SEAWALL DETECTION IN FLORIDA COASTAL AREA FROM HIGH RESOLUTION IMAGERY USING MACHINE LEARNING AND OBIA

by

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This thesis was prepared under the direction of the candidate's thesis advisor, Dr. Hongbo Su, Department of Civil, Environment and Geomatics Engineering, and has been approved by all members of the supervisory committee. It was submitted to the faculty of the College of Engineering & Computer Science and was accepted in partial fulfillment of the requirements for the degree of Master of Science.

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ABSTRACT

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In this thesis, a methodology and framework were created to detect the seawalls accurately and efficiently in low coastal areas and was evaluated in the study area of Hallandale Beach City, Broward County, Florida. Aerial images collected from the Florida Department of Transportation (FDOT) were processed using eCognition Developer software for Multi-Resolution Segmentation and Classification of objects. Two classification approaches, pixel-based image analysis, and the object-based image analysis (OBIA) method were applied for image classification. However, Pixel based classification was discarded for having less accuracy in output. Three techniques within object-based classification-machine learning technique, knowledge-based technique and machine learning followed by knowledge-based technique were used to compare the most efficient method of classification. While performing the machine learning technique, three algorithms: Random Forest, support vector machine and decision tree were applied to test the best algorithm. Of all the approaches used, the combination of

machine learning and a knowledge-based method was able to map the sea wall effectively.

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NOMENCLATURE

OBIA - Object Based Image Analysis

FDOT – Florida Department of Transportation

DEM - Digital Elevation Model

NIR - Near Infrared

DT - Decision Trees

SVM - Support Vector Machine

RF - Random Forest

NLCD - National Land Cover Dataset

UAS - Unmanned Aerial System

RGB - Red, Blue, and Green

GPS - Global Positioning System

ML- Machine learning

KB – Knowledge Based

MLKB – Machine learning combined with Knowledge based.

FSO – Feature Space Optimization

CHAPTER 1: INTRODUCTION

1.1 BACKGROUND AND MOTIVATION

Eight out of the top ten largest cities in the world are located by the coast. In 2018, around one billion of the world's 7.6 billion inhabitants lived in coastal areas (Siegel, 2020). Protection of coast adjacent to a settlement area will contribute in safe habitable environment, enhance visual aspects of life and overall quality of life (Cetin, 2016).

The effects of natural processes and change are particularly vulnerable in coastal areas. Due to the dynamic interaction between the oceans and the land surface, coastal zones constantly keep shifting. In addition, waves and winds along the coast continually erode rock and deposit sediment. Wave action constantly pushes up against the shore of large bodies of water, resulting, in the erosion and flood—land is gradually lost to the ocean, lake, or river (Li et al., 2001). The land area shrinks over time, which can be detrimental to the shoreline environment. The most common measure used to secure the coastal region is the use of shoreline hard structures such as seawalls.

A seawall is a form of coastal barricade constructed where the sea, and associated coastal processes, impact directly upon the upland landforms. It is a construction structure—mostly made of concrete, metal— built parallel to the shoreline to protect areas of human habitation and recreation from the action of tides, waves, or tsunamis (Thomas & Hall, 2015). Seawalls protect the surrounding land and its residents by reducing the eroding effect of ocean waves and reducing the energy of the waves. Seawalls avert waves back to the sea, reducing the risk of disruption and erosion over time.

Seawalls also minimize the consequences of heavy waves in storms and hurricanes, and if they're big enough and strong enough, they can offer a fairly sturdy

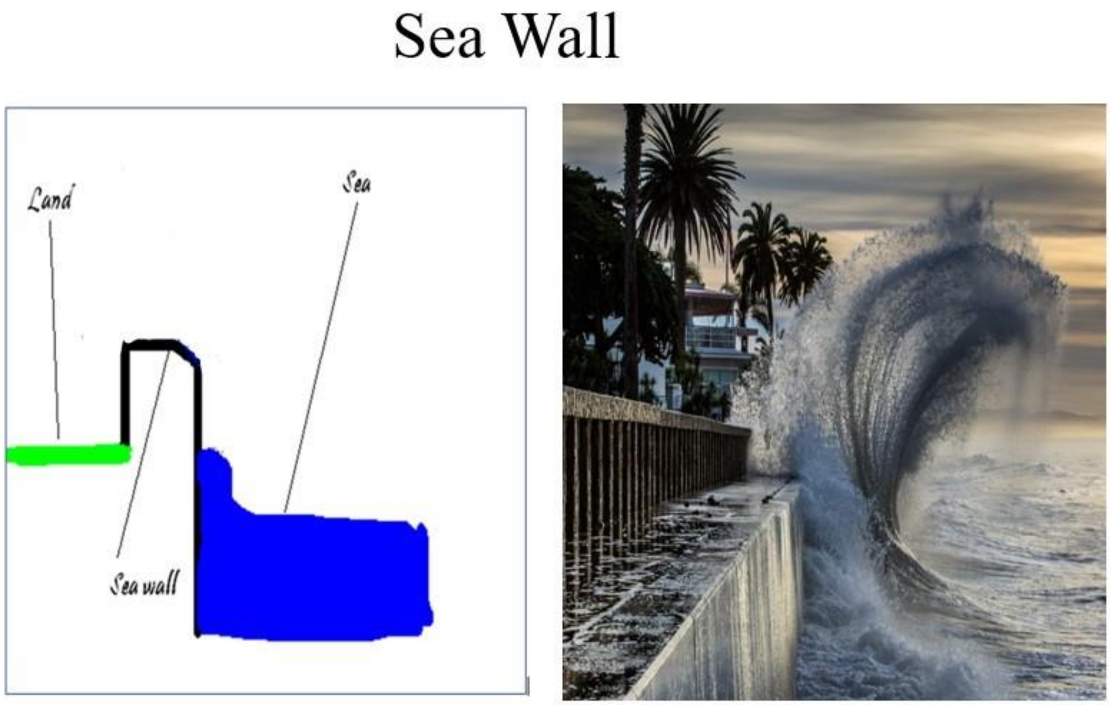

Figure 1: The image on left shows the diagram of Seawall, land and Sea. The image on right is the picture of Seawall in Broward County, Florida. Source: https://cloud-apk.store/away.php

defense against tsunamis. Seawall is a sustainable solution to the problems of settlement onshore—hundreds of year-old seawalls are still doing their job fine. Seawalls built for over a hundred years are still doing their job. For example, The Indian city of Pondicherry has a nearly 300-year-old seawall that stands 27 feet above sea level in some areas. This seawall successfully protected the city from a tsunami in 2004 that towered 24 feet above high tide (JAKKULA & SRIVASTAVA, 2020). Another marvelous example of seawalls is the Afsluitdijik, which was built more than 85 years ago to shield low-lying areas of the Netherlands from flooding. The project, which spanned 32 kilometers and held back the Wadden Sea, is one of the greatest engineering accomplishments and is credited with preventing devastating flooding in large parts of the country (Van Bergeijk et al., 2020). To achieve the full efficiency of seawalls, regular maintenance or replacement is critical. Seawalls will last for a long time if they are built and maintained properly. Property owners all over the globe are seeing the advantages of having seawall construction and repairs done in order to protect the environment and their own property. The foremost step to constant maintenance of seawalls is monitoring them and recoding their precise location or mapping the sea wall. Growing environmental awareness has caught the state government and stakeholders interested in tracing the existing seawalls and their precise locations which is possible by acquiring the. geospatial information of the seawall.

Spatial awareness is a valuable asset in the decision-making process for repairing and maintenance of such infrastructures. It is equally important for the analysis of the present situation of the sea level in low coastal regions such as southeast Florida. The Florida Department of Transportation performs the repair and maintenance of Seawalls in Florida. However, the Florida Department of Transportation urgently needs to develop a more efficient approach for identifying and detecting seawalls in Florida's coastal region instead of in situ surveying. The study aims are to compare various techniques in order to develop the best and feasible method for detecting seawall locations in Florida.

1.2 OBJECTIVE AND SCOPE

This research has a single objective to find the viable and efficient methodology for identifying, extracting, and storing Sea Walls locations in Florida's coastal regions using remote sensing techniques. To meet the objective different classification approaches and machine learning algorithm will be compared for Seawall extraction. The database thus created will be useful for the property owner and decision-makers such as FDOT. A web platform for the systematic Monitoring of seawalls can be published with the support of a database established from this study. Since seawalls are the first structures to be impacted by flooding and tsunamis, the database will provide geospatial knowledge of the seawalls under the context of emerging sea level rise. Through the 2D and 3D visualization of seawalls, it will be able to detect the dynamic changes of the low-coastal region.

1.3 STRUCTURE OF THESIS

The manuscript of the thesis is organized into six chapters. The first chapter — Introduction— gives background information, motivation, significance, and objectives. Chapter 2 discusses the relevant and past studies done in the field of this study. Chapter 3 presents the brief description of the study area. Similarly, Chapter 4 discusses a detailed methodological procedure undertaken for the study: the data and tools used, data processing techniques, image classification approaches, algorithms used in different approaches, and the author's innovation. The finding of the study is explained in chapter 5. It discusses the results of different classification approaches and algorithms used for image classification and compares them based on their accuracy. Finally, Chapter 6 encompasses the summary of findings. It also discussed the limitation and possible future works in the field of study.

CHAPTER 2: LITERATURE BACKGROUND

2.1 SEA WALL AND COASTAL AREA RESEARCHES

The first line of protection against sea waves is the seawall (Irish et al., 2013). There has been a lot of debate in the literature on the nature and use of sea wall in coastal areas (Griggs & Patsch, 2019; Tanimoto & Goda, 1992; Zhu & Chwang, 2001). However, there is still little works done in the task of seawall detection and creating the database of their locations. There is a need for regular and reliable coastal surveying and monitoring, as coastal areas are complex environments influenced by waves, wind, and human activities (King et al., 2017). According to a 2013 report by JL Irish and JD Woodruff, coastal society must learn to cope with a constantly shifting shoreline that is becoming more vulnerable to tropical cyclone flooding. The research also mentioned that we could minimize some of the consequences by implementing adaptive strategies. In 2009, W. Allsop, S. Cork, and H. Jan Verhagen proposed creating and populating a database for all large seawalls in Europe. They did, however, gather the details using conventional visual inspection methods. Manually accessing seawalls may be difficult, and the marine landscape can be vulnerable to the effects of surveying (King et al., 2017). It can be dangerous and time-consuming to walk with heavy equipment such as RTK-GPS and Total stations.

2.2 APPLICATION OF REMOTE SENSING

Remote sensing is a science that investigates and models the phenomena that exist on the Earth's surface and their relationship with the atmosphere (G Camps-Valls 2009). Literature suggests that as satellites and airborne vehicles became more prevalent, remote sensing techniques became common among scientists for environmental tracking and mapping (Hudson & Hudson, 1975).

Manual inspection and detection of Seawall is costly and takes plenty of time (Flocard et al., 2013). Remote sensing methods, for example, come in handy in this case because they allow for the acquisition of information without direct interaction with the target or phenomena. Green, A Edwards, and C Clark collaborated on a handbook on coastal management using spaceborne and airborne remote sensing in 2000, with the conjunction of the United Nations Educational, Scientific, and Cultural Organization (UNESCO). The first National Land Cover Dataset (NLCD) was developed in 2001 using 30-meter resolution Landsat satellite imagery over the United States. According to the literature, satellite imaging occupies a vast geographic area and can depict significant natural phenomena. However, as Q Yu et al. noted in 2006, the spatial and spectral resolution of satellite imagery is comparatively poor compared to airborne imagery.

Unmanned Aerial System (UAS) technology, such as drones, appears to be gaining attention. PC Gray and JT Ridge conducted a report in 2018 in which they used drone imagery to map coastal areas and marine monitoring. If sensors of various types are installed on UASs correctly, they can provide precise and reliable data. The growing practice of using drone-collected imagery is also a result of the relatively recent availability of lightweight, low-cost sensor-carrying drones. Previous studies by Berni et al. 2009 & Saari et al. 2011 demonstrated that drones could be equipped with a range of sensing instruments, such as visible light, near-infrared (NIR), shortwave infrared (SWIR), thermal infrared (TIR), Radar, and Lidar sensors. Drone-borne optical sensors, including visible, NIR, and SWIR, capture data as multispectral or hyperspectral bands (Berni et al., 2009; Saari et al., 2011; Tang & Shao, 2015). Considering the recent literature on the use of drone imagery for related purposes, this project also employs drone imagery for Seawall identification.

2.3 IMAGE CLASSIFICATION AND OBJECT DETECTION

The issue now is how to use the imagery's wealth of spectral and contextual detail. Herold et al. in 2003 successfully applied the image classification to high-resolution imagery for mapping the urban land cover. AK Shackelford in 2004 used 1-meter resolution panchromatic imagery to identify building footprints. Similarly, O Wang et al. in 2006 used aerial lidar data for building footprint extraction. His study used the lidar derivative Digital Elevation Model (DEM) to extract the building from other objects. Shafer et al. in 2011 used drone imagery for detection and counting of Oil Palm trees. This study depicted that the high spatial and spectral information contained in the aerial imagery can detect the object of interest.

During the last decades, apparent attempts have been made to develop numerous methods for the detection of different objects of interest such as roads (Gong et al., 2012; Leninisha et al., 2015; Mayer et al., 2006; Movaghati et al., 2010; Z. Zhang et al., 2011), buildings (Durieux et al., 2008; Karantzalos & Paragios, 2009; Peng & Liu, 2005), vehicles (Grabner et al., 2008; Moon et al., 2002), trees (Haala & Brenner, 1999; Malek et al., 2014). However, there is very little work done in the Sewall detection using high-resolution imagery. To the author's knowledge, this is the first paper where a methodology is being proposed to detect seawalls in the coastal region with the use of very high-resolution drone imagery.

2.4 OBJECT BASED VS PIXEL BASED IMAGE ANALYSIS

Several approaches for remote sensing image classification and object detection have been introduced in the literature. However, pixel-based image analysis and object-based image analysis are two types of classification approaches that stand out most. In pixel-based classification, individual image pixels are evaluated based on the spectral data they offer (thomas & hall, 2015)although, studies later in 2004 by dc duro & se franklin expressed that limiting oneself to use spectral knowledge from an extensive array of possibilities for studying phenomena based on their spatial and physical attributes is unbecoming. High-resolution imagery provides a wealth of contextual information, such as spatial and spectral information, but pixel-based classifications have struggled to make use of this information (haala & brenner, 1999). In the past decade, object-based image analysis (obia) has become an efficient way of extracting detailed information from remote sensing with very high resolution (blaschke, 2010). Instead of pixels, the obia technique divides an image scene into relatively homogeneous structures or areas and then classifies them (c. Zhang & xie, 2013)v walter used an approach in 2004 to combine pixels to create an object, and he achieved better results than the conventional pixel-based method.

In 2014, nabil zerrouki and d. Bouchaffra compared the overall utility of two standard remote sensing image classification approaches: pixel-based and object-based, using various state-of-the-art statistical tests. They found that an object-based image recognition technique outperforms a pixel-based approach for high-resolution imagery. According to previous research by kamal and phinn (2011), object-based image processing techniques can have better precision than pixel-based approaches. They used aerial imagery to map mangrove species and found that object-based mapping performed better (overall accuracy 76 percent, kappa 0.67) than pixel-based mapping, which performed poorly (overall accuracy 56 percent, kappa 0.41). Numerous experiments comparing pixel and object-based performance for different applications have also been conducted. Elements such as the comparison of the object and pixel-based approaches to our specific study are applicable to our review.

When compared to an object-based classification method, pixel-based classification has several limitations. Sw myint, p gober & a brazel in 2011 pointed out the drawbacks: the pixel classification is solely dependent on a pixel's spectral value, whereas object-based classification includes spectral value, texture, and other contextual detail. Another major drawback of pixel-based classification is that it ignores spatial autocorrelation and the group of pixels that need to be considered together as an object. (blaschke, 2010). Since the pixel-based classification method use only the spectral information of pixels and a single-pixel is regarded as a classification object, the result obtained has a noise known as "salt and pepper." (whiteside et al., 2011)

2.5 USE OF MACHINE LEARNING IN OBJECT DETECTION

In this section, we review the machine learning approaches to remote sensing applications. Traditional methods for processing remote sensing imagery were focused on the physical collection, probabilistic methods, and mathematical models. However, they have been associated with a wide range of challenges. (Sisodiya et al., 2020). The issues include but are not limited to the time and labor required for redundant tasks. Artificial intelligence such as machine learning approaches are being used to address these issues. Artificial intelligence (AI) is a concept invented by Alan Turing, a mathematician who set the groundwork for modern computers. In the 1950s, his work becomes well known and gives rise to the concept of "General AI."

Artificial intelligence, such as machine learning, has gained popularity in the remote sensing community in recent years. For instance, decision trees (DTs) were used to create the 2001 National Land-Cover Database (NLCD) landcover classification for the contiguous United States of America (Homer et al., 2007). Machine-learning algorithms are capable of modeling complex class signatures, accepting a range of predictor data as input, and making no assumptions about the data distribution (i.e. are nonparametric). Studies by scientist have consistently shown that these methods yield higher accuracy than conventional parametric classifiers, especially for complex data with a large feature space. (Amaral et al., 2013; Rogan et al., 2003).

The two most prevalent ML approaches used in past years for digital image analysis are supervised and Unsupervised ML classifiers. Clustering is one of the unsupervised techniques for grouping together pixels that have identical spectral characteristics. In 2011, Ashish Ghosh et al. successfully used an unsupervised clustering algorithm for Image classification and change detection. His study concluded that unsupervised classification helped find patterns in data. However, it is not always the case. In 2016 Sayali Jog & Mrudul Dixit used both supervised and unsupervised classification schemes for land cover classification. The performance of both methods judged based on Kappa Coefficient and Overall Accuracy illustrated that supervised classification yielded better results in land cover classification.

The remote sensing literature presents several supervised methods for dealing with the problem of unsupervised image classification. Object detection methods based on machine learning have been used in several studies recently. In 2016, Amanpreet Singh and Aakansha Sharma published a paper to provide a broad comparison of state-of-the-art machine learning algorithms in remote sensing. Different machine learning algorithms such as decision trees, Random forests, Support Vector Machines (SVM), and k-NN were contrasted in their findings. With Test Accuracy of 79 percent and 77 percent, they were able to get the best results from random forest and SVM. Supervised Machine Learning algorithms like SVM and Random forest are successfully used for classifying the imagery. (Ye et al., 2020) Remote Sensing's new trend is the use of the Object-Based Image Analysis concept together with the machine learning approach.

CHAPTER 3: STUDY AREA

Hallandale Beach City is located at south east part of Broward County of Florida. It is bordered by the Atlantic Ocean on the east, Interstate 95 on the west, Pembroke Road on the north and the Miami-Dade County Line on the south. According to the United States Census Bureau, the city has a total area of 4.55 square miles of which 4.21 square miles of it is land and 0.34 square miles of it (7.47%) is water.

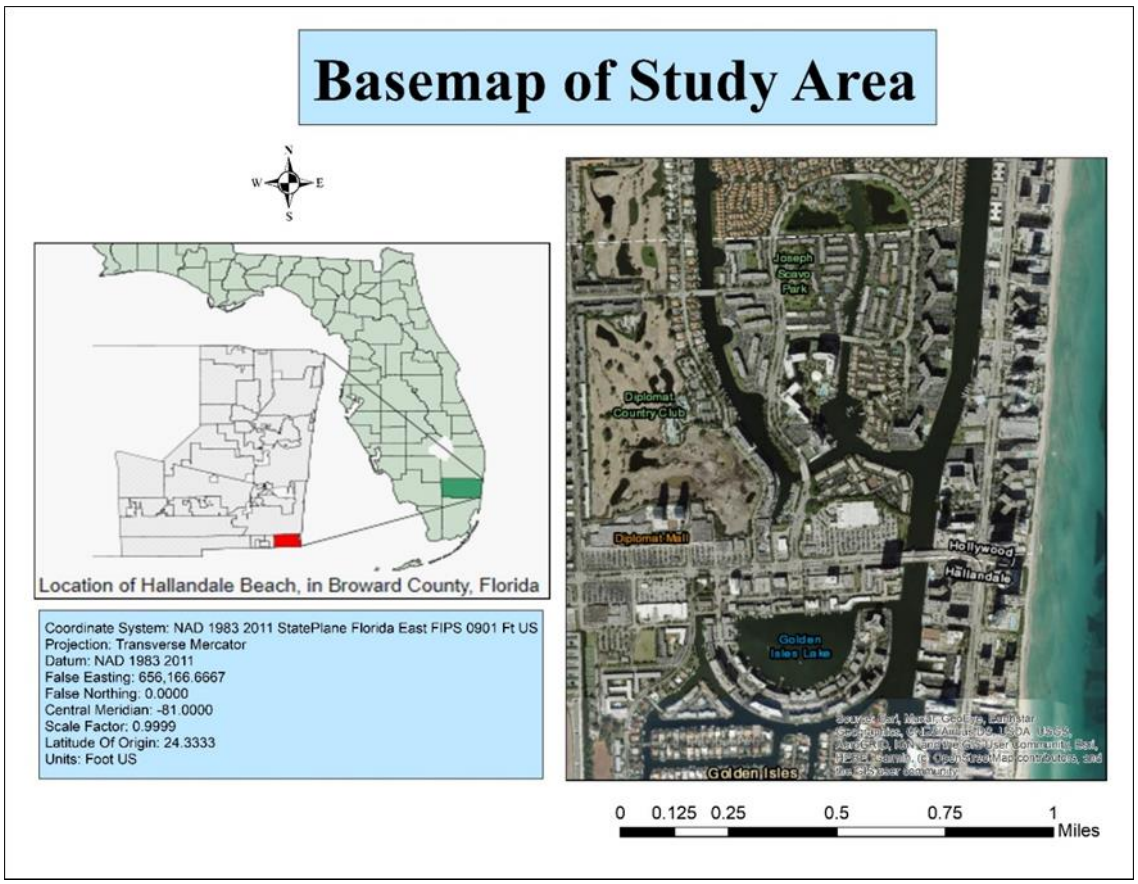

Figure 2: The Location Map of Study Area Hallandale Beach City

Human settlements in this city are located alongside the Atlantic Ocean and Intracoastal waterways. Seawalls have been constructed to protect these lands from early 19th century. The city had incurred the sea wall collapse several times. The recent collapse was reported in of February 21st, 2020, behind Plaza Towers South Condominium. The regular monitoring and maintenance of sea wall in the city is vital.

CHAPTER 4: METHODOLOGY

4.1 DATA ASSEMBLAGE AND SOFTWARE USED

The Florida Department of Transportation (FDOT) provided Very High-Resolution Airborne Imagery of four bands: Blue, Green, Red, and NIR bands with a spatial resolution of 0.25 Feet and a Digital Elevation Model (DEM) with a spatial resolution of 0.5 Feet. The imagery was the output of a project by FDOT in 2017 titled "Control Survey of Photogrammetric Aerial Triangulation and Aerial LiDAR Calibration of the US 27 Corridor from SR 826 to SR 91 and the SR 70 Corridor from I-75 to I-95". According to the report, the aerial photography retrieval took place only on days where the conditions were deemed ideal for collecting imagery with an 80 percent forward overlap. The sun elevation angle of image acquisition was greater than 30 degrees. The images were geographically projected in Universal Transverse Mercator (UTM) zone 17 projection in US Survey feet (US ft) with Horizontal datum of NAD83 (2011). GNSS Vertical heights was referenced to the North American Vertical Datum of 1988 (NAVD88) in feet, using the latest FDOT geoid model (FPRN2016B).

Trimble eCognition Developer 9 was a major software used for data processing. It is powerful development environment for Digital Image Analysis. The ability of this tool to mimic the cognitive powers of the human mind and merge geospatial input data is revolutionary departure from traditional approaches to data processing (Yu et al., 2016). Trimble eCognition also allows development of required feature extraction solutions which speeds and simplifies the interpretation of geospatial data items. Machine learning techniques can be conveniently incorporated into automatic workflows in eCognition (Japitana et al., 2015). Consequently, a novel method for converting mind models, the reasons why a human interpreter can detect objects, or features in geospatial data, into machine language (Rule Set) can be generated. This research has established a rigorous method of rendering information in a semantic network using patented segmentation and classification processes in eCognition Developer.

4.2 CLASSIFICATION APPROACH

In this research, two different classification approaches: pixel-based classification and object-based classification, were used to delineate the sea wall. Similarly, three different techniques in OBIA were tested: Knowledge-Based (KB) technique, Machine Learning (ML) technique, and the final, Machine Learning Followed by Knowledge-based (MLKB) technique. The imagery was segmented into homogenous objects. Multiresolution segmentation was used for segmenting the imagery into groups of similar pixels called objects. The image was categorized into five classes— seawall, sea, shadow, vegetation, and impervious. The result of all the methods was compared.

4.2.1 PIXEL BASED CLASSIFICATION

Pixel-based classification analyzes multispectral information to assign a pixel to a class based on spectral similarities. The pixel-based classification method relies entirely on spectral data, the digital number of pixels, and treats each pixel as a classification object. In eCognition, the Classifier algorithm can be applied either pixel- or object-based. For both pixel and object comparisons, the Nearest Neighbor algorithm was used. Using specified samples for the classes, the closest neighbor technique finds image objects inside a specific feature space. To begin, the software requires samples of each class, which are representative examples. The algorithm looks for the sample pixel/object closest to each image object in the defined feature space after establishing a representative collection of sample objects. The distance (d) in feature space between a sample object and the image object to be identified is standardized by the standard deviation of all feature values so that the features of different range can be combined in the feature space for classification. Equation 1 shows the formula used for calculating the distance in eCognition.

$$d = \sqrt{\sum_{f} \frac{vf(s) - vf(O)}{\alpha f}} \tag{1}$$

$Where,$

$d = Distance\ between\ sample\ object\ and\ image\ object$

$vf(s) = Feature\ value\ of\ sample\ object\ for\ feature\ f$

$vf(o) = feature\ value\ of\ image\ object\ for\ feature\ f$

$\alpha f = \ Standard\ deviation\ of\ the\ feature\ values\ for\ feature\ f$

The two approaches were tested using the same training data, features, and classification algorithms in eCognition. Results were then compared on a per-pixel basis for both object-based and pixel-based methods to avoid biases discussed in the next chapter. However, due to relatively lower accuracy, the Pixel-based approach was not used for further analyses.

4.2.2 OBJECT BASED APPROACH

Segmentation

The vital task for OBIA is the segmentation of the images into spectrally homogeneous, contiguous image objects (Benz et al., 2004). A Multiresolution segmentation algorithm embedded within the eCognition Developer was used to delineate the image into objects. This bottom-up region merging procedure starts with a single pixel-sized object and merges them in several loops into pairs to form larger units as long as the "scale parameter" is not locally exceeded (Benz et al, 2004). Multiple parameters are required for the multiresolution segmentation technique. The first parameter is scale, which specifies the average size of the segments at a given level. Following that, the composition of the homogeneity criterion: shape and compactness was explored. The shape determines the extent to which spatial versus spectral values influence segmentation. Compactness decides how compact in size the resulting segment will be. While several tools have been created to automate portions of the parameter selection process (Y. Zhang et al., 2010), human interpretation of the results and subsequent parameter modification remains a common practice that produces acceptable results. The segmentation result using various parameters is detailly discussed in Chapter 5, Result under the Segmentation heading.

4.3 MACHINE LEARNING FOR SEA WALL DETECTION

After identifying the best segmentation size and parameters as discussed in the previous chapter, the samples were selected from imagery for five different classes—seawall, sea, vegetation, shadow, and impervious layer. The impervious layer included all the remaining components of the image like buildings, roads, parking lots, footpaths.

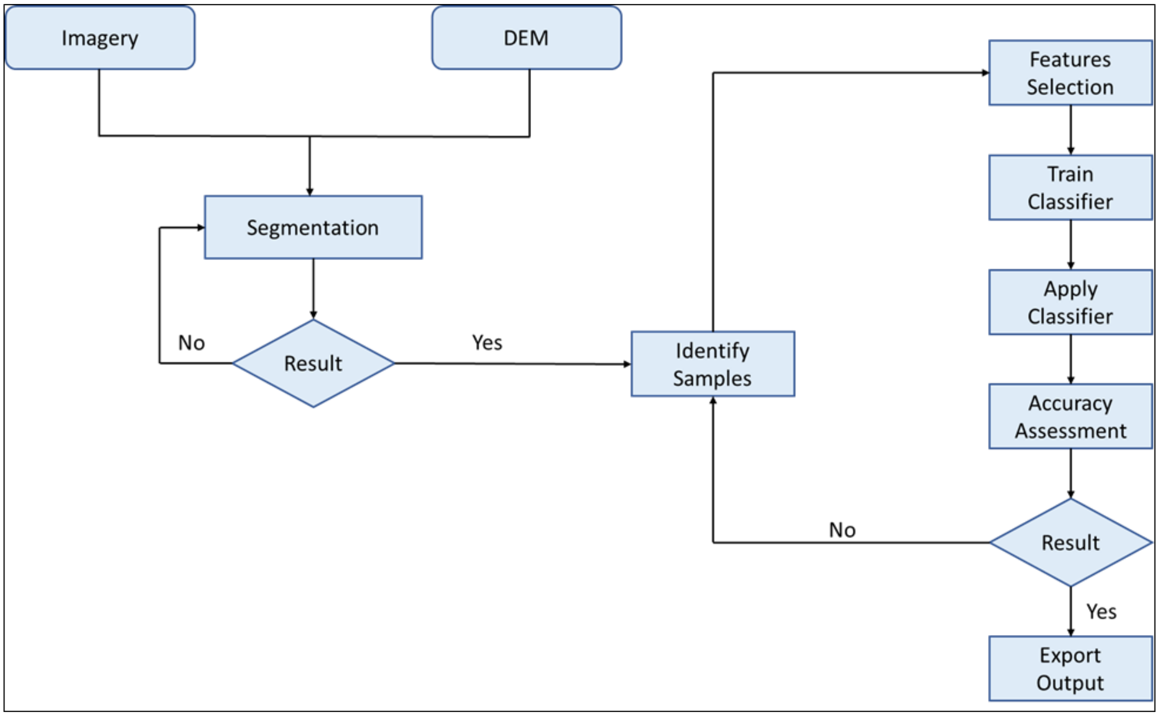

Figure 3: Workflow diagram of Machine learning method in eCognition Developer

Following sample collection, a detailed statistical study was performed to compare the attributes and histograms of image objects samples of various classes. Feature space Optimization, a method to mathematically calculate the best combination of features in the feature space, was applied to select the important features. The best features were chosen for training the models. The samples were then used to train classifier models using SVM (Support Vector Machine), Decision Tree, and Random Forest statistical classification algorithms. The trained models were used on several tiles within the imagery. Then the truthfulness of the classified imagery was quantitatively weighted using Overall Accuracy, Producer Accuracy, and User Accuracy. The Accuracy Assessment was performed for different models using different classifier algorithms and the account of processing time of each classifier training and application.

4.3.1 SAMPLE SELECTION

After creating meaningful image objects by segmentation, samples were made for each class: sea, sea wall, vegetation, shadow, and impervious. It is essential to create training samples of all the feature classes besides the object of our interest (i.e., seawall) to identify training samples of all recognizable object classes within the whole image. So that other classis could be masked out in a later step. Training and validation samples were collected manually using the visual interpretation of the imagery. The objects to specify samples could also be imported as a shapefile containing samples and class values. Still, since the meaningful objects were distinguished in the previous step of multiresolution segmentation, it was efficient to use the same output for sample selection through a manual process. Figure 4 shows the area of the section sample was taken from imagery. The number of objects for sample selection of each class is shown in table (1) below.

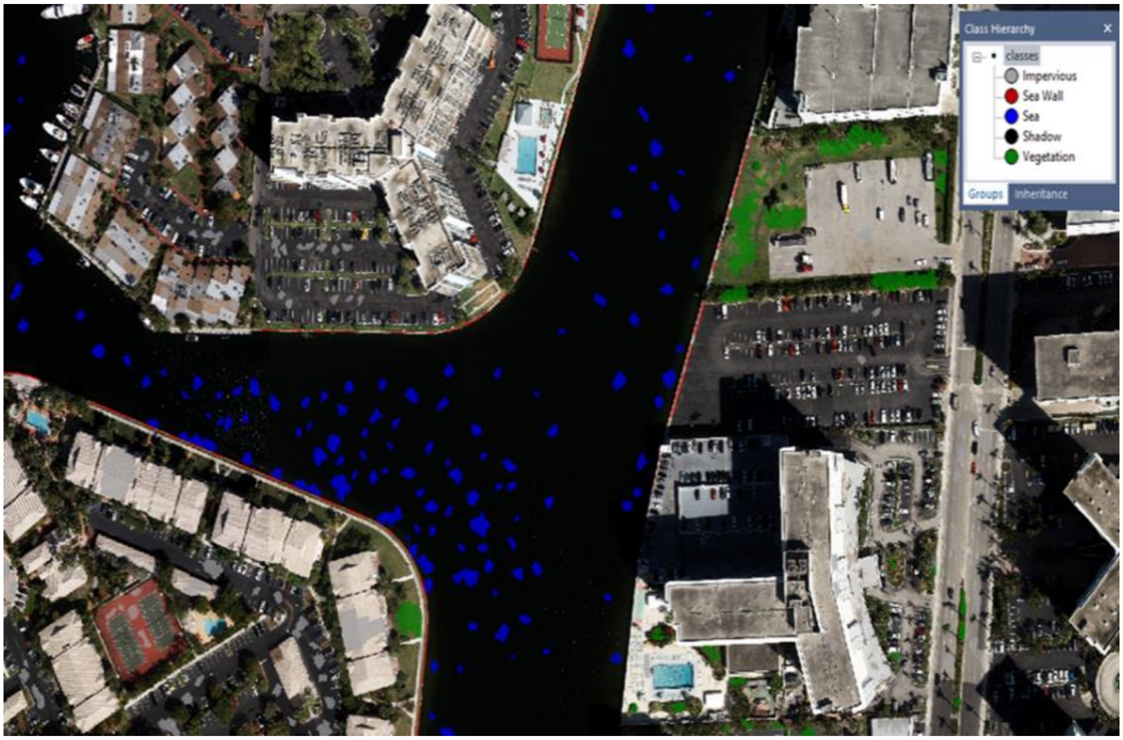

Figure 4: Image showing the sample taken for training and validation.

Table 1: The sample object number per class

Class	Number of Objects
Seawall	260
Sea	370
Vegetation	450
Impervious	480
Shadow	320

4.3.2 FEATURE SPACE OPTIMIZATION

After collecting adequate samples, a comprehensive statistical analysis of samples of all the classes was performed. The features which were providing the best separability among the classes were selected. eCognition Developer provides a feature selection tool for classification called Feature Space Optimization (FSO). The FSO tool evaluates which features offer the best class separability given a collection of training samples and features. When the addition of features does not increase the classifier's performance, the separation curve declines. 24 features that included spectral, geometric, and textural values were provided, and the FSO tool extracted the 10 best. Features beyond the top ten do not improve the classifier's discriminative power. Given the 24 features, the FSO tool determined a subset of features that offers the optimum separation distance out to a given dimension (Trimble, 2014). A graph (Figure 5) is displayed as part of the output to demonstrate change in separation when added features.

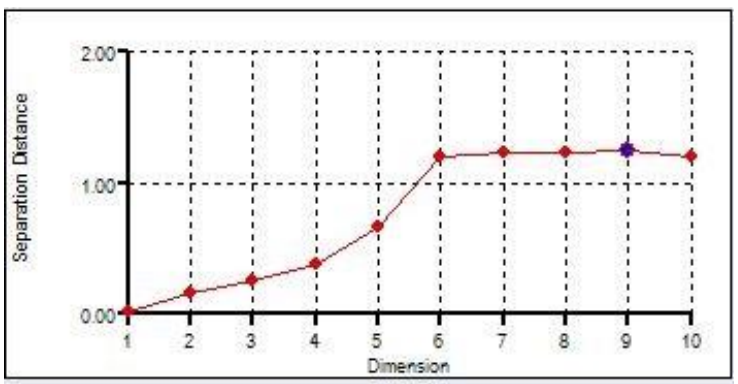

Figure 5 : Feature Space Optimization output graph

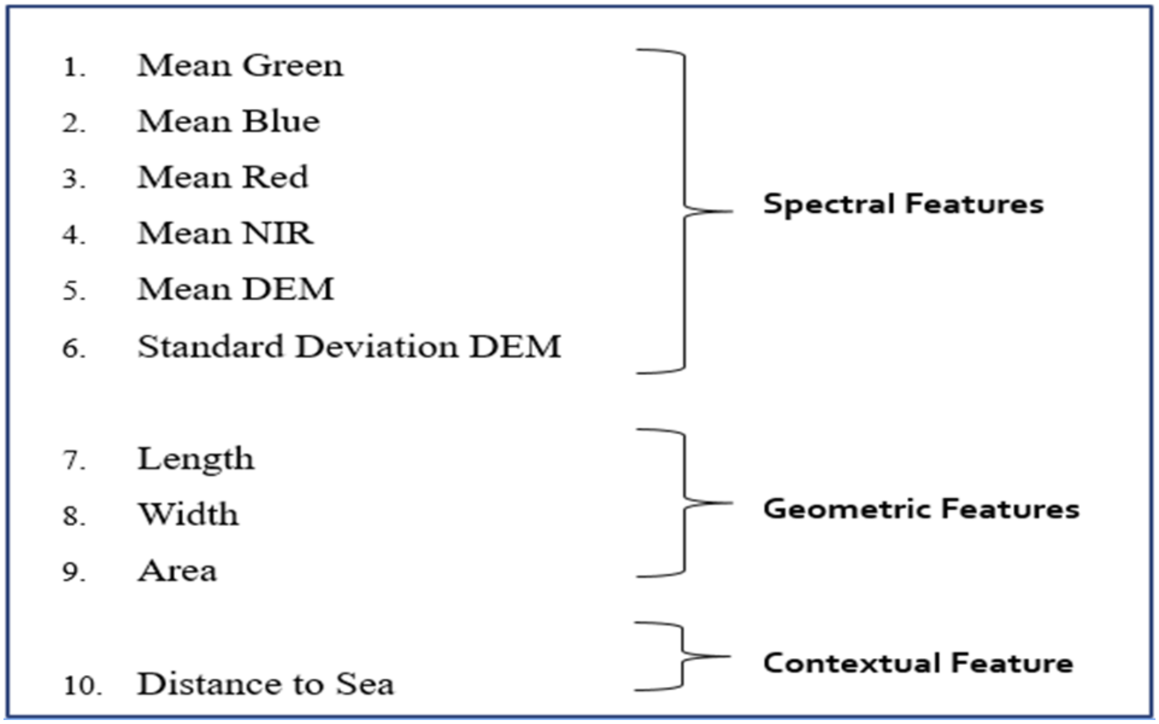

Figure 6: The features selected using Feature Space Optimization (FSO) tool.

4.3.3 TRAIN AND APPLY CLASSIFIER MODEL

A supervised classification algorithm is used for the classification of imagery. It is a machine learning method that develops models for class prediction using a known dataset known as the training dataset. The algorithm compares patterns with previously labeled data to determine the label assigned to the new objects. After selecting samples and features, three different classification algorithms were tested in eCognition Developer— Support Vector Machine (SVM), Random Forest, and Decision tree. These classification approaches are known as nonparametric machine learning approaches because they make no strong assumptions about the training data sets. Since no assumptions are made, the algorithms can learn any membership function from the training data. The three classifiers are described briefly below.

A Decision Tree is a classification approach that involves sending a dataset to a sequence of binary decisions based on feature values to classify it (Quinlan, 1996). A decision tree may be trained by taking the training data set, dividing it based on some feature value, and recursively partitioning each subset until all of the data in the subset belong to the same class, or further recursion adds no value to the classification (Friedl & Brodley, 1997). eCognition provides users with the ability to customize several parameter — Maximum depth, Cross-validation, SE rule, Truncating the branch.

The classification tree is generated from the learning sample for cross-validation, and its predicted accuracy is checked with test samples. Maximum depth limits the depth of the tree and results in recursive comparisons. Any terminating branch of the tree must have samples greater than the minimum sample count, keeping trees from becoming excessively complicated and overfitting the data. The Cross-validation folds allow us to test the correctness of our model by comparing it to the training data. The data is divided into N folds that are chosen at random. One is kept as a validation set, while the others are utilized for training. This enables us to select the training model that best fits a given random validation set generated from the training data (Alpaydin, 2020).

The remaining parameters are for pruning the tree to handle outliers in the training data more effectively. A 1SE rule is a preprocessing approach for pruning branches while the tree is being built. Pruning is done on the smallest tree with an error rate smaller than the reported minimum plus one standard error (Breiman et al., 1984). Truncating is a post-pruning technique that removes unnecessary branches, allowing the remaining branches to cover the most significant number of examples available (Alpaydin, 2020). Finally, surrogate splits are also possible using the Decision Tree trainer. This enables a node to divide not just on its primary feature but also on a secondary feature that produces a comparable split. This lets us catch items that are outliers in one characteristic but inliers in another (Breiman et al., 1984). The parameters in the process tree used for training and applying the model using DT are shown in figure 7.

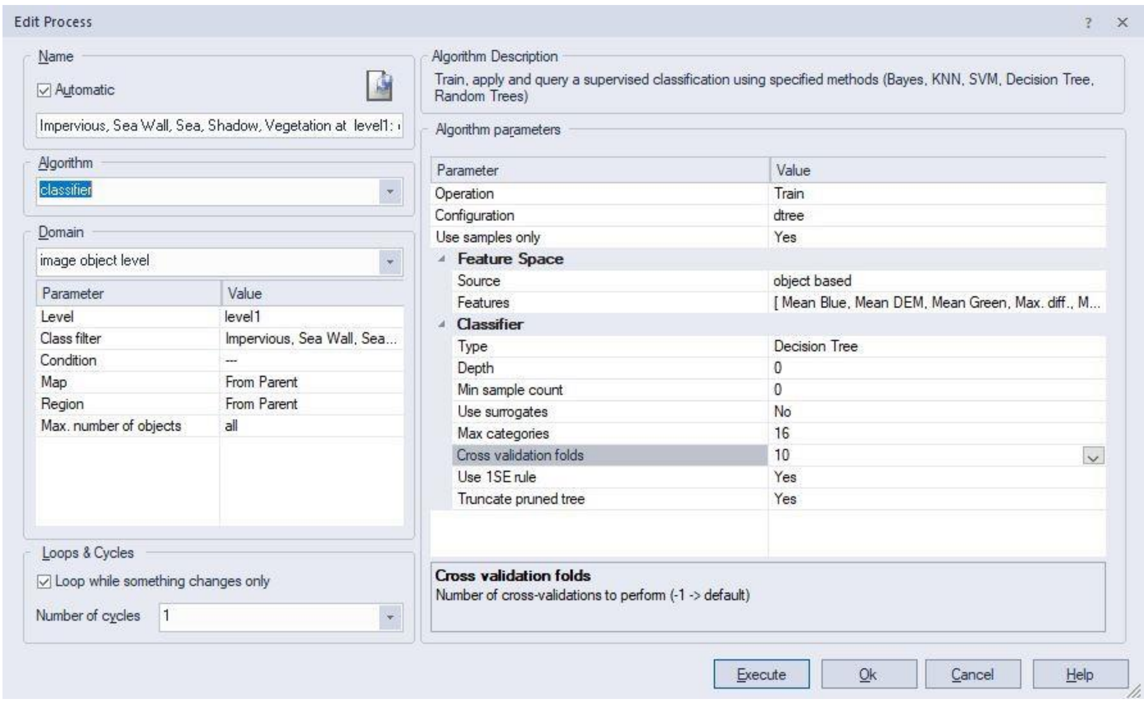

Figure 7: The imagery showing the parameters and algorithm used for training Decision tree.

A Support Vector Machine (SVM) is a supervised learning algorithm for data analysis and pattern recognition used for classification and regression analysis. The basic SVM takes input data sets and predicts potential classes the input data belong to. Given a series of training samples, each sample is labeled as belonging to one of two categories, and the SVM training method constructs a model that classifies new instances. An SVM model represents the instances as points in space, projected in such a way that the instances of the distinct categories are separated by a large gap. New instances are then mapped into the same space and classified according to which side of the gap they land on. (Malek et al., 2014).

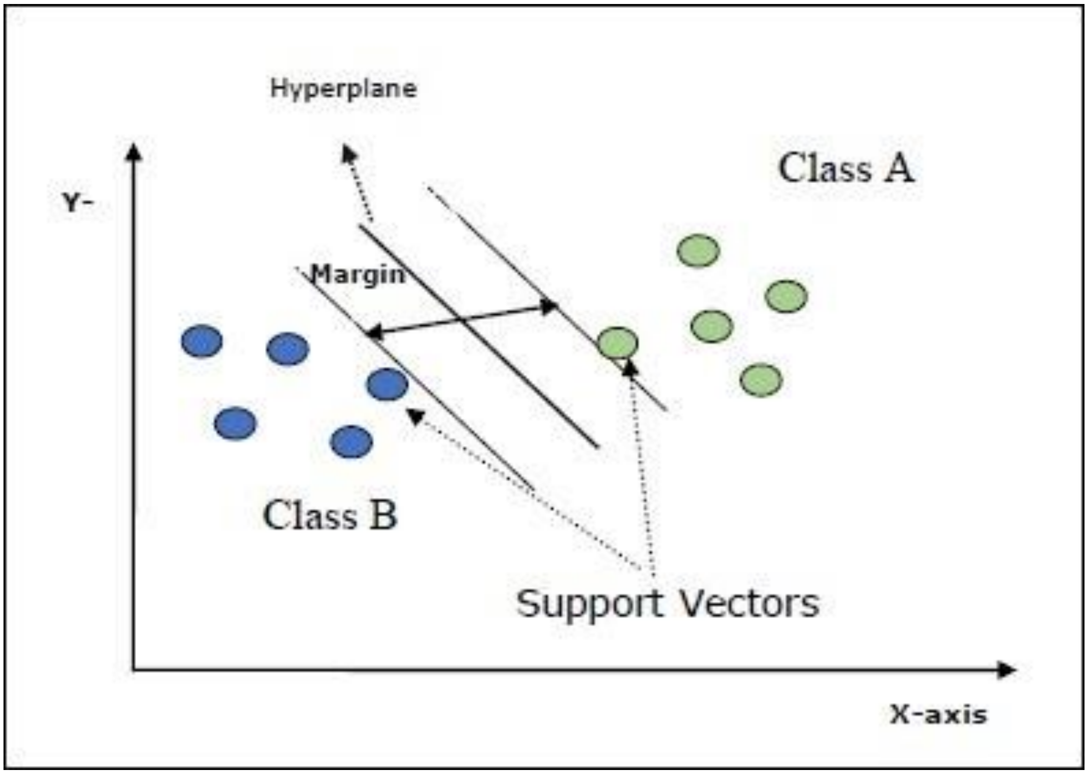

Figure 8: Image showing concept of Support Vector Machine.

SVMs are based on the notion of decision planes that define decision boundaries. A decision plane distinguishes between a collection of items that belong to distinct classes. When the data is transformed into an N-dimensional feature vector, the support vector machine attempts to fit a hyperplane to maximize the margin distance between samples from each class (Safavian & Landgrebe, 1991). eCognition supports the Radial Basis Function Kernel, whose gamma parameter is adjustable. Gamma values less than 1 result in a smoother choice border, whereas values greater than 1 result in a more complicated choice border (eCognition Developer User Guide). The image of the process tree used for training and applying the model using SVM and their parameters are shown in Figure 9.

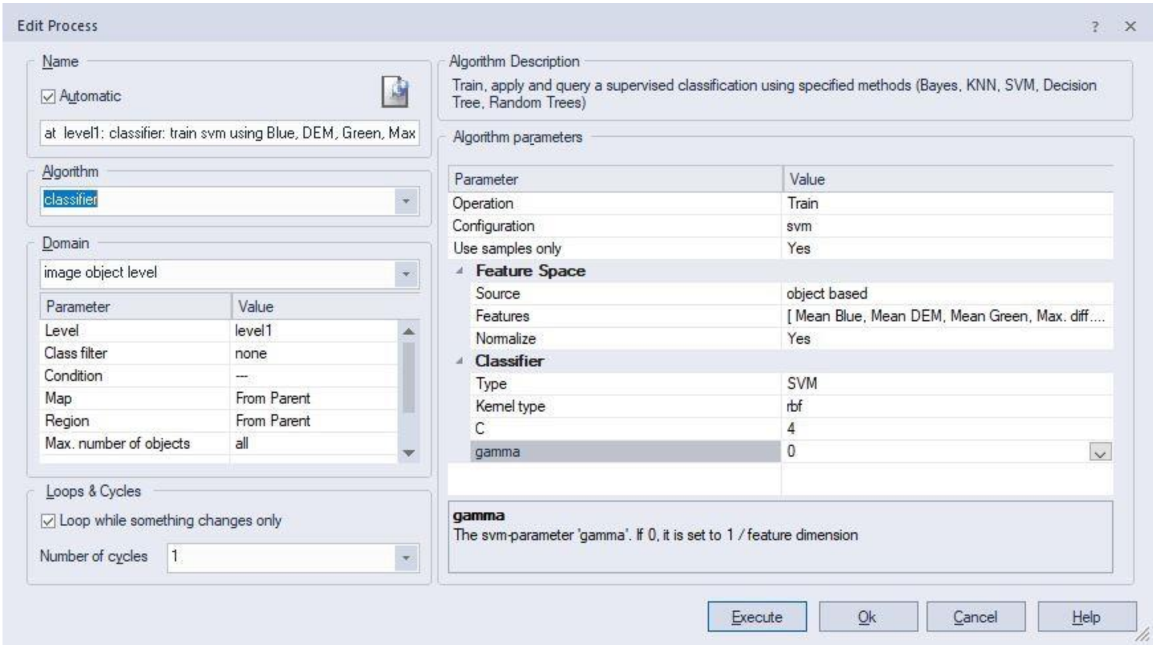

Figure 9:The imagery showing the parameters and algorithm used for training SVM.

Random Trees, also known as Random Forests, use bootstrap aggregation to produce an ensemble of decision trees. The random trees classifier is more a framework than a model (schematics shown in figure 10). It classifies every tree in the forest using an input feature vector. The training sample gets a class label at the terminal node where it ends up. This indicates that the label with the most "votes" gets allocated. The random forest forecast is obtained by iterating this over all trees. All trees are trained with the same characteristics and distinct training sets derived from the initial training set. This is done using the bootstrap process, which selects the same number of vectors in each training set as in the initial set (=N) (eCognition User Guide).

Random Forest combines numerous decision trees to reduce overfitting and bias-related inaccuracy and produce usable results (Breiman et al., 1984). Random forests can employ surrogates and can be subjected to many of the same characteristics as a conventional decision tree, such as depth, minimum sample count, and maximum categories. Additional parameters include active variables- the number of randomly selected features to be considered at each tree node, forest accuracy- a target for the desired level of accuracy, and a termination criterion that can be set to the maximum number of trees, forest accuracy, or both. The image of the process tree used for training and applying the model using random forest and their parameters are shown in Figure 11.

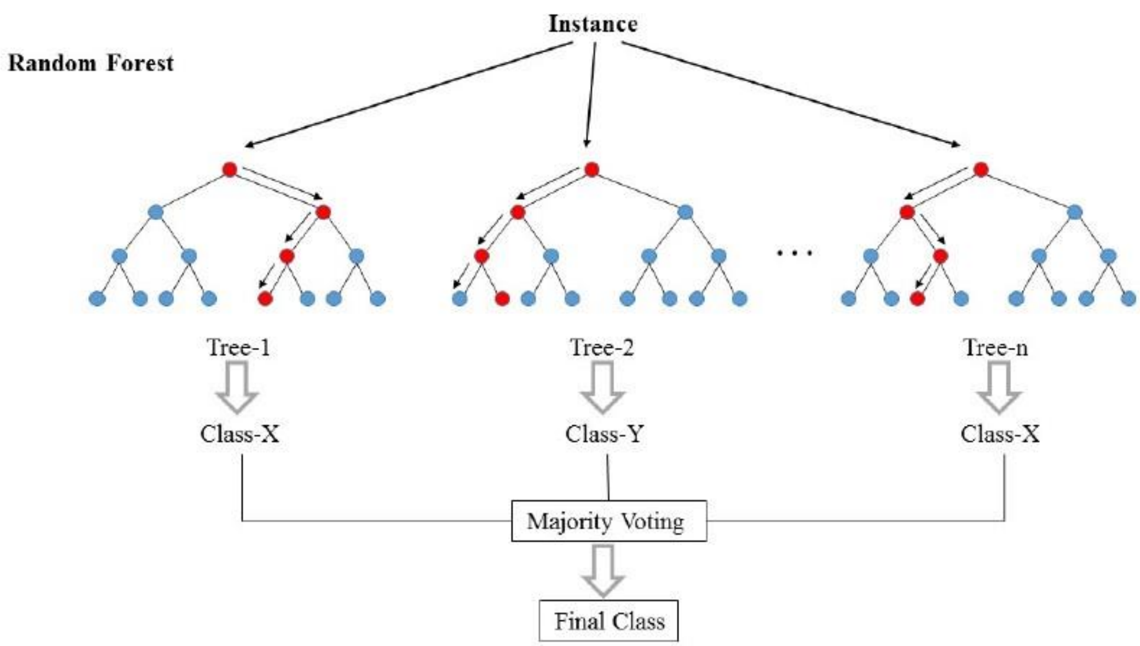

Figure 10: Image showing concept of Random Forest

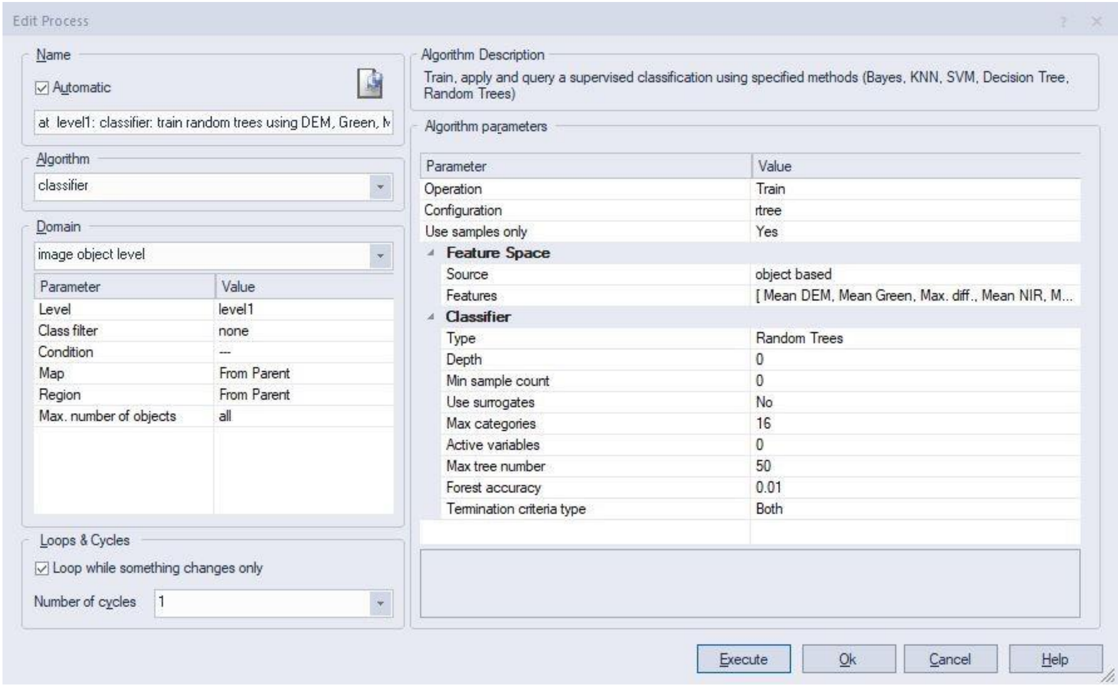

Figure 11: The imagery showing the parameters and algorithm used for training Random Tree

4.4 KNOWLEDGE-BASED APPROACH

The knowledge-based image classification method was applied using eCognition Developer rulesets. As a machine learning technique, data processing begins with segmentation. The rule sets were then defined to classify segmented regions (i.e., those extracted from images) as semantic objects (i.e., concepts of the knowledge base). The use of domain knowledge for automatic seawall identification was a significant challenge, and the formalization and exploitation of this Knowledge was a major issue. The technique is based on the use of rules to define the characteristic appearance of Seawall and other class objects. In this thesis, the methodology for creating a knowledge-base of objects that allows for the interpretation of imagery and DEM to automatically map the Sewall is described. The workflow of image processing using the Knowledge-based technique is shown in figure 12

Rule set Developed to classify each class are discussed below:

i. Arithmetic Indices

As a merged imagery and DEM was segmented in eCognition, the arithmetic values of the layers were modified to obtain the indices which would further assist the classification process.

INDEX 1 (NDVI)

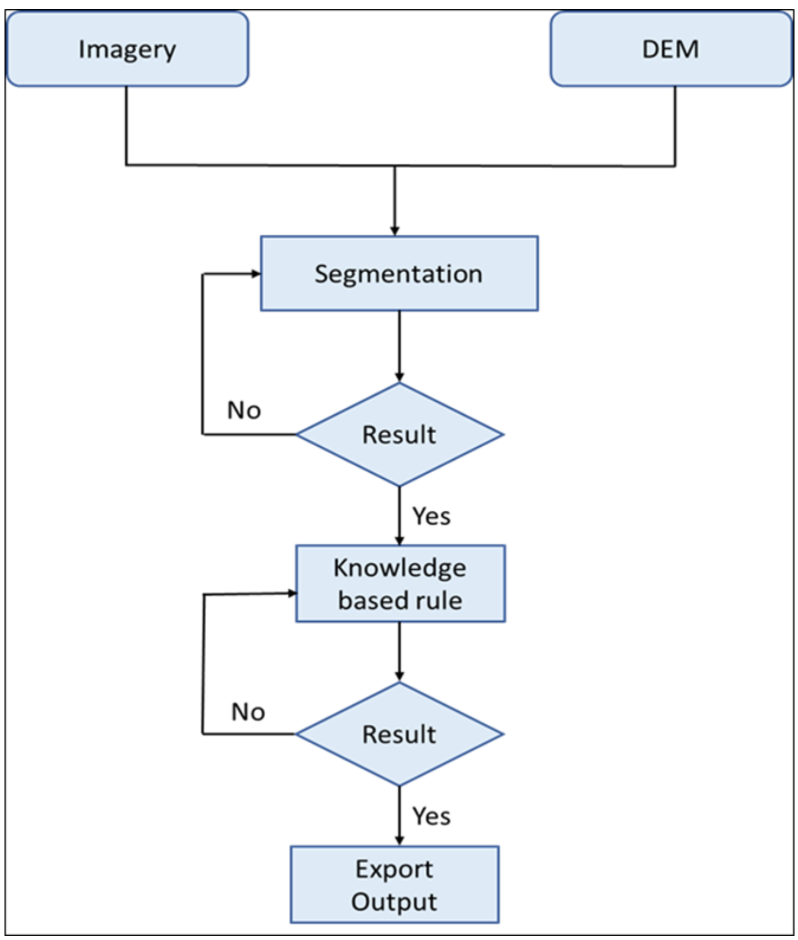

Figure 12: Workflow diagram of Knowledge-based method in eCognition Developer

To determine the density of green vegetation on a patch of land Normalized Difference Vegetation Index (NDVI) was used. It was used to mask identify and mask out the vegetation. The two-color bands or wavelength were used-band three, which is red, and band 4, which is Near-infrared. The formula used is shown below in equation 2.

$$NDVI = \frac{NIR - Red}{NIR + Red} \tag{2}$$

INDEX 2 (NDWI)

Normalized Difference Water Index (NDWI) is another index used to develop a ruleset. This index helped to identify the sea. The formula used is shown below in equation 3. The two-color bands green and NIR bands are used for calculation.

$$NDWI = \frac{NIR - Green}{NIR + Green} \tag{3}$$

ii. Classification of Sea

Classification of the sea was done considering features such as INDEX 2 and DEM. The threshold condition used was

a. NDWI > 0

b. DEM < 1.

iii. Classification of Seawall

The following condition were applied for classification of Sewall's.

a. Distance to sea threshold smaller than 8 feet (Distance < 60 pixels)

b. DEM value of object 1 feet to 5 feet. (1 < DEM <5)

c. Width length smaller than equal to 1 foot.

d. INDEX 1 < 0.3

iv. Classification of Vegetation

The following threshold was used for separation of Vegetation from imagery.

a. NDVI value greater than 0.3

b. Mean Brightness value greater than 45.

v. Classification of Shadow

The following condition were used for unclassified objects to identify and mask out the shadow.

Brightness value smaller than 45. The Sewall's located inside the shadow area was later retrieved by using another ruleset using the brightness value of the imagery. The similar spectral signature as seawall class was studied and extracted from the class of shadow and reassigned them as seawalls.

4.5 MACHINE LEARNING FOLLOWED BY KNOWLEDGE BASED

Both Machine learning and Knowledge-based methods were tested individually, and their accuracy assessment was evaluated. Furthermore, to enhance the accuracy of seawall, a third method was introduced, combining two previous methods. The final output obtained by the Machine learning classifiers was then introduced to the knowledge-based rule set as discussed earlier. This method is a novel technique in automatic seawall detection where we utilized the machine learning algorithm and enhanced them by using expert knowledge on the objects.

Machine learning helped us to detect seawalls from large imagery within a short period. The standard and obvious errors by Artificial intelligence were corrected using the knowledge at hand. The seawalls, which were misclassified as Impervious layer by machine learning, were again assigned to Sewall's class with developed rule sets. Similarly, the impervious layer at the top of the building and side of the roadways assigned to seawall was reassigned to impervious with ruleset using DEM and other attributes such as distance to the sea. The final method's result compared to previous ML and KB methods is discussed in the Result chapter

4.6 ACCURACY ASSESSMENT

The classification results of all methods and approaches are compared using the confusion matrix in eCognition Developer's Accuracy Assessment tool. A confusion matrix is a table that contains predicted classification results in a column and actual classification results in rows. As such, the chart's diagonal indicates accurate predictions. The Producer Accuracy and User accuracy were computed and analyzed along with Overall accuracy. The number of objects correctly identified by the classifier in the validation data is referred to as producer accuracy. This gives how often features on the ground are correctly shown on the classified map or the probability that a specific class of an area on the ground is classified as such. User Accuracy tells us how often the class on the map will actually be present on the ground. User accuracy is the accuracy from the point of view of a map user, not the map maker. The equation used for the calculation are shown in equation 4, 5 and 6

$$Overall\ \ Accuracy = \frac{Correctly\ classified\ sites}{Total\ number\ of\ reference\ sites} \tag{4}$$

$$Producer\ Accuracy = \frac{Correctly\ classified\ reference\ sites}{Total\ number\ of\ reference\ sites} \tag{5}$$

$$User\ \ Accuracy = \frac{Correctly\ classified\ sites}{Total\ number\ of\ classified\ sites} \tag{6}$$

4.7 INNOVATION IN THE APPROACHES

This research pioneered an approach to sea wall detection by integrating the principle of Object-Based Image Analysis with a machine learning approach. The spatial locations of Seawalls in low-lying coastal areas, such as South Florida, can be determined using the methods developed in this thesis.

Similarly, the most challenging part of the study was to incorporate the hidden portion of the sea wall in the image. This research successfully extracted the sea wall obscured by shadows. For this Author first made a different class named shadow, which included all the shaded regions of the image. The shadow class was further reclassified to extract the sea. It helped us map the significant portion of the sea wall concealed by shadows. Similarly, other innovative techniques implied in this research are DEM use for making rule sets in a knowledge-based approach. The fundamental concept behind using DEM is the relative consistency of its height and notable difference in height with other structures– such as buildings.

The combination of knowledge-based and machine learning approaches was another innovative approach to highlight. The iterative advantage of machine learning combined with human cognitive ability – in a knowledge-based approach– resulted in the extraction of sea walls with higher accuracy.

This study is expected to be helpful for potential researchers in a related field of Object-Based Image Analysis. This study used the existing machine learning algorithms such as SVM, Decision Tree, and Random Forest and improvised them using the parameter tuning and then applying knowledge-based rulesets in eCognition to obtain a reliable result. Additionally, this study seeks to address the technical difficulties associated with object detection and classification, such as those caused by shadow effects. This study aimed to contribute to the literature by demonstrating the application of machine learning and OBIA to high-resolution remote sensing imagery to detect seawalls and create a database of seawalls

CHAPTER 5: RESULTS AND DISCUSSION

The shapefile of sea walls of Hallandale Beach city was exported after the acceptable classification results using all three methods explained in the previous chapter of Methodology. The accuracy of all the methods is compared, and the best approach for sea wall was concluded. The result of all the methods is discussed below:

5.1 PIXEL BASED VS OBJECT BASED APPROACH

For Seawall detection, traditional Pixel-based image classification was compared with the Object-based image classification. The two approaches were tested using the same training data and classification algorithms in eCognition. Figure 7 and Figure 8 show the results obtained from Pixel-based and Object-based approaches. As can be seen from the images, the object-oriented classification technique outperforms the pixel-based technique. The salt-pepper effect was observed in all pixel-based classification results; on the other hand, Object-based Image Classification results had no such effect. The spectral properties of the buildings, roads were similar to the seawall in pixel-based approaches, and no additional characteristics can be utilized to identify them; hence the building and concrete are misclassified as Sewall. Also, the spectral properties of the sea and shadow were similar; therefore, the misclassification was observed between these classes.

Table 2: Table comparing accuracy assessment of classification approaches.

Classes	Object based		Pixel based	
	User accuracy (%)	Producer accuracy (%)	User accuracy (%)	Producer accuracy (%)
Seawall	81	82	74	67
Sea	80	82	65	68
Vegetation	82	84	74	71
Shadow	76	78	69	71
Impervious	78	83	68	72

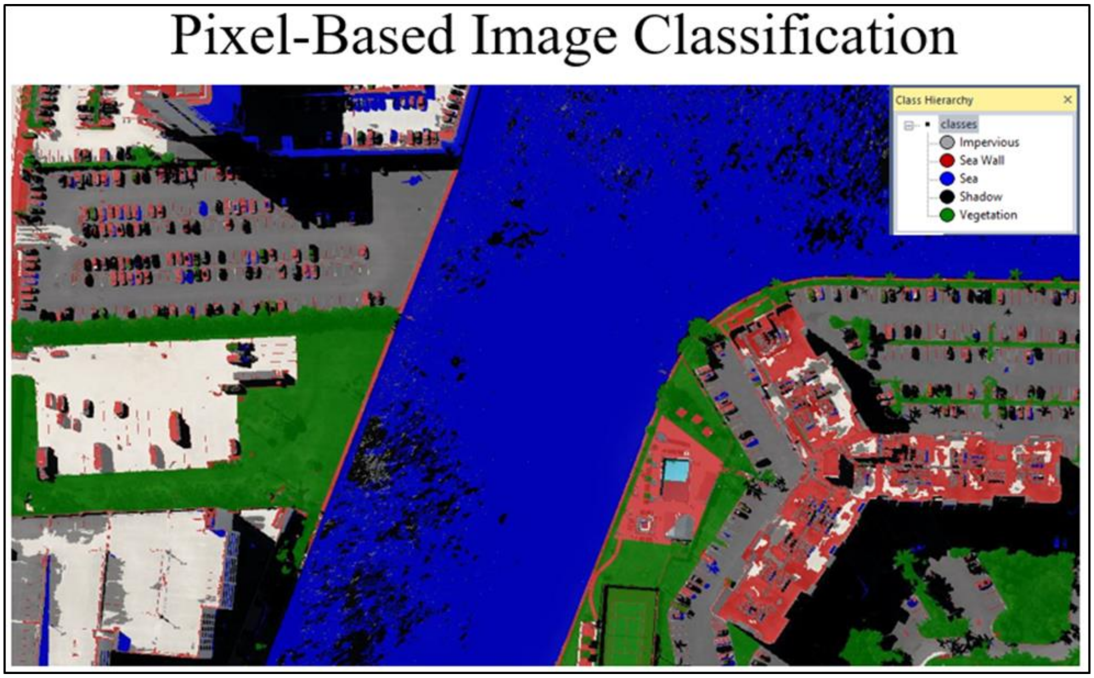

Figure 13: Image showing the classification result of Pixel based approach.

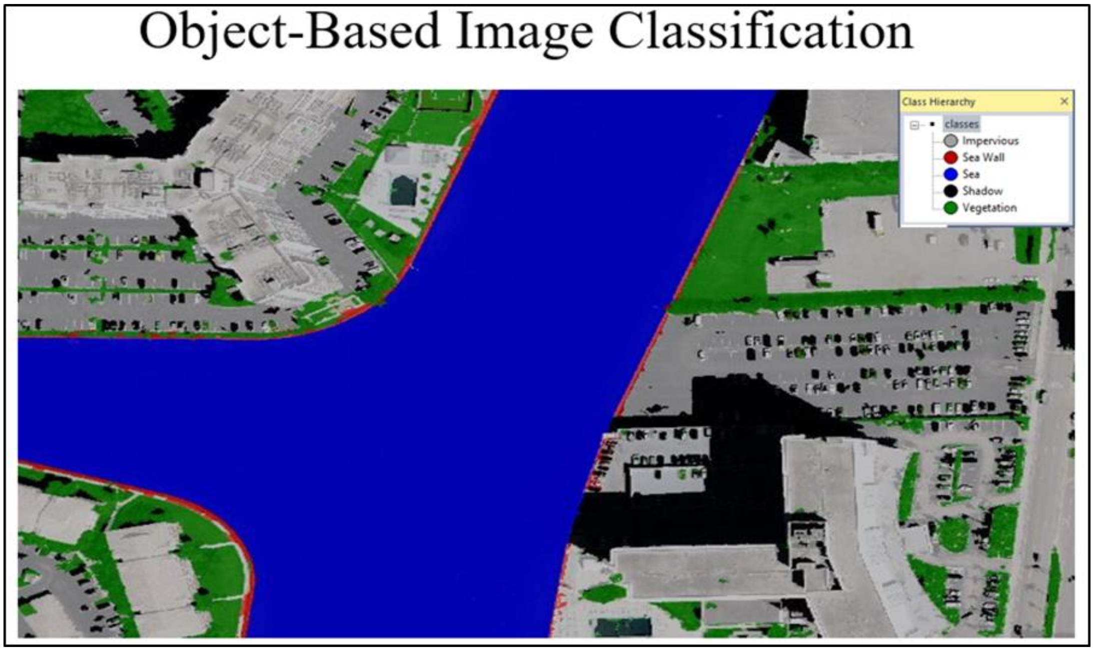

Figure 14: Figure showing classification result of Object based approach.

5.2 SEGMENTATION

Proper segmentation was achieved by adjusting the parameters so that the objects that comprise a similar physical identity of seawall retain their distinguished physical identity. The segmentation results were obtained using six scale parameters from 20 to 120 at an interval of 20, and the criterion's results were visually interpreted to achieve the most suitable segmentation parameters. According to the experimental results, scale values less than 20 created segments that were, in general, over segmented compared to all of the classes of interest, particularly Seawalls. Similarly, the parameters more than 120 resulted in under-segmented segments. As a result, segmentation parameters less than 20 or greater than 120 were not applied. For segmentation, all four spectral bands and DEM as the fifth band were given equal weights to get full utilization of spectral and geospatial information about the study area. The shape/color weights were set to 0.6/0.4 to emphasize the object's shape above the spectral information. This was done to account that most of South Florida's seawalls are rectangular in design. Weights for smoothness and compactness were set to 0.5/0.5 to ensure that neither compact nor non-compact segments were favored. To illustrate the effect of the scale parameter on segmentation results, Figure 9 shows segments created using three different scale parameters on a small subset of the image. Figure 9 (a) demonstrates a poor segmentation result with too many image objects per visually identifiable object. Figure 9 (b) shows an example of good segmentation, with segmented image objects encompassing visually recognized objects well. Similarly, Figure 9 (c) depicts an example of unsatisfactory segmentation findings, with an image object that is too large for visually recognizable objects.

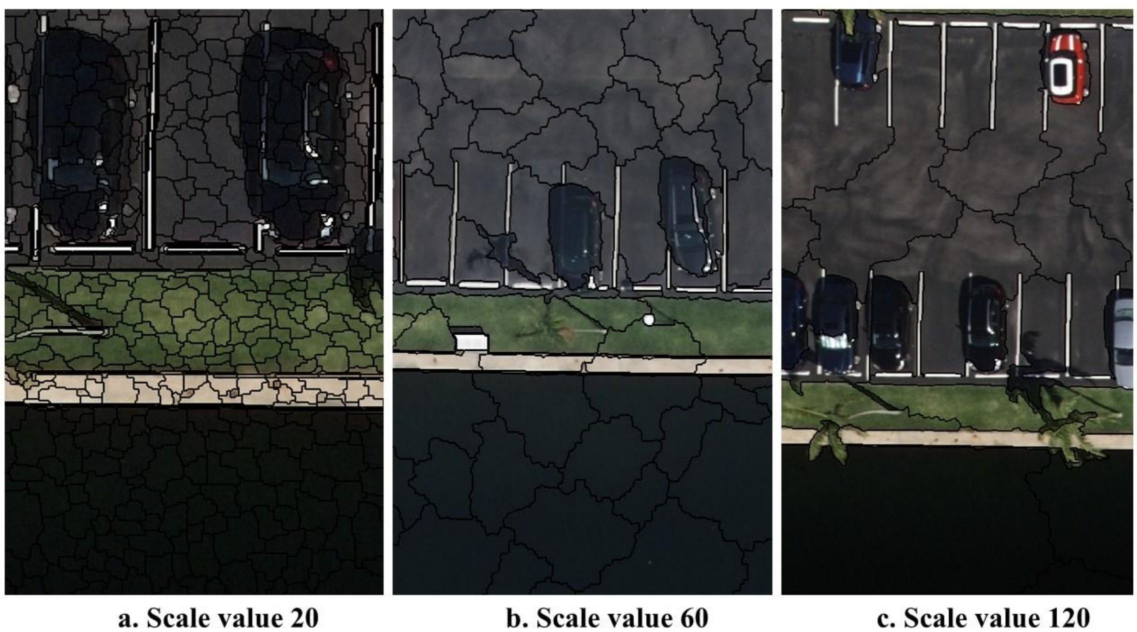

Figure 15: Results of the Segmentation Process using different scale parameters value 20 (a), 60 (b) and 120 (c)

5.3 COMPARISON OF MACHINE LEARNING ALGORITHMS

Accuracy assessment of the classification result using three different machine learning algorithms: Decision Tree, Random Forest, and Support Vector Machine (SVM) are discussed here. The samples and the features used for training all three classifiers were the same. As can be seen in table 3 of accuracy assessment, Random Forests shows a promising result and proved to be better for supervised classification of seawalls, having producer accuracy of 84% and user accuracy of 88 % in the class of Seawall. The overall accuracy obtained by Random Forest was 85%. However, all three algorithms showed remarkable results, with an overall accuracy of around 80% for all. SVM and Decision Tree had Overall accuracy of 82 % and 80 %, respectively.

Random Forests algorithm is easier to integrate into eCognition, relatively time-efficient, and accurate than other classifiers. It took ten minutes and 30 seconds to train and apply the Random Forest classifier in eCognition whereas, SVM and DT took slightly more time than Random Forest. The processor used was Intel (R)Xeon (R) CPU E-5 2630 @ 2.30GHz..

Table 3:Table showing the accuracy assessment of machine learning algorithms

Classifier	**Producer Accuracy (%)**	**User Accuracy (%)**	**Overall Accuracy (%)**	**Time taken (minutes)**
Support Vector Machine	81	86	82	13.26
Random Forest	84	88	85	10.32
Decision Tree	76	83	80	12.08

5.4 COMPARISON OF OBJECT BASED APPROACHES.

In this section, three different object-based methods for seawall detection are compared. Figure 16 depicts a bar graph with the percentage on the vertical axis and the methods on the horizontal axis. For the class of Seawall, the Knowledge-based method had producer accuracy of 74%, and user accuracy was 94.7%. Secondly, the producer accuracy of the machine learning method increased by 8% more than knowledge and was 82 %. However, the User accuracy decreased by 6 % and was 86 %. The best result was obtained by the third method, which is the combination of Machine learning and Knowledge-based rulesets. The User accuracy was 92% which is the highest among both previous methods, similar for the Producer accuracy, which was 96%. As of sequential manner, Machine learning was followed by Knowledge-based. The classification result obtained by machine learning algorithm was refined by Knowledge-based. Furthermore, the accuracy was compared with the previous methods.

The third method (MLKB) is used to detect seawall boundaries as polygon shapefiles suitable for further processing in ArcGIS. This novel method was used to detect seawall in all the study areas; the result is shown in Figures 17 and 18.

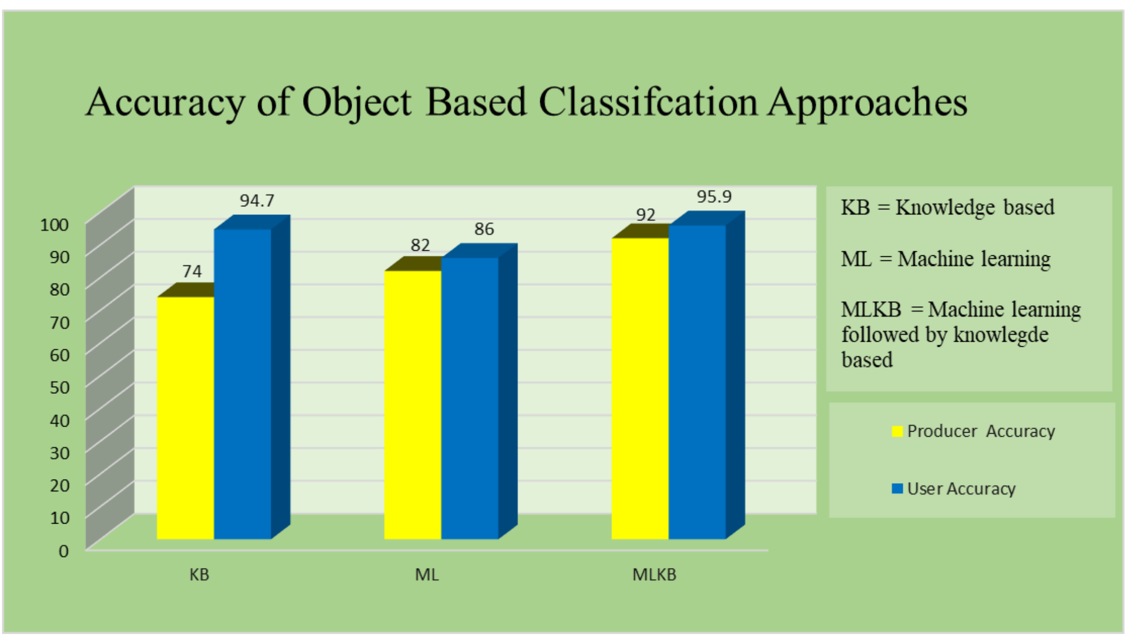

Figure 16: Comparison of Object Based Approaches

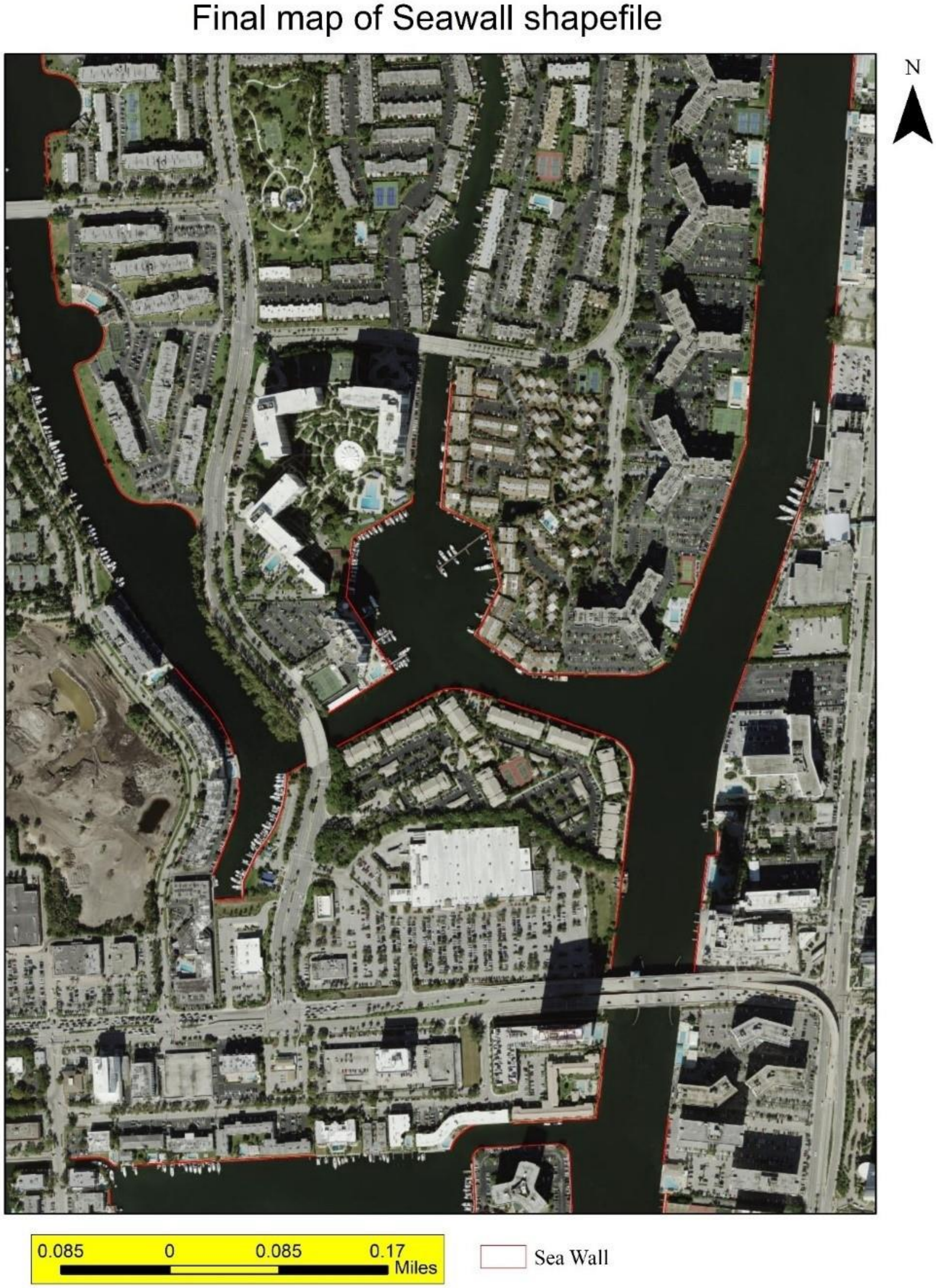

Figure 17: Final map of sea walls of Hallandale Beach City

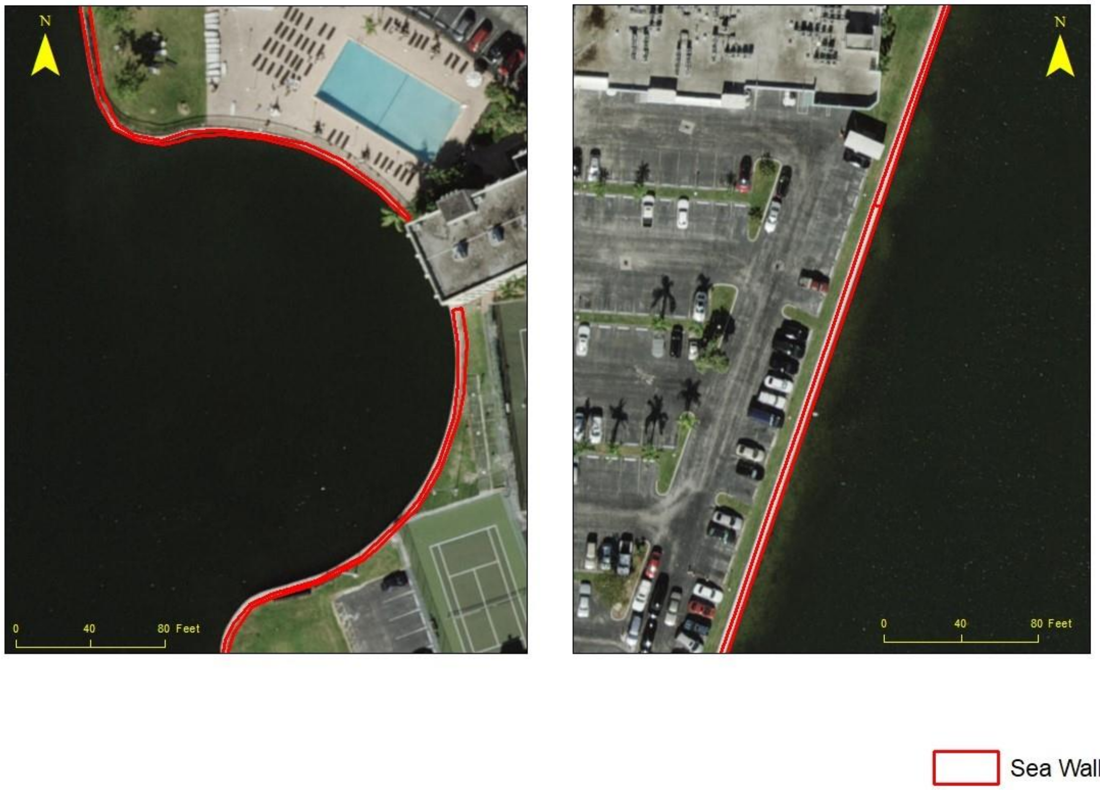

Figure 18: Map showing enlarged portion of study areas seawall

CHAPTER 6: CONCLUSION

6.1 CONCLUSION

The main goal of this research was to develop a methodology to extract seawall boundaries. The Object-based approach of seawall detection guarantees the classification by making full use of information from high-resolution imagery rather than using the traditional pixel-based approach for object detection. As discussed in the Methodology chapter, this study tested several techniques to delineate the sea wall boundary using high-resolution imagery. However, based on the methods tested, a combination of machine learning followed by a knowledge-based approach was the most efficient classification technique.

The use of DEM along with Multispectral imagery was vital for data processing. Though spectral values helped to classify the components of the image, the objects having a similar spectral value were misclassified. The altitude information from the DEM distinguishes the sea wall from other components having similar spectral values in multispectral imagery — it was due to the height barrier for the class seawall. In this research, a comparison between three different machine learning algorithms was also performed. The Machine learning method used algorithms such as Support Vector Machine, Decision Tree, and Random Forest and compared the final result through visual inspection and accuracy assessment. The outcome of this method is highly affected by choice of algorithms. Out of the three algorithms used, random forest resulted in the best output. However, the major problem with the machine learning approach was the misclassification of objects. Impervious layers such as buildings or roads were misclassified as a sea wall. Similarly, the other method, the Knowledge-based approach, also showed a good result. However, it was not reliable because the producer accuracy was significantly low (74%).

The problems incurred in both methods were resolved using machine learning followed by a knowledge-based approach. The misclassified objects in the machine learning approach were accurately reclassified by setting the rule sets in a knowledge-based approach. The method is efficient in terms of accuracy and time.

6.2 RECOMMENDATIONS AND FUTURE WORK

The methodology and analysis presented in this thesis have few limitations and might need future works. Firstly, complete tracing of the sea wall was not possible due to vegetation and other coverings. For example, some parts of the wall in the imagery were covered by vegetation or other mega structures like bridges and buildings—future studies for masking out such features to extract the boundaries completely. Alternatively, any simulation studies to anticipate sea wall location can be done.

Another limitation of this research is this it is a semi-automated method. Human intervention is mandatory for suitable segmentation parameter selection and feature selection, which was rigorous and time-consuming. Future studies can be done to make it fully automated algorithms as Deep learning.

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