the conclusions.

Assets and downsides have been found for both Random Forests and Otsu and is suggested that the choice depends on what is intended with them. The free coarse resolution data is suggested in the literature that does not necessarily result to less accuracy in classification methods.

Preface

The author of this thesis, Michail Tsatsakis created this report for the framework of the final project and completion of the Master of Science in Geoinformatics at Aalborg University Copenhagen.

The idea for the topic of this thesis was inspired and guided by my supervisor, Associate Professor Jamal Jokar Arsanjani and Mikkel Lydholm Rasmussen from DHI GRAS. I would like to share here my sincere gratitude for their time and help.

Many thanks as well to all the staff at DHI GRAS who have been really supportive and special thanks to Rasmus Eskerod Borgstrøm who opened the opportunity to me to be along the people of GRAS and work together and to Kenneth Grogan for his contribution to this thesis.

Abbreviations

CART: Classification Algorithm Regression Tree

DEM: Digital Elevation Model

DSAS: Digital Shoreline Analysis System

EPR: End Point Rate

ESI: Environmental Sensitivity Index

HWL: High Water Line

ML: Machine Learning

NIR: Near-Infrared

RM: Random Forest

SLC: Scan Line Corrector

SVM: Support Vector Machines

SWIR: Short-Wave Infrared

TM: Thematic Mapper

USGS: United States Geological Survey

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1 Introduction

The core of human activities is situated along coastal areas, these are areas are of high economic interest and change significantly enough over time naturally as well as from human intervention having consequences in the environment, societies, and ecosystems. From this dynamic of the coastal areas arises a neuralgic need of studying them, estimate trends and plan forward. One of the key features needed to be studied and mapped is the shoreline. The location of the shoreline and the changing position of this boundary through time are of elemental importance to coastal scientists, engineers, and managers (Boak and Turner 2005). In respect to the needs of these specialists, and in contribution to the subject but as well for self-development, this thesis engages the topic of shoreline mapping. It approaches the topic from the applications of remote sensing and geographical information systems.

1.1 Initiation to the problem

A case study was implemented after an order from oil companies for mapping coastline change with remote sensing technics with the author of this thesis contributing to the work of the study. High-resolution commercial satellite imagery was used to manually digitize the coastline according to the high-water line. The study was conducted within the framework of environmental crisis prevention, where interventions needed to be made had to take in consideration the coastline movement.

Areas of high oil spill hazard can elaborate data of coastline change for the ESI mapping. ”However, a significant data gap exists across many low- and middle-income countries in the aspect of environmental monitoring.”(Lawal and Oyegun 2017)

Lawal and Oyegun suggest that countries with the higher oil spill do not have the resources to conduct the necessary studies to prevent environmental disasters. An example of the high-cost study is of the one mentioned in the case study.

The high-resolution satellite imagery is expensive to acquire thus makes this method restrictive for the general public, or for testing purposes. The method implemented in the case study demanded many working hours for the process of manual digitization. These two deficiencies of the method led to the research of a method that could lower the cost, ease the restrictions of who can implement it and can minimize the prerequisites such as the working hours to produce a coastline study.

The concept is rooted in the idea of increasing access to information and the tools that produce it and give it growth. This would mean simplifying technologies, lowering their cost and time, these 3 points could sum up to what is needed to look for. Stressing to an Ideal objective the most realistic approach is to optimize. This optimization as a prospect tries to address the problem of how to increase accessibility in producing coastline studies. To try to achieve the opening of the coastline studies, the method to be found would have to consider the challenges of the best compromise between accuracy, quality of results and time of production with automating procedures and lowering cost since these are counteractive. The research was aiming for an example set of coastline dynamic study, open to the public and with free data so that it could be reproduced in other areas and bigger scales with minimum technical knowledge requirements.

Simpler and effective technics give motivation for people to use them and with this way, more people engaging in the information production and to the general growth.

Answering the questions of where and why? This thesis revolves around a case study that needed answers. The delivery of a coastline change report, with remote sensing technics, was asked and it was produced. The work produced, besides introducing the author to the ideas and concepts of coastline monitoring offered an area of study with a problem. Solving the problem, from the extent of the disciplines of remote sensing can be done in numerous methods and these had to be investigated as well.

The focus is on developing a method of extracting accretion/erosion rates and monitoring spatiotemporal coastline change with the above-mentioned 3point criteria.

1.2 Background

The area of interest has been studied in the past from Ogoro (2014) whose study affirmed widespread erosion and flooding from 1986 to 2011 to the island. Adegoke et al. 2010 performed a study with a wider area, but with only two timestamps, 1986 Landsat TM and 2003 Landsat ETM+ of the Niger Delta where part of the study was attributed for Bonny island. Eludoyin, Oduore, and Obafemi (2012), used Landsat TM imagery of 30m spatial resolution of 1986, 2001, 2003, 2006 and Nigersat image with same resolution of 2004. Their study found as well that the island has been eroded by natural and human intervention and suggests measures of environmental restoration. The studies mentioned, performed with different methodologies and outputs from the one this study tries to attempt. There is a common ground to the previous studies that they were also conducted with free coarse resolution data, however, their method did not try to automate any processes.

Vast research has been conducted in remote sensed, coastline detection. Weismiller in 1977 analyzed Landsat MSS temporal data to detect changes in Matagorda Bay region of Texas by computerized procedures. He used a non-supervised approach utilizing the maximum likelihood classifier.

Researchers have implemented a time series study with the desideratum to be the distinction between the water body from the soil, namely Sarp and Ozcelik published in 2017 a study that evaluated SVM performance incorporated with various indices concluding in NDWI giving the best results in their time series of Lake Burdur.

There is a toolbox for ArcMap for coastline extraction based on maximum likelihood classification('Landsat Toolbox for Shoreline Extraction' n.d.)

Taking in consideration the background and the scope of the work documented here, the research for the method to be implemented, in order succeed the goals of this project, led to the following approach: Acquire free imagery to have a time series, classify each image in two classes, namely water, and land. Extract from the boundary of the classes the coastlines and calculate the rates of accretion/erosion and present the coastline change. Compare the results of the different classification methods.

1.3 Problem Statement

The problem statement results from all the aforementioned initiation to be summed up in:

How to map the coastal change in our area of interest?

Surrounding the problem statement leads to general queries of how the problem is going to be addressed. Having in mind the criteria set for the approach of this study the following unfold.

1.3.1 Objectives and Research questions:

Which free data to be used, which software and tools to choose, what processes can be automated and with what methods?

How the results would be presented, what would be measured in the aspect of the change?

The preliminary objective is to map the coastline change of our area of interest with the best possible results.

Assessing the results is an objective as there has to be found a way that to be done.

The method to be developed besides the points that stress the need to acquire minimal resources has to be easy perceivable to reproduce the method.

That mentioned it makes this report itself of a significant value to the objectives unfold here. To explain, proposing a method for it be used widely that optimizes simplicity and reproduction consistency, the method has to be documented very well and understandable. It has to resemble an easy to follow manual but still keep the academic standards adding up to the universality character.

The method has to be designed in order to have the least repetitive and manual tasks.

The needs of the study, that of a the time series study, require a production line approach.

2 Study Area and Material

In this chapter general information of the area of interest will be presented as well reasons of why this area came to an interest for this project will be highlighted. It will next continue with the presentation of the data being used and tools.

2.1 Study Area

The study area of this thesis is Bonny Island of Rivers State, Nigeria. The area is located in the broader Niger Delta between the latitudes of 8 °22’N and 8°31’N and longitudes of 5°3’E and 5°19’E. The island is classified as tropical hot monsoon climate by the Köppen climate classification that follows heavy rainfall with significant flooding from April to October, thus clear sky data availability for the rest of the months and in specific around January. The climate is characterized by high temperatures and high humidity. Geologically is compromised by alluvial sedimentary basin and basement complex with a soil of sandy to sandy loam. Raffia palms, thick mangrove forest, and light rainforest is the vegetation of the island. (Eludoyin, Oduore, and Obafemi 2012)

Figure 1: Location schema of the area of interest

"In the early 1990s the Federal Government of Nigeria, in collaboration with 3 international partners, Shell Gas BV., CLEAG Limited [ELF] and AGIP International BV. started the multibillion-dollar project Nigeria Liquefied Natural Gas Limited (Nigeria LNG).[1] Due to its strategic position, the island hosts various oil companies including

Royal Dutch Shell, Mobil, Chevron, Agip, and Elf.” (‘Bonny Island – Hometown.Ng™’ n.d.)

2.1.1 Case Study

In Bonny Island, oil companies in the 70’s deployed underground oil and gas pipes from the land inwards the sea. From the underground installation of these pipes until recently, some parts were exposed at the surface due to erosion (see following figures), where there would be no support from the ground and the pipes would be subject of stress from water currents and sentiments. Other problematic cases would be that the pipes would be buried excessively from accretion to the point that the mass surrounding them would cause over-insulation that could potentially over-heat them and along with the weight’s stress combined could damage them.

The hazard of the pipes being cracked as explained above and causing a leak/spill is depended by the erosion and accretion that are possible to study by mapping the movement of the shoreline in time and extracting the erosion/accretion rates. The case can be framed as environmental disaster prevention. The study will focus on the southern coast of the Island where there was the request of the case study.

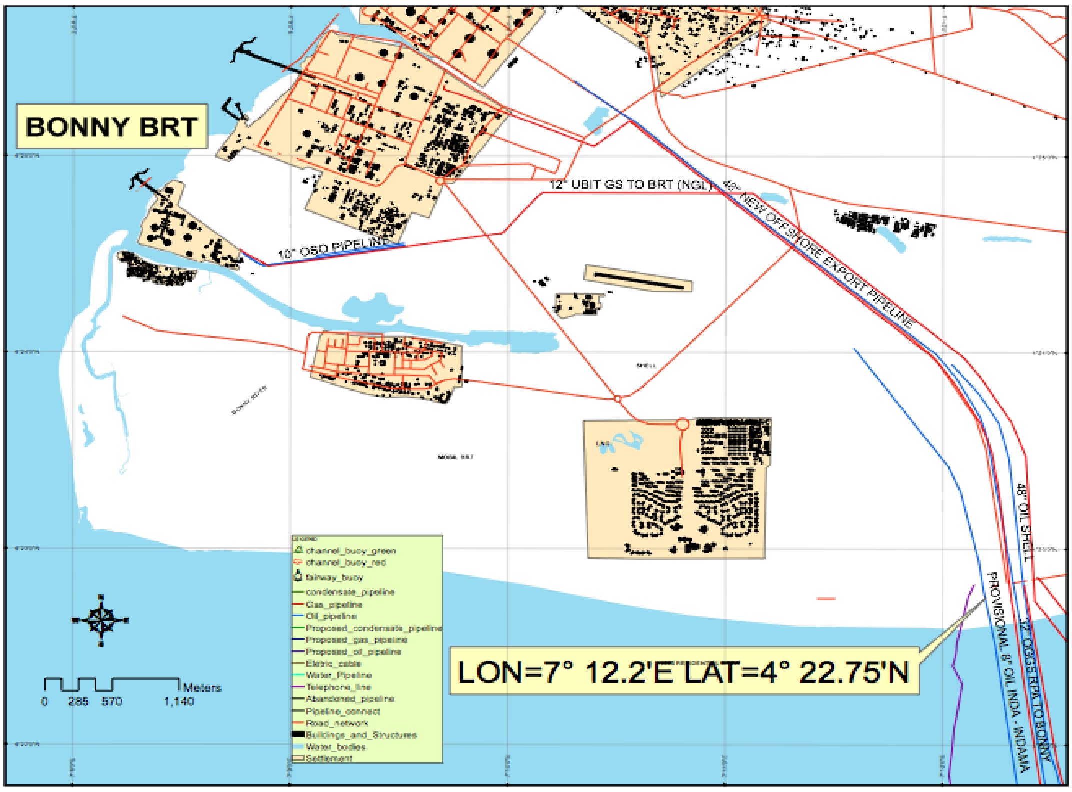

Figure 2: Schema of the island with pipes crossing on the south-east (provided by DHI GRAS)

Figure 3: Exposed pipe photo (provided by DHI GRAS)

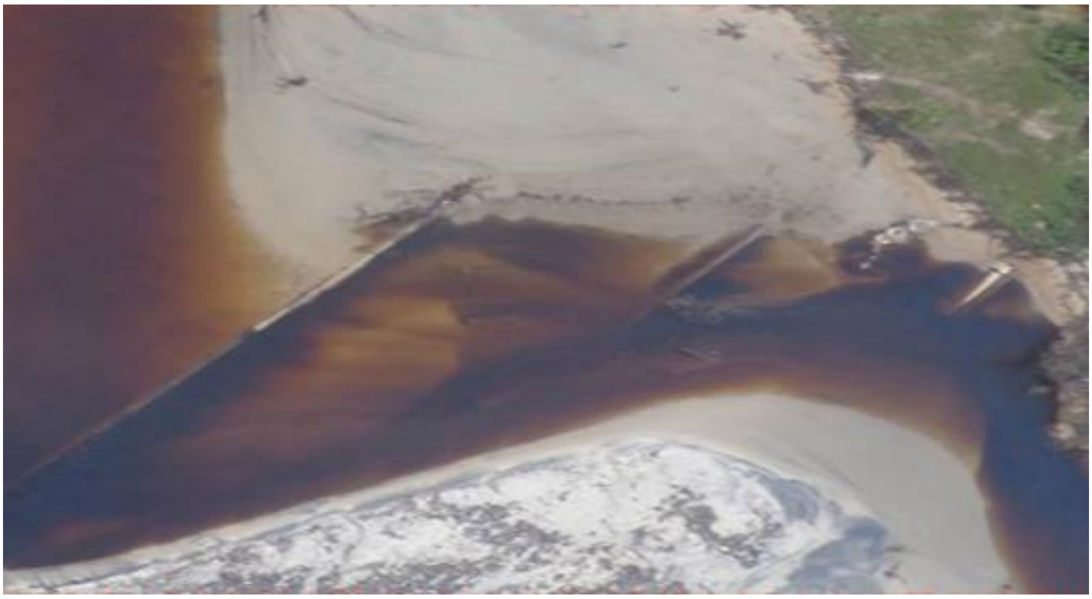

Figure 4: 3 parallel exposed pipes (provided by DHI GRAS)

2.2 Data

In acquiring the data of the study with the imagery following the principles stated in the problem statement, the results of the literature research pointed to the direction of "an alternative remote sensing image used for coastline extraction is the popular Landsat series imagery, because of its free access, large revisit coverage and long-term data record" (Liu et al. 2017).

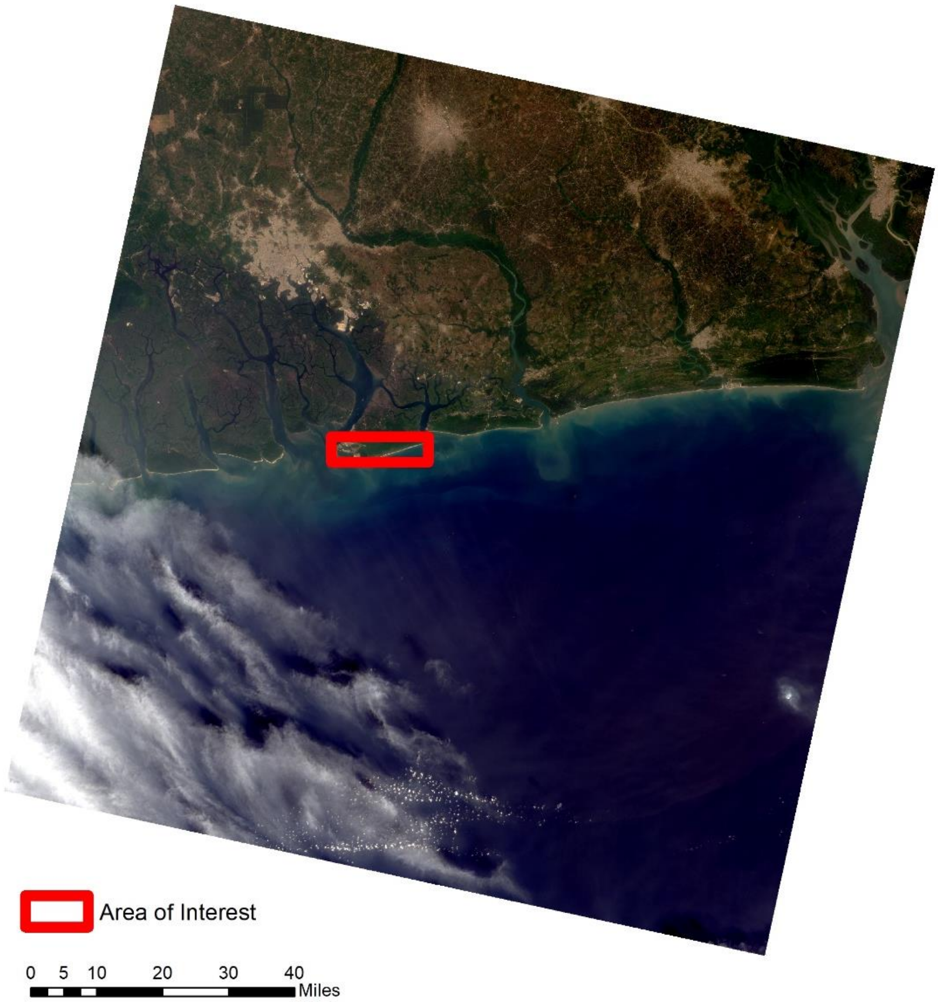

Figure 5: Sample of the raw imagery in RGB composite from Landsat 8

Using the platform of Landsat for all the imagery of the time series would ensure a consistency of the quality and format of the data, however in manners of the timestamp there would be a loss for a decade from 2003 when the Scan Line Corrector ceased to operate('SLC-off Products: Background | Landsat Missions' n.d.) with the consequence of having failure lines of no data(e.g. in figure 6 below where the error line excludes parts of the coastline).

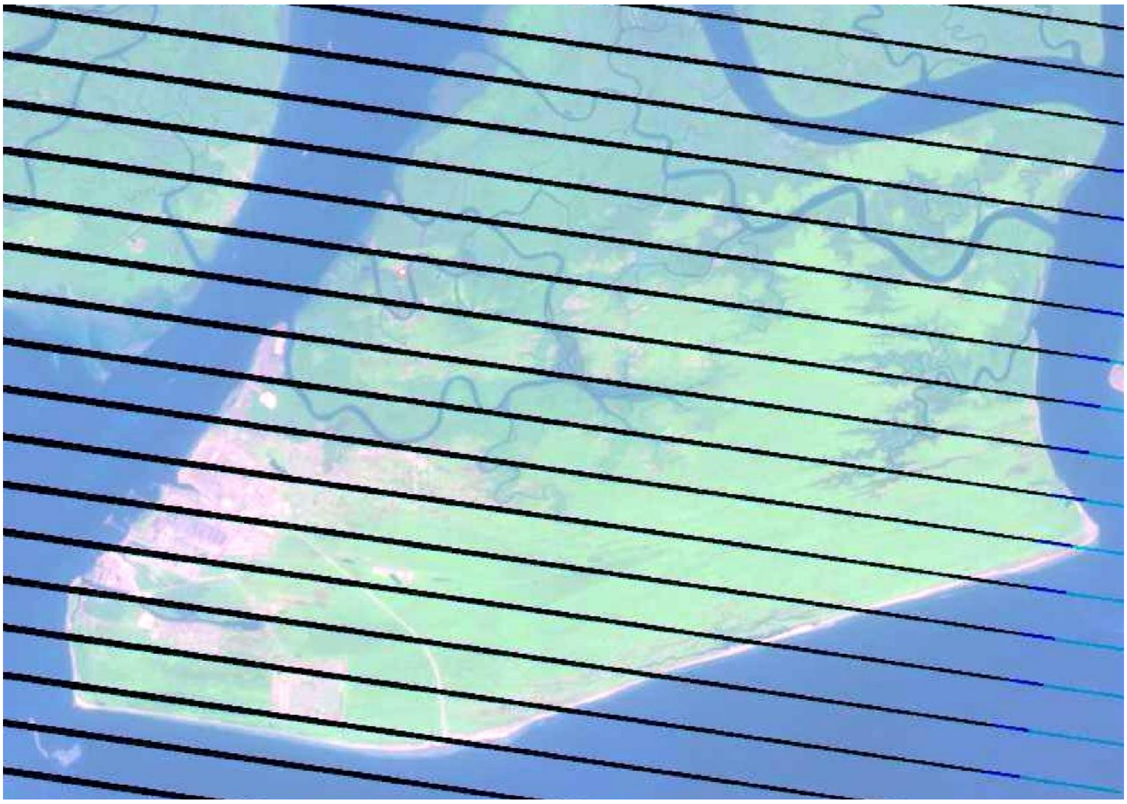

Figure 6: Landsat 7 imagery of Bonny island with SLC error lines

Another factor by which the data is chosen is cloud coverage and in specific clouds intersecting hiding the coastline. That mentioned the timestamp was chosen accordingly the least cloud coverage and excluding the imagery with SLC error and cases combined. These were avoided as it can raise a new topic of research to deal with that is not in the main focus of this study.

The imagery used was acquired partly from the United States Geological Survey platform ('EarthExplorer - Home' n.d.) with the Bulk Download Application and imagery from Landsat. The most recent part of the time series was collected from 'Remote Pixel | Satellite Search' n.d. A summary of the imagery used is presented in figure 6 with highlights of the metadata (MTL.txt) file of each dataset. To add in the information of Figure 7, the projection of the data is WGS84 32 UTM and the format of the imagery was GeoTIFFs.

Date acquired	Sensor	Spacecraft ID	Product ID/Scene ID
01/25/2018	(OLI, TIRS)*	Landsat 8	LC08_L1TP_188057_20180125_20180206_01_T1
01/06/2017	(OLI, TIRS)*	Landsat 8	LC81880572017006LGN00
01/04/2016	(OLI, TIRS)*	Landsat 8	LC81880572016004LGN00
01/17/2015	(OLI, TIRS)*	Landsat 8	LC81880572015017LGN00
01/14/2014	(OLI, TIRS)*	Landsat 8	LC81880572014014LGN00
05/19/2013	(OLI, TIRS)*	Landsat 8	LC81880572013139LGN01
01/08/2003	(ETM+)**	Landsat 7	L71188057_05720030108
12/17/2000	(ETM+)**	Landsat 7	L71188057_05720001217
12/19/1986	(TM) ***	Landsat 5	LT05_L1TP_188057_19861219_20170215_01_T1
10/10/1984	(TM) ***	Landsat 5	LT05_L1GS_188057_19841010_20170220_01_T2

*Figure 7: Imagery summary from metadata. *Operational Land Imager (OLI) and Thermal Infrared Sensor (TIRS), ** Landsat Enhanced Thematic Mapper Plus (ETM+), *** Landsat Thematic Mapper (TM)*

Data Preparation

For the analysis of this project, most of the workload took part in the preparation of the data that the steps followed are going to be presented here throughout in the implementation chapter. Nevertheless, there was some preliminary preparation needed for some data, that is attached to the technicalities and particularities of the source of the data. For this study, it was only the need for the registration of the imagery.

2.2.1 Georegistration of Imagery

From the imagery being presented in summed up in Figure 7, the images of the timestamp of 1984, 2000 and 2003 had to be geo-registered as for instance 1984 is Tier-2 from the TM Collection 1 where only "Tier 1 (T1) – Contains the highest quality Level-1 Precision Terrain (L1TP) data considered suitable for time-series analysis. The geo-registration is consistent and within prescribed tolerances [<12m root mean square error (RMSE)]." ('Landsat 4-5 Thematic Mapper (TM) Level-1 Data Products | The Long Term Archive' n.d.)
These images were rectified with the georeferencing tool of ArcMap by overlaying them with T1 imagery.

2.3 Software

ArcGIS 10.5 was used for the preparation, processing, and visualization of the data as these will be presented further in the methodology chapter.

The Digital Shoreline Analysis System (DSAS) version 4.4 extension for ArcGIS enabled the calculation of shoreline rate-of-change statistics from multiple historic shoreline positions ('USGS OFR 2008-1278: The Digital Shoreline Analysis System (DSAS) Version 4.0, an ArcGIS Extension for Calculating Historic Shoreline Change, Title Page' n.d.).

The Otsu, Threshold classification and Random Forest Classification were conducted in R Studio.

3.1 Methodology

The methodology chapter is dedicated to reporting all the methods been used for the creation of this study. It consists of one subchapter that intents to cover key points of the theory needed, to understand what this study attempts to achieve and how. This theoretical part sets the foundations for what in the second part of the chapter is going to plot out. The second part goes through the implementation, describing how tools were used and the workflow.

3.1 Theoretical Background

For this report to be defended and stand ground It is necessary to delineate some concepts and basics of the methods that are going to be used to their generic extent complying with the goals of this thesis.

Classification Algorithms

The data as presented are images where from we need to extract a feature, that, to be identified in computation, must fit in a class or be indicated by classes. Seeking for automation technics that are optimizing remote sensing work and in specific the pixel-based classification methods, the author has chosen to perform his analysis with Random Forests and Otsu's thresholding

3.1.1 Random Forests

The Random forest classification algorithm is a pixel-based machine learning method the extension of which is used in this thesis was developed by Breiman 2001 who added up to the majority vote and random splitting. The method creates rules of if-than conditions to classify objects. The rules are developed according to training data sets given samples and they are decision tree based. The algorithm can be tuned by the parameters of determining the number of trees and of the input variables of each node of the tree (Bayram et al. 2017).

The training data are used as learning data the 2/3 and the rest 1/3 of is used as test data. The bootstrapped technique is used to resample the input variables to subsets that will determine a split for each node of the CARTs being deployed. The CART algorithm incorporates the Gini impurity to perform the node's split where it selects the variables with the lowest Gini. When the Gini results to zero then the branching ends (Bayram et al. 2017). Accuracy estimation is conducted with the out of the bag data by running them down the decision tree. In order to classify each tree in the votes for the most popular class and the pixel's class will be determined by the majority vote(Gislason, Benediktsson, and Sveinsson 2006).

The random forest classifier has advantages upon it was selected for this thesis. The Its performance does not overfit, and it does not require guidance. It can analyze the weight of the input variables so to extract features and detect outliers (Benediktsson, Chanussot, and Fauvel 2007). It can deal with categorical variables, unbalanced data, and missing values (Pal 2005). The mentioned assets along with its multisource classification ability make it a tool of choice for this study.

3.1.2 Otsu's Thresholding

Nobuyuki Otsu formulated a method that calculates an "...optimal threshold automatically from a gray image and the threshold maximize the inter-class discrepancy. Previous researches have proved that Otsu method can successfully be applied to map water bodies from Landsat imagery."(Liu et al. 2017)

The dynamic to partition a raster image by minimizing the intraclass variance(Wang et al. 2017), makes this method a powerful tool in binominal classification.

Otsu's method is nonparametric and unsupervised with a procedure that utilizes only the zeroth and the first-order cumulative moments of the gray-level histogram. "It is straightforward to extend the method to multi-threshold problems. Taking into account these points, the method suggested in this correspondence may be recommended as the most simple and standard one for automatic threshold selection that can be applied to various practical problems.”(Otsu 1979)

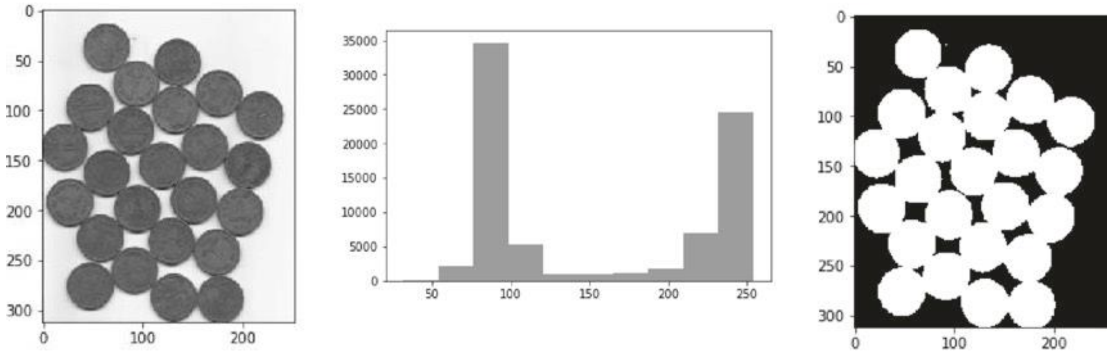

Figure 8: Binary thresholding method based on a histogram of pixel intensities (Pattanayak 2017)

Satellite-Derived Indices

Various indexes have been developed to optimize the distinction between classes and features in imagery. Their function can be perceived as an equalization of the imagery focusing on specific spectral characteristics needed to be highlighted or separated. This study uses NDVI and NDWI.

3.2.1 NDVI

The Normalized Difference Vegetation Index has been developed to distinguish the health and vigor of green vegetation and it can be utilized to identify two more classes, namely water and soil (Al-mansoori and Al-marzouqi 2016).

NDVI is calculated by the equation below, where NIR stand for near-infrared reflectance values and Red for red reflectance values:

$$NDVI = \left(\frac{NIR - \mathrm{Re}\,d}{NIR + \mathrm{Re}\,d} \right)$$

3.2.2 NDWI

The Normalized Difference Water Index was developed to "..primarily to delineate open water features and to enhance their presence in remotely sensed digital imagery while simultaneously eliminating soil and terrestrial vegetation features."(McFeeters 1996). McFeeters adopted the format of the NDVI to separate water bodies from other land-cover features based on the spectral characteristics. The NDWI values range from -1 to 1 and the threshold for separating water from non-water is 0 where when NDWI > 0 then the cover type is water and for NDWI ≤ 0 the cover type is non water The equation that computes the index is as follows, where Green the reflectance from the green band and NIR from the near-infrared (Ji, Zhang, and Wylie 2009).

$$NDWI = \left(\frac{Green - NIR}{Green + NIR} \right)$$

3.3 Defining the Shoreline

"An idealized definition of shoreline is that it coincides with the physical interface of land and water"(Boak and Turner 2005). The defined border of land and water that is asked to be mapped as the shoreline can be challenging to establish by interpretation of an image of a beach. The line in demand has many indicators, visually interpreted and situated differently in the bibliography (see Figure 9 & 10). However this thesis will use the High Water Line(HWL), not only because is the most common in use but due to the resolution of the data to be used that can restrict the distinction of other indicators and as Boak and Turner 2005 suggests: "In practice, the decision as to which shoreline indicator to use at a specific location is almost always determined by data availability."

Referring to the data availability, some indicators may not exist in some imagery while it is found that HWL it the most prominent.

The selection of the HWL can be problematic in some cases compared with other indicators. "Smith and Jackson (1992) note that the width of a beach is not a single parameter and that large variations can occur over a single day." And "Even when the high water line can be detected on aerial images that pseudo-shoreline changes are caused by short-term water fluctuations resulting from anomalously high- or low-water levels at the time of photography."(Camfield and Morang 1996)

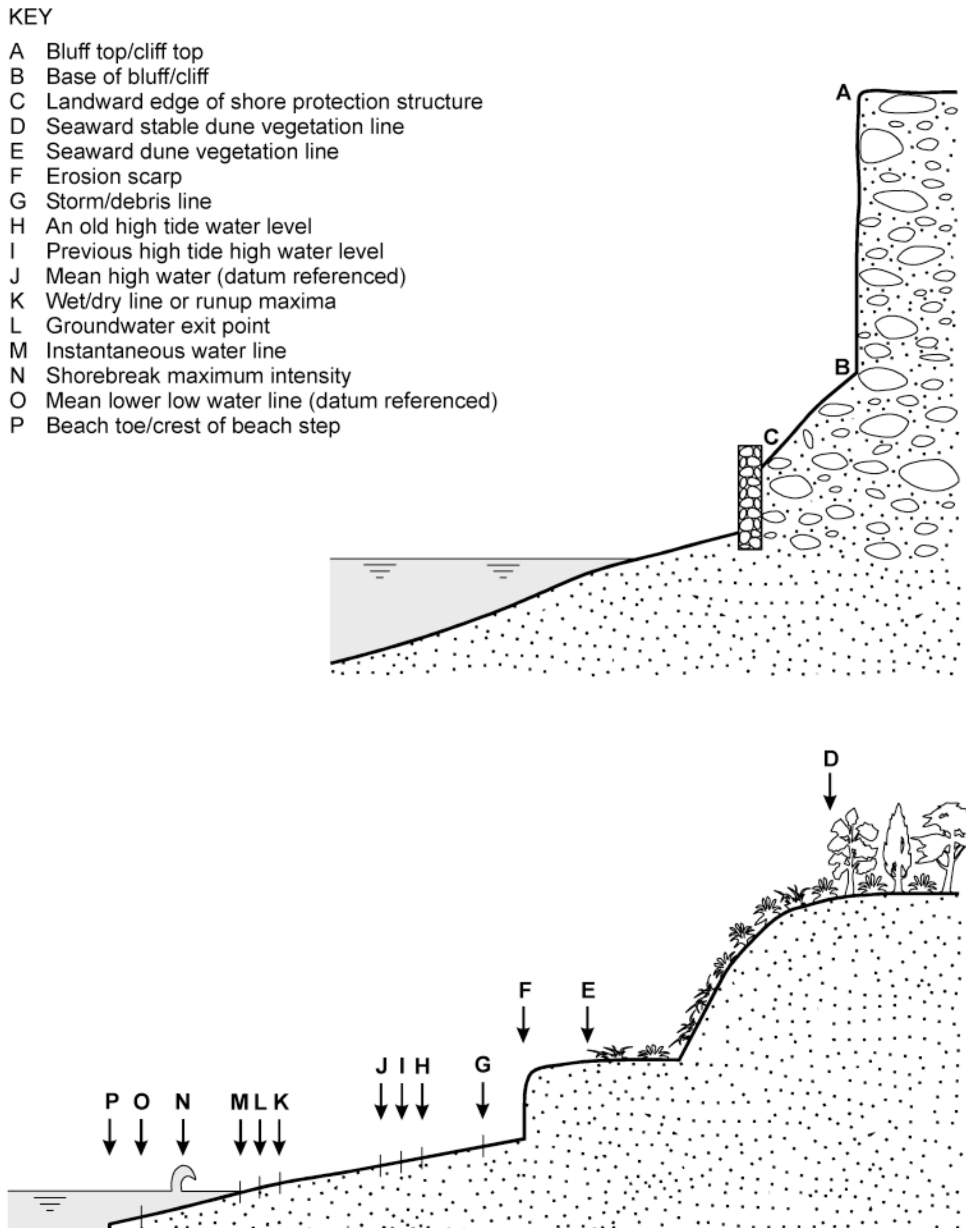

Figure 9: Sketch of the spatial relationship between many of the commonly used shoreline indicators. (Boak and Turner 2005)

Figure 10: An example of a range of visibly discernible shoreline indicator features, Duranbah Beach, New South Wales, Australia. (Boak and Turner 2005)

3.2 Implementation

In this chapter, the implementation will be described and justified. The presentation of the work done is mapped with workflow diagrams that will be explained

Having a time series in to produce, which for each timestamp there are many bands to be processed and as well to produce the NDVI and NDWI composites. The number of images to be handled result to the need of automation of some processes and the design of a production line workflow since many steps have to be repeated.

Workflow Diagrams

3 workflow Diagrams have been designed each one for the stages of the production deployed.

The first Diagram is a brief description of the procedure took part for each timestamp separately until the resulting of the classified rasters with the classes of water and land. The second diagram maps the stage for the process to extract each coastline from the classification rasters and the last diagram goes through the process of producing the data to be analyzed that sum up all the timestamps together and being cited in one time series.

Workflow stage 1

The classification methods to be used, presented already, was Otsu's and Random Forests. The inputs to be used for the classification are selected according to the sensibility to highlight the classes of land and water. Otsu' algorithm can have one source input, grayscale and that will be the NDWI. For Random Forest the possibility of multisource classification will be used in giving in as inputs the bands of Blue, Green, Red, Near Infrared, Shortwave Infrared, and the composites of NDVI and NDWI respectively. All these inputs have to be produced. In this stage the production of these inputs and of the classification images will be unfolded with the diagrams flow of Figure 11.

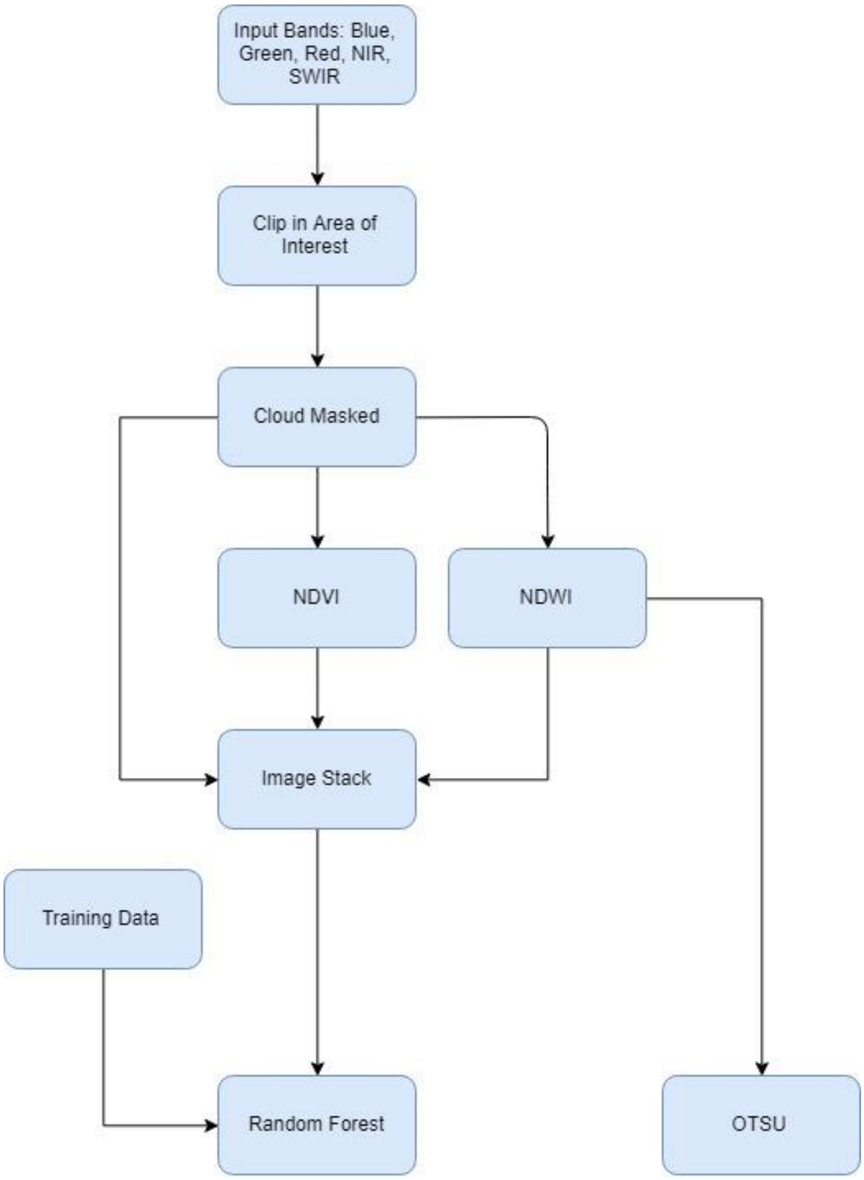

Figure 11: Stage 1 workflow

3.2.1 Clip in Area of interest

As mentioned in previous chapters the study is focused on a specific area that of the southern coast of Bonny Island, for that reason the data had to be clipped in the area of interest, resulting as well to a reduced size of data, faster to manipulate and process. The size of the area of interest is ideal for visual inspection even to the pixel level. The area of interest would be framed with a polygon shapefile created in QGIS with CADDIGITIZE ('QGIS Python Plugins Repository' n.d.) tool in order to ensure the shapefile's topology as it was observed that creating the shapefile with other GIS tools would disrupt the positioning.

Having a big number of images the process was automated with a creation toolbox in ArcMap and with the use of Model Builder as shown in Figure 12 below.

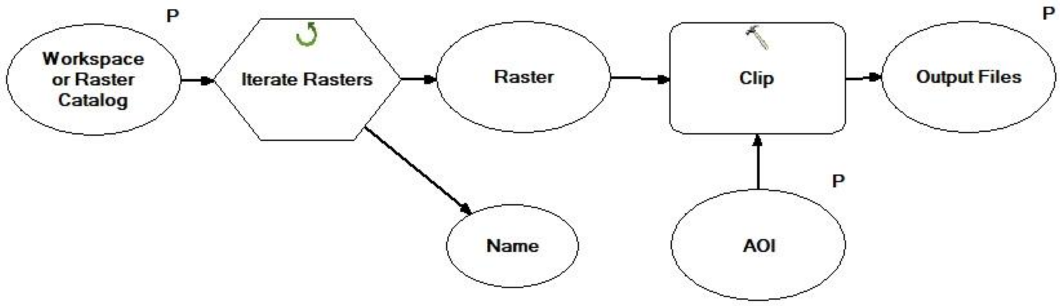

Figure 12: Clipping Model

3.2.2 Cloud masking

Since it was decided that the classification will be done with two classes, the feature of a cloud would be classified either as a land class or as water. This conflicts with this study only when the cloud intersects with the feature tried to be extracted, which is the coastline. For the clouds hiding the coastline, it was chosen that they would be masked manually.

The approach used for the masking was to use the Raster Calculator in ArcMap to process the imagery with No Data values in the areas with clouds. The idea was to incorporate The raster of the image need to be masked with another raster mask.

Polygon shapefiles would be drawn upon the areas being covered by clouds. Not all clouds would be covered but rather just the ones covering coastlines and their continuation in the inland if there was one.

A production of a raster from the polygon created would take place where the raster would have the size and geolocation of our clipped imagery. That information to be set would be given from the properties of the clipped imagery in Source -> Extend section. The raster would be created in GDAL with the rasterize tool with the command in OSGeo4W Shell as shown in the figure below.

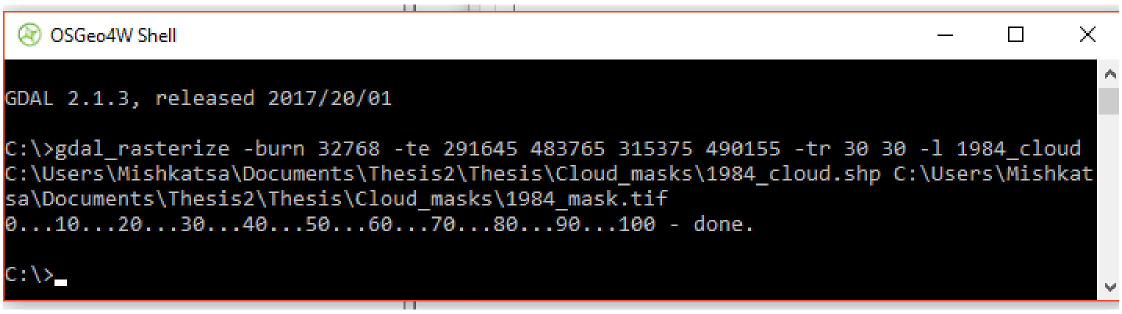

Figure 13: Gdal rasterize command for the creation of cloud mask

The raster created in Gdal would burn the pixels In the extent of the polygon shapefile with the value of 32768.

After the creation of the mask raster, Raster Calculator in ArcMap would be used with following formula as shown In Figure 14.

```
SetNull("%mask%" > 1,"%Raster%")
```

Figure 14: Raster Calculator formula for masking with the cloud layer

The formula in Figure 14 would produce our masked raster with the unwanted pixels set with No Data value.

The mask had to run for all bands separately and the reason is the mask method being implemented cannot produce composites with many stacked layers. To deal with all the bands, again, an iteration model was created in the design of the one in Figure 12.

3.2.3 NDVI and NDWI composites

NDVI and NDWI were produced according to the formula presented in the theory chapter. As there are many timestamps from where the mentioned here composites have to be produced, a model was created in the toolbox of the project. The model produced a tool that would ask as inputs the required bands for NDWI or NDWI, respectively Near IR Band, Green Band and Near IR Band, Red band.

The model is using raster calculator with the following formula:

(Float("%Green Band%"-"%Near IR Band%")) / (Float("%Green Band%" +"%Near IR Band%"))

Figure 15: NDWI formula in raster calculator

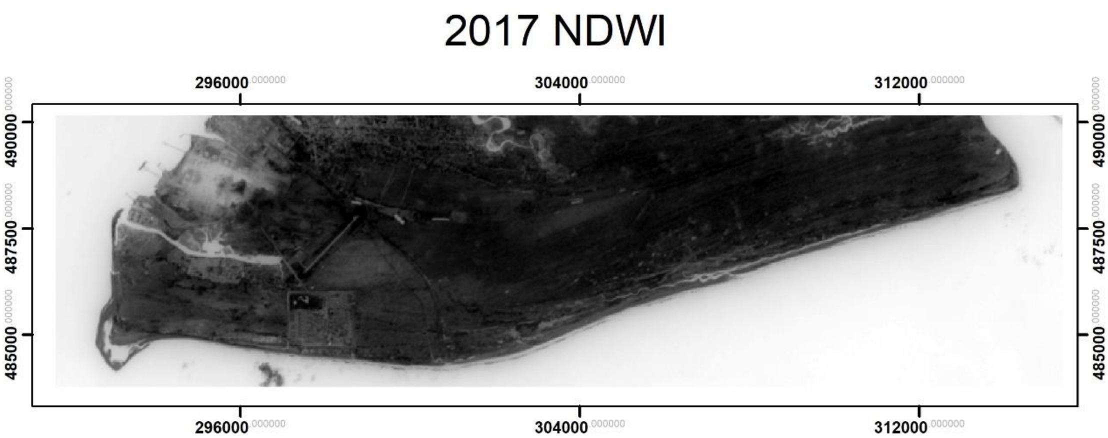

Figure 16: NDWI composite of 2017

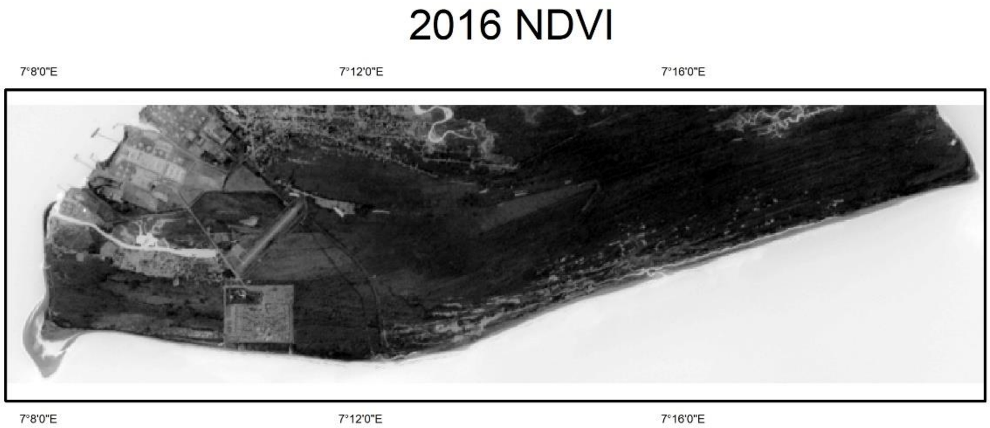

Figure 17: NDVI composite of 2016

3.2.4 Image Stack

For the production of the image stack the Composite Bands (Data Management) tool from ArcMap was used by giving as an input the 5 Bands mentioned, NDVI and NDWI.

3.2.5 Otsu’s classification in RStudio

The Otsu’s classification was conducted in R with the whole script being used attached in the Appendix. This thresholding method has one input as it has already been discussed in the theory section. The input being produced from previous step was each timestamps NDWI composite. The method cannot be tuned or controlled and the only editing taking place is giving the input in the script in the following lines presented in Figure 18.

```
setwd("C:/Users/Mishkatsa/Documents/Thesis2/Thesis/Cropped/1984/Masked")

Layer <- "1984_NDWI.tif_M.tif"
```

Figure 18: RStudio, lines from Otsu's R script of setting the input

The script would also return the statistics being performed by the script in RStudio and are presented in the Appendix.

A sample of the classification resulted is shown in Figure 19 where 2 classes can be distinguished when viewed in ArcMap.

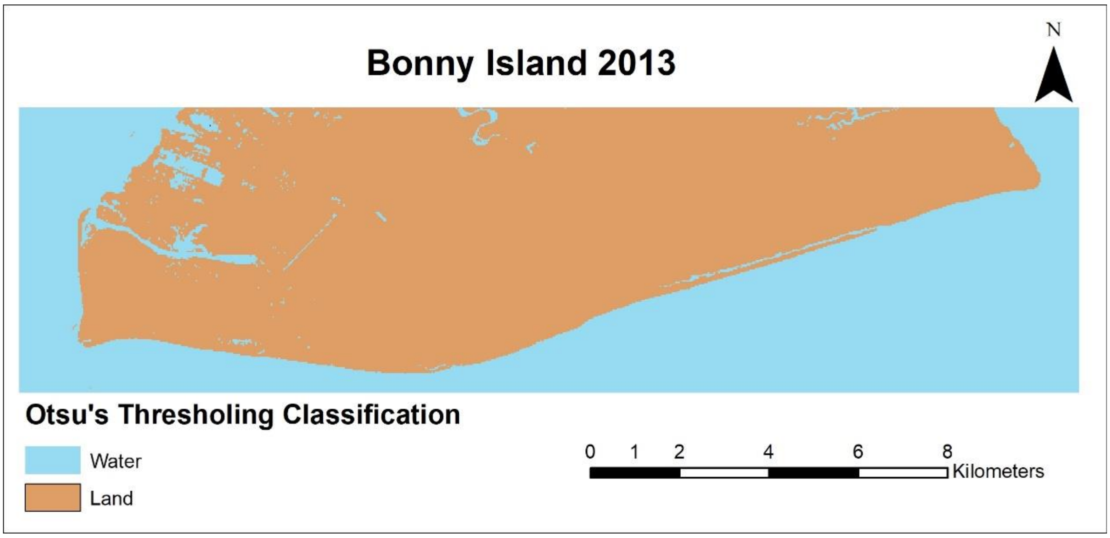

Figure 19: Otsu's Classification method result in 2013 timestamp

3.2.6 Random Forests classification in RStudio

The Random Forest classification algorithm script ran in RStudio, required as an input for the methodology decided, the Image Stack being created and the Training Data.

The training data were created with polygon shapefiles for each time stamp since our imagery is heterogeneous.

"In addition to being as large as possible, the training data sets used in RF classification should also be (a) randomly distributed or created in a manner that allows for the class proportions of the training data to be representative of actual class proportions in the landscape and (b) should have minimal spatial autocorrelation to improve classification results and to mitigate inflated estimates of RF out-of-bag classification accuracy."(Millard and Richardson 2015)

Following as a guide the above mentioned, the Polygon shapefile of the training data had the minimum of 244 polygon samples and the maximum 300, where each polygon feature would fit at least of 10 to 20 pixels of samples. That said, can be calculated that there would be a median input of training data of 4080 pixels. In Each polygon, the class of water or land would be attributed.

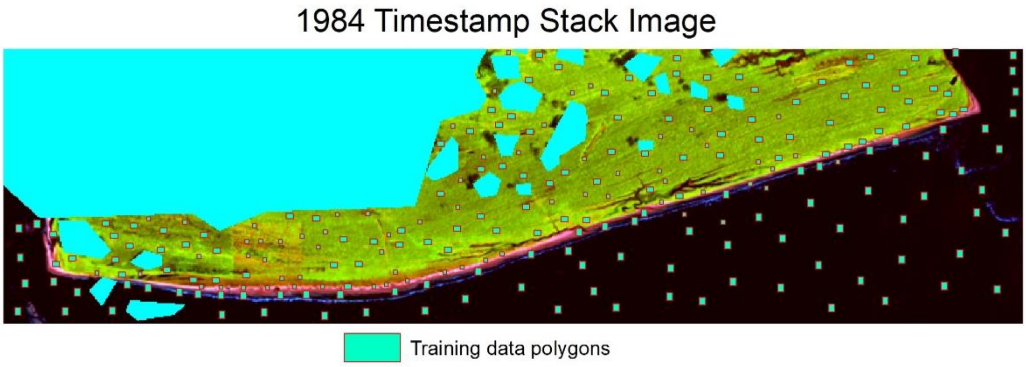

Figure 20: Training data coverage overlaid in 1984 cloud masked stack image

The script being used in to run Random Forests is attached in the Appendix. The number of trees was set to 200. The sample was set to be resampled with 1500 pixels per class. A sample of the results can be seen in Figure 21.

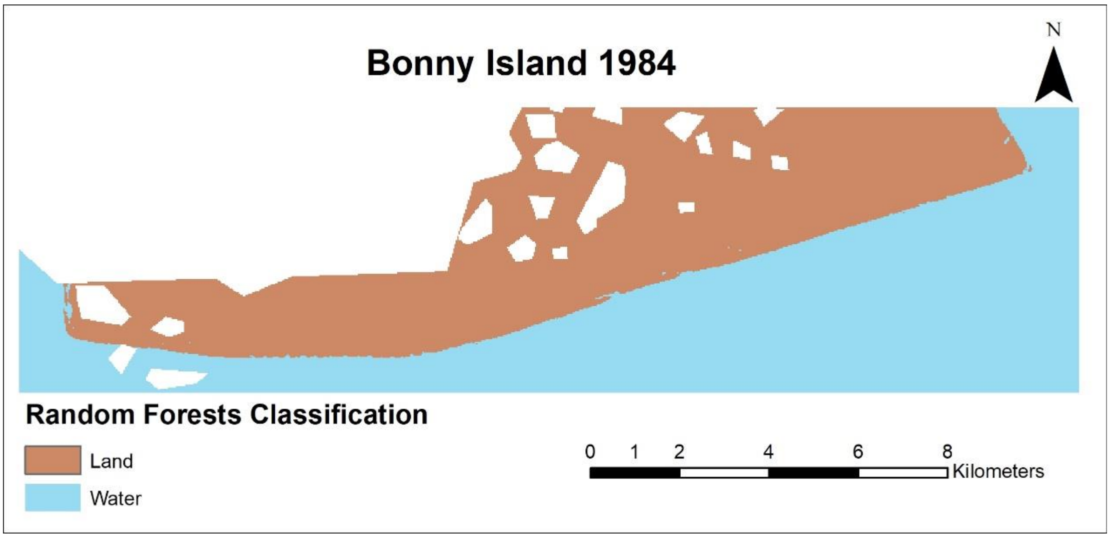

Figure 21: Random Forest classification result, with cloud mask appearing as No Data

Workflow Stage 2

Having the classified rasters for each timestamp, the workflow is presented in Figure 22 had to be implemented for each timestamp and for both classification methods separately.

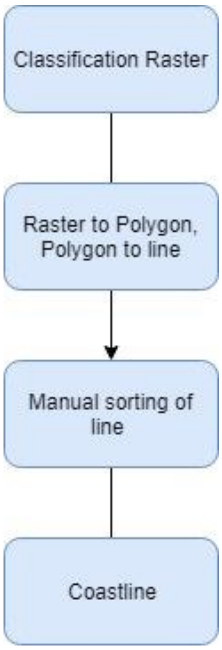

Figure 22: Stage 2 workflow diagram

3.3 Raster to Polygon and Polygon to Line

ArcMap tool Raster to Polygon would be used initially where from the results the redundant polygons would be deleted, these would be the ones no relating to the coastline. Then the tool Polygon to Line would be used where it would result to many lines that had to be sorted in order to keep the ones only representing the coastline. The sorting will be made with visual interpretation where parts in feature continuity would be merged and the rest would be deleted.

This work would result in two coastline shapefiles (for Otsu and RF methods) for each date of our timestamp. The shapefiles of each timestamp then would be merged into one with the Merge (Data Management) tool of ArcMap producing the two shapefiles for each method. Otsu's classification method produced the shorelines seen below in Figure 23.

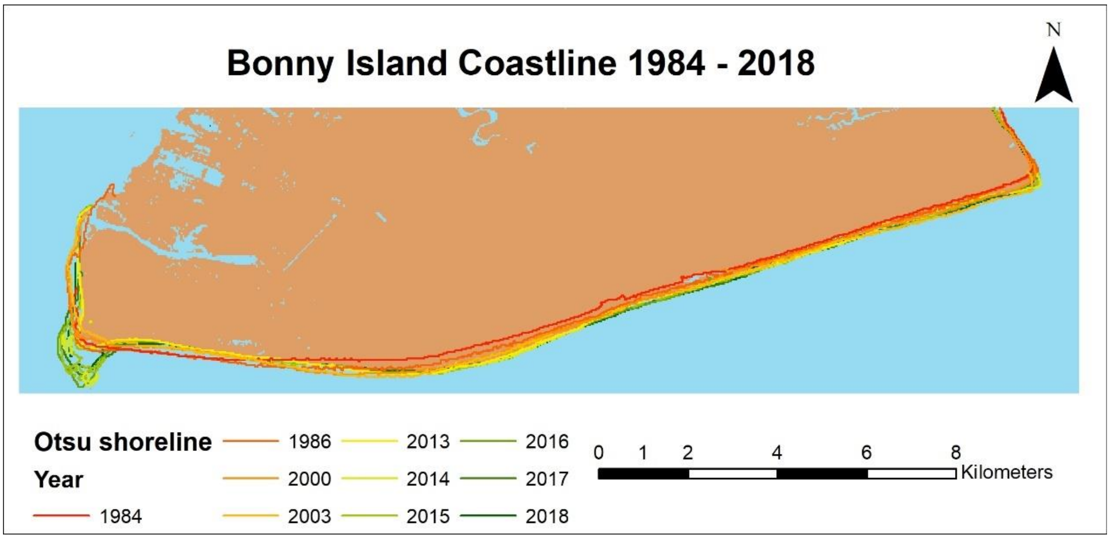

Figure 23: Coastlines from 1984 to 2018 extracted with Otsu's classification method

Workflow Stage 3

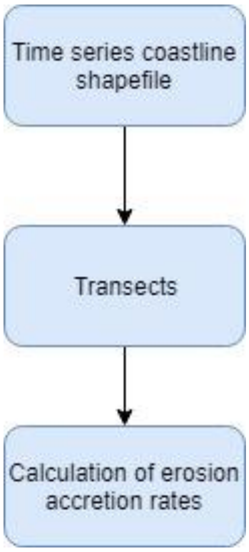

Figure 24: Workflow Stage 3 diagram

3.4 Transects and Calculation of EPR Rates

Having the time series coastlines, the next steps to produce results for the analysis took place with the use of DSAS tool. DSAS tool works with a specific format in the data to be input. The coastline is the data to be input and therefore was altered according to the criteria in the manual of DSAS (Thieler, E.R., Himmelstoss, E.A., Zichichi, J.L., and Ergul 2017).

The data to be processed in DSAS had to be imported in an ArcMap Personal Geodatabase. Then, a Baseline had to be drawn from where the transects would be deployed, this was done manually, creating a line feature in the Personal Geodatabase. The coastlines and the baseline are the only to inputs.

The DSAS tool to be used must first to have the Default Parameters to be set where the coastline to be analyzed is chosen and the baseline. The spacing of the transects in meters are selected, where they were selected for 50 meters and the transect length to 1800 meters.

When the parameters where set properly the transects would be created with the as seen in Figure 25.

Figure 25: Shorelines, Baseline and the Transects deployed

With the creation of the transect, the statistics can be calculated from the cross-section of the transects with the coastlines.

For the purposes of this project, the End Point Rates were selected to be calculated that give the yearly shoreline movement in meters. The output of the calculation are tables that will be joined with the transects by object ID, this last step is to clip the transect in the extent of shoreline movement but also to have the statistics in the attribute table of the transects so the analysis can be visualized in the Layer Properties->Symbology in ArcMap.

3.5 Validation Method

For validation, the method chosen will be discussed in the results chapter, here the implementation of the validation will be briefly described.

The coastlines of 1986 and 2003 where overlaid and the tool Feature to Polygon (Data Management) would, then the geometries of the polygon would be calculated, that would give out the area of accretion and erosion. In Figure 26 the polygon produce can be seen with coastlines of 1986 and 2003.

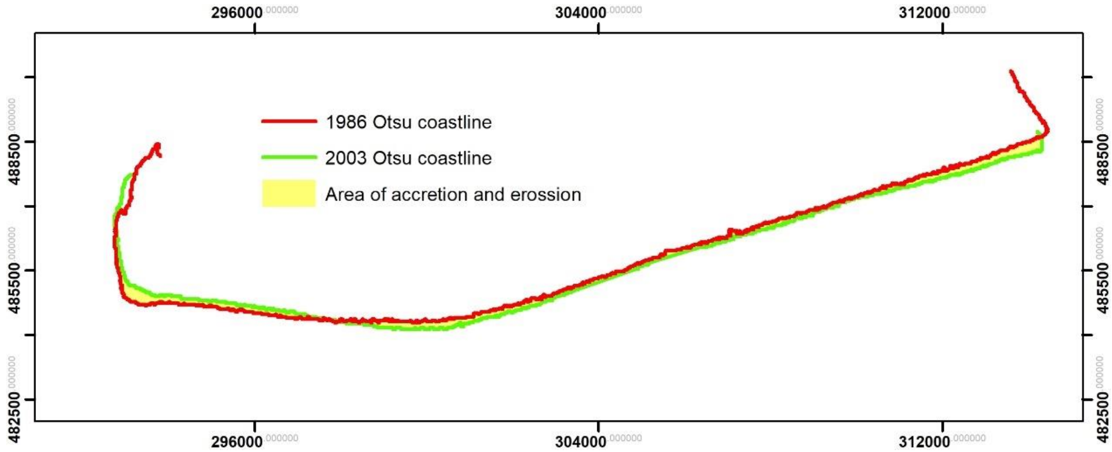

Figure 26: Validation method resulted in polygons for Otsu approach

The same method was applied for the comparison of the coastlines produced by RM and Otu classification. Each date would be overlaid with its pair coastlines to create the polygons in between the two coastlines. The area of the produced polygons would be computed and summed up in one area per date. This area is a measurement that indicates the difference between each method.

4 Results

In assessing the results, the author took in consideration that the classes to be determined and mapped are only two and very distinct even from the imagery in respect of the visual interpretation and as it was shown for the algorithms to classify as well.

However the focus of this report is not as much for the distinguishing between the two classes in general but it interests more of the challenge that the two classes have a shared boundary where, while as explained in theory we can define it by general admission and in respect to the proposed diagrams, still there are the transition areas from one class to the other where is hard to set the border of the coastline and define class. With the methods implemented, having a 30-meter resolution, it could be assumed that some pixels can be very ambiguous in the aspect of class in probability with the pixels surrounded. However, a research suggests that "the overall classification error decreases with increasing spatial resolution if the class variance remains constant…" since "…an increase in spatial resolution usually gives an unfavorable effect on the classification performance of ' pure' pixels due to increased class variance"(Hsieh and Lee 2000). These references question the analogy assumptions of low-resolution data means low classification accuracy.

An accuracy assessment could be deployed for the classification results, but in this case would prove redundant as there are not any misclassified pixels on both methods but rather a zone of ambiguity, that of the proximity of the coastline.

Instead of having an accuracy assessment of the classification data, the product of it can be assessed, that of the coastlines. The coastlines produced can be compared between the two methods of classification as well with other validated or with other relevant data.

4.1 Otsu Classification method results

The Otsu method produced satisfying results that as explained in the introduction of this chapter have the difficulty in assessing them. Despite this difficulty, a visual interpretation approach is going to be performed.

Coastlines produced are overlayed in the NDWI composites and the coastlines position is assessed in Figures 27 and 28.

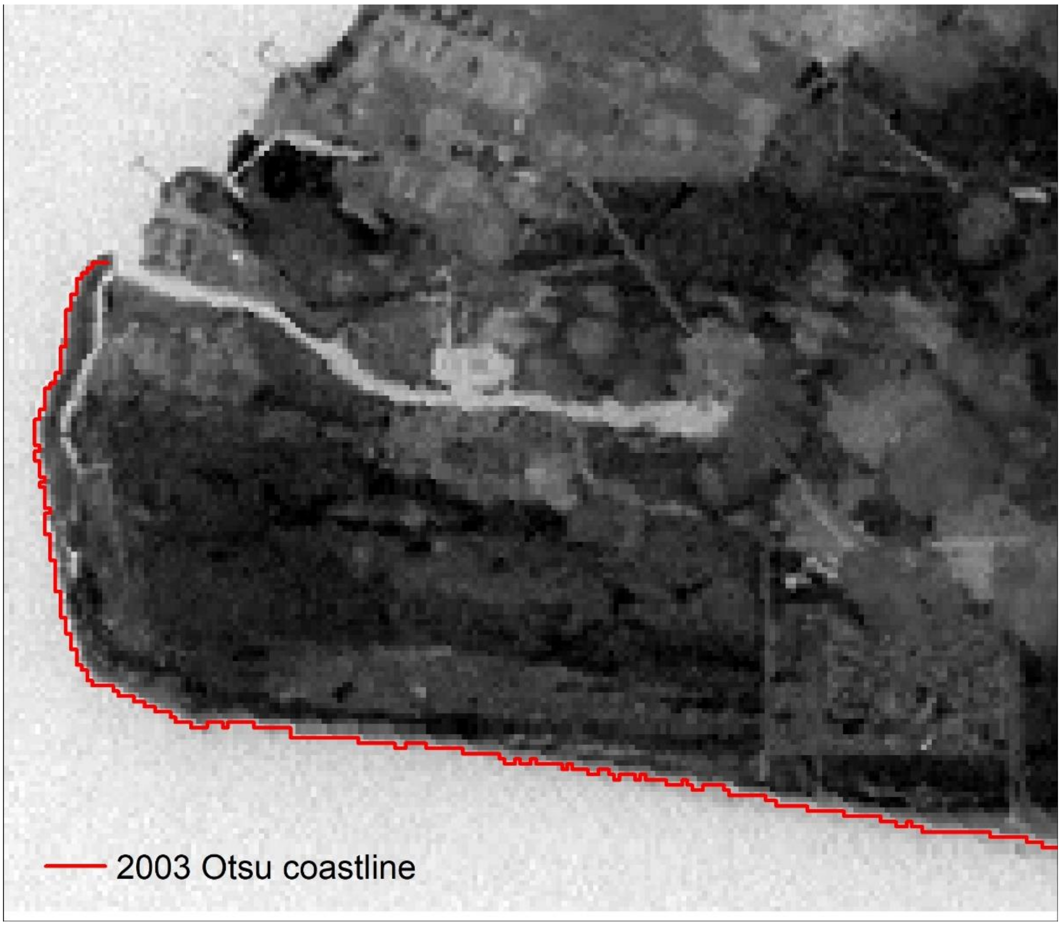

Figure 27: Detail of 2003 NDWI composite with Otsu coastline

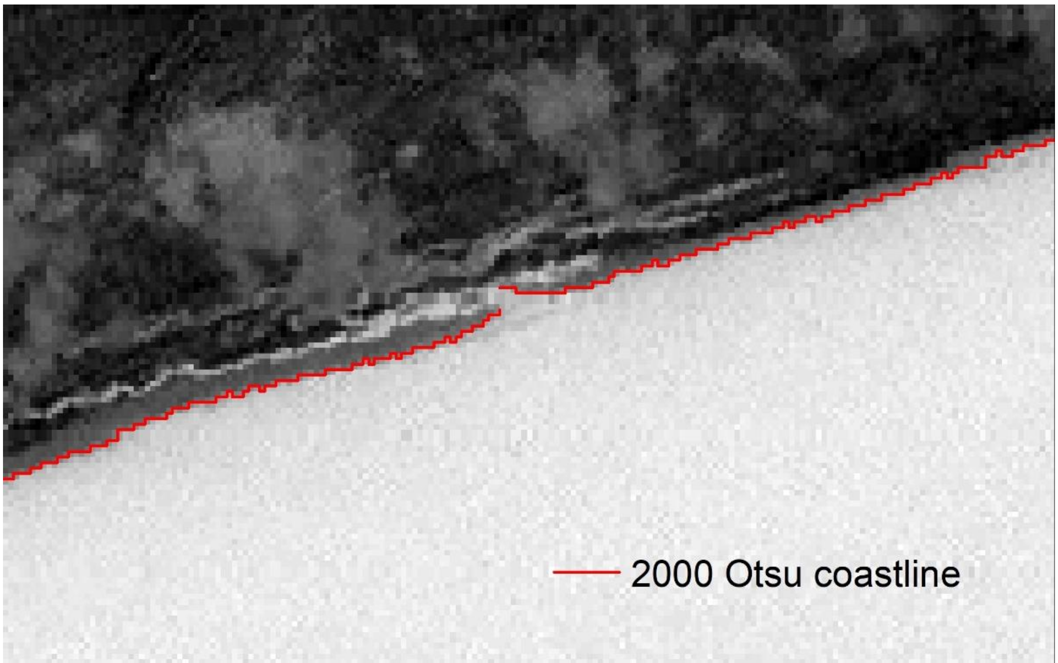

Figure 28: Detail of 2000 NDWI composite with Otsu coastline

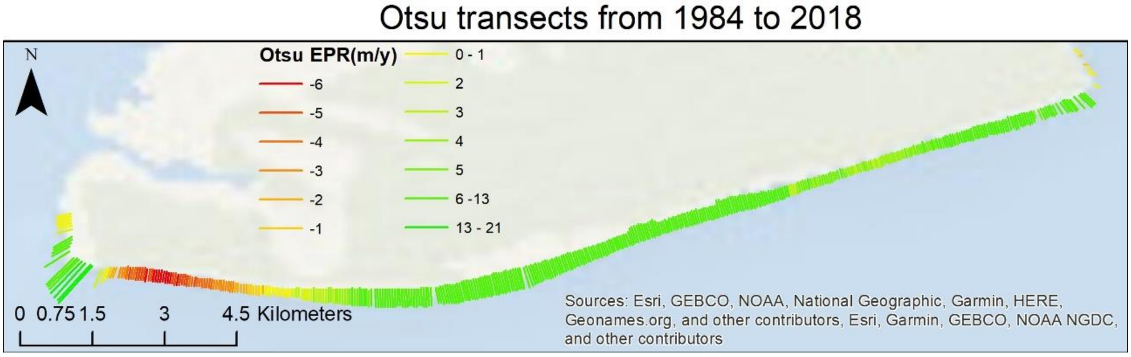

Figure 29: Otsu transects from 1984 to 2018 overview

In Figure 29 trends of accretion and erosion can be identified by location of the Island while it also resembles the trends of the data in the validation chapter and in specific about the localities of the trends. More information can be extracted in the diagram in Figure 30, it is given that the most prevalent rate is of accretion between 4 and 10 meters respectively.

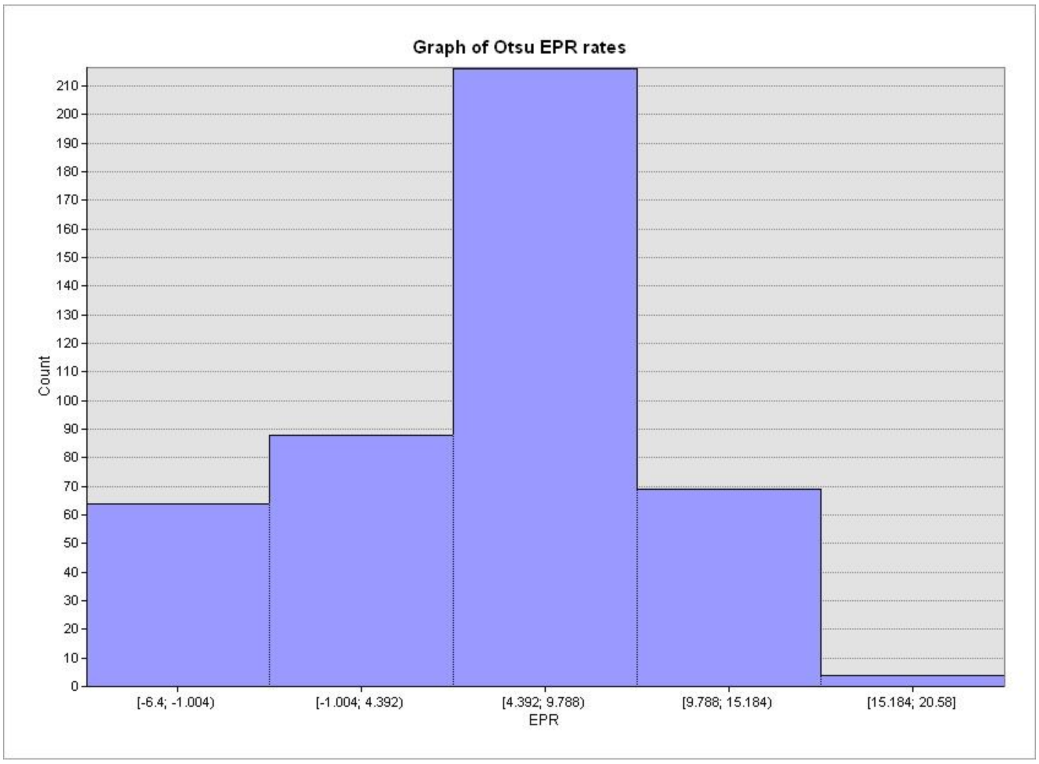

Figure 30: Histogram of EPR rates in meters per year

4.2 RF classification method results

The following figures are given samples of the success of the RF classification to extract the shoreline, by visual interpretation where the coastlines are drawn along the right features.

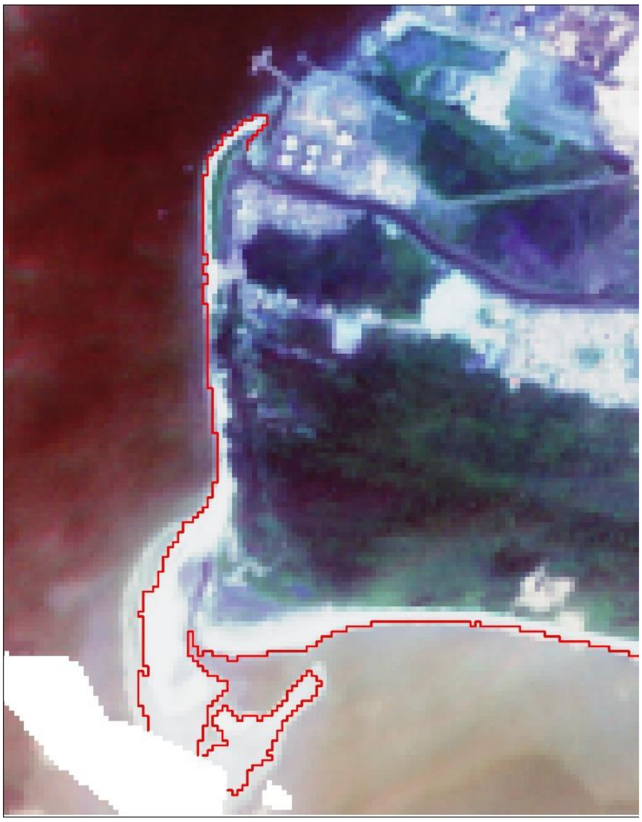

Figure 31: Detail of line extracted with RM from 2015 stack image

Figure 32: Detail of line extracted with RM from 2014 stack image

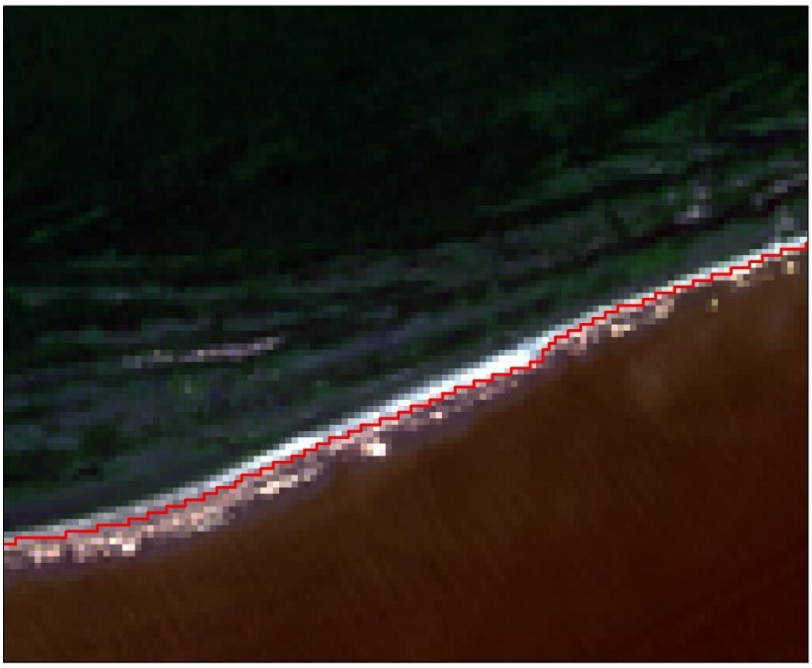

Figure 33: Detail of the line extracted with RM from 2013 stack image, pixel level

In figure 33, in pixel level scale, it can be observed that the line separating land from has classified the breaking of the waves zone, that creates the foam and thus the color impression of the land part of the beach, as water. So, it is visible in the examples given in the figures the consistency of the results of RM.

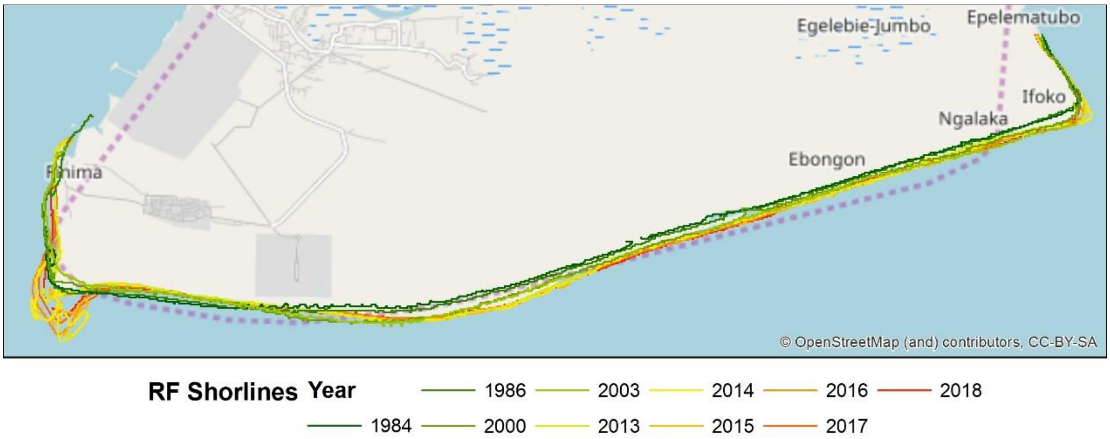

Figure 34: RF time series coastlines overview

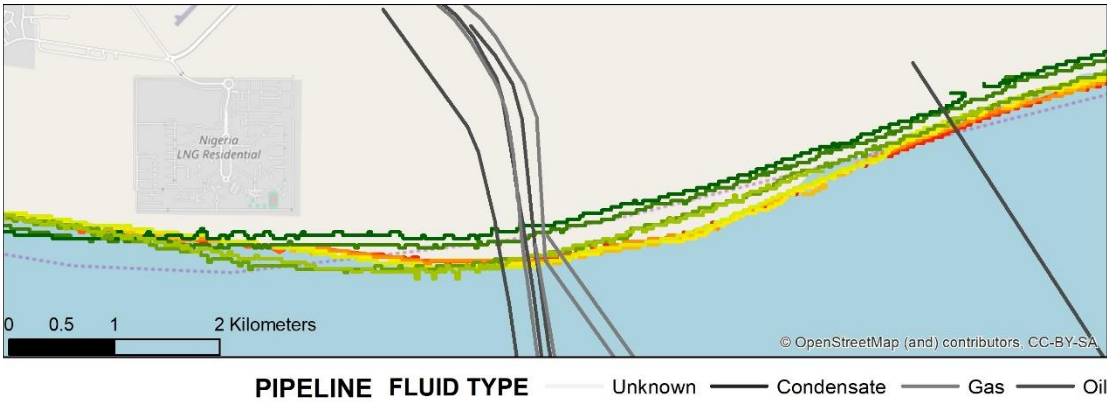

Figure 35: RF time series coastlines, case study extent view with pipes overlaid

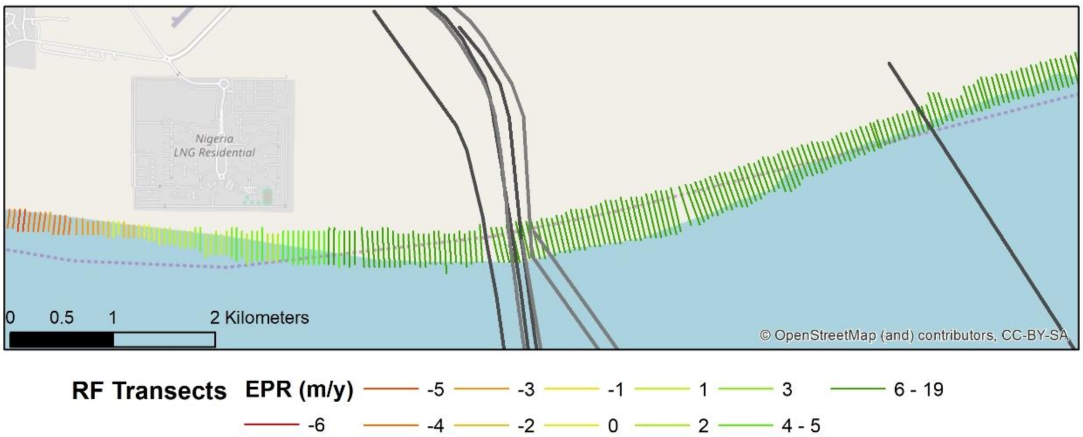

Figure 36: RF transects from 1984 to 2018 with EPR rates, in case study area

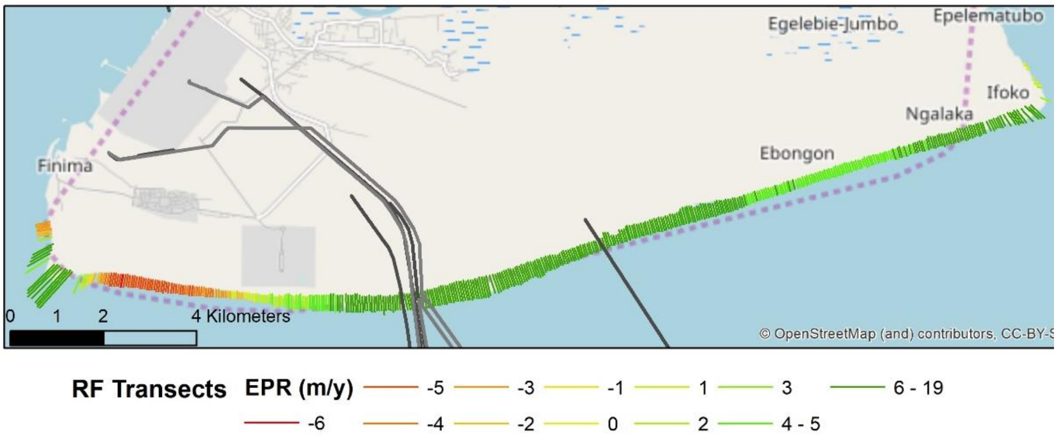

Figure 37: RF transects from 1984 to 2018, overview

In the results of the Figures 34 and 37 can be observed that there in the most west quarter of the coastline there is an erosion trend ranging from -1 meter per year to the dominant rate erosion that is of below -5(red zone of the map). In regard to the accretion, the dominant rate is from 4 meters to 9 meters per year according to the diagram in Figure 38.

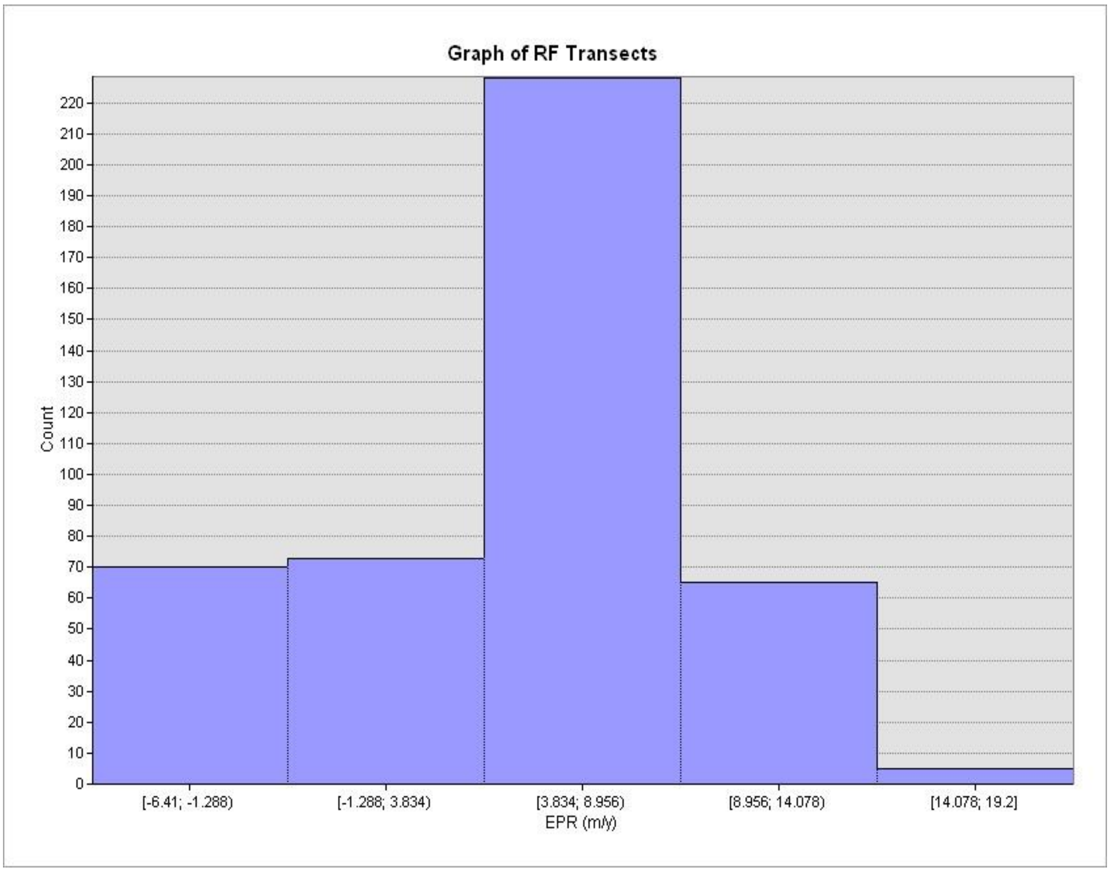

Figure 38: Histogram of RF EPR rates

4.3 RF and Otsu Methods Comparison

In the introduction of the results chapter, it is mentioned about the difficulty in assessing the accuracy of the extracted coastline, this continues to be a challenge when comparing the two methods of extraction applied in this paper.

Another very important consideration when comparing the two methods is that the method uses different input layers, Otsu with NDWI and RF with the stack of 7 Bands. The Otsu method can be and is very consistent in elaborating the NDWI, in the sense that when overlaying the NDWI, the human interpreter who would decide where is the coastline, would have placed it on the same location. The stack of images being multisource, the bands combine surely can indicate something different.

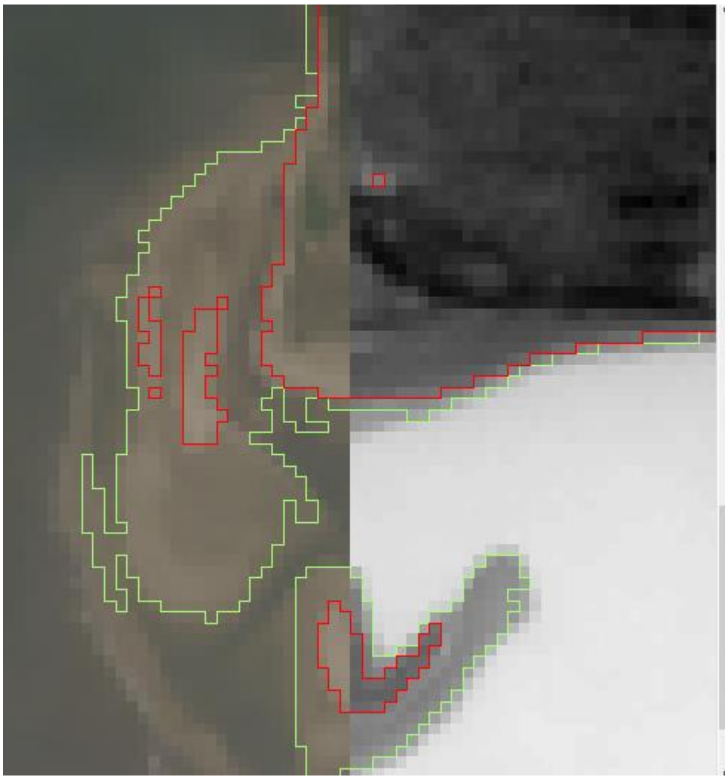

Figure 39: RT in green line and Otsu red line, swiped background with stack image on the left and NDWI on the right, for 2014 timestamp

An extreme difference in the classifications due to the aforementioned factors can be seen in figure 39, while the most common spatial relationship between RF coastlines and Otsu ones is shown in Figure 40.

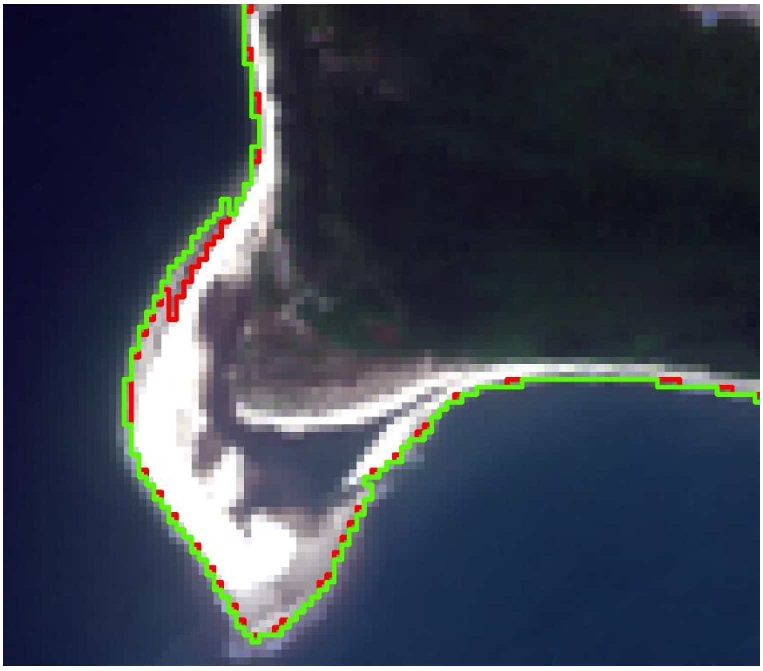

Figure 40: RF coastline in green and Otsu coastline in red color, overlaid in 2016 stack image

When overlaying the coastlines for each date, the two different methods relate spatially by overlapping and if not the case, the lines seem slightly shifted away between them. For that reason overlaying both of them in an overview of the study area scale would not signify anything rather than they would appear in as one of the same.

On a pixel level, the distance between the lines them would vary from one to 3 pixels, resulting to a long difference in meters. Given that the classifications performed in pixels, the assessment of the different positioning of the line makes sense to be measured in area.

The results from both methods can be characterized as valid from visual assessment even though they are slightly different creating the contradiction that there is not only one valid location of the coastline but two, one for each method.

The products of the classification methods used can be compared with the approach of the validation method mentioned in that chapter.

Comparing the area created in between the coastline of Otsu and RM gives the following results per year.

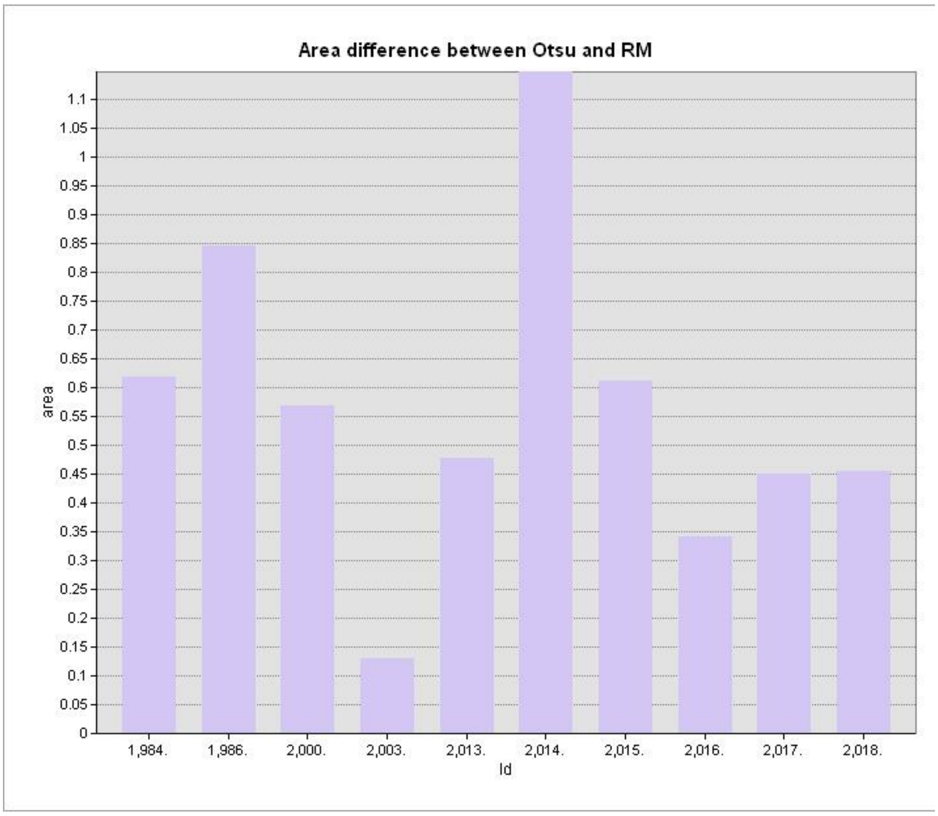

Figure 41: Graph of the area between the coastlines of RM and Otsu, for each year in km^2

The maximum difference observed is 1.1466 km^2, the minimum is 0.3411 km^2, with an average of 0.563571 km^2 and a standard deviation of 0.263521 km^2.

The transects from Random Forest give an average rate of 5.011m accretion per year and Otsu's transects have an average rate of 5.025m accretion per year that makes the results of the transects almost identical.

5 Validation

A study reporting its results for the area from Bonny river to Andoni river happens to be the south coast of our area of interest and the information given is the erosion and accretion area, -0.995 km^2 and 2.21 km^2 (Adegoke et al. 2010). These data were produced with the study conducted with 2 Landsat images, from 1984 and 2003, and these two rates will be compared by producing the polygon between the shorelines of 1984 and 2003.

Otsu's classification produced a polygon of -0.845869 km^{2}erosion and 2.19715 km^2 of accretion from 1984 to 2003.

RF classification produced a polygon of -0.700986 km^2 erosion and 2.80581 km^2 accretion.

The measurements of the Otsu' classification method is closer to the ones extracted from Adegoke 2010.

The erosion is observed in the western quarter while the rest three-quarters of coast in the east have been accreted.

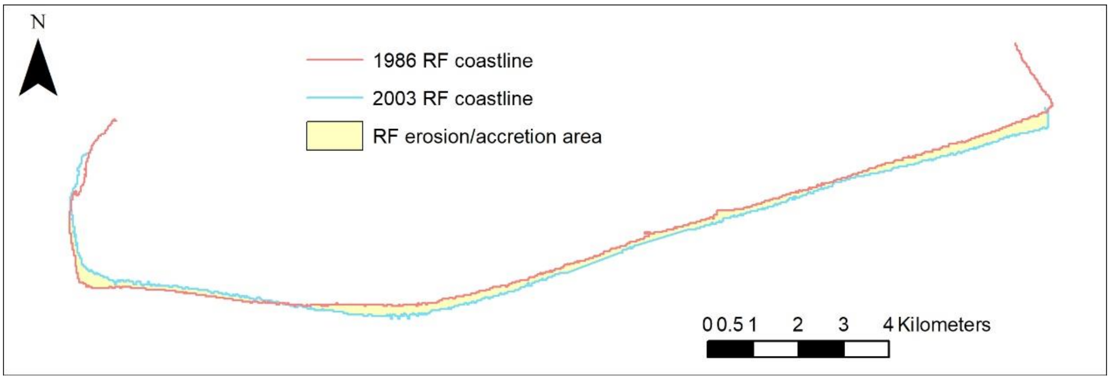

Figure 42: RM coastlines for area validation from 1986 – 2003

The study of Joshua and Adekunle (2015) concludes that the shoreline has been found to be eroding away at an annual rate of 10m-30m along the Finita-Singi beach area from 1975 to 2011, this area corresponds to the western quarter of the coastlines this report extracted and where erosion was also measured for that period of time. The time series utilized in the thesis had a gap of ten years when meantime in the area of Finita-Singi had a change of a dynamic is happening where accretion takes place. So according to Joshua and Adekunle (2015), this change takes place after 2011 wherein the tip of that quarter in this thesis results of accretion are presented as it can be seen in Figures 29, 34 and 37. To validate analytically with the Joshua and Adenkunle report is possible, with a lot of editing on the selection of the time stamps and with restricting the area of study to that of the same area extent of the validation data.

The literature research on Bonny Island did not lead to any other free existing georeferenced data and of adequate scale to be validated and the same would apply for DEM data to be found.

Other data to be compared are the following in Figure 43.

Years	Land gain (sq km)	Land Loss (sq km)	Shoreline difference	Percentage Loss	Percentage gain
1986 – 2001	402.4	1819.4	-1417	82	
2001 – 2006	2078.89	4588.38	-2509.49	69	
2006 - 2011	2551.12	1781.96	769.16		41

Source Authors' Analysis, 2012

Figure 43: Bonny Island shoreline change rates (Ogoro 2014)

As well another study for the results to be compared that its measurements are presented in Figure 44 and 45.

Table 1: Coastline change summary for the four epochs

Change	1986 to 2000 (sq m)	2000 to 2003 (sq m)	2003 to 2007(sq m)	2007 to 2015 (sq m)	1986 to 2000 (%)	2000 to 2003 (%)	2003 to 2007 (%)	2007 to 2015 (%)
Erosion	5327205.43	3282130.54	1578686.62	2061886.06	75	60	37	23
Deposition	1767240.88	2151917.89	2666089.44	7079598.76	25	40	63	77
Total	**7094446.3**	**5434048.4**	**4244776.1**	**9141484.8**	**100**	**100**	**100**	**100**

Table 2: Coastline change for Bonny Island (1986-2015) as derived from transect

	Rate of change(m/yr)		Area change (m^2)			
Years (Epochs)	**Deposition**	**Erosion**	**Deposition**	**%**	**Erosion**	**%**
1986 to 2000	4.24	6.19	1,767,240.88	33	5,327,205.43	67
2000 to 2003	26.01	29.34	2,151,917.89	40	3,282,130.54	60
2003 to 2007	20.41	29.34	2,666,089.44	37	1,578,686.62	63
2007 to 2015	165.10	79.25	7,079,598.76	77	2,061,886.06	23
1986 to 2015	**53.9377**	**33.3658**	**6,992,962**	**76**	**2,256,709**	**24**

Figure 44: Bonny Island shoreline change measurements (Okujagu and Beka 2016)

Period	Advanced (Gain) (sq km)	Retreat (Loss) (Sq Km)	Total (Sq Km)	Shoreline Difference (Sq Km)	Percentage Loss or Gain (%)
1986-2001	419.31	1793.24	2212.55	-1793.24	-81.04
2001-2003	1200.43	1246.46	2446.89	-46.03	-1.88
2003-2004	858.46	3408.68	4267.14	-2548.22	-59.72
2004-2006	2460.30	2450.03	4910.33	10.27	0.21

Figure 45: Bonny island shoreline change (Eludoyin, Oduore, and Obafemi 2012)

The tables cited above, outline the whole coastline of the island while this report was focusing on just the southern coast, so the validation approach is becoming a far reach, although a preliminary overview can be done.

5.1 Validation with High-Resolution Case study

As mentioned in the introduction and in other parts of the thesis, a high-resolution study was conducted with the author of this paper participating in the implementation. The data produced from that study are not optimal for validation as they cover a small part of the area of study, nevertheless, a comparison can be made. The high-resolution study has only two matching timestamps with the ones produced by this research, the ones of 2014 and 2017.

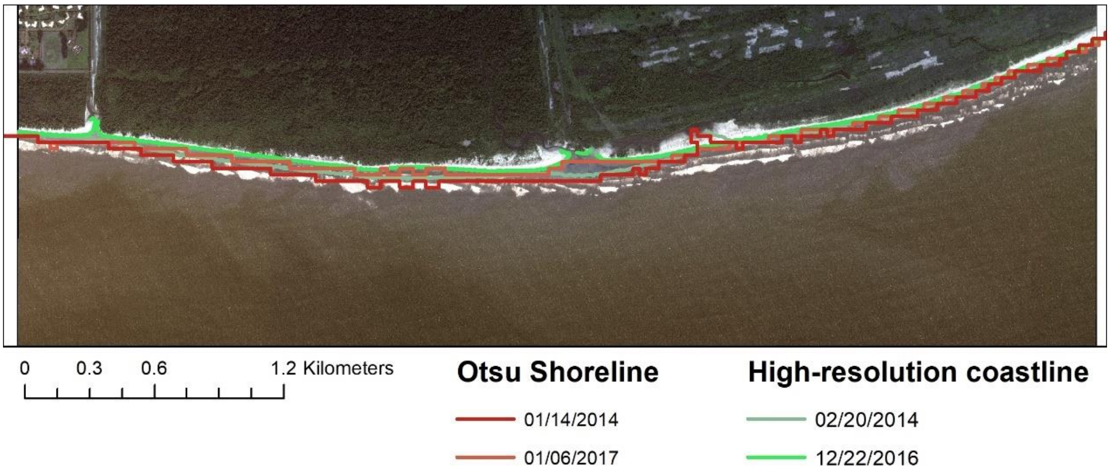

Figure 46: Coastlines digitized with high-resolution imagery along with Otsu extracted shorelines from coarse-resolution imagery

The Otsu shorelines of the same dates with the high-resolution extracted coastlines are embedded almost parallel and following the same pattern. It can be remarked again that the accuracy might not be precise, but it can be utilized for coarse observation. A closer look with another scale level so we can instruct some correlation indicate very good results if the interest is not that of the exact position, but of proportional one. To clarify the proportional aspect, it suggests that both methods can potentially give the same rates of erosion(see Figure 46.).

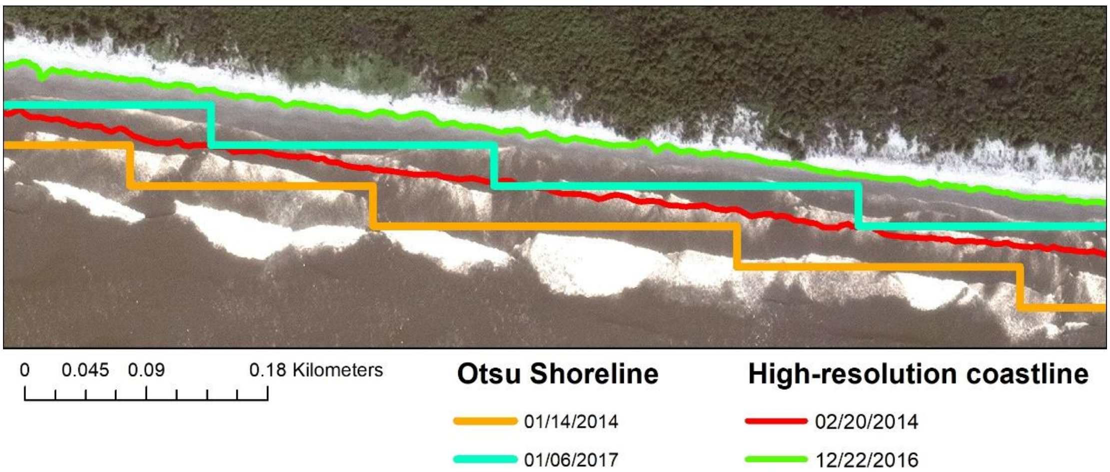

Figure 47: Detail of high and coarse resolution extracted shorelines

In Figure 47 it can be said that very useful spatial correlations between the coastlines can be made to give some validity to the coarse resolution study. Validity can be attributed when it aims for generating transects and erosion/accretion rates. Describing Figure 47, it can be seen that the distances between the different dates are the same in both methods and the general consistency between them.

6 Conclusion and Discussion

The presentation that follows is going through the key results of the study that answer as well to the problem statement and research questions.

From the results chapter, we can briefly conclude that the south coast of Bonny island, when studied for the time 1984 to 2018, is under the regime of accretion with the land expanding with 6 to 11 meters per year. It seems that 75.5% of the coastline area grows since 1984, including the area of the case study where the pipes are installed. The average accretion rate from the Random Forest transects is 6.74m and Otsu Transects 6.91 meters per year and that again is an almost same rate.

An exception to that trends is on the western part of the island where erosion is observed with the land withdrawing with rates of about -6 to -3.5 meters per year. For that eroding part, RF transect tables give an average of -4 m per year and Otsu transect tables give an average of -3.68 m per year, perspectively, values almost identical.

Confirming the alignment of Otsu's and Random Forest results from the transect, the average of the rates from Otsu is 5.011 m per year and from Random Forest is 5.025 m per year

Results partly validated were conducted for the time of 1984-2003 only with two timestamps. In this test, the Otsu's classifier proved more accurate with the cross-validation data where the classification would result in -0.845869 km^2 of erosion and 2.19715 km^2 of accretion and the validated values were 0.995 km^2 of erosion and 2.21 km^2 accretion in 19 years.

When summing up what the above measurements indicate, a consistency in between the methods of Otsu and Random Forest becomes obvious. The statistics produced by the transects show an almost identical agreement to the results between the performed methods, However, one of the validation methods that used the change in the area showed that Otsu's method is more accurate.

Regarding the results of this study, beyond the quantitive ones assessed, we can conclude on the following:

The method unfolded here can be very useful according to the desired scale of the study(Wu and Li 2009).

The area that this study was conducted, was proper to test this method since drastic changes were recorded although there was some lack from the aspect of validation data.

Regarding the comparison between Random Forest and Otsu classification for the purposes of coastline extraction, the results led to the conclusion that they have both respectively a similar accuracy. A meaningful comparison would be that of the ease of deploying the methods. Otsu method needs only one input and no tuning is required. This can be an asset in the aspect of the time required to classify and the preparation which is minimized. The disadvantage though could be that no correction to the delivered result can be done. Random Forest from the other hand can be tuned and better trained to optimize accuracy. However, the preprocessing of classifying with Random Forest can be time-consuming and very depended on the operator due to the need of the training data.

All the software that was used was free except ArcGIS where the student license was used, However, QGIS could have been used instead. This fact makes this method consistent with one of its goals concerning the accessibility to be reproduced in other areas and so on.

Overall, the methods used, assessed by the initial scope of this study, that of a simple, fast track and straightforward process to extract shorelines and monitor coastal movement has been successful.

The author is not an expert on coastal engineering and management, setting the limitations to suggestions about the actions to be undertaken addressing to the change of the coastline analyzed here. However, having in mind that in the island there are oil and gas industry investments and infrastructure, it stresses out the need to take measures for prevention of oil and gas spill and leakage. What can be suggested in specific is that the local communities and corporation operating in the island to coordinate together to be consistent with the response of what the Environmental Sensitivity Index(ESI) can indicate. The results and data produced here can also be incorporated for the ESI mapping.

7 Future prospects

The method attempted in this thesis could be definitely improved by many aspects, some of them are proposed below:

The area of study could be much larger as that is as well the initial developing idea.

The time series could be analyzed for circular coastline change patterns. These changes would concern times that accretion would change to erosion and the opposite. When this is observed the time series could be separated in subseries.

Tides and their consequences in the HWL position observed could be brought into the study.

The method could have been conducted in some other area where the data availability would be different adding up to the accuracy assessment and validation

A more analytical time-series could be implemented, with more timestamps. This could be succeeded with the elaboration of the Landsat 7 imagery for 2003 to 2013. There are methods for the SLC failures to be corrected(Scaramuzza, Micijevic, and

Chander 2004) but the ones tested resulted in poor outcomes, but not sufficient testing on the methods has been done. The offset, in some pixels uppon the potential zone of the coastline, can be tolerable depending on the scale of the study.

An upgrade of the study making it broader would be to introduce other classes in the analysis, for instance, vegetation, rocks, or sand. Classes that share a boundary with the water class. The incorporation of the previous along with the use of DEMs, for the slope, can give the face-type of the shoreline and conduct a geomorphic shoreline classification(Davies 2011).

Cloud Masking could be automated with algorithms(Foga et al. 2017) instead of the manual editing and that would add up to main objectives of the method tried to be developed here, that is to maximize automated processes.

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