AHMAD KAMIL BIN MAT NAWI BACHELOR OF SURVEYING SCIENCE AND GEOMATICS (HONOURS) AUGUST 2023

DETERMINATION OF MANGROVE HABITAT USING OBJECT BASED IMAGE ANALYSIS FROM CHERATING TO PEKAN

AHMAD KAMIL BIN MAT NAWI

2019675974

SCHOOL OF GEOMATICS SCIENCE AND NATURAL RESOURCES

COLLEGE OF BUILT ENVIRONMENT

UNIVERSITI TEKNOLOGI MARA MALAYSIA

AUGUST 2023

DETERMINATION OF MANGROVE HABITAT USING OBJECT BASED IMAGE ANALYSIS FROM CHERATING TO PEKAN

AHMAD KAMIL BIN MAT NAWI

2019675974

Thesis submitted to the Universiti Teknologi MARA Malaysia in partial fulfilment for the award of the degree of the Bachelor of Surveying Science and Geomatics (Honours)

AUGUST 2023

CONFIRMATION BY PANEL OF E XAMINERS

I certify that a Panel of Examiners has met on 18 August 2023 to conduct the final examination of Ahmad Kamil Bin Mat Nawi on his Bachelor of Surveying Science and Geomatics (Hons) thesis entitled "Determination of Mangrove Habitat Using Object Based Image Analysis in Pahang" in accordance with Universiti Teknologi MARA Act 1976 (Akta 173). The Panel of Examiner recommends that the student be awarded the relevant degree. The Panel of Examiners was as follows:

Fazly Amry Mohd, PhD
Senior Lecturer
College of Built Environment, CBE
Universiti Teknologi MARA
(Supervisor)

Mohd Khairy Kamarudin,
Senior Lecturer
College of Built Environment, CBE
Universiti Teknologi MARA
(Co- Supervisor)

Ashnita Rahim, PhD
Senior Lecturer
College of Built Environment, CBE
Universiti Teknologi MARA
(Panel 1)

Nurul Ain Mohd Zaki, PhD
Senior Lecturer
College of Built Environment, CBE
Universiti Teknologi MARA
(Panel 2)

SR DR ROHAYU HARON NARASHID
Center of Department
College of Built Environment, CBE

Date: 18 August 2023

DECLARATION

I declare that the work on this project/dissertation was carried out in accordance with the regulations of Universiti Teknologi MARA (UiTM). This project/dissertation is original and it is the result of my work, unless otherwise indicated or acknowledged as referenced work.

In the event that my project/dissertation be found to violate the conditions mentioned above, I voluntarily waive the right of conferment of my degree of the Bachelor of Surveying Science and Geomatics (Honours) and agree be subjected to the disciplinary rules and regulations of Universiti Teknologi MARA.

Name of Student	:	Ahmad Kamil Bin Mat Nawi
Student's ID No	:	2019675974
Project/Dissertation Title	:	Determination of Mangrove Habitat Using Object Based Image Analysis from Cherating to Pekan
Signature and Date	:	1st August 2023

Approved by:
I certify that I have examined the student's work and found that they are in accordance with the rules and regulations of the School and University and fulfils the requirements for the award of the degree of Bachelor of Surveying Science and Geomatics (Honours).

Name of Supervisor : Sr Gs. Dr Fazly Amri bin Mohd
Signature and Date : 3rd August 2023

ABSTRACT

Mangroves are a major coastal feature and an integral part of the forest ecosystem in tropical and subtropical regions of the world. It provides essential ecosystem services to nearby communities. Destroying mangrove trees will have an adverse effect on the ecosystem, which will harm locals and their way of life. Despite their significance, coastal area development has a significant effect on decreasing land cover. Degradation of mangrove natural areas is often a result of development, and degradation of the mangrove area in the coastal area has long been a sensitive subject. So, it is an important research to understand the condition of mangroves habitat for the future environment. This research about the classification of the satellite Sentinel imagery for mangrove habitat in Pahang. Thus, two (2) image with different year which is 2019 and 2022 were used in this research to identify mangrove areas and determine the healthiness of mangrove habitat. The method used to process the data are by using Object Based Image Analysis (OBIA). It was new method of classification of the satellite imagery. In this research, the finding show that mangrove area is 1.6285 hectares in 2019 and 1.8059 hectares in 2023. The research result show that the mangrove area has increased up to 0.1774 hectares. The Normalised Difference Vegetation Index (NDVI) will be modelled to estimate the healthiness of mangrove forest. The NDVI range in 2022 is from 0.15 to 0.68 while in 2019 is from 0.15 to 0.50 This discovery will provide information about mangrove habitat in Pahang that is useful and should be taken into account when planning future development and managing natural resources along of the Pahang coastline.

Keywords: Mangrove, Remote Sensing, Geographic Information System, Normalized Difference Vegetation Index, Object-Based Image Analysis

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF ABBREVIATIONS

Abbreviations

NDVI	Normalise Difference Vegetation Index
EVI	Enhanced Vegetation Index
SAVI	Soil-Adjusted Vegetation Index
MLC	Maximum Likelihood Classification
SVM	Support Vector Machines
LULC	Land Use Land Cover
NIR	Near Infra-Red
OBIA	Object Based Image Analysis

LIST OF NOMENCLATURE

Nomenclatures

ha	Hectares
km^2	Kilometer Square
N	North
S	South
mm	Millimeter
m	Meter
E	East
cm	Centimeter
kg	kilogram

CHAPTER ONE

INTRODUCTION

1.1 Research Background

Mangroves are a major coastal feature and an integral part of the forest ecosystem in tropical and subtropical regions of the world (Conrad, 2022) are shown in Figure 1.1. The mangrove is a type of ecosystem that exists in the intertidal zone or among plant families that have adapted well to the coastal environment (Mondal et al., 2019). Their biological and morphological capacities for surviving in situations with saltwater, saturated substrates and regular tide inundation have long been recognized. Mangroves are a worldwide significant ecosystem that are responsible for a wide variety of ecosystem system services, including the sequestration and storage of carbon, the protection of coastal areas, and the improvement of fisheries (Bunting et al., 2022). Having an understanding of the dynamics of a mangrove enables the world to make projections about the future condition of the numerous ecosystem services that it offers (Lombard et al., 2021).

Figure 1.1: The Mangrove Tree (Conrad, 2022)

Mangrove ecosystems are among the most productive and carbon-dense on the entire globe. Lombard et al., (2021) say that they are a prominent target of global conservation efforts because they can help reduce climate change by sequestering carbon. Despite the importance they have, the area covered by these ecosystems is continuing to decrease, and they are also being degraded and transformed for a variety of causes, including the development of metropolitan areas, aquaculture operations, and agricultural practices (Hamzah et al., 2020). In point of fact, the rate of destruction and degradation of mangrove forests today is comparable to or even higher than that of the loss of other ecosystems that are more visually appealing, such as rainforests and coral reefs (Valderrama-Landeros et al., 2017). According to studies, deforestation has resulted in the loss of 20-35% of global mangrove forest acreage during the 1980s (Zhang et al., 2021). Therefore, it is vital for the purposes of conservation and management to have a map of the mangrove forest that is both accurate and up to date with its data.

Mangrove forests are important both ecologically and economically, thus it's important to monitor and assess their state and geographic distribution in order to inform conservation and restoration initiatives. Given that many mangrove forests are inaccessible due to the flooded, soft sediment environments in which they thrive, the ability to properly estimate huge areas of mangrove cover and rates of change using remote sensing data would be of tremendous assistance to these efforts (Valderrama-Landeros et al., 2017). Since satellite sensors are better than people at figuring out the details and keeping an eye on the changing structure of mangrove forests, this technology has been widely used to study mangroves for things like management, inventorying, mapping, and noticing changes (Halim et al., 2019).

The purpose of this research is to carry out a feasibility study on classification of the satellite imagery via OBIA approach based on NDVI in Pahang for determination of mangrove habitat and condition. The area under investigation is from Cherating to Pekan in Pahang which is being utilized in a sustainable manner and the most important aspect that has an effect on the parameters to classify the mangrove habitat using satellite imagery using object based image analysis is proposed. Due to the location's proximity to the open sea, the aspect is lower compared to other regions, yet a number of characteristics must still be reviewed and evaluate their impact. They will be determining by the value based on the vegetation index.

This research will employ object based image analysis to classify the mangrove habitat. The Normalized Difference Vegetation Index (NDVI) will be used as a main parameter to get the condition of the mangrove. Other aspect such as characters, appearances and denseness also will become the suitable parameter for the condition of mangrove. By determine and classify all the parameter, the condition of mangrove can be identified. When it comes to long-term viability and economic growth, the entire process will benefit both sides.

1.2 Problem Statement

In spite of the fact that mangrove areas are among the most important marine habitats on the planet because of the unique opportunities they present for ecosystems and biodiversity, these areas have been rapidly degrading over the past few decades, and most of the remnant environments are struggling from intensive human use. Urbanization, deforestation, farming of shrimp, coastal development, excessive lumber and firewood harvesting, household sewage disposal, petroleum discovery contamination, salt production, and tin mining are only a few examples of human activities that pose serious threats to mangroves. (Idris et al., 2022). They have a significant impact on the creation of windbreaks, the stabilization of shorelines, and the preservation of ecological system and biodiversity (Wang et al., 2018). Destroying mangrove trees will have an adverse effect on the ecosystem, which will harm locals and their way of life. Degradation of mangrove natural areas is often a result of development, and degradation of the mangrove area in the coastal area has long been a sensitive subject, as the 2004 tsunami in Malaysia showed (Topah et al., 2022). Therefore, mangrove forest habitats should be constantly maintained due to their tremendous influence on environmental, biophysical, and socioeconomic issues (Asri et al., 2021). The fact that mangroves constitute an important supply of food, timber, medicines and fuel makes them an essential component of environmentally friendly and human lifestyles (Safe’i et al., 2021).

It is important to map the distribution of species and plant communities in mangrove areas in order to make inventories of wetlands, measure change over time, measure biodiversity and to map the area. In mangrove areas, which are sometimes inaccessible due to flooding, remote sensing plays a vital role by providing a rapid and effective means of ecological subsequent monitoring and baseline mapping. It is common for mangrove ecosystems to be located in far-flung and difficult-to-reach regions, making field surveys and data collection from aircraft challenging and time-consuming endeavours (Kamal & Phinn, 2011). Previous researchers utilized Google Earth Engine to compare satellite images of mangrove alterations. One of the various methods frequently employed in research on mangroves is the combination of Remote Sensing and Geographic Information System. There is many previous research used satellite images for image analysis in urban tree study and mangrove delineation (Mokhtar et al., 2022). However, studies about classification of condition mangrove not yet been adequately handled. Goldberg et al., (2020) mention that most of the research focus only on coastal area using GIS and are related to coastal vulnerability only. Thus, the research's aim is to carry out a feasibility study on classification of the satellite imagery via object based image analysis for determination of mangrove habitat and condition.

1.3 Aim of the study

The research's aim is to carry out a feasibility study on classification of the satellite imagery via Object Based Image Analysis (OBIA) approach based on Normalized Difference Vegetation Index (NDVI) from Cherating to Pekan for determination of mangrove habitat and condition.

1.4 Research Objectives

i. To classify the mangrove classification using satellite imagery on Pahang by using Object Based Image Analysis (OBIA).
ii. To identify the healthiness of mangrove habitat using vegetation index.
iii. To determine the healthiness of mangrove habitat.

1.5 Research Question

i. How to classify the mangrove habitat using satellite imagery?
ii. How to identify the healthiness of mangrove habitat around Pahang?
iii. How to determine the healthiness of mangrove habitat at Pahang?

1.6 Significance of Study

As a result, the purpose of this study is to carry out a feasibility study on classification of the satellite imagery via Object Based Image Analysis (OBIA) approach based on Normalized Difference Vegetation Index (NDVI) in Pahang for determination of mangrove habitat and condition. To achieve this goal, the study recommends examining the land use land cover of mangrove, followed by determine the healthiness of mangrove habitat using vegetation index. We can identify the factor that can affect the healthiness of the mangrove through the use of remote sensing technology and GIS in order to be more sustainable in the future. The Object Based Image Analysis (OBIA) will be used in this study to obtain the information about the mangrove healthiness Normalized Difference Vegetation Index (NDVI). The relationship of Normalized Differences Vegetation Index (NDVI) and Land Use Land Cover (LULC) of mangrove will be analysed to promote more sustainable exploration.

The finding of this research can be used to improve existing studies by implementing OBIA (Object Based Image Analysis). Hence, the result obtained are envisaged to show that the mangrove area can kept shoreline from changes. Moreover, identifying the condition of mangrove can help to ensure better understanding of the element causing mangrove degradation.

CHAPTER TWO

LITERATURE REVIEW

2.1 Introduction

This study's chapter includes an overview of the literature review, a context, a research hypothesis, and a glossary of words.

2.2 Mangrove

The world's mangrove forests represent one of the most valuable maritime ecosystems, as they provide a large variety of habitats for a wide variety of species. Mangrove forests are located along the coastline, tidal wetlands, and seawater systems that migrate inland through torrents, seawater, and river tail waters. It's a sanctuary for marine life since it prevents erosion of the coastline while simultaneously providing food and shelter (Topah et al., 2022; Hamzah et al., 2020). In terms of ecosystem services, mangroves offer shelter from storms and tides, protection from coastal erosion, nutrient availability, water quality enhancement via filtering of sediment and contaminants, flood mitigation, climate regulation, and protection of the surrounding marine ecology (Hamzah et al., 2020; Yunus et al., 2018). Mangroves perform a number of ecosystem services, including serving as a natural protection, a nursery area, a shoreline stabilizer, a source of nutrients and sediment, a storm barrier, a flood and river management system, a source of water quality, and a frontier that shields coastal land from the damaging impacts of storms, tides, and tidal waves (Ellison, 2014).

There is a delicate ecological balance between the importance of mangroves, their distinctive structural design, and the unique ecological role they play, and the threats posed by the changing climate. Because of the vast quantity of carbon that is available within both the below and above ground biomass, the preservation of mangrove forests is coming to be seen as an increasingly important factor in the fight against and the development of strategies to adapt to the effects of climate change (Hamzah et al., 2020). Tree biomass stores carbon, which is ultimately lost through decomposition and exported to neighbouring ecosystems (Carugati et al., 2018). It is believed that the potential of mangroves to store carbon is between 990 and 1074 t/ha, making them the sort of forest that can store the most amount of emissions compared to any other species (Donato et al., 2011).

As a result of the significance of mangroves that shown in Figure 2.1, governments in many parts of the world have recently enacted legislation designed to preserve these ecosystems. (Jia et al., 2018). To the local inhabitants, these ecosystems are of the greatest importance since they provide fishing products (such as fish, shrimp, crabs, and mollusca), timber goods (such as firewood and structural materials), and recreational purposes such as eco-tourism (Wang et al., 2018; Walters et al., 2008). In spite of their significance, mangroves are being lost at a rate of 1%–2% every year on a global scale, and this rate has increased to 35% over the course of the past 20 years (Carugati et al., 2018). Changes in the climate, such as rising sea levels and altered rainfall patterns, as well as human activities, such as urban growth, mining, aquaculture, and excessive harvesting of timber, fisheries, shellfish, and crustaceans, pose significant dangers to mangrove environments. Therefore, it is clear that human pressures pose a significant risk to the mangrove forest (Khalik & Afzan, 2020). The aquaculture industry, one of the fastest-growing animal-producing segments, is also a major threat to the mangrove forests (Ottinger et al., 2016).

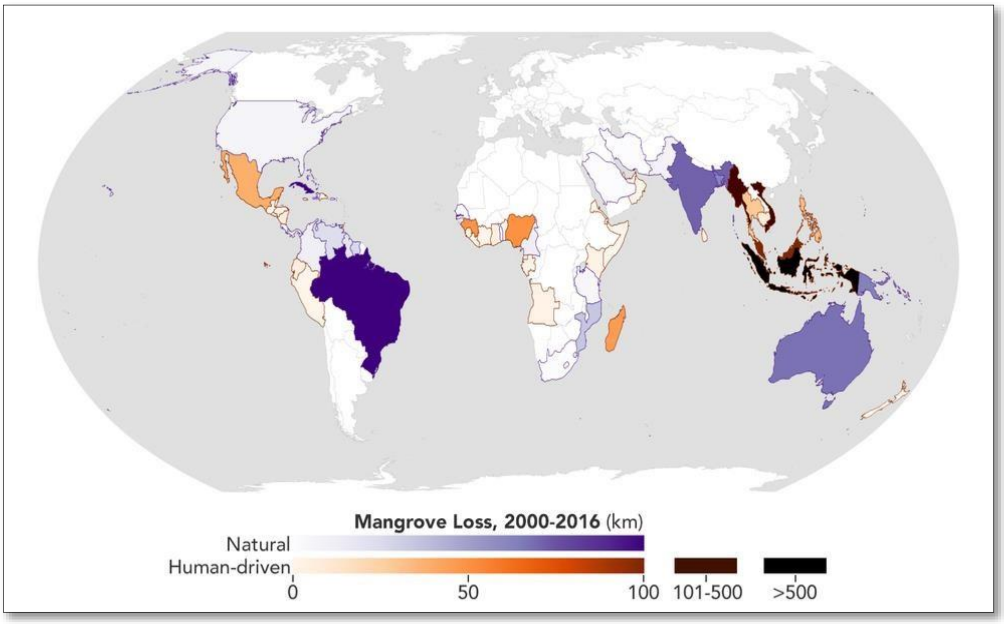

Figure 2.1: The Locations and Kilometers-Long Extent of the Loss of Mangrove Habitat (Merzdorf, 2020)

2.2.1 Mangrove in Malaysia – Pahang

Malaysia is one of the countries in South East Asia with the greatest concentrations of mangroves (Omar et al., 2018). Mangrove forests can be observed on all coastlines, but the greatest concentrations can be discovered in Sabah and Sarawak (Shukor, 2004). The most of the mangrove habitat can be found on the west coast, which is more protected. Mangrove forests are abundant in Malaysia and may be found in the country's muddy coastlines, lagoons, and all along its rivers. These areas are all influenced by the tides. Mangrove forests are a distinct ecosystem that are typically found along protected coasts (Halim et al., 2019). These woods thrive in salty soil and seawater and are exposed to frequent inundation by both fresh and salt water. Mangrove forest elements have a great commercial value, including fuel wood and lumber, many types of fish, crabs, and shrimp, and medicinal seeds and fruit. Furthermore, mangrove forests can be used for other purposes such as agricultural, aquaculture, shipyards, landfills, and the development of fishing dock.

Omar et al., (2019) said that Malaysia has 629,038 ha of mangrove forests, of which Sabah has 22%, Sarawak has 61%, and Peninsular Malaysia has the remaining 17% are shown in Figure 2.2. Approximately 52% of the coastline of Malaysia is covered with mangroves. Pahang is located on the east coast of Peninsular Malaysia and has 2159.90 ha of mangroves, which are inhabited by Sonneratia alba and Rhizophora mucronata (Saad et al., 2009). The species exhibit lot of variety among some of the kinds, which can be seen in some regions as a specific zonation pattern. On the shoreline deposits in which there is soft, deep mud, there typically is an Avicennia-Sonneratia community, though the Rhizophora-Bruguiera woodland is the most prevalent. The tremendous development operations in Pahang have put great strain on the coastal ecology. The current risks to Pahang's mangrove forest arise mostly from residential and industrial development, followed by fishery and some other associated matters. Coastal development is one of the key factors that have reduced the distribution of mangroves along the Pahang coastline (Hamzah et al., 2020; Carugati et al., 2018; Saad et al., 2009). Continuous monitoring of mangroves over time is required to ensure the survival of mangroves and the development of sustainable coastal zones.

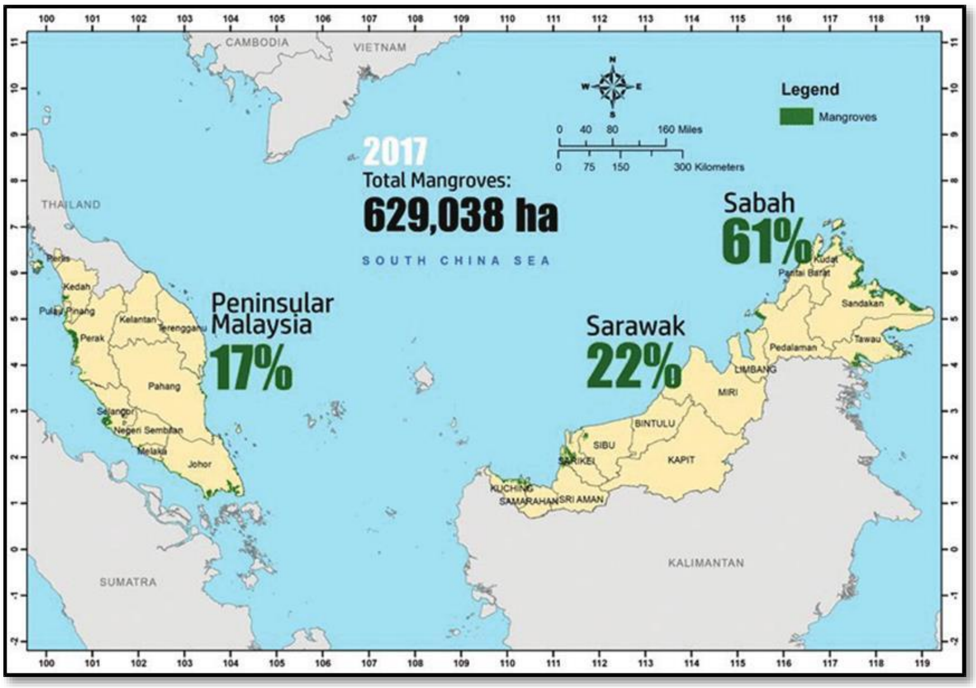

Figure 2.2: The percentage of land covered by mangroves in Malaysia (Omar et al., 2019)

2.2.2 Type of Mangrove

Mangroves are a type of tropical plant that thrives in salty, saline, and sometimes flooded soil. The spread of mangroves appears to be significantly influenced by soil type, climatic conditions, salt water, tidal fluctuations, and others. Variations in the structure and composition of the habitats of mangroves result in distinct mangrove ecosystem categories. Rivera-Monroy et al., (2017) divide mangrove forests into several categories, including riverine mangroves, mangroves along the coast, and trees across the basin. Each type has its own unique traits and ecological roles that help make the coasts more resilient and provide ecosystem services. Different mangrove species each have special functional characteristics that affect how an ecosystem works. According to Rivera-Monroy et al., (2017), prominent mangrove species like Sonneratia, Avicennia, and Rhizophora play important roles in the stability of sediment, cycling of nutrients, and creation of habitat. Foreseeing how shifts in species composition might affect ecosystem functions requires an understanding of these functional roles.

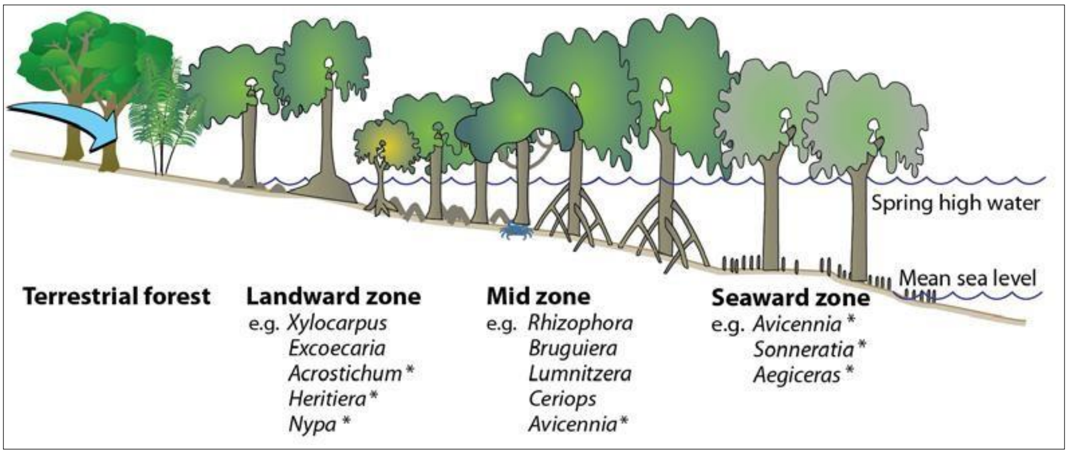

Figure 2.3 Mangrove Species Differ Depending On the Zone (Waycott et al., 2011)

Avicennia, also referred to as the grey mangrove, is an essential plant in ecosystems of mangroves all over the world. A. marina, one of the primary mangrove species, provides vital ecological functions and helps coastal habitats remain stable and resilient. They are usually 10 to 14 meters long and have medium grey or white bark that comes off in stiff, crumbly chunks (Baishya et al., 2020). On the upper surface of their dense, glossy, and brilliant leaf color are small hairs, while the undersides are gray or silvery white. They have growing 20 cm long pneumatophores (Baishya et al., 2020).

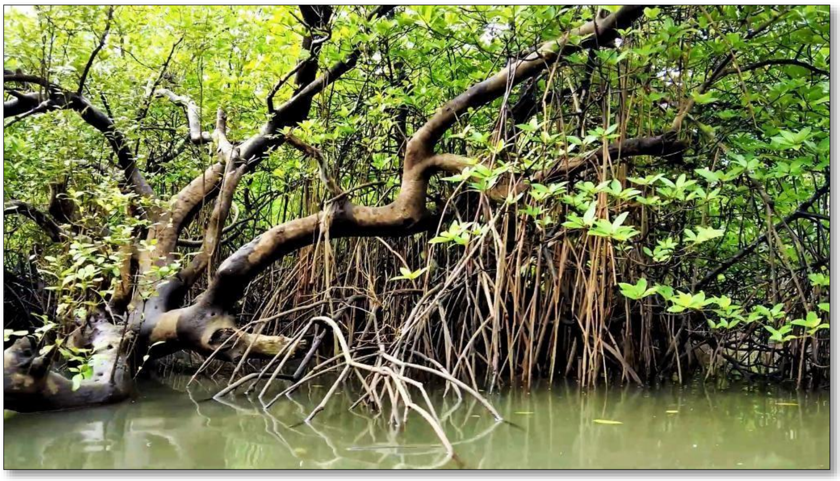

Figure 2.4: Avicennia Species (Midhun Vijayan, 2023)

The stability and operation of mangrove ecosystems depend heavily on Rhizophora species. Their deep root systems offer great coastal defence against storm surges and erosion. Alongi (2020) shows that Rhizophora species help mitigate global warming and maintain the condition of coastal waters by sequestering carbon and cycling nutrients.A variety of coastal ecosystems can thrive in Rhizophora woods because of its intricate structure and extensive root system. Alongi (2020) provide evidence of the high biodiversity connected to Rhizophora stands, with a focus on their role as nascent habitats for numerous aquatic life, including shrimp and fish.

Figure 2.5: Rhizhopora Species (Martin Mergili, 2004)

Bruguiera species adapt well to the intertidal zone's changing environment. Bruguiera's pneumatophores promote gas exchange in wet soils and anaerobic survival (Kathiresan and Bingham, 2001). Also, their viviparous propagules give them a competitive edge by letting the seedlings grow before they spread (Aluri et al., 2016). Reproductive methods of Bruguiera species affect population dynamics and habitat colonization. Bruguiera gymnorrhiza's propagules can survive for long durations, allowing tidal currents to disperse them. Aluri et al. (2018) researched its reproductive biology.Bruguiera stands are vital nursery habitats for many coastal and aquatic species. Bruguiera trees provide shelter and food for many fish, crabs, and birds, increasing coastal ecosystem biodiversity, according to Dahdouh-Guebas et al. (2016).

Figure 2.6: Bruguiera Species (Gennu, 2022)

2.3 Vegetation Index

In remote sensing applications, the vegetation index has been used for very long time to track the temporal changes that are related with vegetation (Anim et al., 2013). Vegetation indices are often calculated by performing nonlinear or linear component operations on remote sensing - based near-infrared (NIR) and red spectral information, which are simple and useful metrics for evaluating vegetation and growth state. The highest vegetation index composite uses the highest value of the vegetation indices within a specific time frame as the criteria for the remote sensing information. This choice is made using the highest value of the vegetation indices.

2.3.1 Normalized Difference Vegetation Index (NDVI)

The NDVI inside the vegetation indices is among the most commonly employed methodologies in such assessments due to its excellent association with photosynthesis rate, which serves as basis for its use in estimating the net primary output (Nalawade et al., 2022). The Normalized Difference Vegetation Index (NDVI) is calculated using the properties of vegetation, which include a discernible absorbance in the red wavelength and a very high absorption in the NIR region (Hamzah et al., 2020). This method has been implemented in order to observe the chlorophyll content distribution of the natural flora that covers the surface of the earth. NDVI is computed using Equation 1 (Omar et al., 2020).:

$$\text{NDVI} = \frac{NIR - RED}{NIR + RED} \tag{1}$$

Which band RED and NIR represent the visible red reflectance value and NIR reflectance value, respectively. The range of NDVI output values is between 1 and +1. Generally, healthy vegetation has a high NIR reflectance and substantial absorption in the red spectral band (Donoghue, 2001). Positive values represent various vegetation classes, whilst near zero and negative values represent non-vegetation classes such as snow, barren land, water, and urban areas (Muhsoni, 2020).

2.3.2 Enhanced Vegetation Index (EVI)

The Enhanced Vegetation Index (EVI) improves on the NDVI by addressing its drawbacks. EVI has gained appeal in remote sensing situations because to its greater susceptibility to vegetation shifts and reduced impacts from weather conditions and foreground soil reflectance. When compared to NDVI, EVI is more sensitive in high biomass situations and less susceptible to saturation effects at greater vegetation densities. According to Towers et al., (2019), EVI outperformed NDVI in boreal forests during peak growing seasons. EVI has been used to measure how plants react to things like temperature change, changes in land use, and disturbances. Zhang et al. (2017) used EVI to investigate the effects of drought on agricultural health and discovered that EVI was an accurate measure of vegetative distress during dry times. EVI aids preservation and environmental monitoring.

2.3.3 Soil-Adjusted Vegetation Index (SAVI)

A vegetation index called the Soil-Adjusted Vegetation Index (SAVI) was created to lessen the impact of foreground soil reflectance on vegetation estimates made using remote sensing data. SAVI has been widely utilized in a variety of disciplines, including forestry, agriculture, and environmental monitoring, because to its more sensitive nature to vegetation conditions in places with changing soil brightness. SAVI is especially helpful in places with minimal vegetation or exposed soil because it incorporates the soil-adjustment factor, which makes it less sensitive to changes in foreground soil reflectance. Ranjan et al. (2019) compared SAVI and NDVI in desert regions and discovered that SAVI did a better job of capturing modifications to vegetation and enhancing tracking of vegetation in those regions than NDVI. SAVI has been used in environmental studies to evaluate the dynamics and health of the plants in different situations. Wang et al. (2016) used SAVI to analyze vegetation changes in aquatic ecosystems, demonstrating the index's potency in capturing differences in vegetation parameters in these delicate settings.

2.4 Classification of Mangrove

Globally and regionally, mangrove habitats can be effectively mapped and classified using remote sensing technologies. It has been used to categories mangrove environments at various phases of succession. Machine learning methods were applied to multispectral satellite imagery by Swamy et al. (2018) in order to classify the various successional stages, which ranged from pioneer mangrove forests to mature mangrove forests. Common methods for categorizing mangroves include spectral analysis and vegetation indices. Mumby et al. (2016) used spectrum analysis methods to distinguish between various species of mangroves based on their distinctive spectral signatures. Mangrove health and density have been evaluated using vegetation indexes like NDVI and EVI. OBIA has also acquired attention for its capacity to classify objects based on their geographical environment. Gandois et al. (2019) classified mangrove species and assessed vegetation changes over time using OBIA and high-resolution satellite imagery. OBIA makes it easier to figure out where different mangrove habitats are by looking at the size, shape, and placement of items.

Table 1.1: Criteria for Mangrove Damage

Condition	Criteria	Cover (%)	Density
Good	Very dense	> 75	> 1500
	Medium	$\geq 50 \leq 75$	$\geq 1000 \leq 1500$
Damage	Rare	< 50	< 1000

Source: Standard criteria for damage to mangrove forests established by the Ministry of Environment RI No. 201 in the year of 2004 (Efriyeldi et al., 2020)

2.4.1 Object Based Image Analysis (OBIA)

OBIA is a pixel-based approach substitute that uses picture objects as the basic evaluation tool rather than individual pixels. By arranging a group of pixels into forms that meaningfully reflect the objects, this technique seeks to get around the issue of the per-pixel method's usage of false square cells. OBIA is designed to deal with more complicated classes that are determined by geographical and hierarchical interactions both before and after the classification process. The OBIA approach leverages the image segmentation process' built-in objects and segments to classify data, which is subsequently categorized in accordance with a predetermined classification scheme (Pasaribu et al., 2021). Image segmentation is a fundamental stage in OBIA classification in which contiguous pixels with comparable spectral features are grouped into homogenous objects. Benz et al. (2004) developed the multi-resolution segmentation approach, which is now commonly employed in OBIA to create meaningful image objects for categorization. OBIA classification enables multiscale object analysis by integrating diverse spatial resolutions and disparate data sources. Lang et al. (2018) used OBIA classification to map land cover in heterogeneous landscapes by integrating high-resolution optical and medium-resolution radar data for improved classification accuracy. The precision of subsequent element feature extraction and classification is primarily dependent on the quality of image segmentation. Multiple algorithms were utilized at each level of categorization to create a rule set, and its application is tailored to the user's requirements for categorizing things into certain classes (Lombard et al., 2021).

2.4.2 Supervise Classification

Supervised classification is a frequently used remote sensing approach for mapping and classifying land cover and land use categories based on labeled training samples. Different classification strategies and accuracy evaluation methods have been created and used in a variety of settings, including metropolitan centers, agricultural areas, forested areas, and wetlands. The availability of high-resolution remote sensing data and further developments in supervised classification algorithms are likely to expand its uses in land resource management, environmental monitoring, and ecosystem studies. Supervised classification has been used to map land cover in urban contexts with rapid land-use changes and complex spatial patterns. Foody and Mathur (2004) investigated the application of SVM and MLC for urban land cover classification and established their efficacy in accurately mapping urban features. Land use mapping is critical in agricultural regions for monitoring crop types and agricultural activities. The mapping of land usage in agricultural landscapes has been done using supervised classification methods such Decision Trees and Random Forest (Jin et al., 2017). These studies emphasize the usefulness of supervised classification and remote sensing data in assisting methods in precision farming and land management. For forest cover mapping and monitoring, supervised classification has been widely used. Liu et al. (2015) compared how well MLC and SVM did at mapping forest types and evaluating forest changes. This showed that supervised classifiers can help with forest resource management and protection efforts.

2.4.3 Unsupervised Classification

Unsupervised classification is a frequently used technique in remote sensing for finding patterns and structures in data without the need for specified training examples. Segmenting images into objects based on their shared spectral characteristics requires the use of unsupervised classification. In his assessment of the application of unsupervised classification to object-based methods, Blaschke (2010) emphasized the significance of taking spatial context into account when mapping land cover. Unsupervised classification is useful in hyperspectral remote sensing for separating spectral signatures and endmembers from complicated spectral data. Plaza et al. (2002) examined unsupervised techniques for hyperspectral image processing, highlighting its capacity for identifying minute spectral changes and spectral mapping of materials. In the mapping of vegetation and the analysis of habitats, unsupervised categorization has been widely used. Foody and Mathur (2004) investigated unsupervised vegetation mapping techniques, emphasizing its potential for identifying ecological areas and vegetation classes in remote sensing data.

2.5 Accuracy Assessment

Remote sensing investigations must assess categorization results' accuracy. Measure the classification's precision by contrasting it with external references. Olofsson et al. (2014) studied the different accuracy assessment methods used in mapping world land cover. They showed how important quality assessments are for getting accurate information about land cover. This method's effectiveness is assessed by contrasting the image of the LULC classifying result with other sources of information, including field data and topographic maps. The kappa accuracy gives a statistically valid evaluation of the quality of categorization and was utilized for the purpose of evaluating the total class accuracy, as indicated in Equation 2 (Hamzah et al., 2020).:

$$\hat{K} = \frac{N\sum_{i=1}^{r} Xii - \sum_{i=1}^{r} X_{i+}X_{+i}}{N^2 - \sum_{i=1}^{r} X_{i+}X_{+i}} \qquad (2)$$

Where:

r	: Number of rows/columns in confusion matrix
Xii	: Number of observation in row i and column i
Xi+	: Total number of row i
X+i	: Total number of column i
N	: Number of observation

CHAPTER THREE

RESEARCH METHODOLOGY

3.1 Introduction

This chapter details the research process and outcomes. The methodology was developed in order to facilitate the accomplishment of the aims and objectives of the research. This chapter discusses the four-stage procedure of data collection, data processing, and result and analysis.

3.2 Methodology

The processing work that was done to reach the aim and objective of the study will be brought to a close by the research methodology section. The overall procedures for conducting the research are depicted in Figure 3.1. This project's approach consists of three major phases which is I) planning, II) data acquisition, and III) data processing and IV) result and analysis.

The first phase entails a research review and region identification, often known as data collecting. The study area chosen for this research is from Cherating to Pekan, Pahang. The proposed study location was selected for no other reason than to serve the needs of the research. The selection of Pahang was made because the mangrove ecosystem in that region has become an essential component of the regional fishing industry. Therefore, the objective of the research was to classify the mangrove habitat in Pahang.

The next phase is data processing which applying pre-processing of satellite imagery to the focused area. The extracted information will be processed for the classification of mangrove and determination of the vegetation index. The method used in this section is Object Based Image Analysis (OBIA). The Algorithm proposed is Normalized Differences Vegetation Index (NDVI) to determine the healthiness of mangrove habitat.

The results and the analysis make up the last phase. In order to understand the final outcome of this research, the analysis that was done is explained. As far as this study is concerned, the researcher's goal is to identify how the Normalized Differences

Vegetation Index (NDVI) and the Land Use Land Cover (LULC) of mangroves are related to one another.

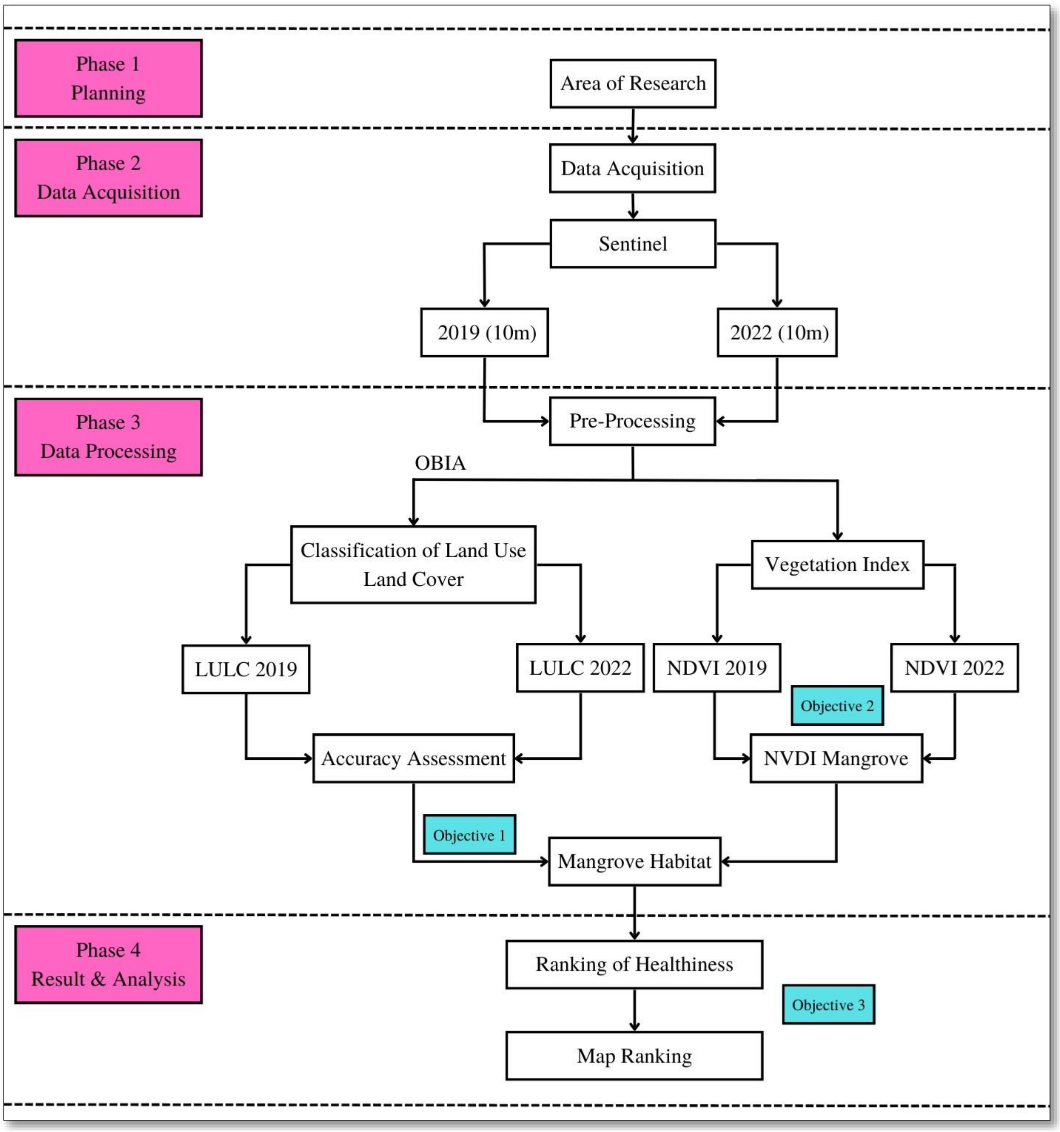

Figure 3.1: Research Methodology Workflow.

3.3 Study Area

The research was carried out along the Cherating-Pekan beachfront of the Pahang state, which is situated on the East Coast of Peninsular Malaysia are shown in Figure 3.2 and looks out over the South China Sea. It location between 04°07’38’’N, 103°23’45’’E (Cherating, Pahang) and 03°32’05’’N,103° 27’ 41’’E (Pekan, Pahang). The sandy shoreline that runs along the Cherating and Pekan coastal areas is almost 84 kilometers long. The mangrove regions are situated along the Cherating, Ular, Kuantan, and Penor rivers. These regions are not only an important element for the local fisheries sector, but also serve as crucial breeding and feeding grounds for a wide range of aquatic and intertidal organisms.

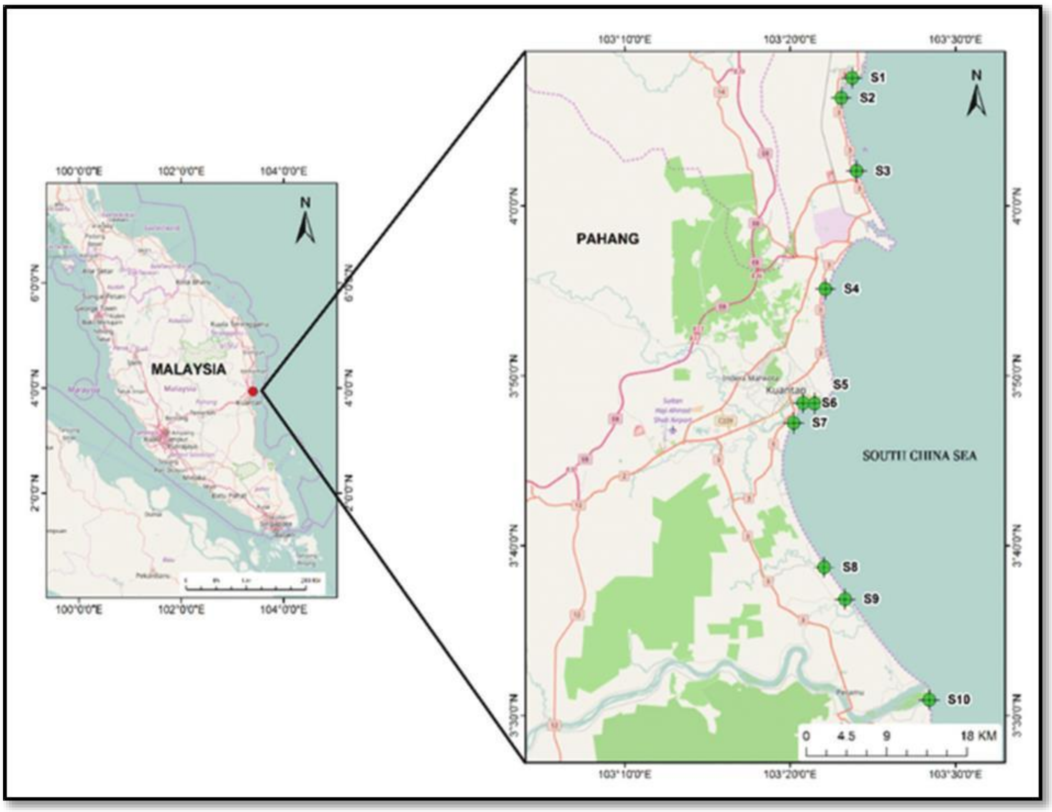

Figure 3.2: Map of Pahang shoreline, Malaysia.

3.4 Data Processing

3.4.1 Satellite image

The satellite imagery of Sentinel 2A came from the Copernicus website, which has a free resource. The multi-spectral imager aboard Sentinel-2A has 13 separate spectral bands, covering the entire spectrum from the visible to the infrared. Depending on the spectral band, the satellite can record images with a resolution of 10, 20, or 60 meters. This multi-spectral capability makes it possible to recognize different types of land cover, as well as to evaluate the health of the plants and the purity of the water. However, just 10 meters' worth of resolution was chosen because this research will use picture categorization. High pixel resolution results in accurate image classification.

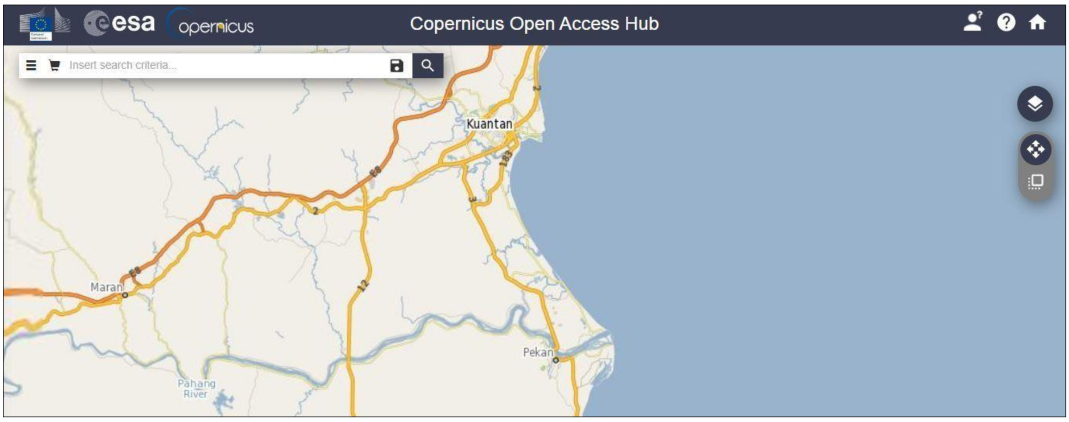

Figure 3.3: Copernicus Open Access Hub Display

3.4.2 Pre-Processing

Layer stacking was used to aggregate different raster layers (images) into one large image to use as a starting point for the data. The primary objective of layer stacking is to produce a single image containing data from different spectral bands or sources. Then, radiometric calibration is carried out to convert digital numbers into physically relevant quantities like reflectance or radiance. Geometric correction is then applied to reduce distortions induced by the curvature of the Earth and sensor orientation, allowing the images to be aligned with their correct geographical locations. Atmospheric correction is essential for compensating both absorption and scattering effects in the atmosphere, supplying surface reflectance values and allowing quantitative analysis. Finally, regions of interest or subsets of data can be chosen to narrow the scope of the investigation.

3.4.3 Object Based Image Analysis (OBIA)

Image segmentation is the first step in the process, which divides the image into homogeneous parts using algorithms that take into account spectral, spatial, and textural features. The following step involves removing features, or metadata, from these image objects. Then, supervised classification is carried out on a training dataset utilising objects that have been manually annotated with their respective classes. Randomly selected sample areas within each class were then selected using polygons to show their geographic scope. During these training examples, feature values were taken from objects that had been split up. Post-processing operations, such as object refining and merging, can be used to enhance classification precision and object coherence.

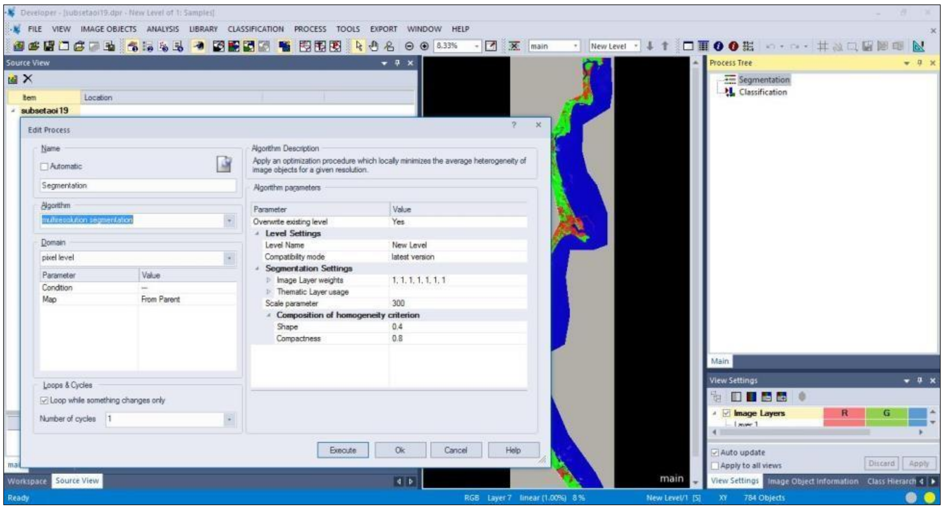

Figure 3.4 OBIA in Ecognition Software

3.4.4 Land Use Land Cover (LULC)

The image data is then processed to obtain a collection of pertinent features. These attributes could involve spectral information from various bands, texture measurements, and any other auxiliary data that is accessible. A classification algorithm (such as Support Vector Machines or Decision Trees, for example) is trained to learn the correlations between the extracted features and the relevant land cover classes by making use of the training dataset. This allows the algorithm to more accurately classify images. The algorithm constructs a decision boundary so that it can differentiate between the various classes using the feature space as the basis. As soon as the model has been trained, it is used to categorise each pixel or image object into one of the specified land cover classes, and it is then applied to the entire image. The algorithm assigns the most likely class to each pixel or object by making use of the features that were retrieved from it as well as the decision boundary.

3.4.5 Accuracy Assessment

After OBIA and LULC, the accuracy assessment will determine if the classes werecorrectly classified. An accuracy study was done to see how accurate and reliable the land cover classification results from using the OBIA method are. Classified land cover maps and ground truth data were evaluated for precision. The first stage is to gather reference data, often called ground truth data, that accurately depicts the actual land cover or featureclasses in the research area. This data can be gathered through field surveys, high-resolution imaging, or dependable datasets. Next, create a sampling technique to compare classified and reference data. Random or systematic sample locations are chosen across the study region to guarantee a representative and untainted assessment. The categorized data and reference data are compared using sample points to build an error matrix. The error matrix depicts class counts of correctly classified and misclassified data. Accuracy metrics are produced from the error matrix to evaluate classification performance.

3.4.6 Normalized Difference Vegetation Index (NDVI)

NDVI has several uses, including in farming, tree-planting, ecology research, and urban development. NDVI is employed in agriculture to monitor crop health and evaluate the efficacy of irrigation and fertilisation practises. In forestry, NDVI is used to monitor tree density, tree health, and replanting operations. NDVI is a useful tool in environmental monitoring for gauging the effects of shifting land uses and environmental deterioration. It took the Red band and NIR band to generate the indices in order to get the mangrove's NDVI value. The algorithm for NDVI had been put into the software so that it could figure out the number of NDVI. NDVI values are calculated for each picture pixel. Reflectance values are normalised to -1 to +1. The NDVI values are used to build an NDVI map, where the hue or saturating level of each pixel is indicative of the mangrove's vitality. The NDVI map shows where vegetation is located and how healthy it is within the research region. Higher NDVI values mean the mangrove are healthier and there are more of them, while lower values mean the mangrove aren't as healthy or there aren't as many of them.

3.4.7 Ranking of Healthiness

This study will show how the overall health of mangrove plants evolved over the selected two-year time frame. The standard criteria for mangrove healthiness will be divided into three categories depending on the level of health of the mangrove forests. These categories will be high, medium, and low. The category level of healthiness for mangrove forests will be developed utilising the interpolation method as the final output. The necessary analysis to build category-based maps of the mangrove ecosystem's health.

Table 2.1: Standard Criteria for Mangrove Healthiness

Condition	Criteria	Cover (%)	Density
Good	High	> 75	> 1500
	Medium	≥ 50 ≤ 75	≥ 1000 ≤ 1500
Damage	Low	< 50	< 1000

3.5 Software Used

3.5.1 Erdas

Erdas Imagine is an image processing application that can manage geospatial, non-geospatial, and vector pictures and data. Erdas can also process hyperspectral pictures and LiDAR data from a variety of sensors. A 3D viewing tool (Virtual GIS) and a vectors modelling module are also included. Among computer languages, EML is the "mother tongue" (Erdas Macro Language). It is also integrated into some other GIS and remote-sensing applications, and various other software packages (*.img files) can access the imagery storage format. Leica Geosystems added ER Mapper to their mapping toolbox as well. Erdas Imagine is much more firmly integrated into GIS than other image analysis software programmers, making this bundle valuable.

It is potential to see objects that would otherwise be unseen by changing the placement of data in photos. Photographs with high contrast or reflective surfaces could be helpful inside a variety of contexts, including botany research and mineral extraction. For instance, these can be used for spatial model processing, linear extraction, data import/export in several formats, Orto-rectification/picture mosaicking, automatic image map extraction, and so on.

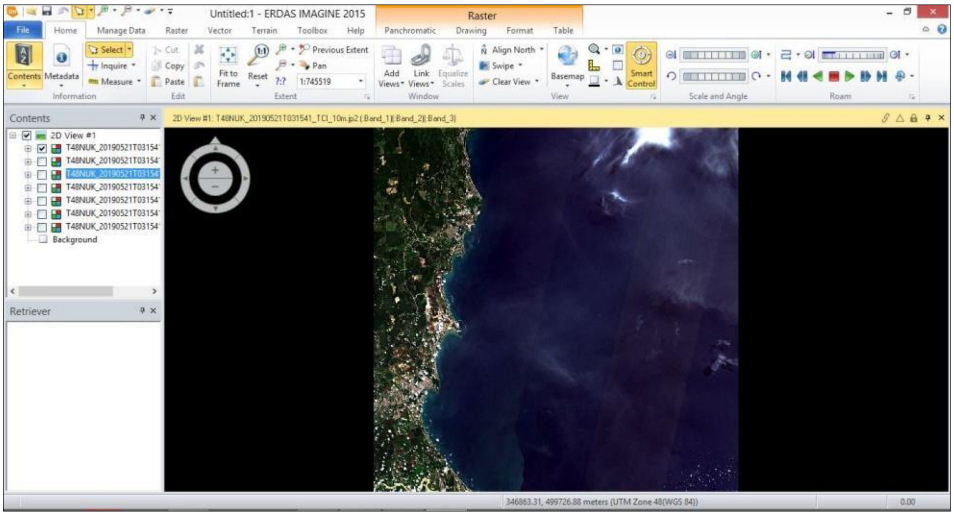

Figure 3.5: Erdas Interface

3.5.2 ArcGIS

A geographic information system, sometimes known as a GIS, is a type of application software that can gather, store, manipulate, analyse, manage, and display different kinds of geographic data. To put it another way, geography indicates that every piece of data is geographical. Any piece of information that may be categorised as "geographic" is considered to be part of the field of geography.

ArcGIS is a platform for managing maps and geographic information. ArcGIS is used to produce maps, obtain spatial data, and process map data. It also refers to the sharing and discovery of geographical knowledge, the utilisation of maps and geographic information in a range of applications, and the management of geographical data inside a database.

ArcGIS Enterprise includes server-based software and mobile apps. ArcGIS's capability can be expanded by purchasing add-ons known as extensions, which can be done independently. Professionals can also get an ArcGIS certification through Esri's training programmes, which range from introductory to advanced.

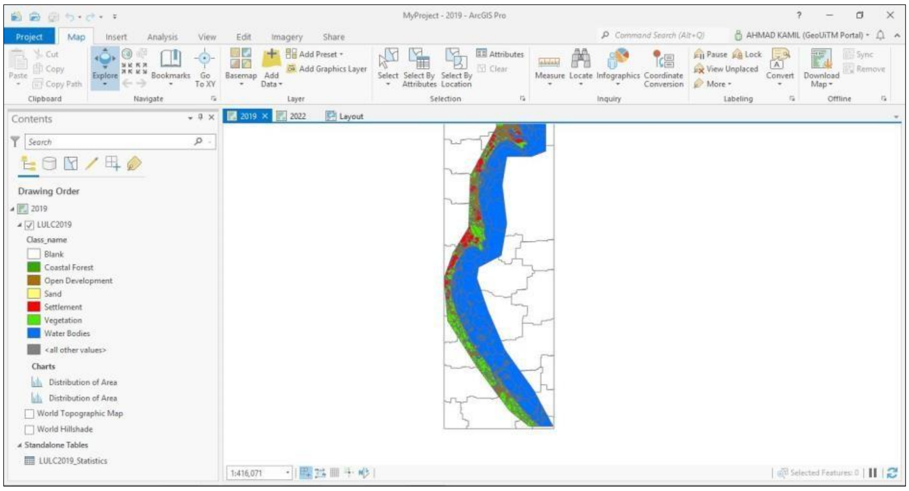

Figure 3.6: ArcGIS Interface

3.5.3 Ecognition

Professionals in GIS, remote sensing, and data science use Trimble eCognition software to automate geographic data analytics. Users can create feature extraction solutions in order to convert geo-data into geo-information. The options are limitless. eCognition can combine a wide range of geographic data, including 3D point cloud data, spectral raster data, and thematic data from GIS vector layers. Images can communicate with point clouds, vectors with images, and all three with one another. Users may utilize the full potential of their input data, regardless of the dataset or source. The eCognition Suite includes three distinct components that can be used independently or in tandem to tackle even the most difficult image analysis problems.

CHAPTER FOUR

RESULTS AND ANALYSIS

4.1 Introduction

In this part, the results are listed and analyzed so that the study's goals can be met using the parameters used. OBIA which stands for object-based image analysis is used in conjunction with a geographic information system (GIS) to locate areas with mangroves.

4.2 Mangrove Classification Using Object Based Image Analysis (OBIA)

The advanced technique known as object-based image analysis (OBIA) is used in remote sensing and image processing to examine digital images based on the traits and connections of specific objects within the image. OBIA takes into account the spatial context and relationships between neighbouring pixels, in contrast to pixel-based analysis. Segments, or picture objects, are constructed based on commonalities in spectral, spatial, and contextual features. The extraction of characteristics such as shape, size, texture, colour, and contextual information from these objects enables algorithmic categorization into various categories. OBIA delivers more accurate interpretation by taking object context into account and combining diverse data sources, and it has applications in land cover mapping, urban planning, environmental monitoring, agriculture, and disaster management.

4.3 Segmentation of Image

Segmentation based on shape, size, and compactness is a powerful way to pull meaningful things out of digital images. Utilizing these three crucial variables makes segmentation more effective and robust, producing findings that can be believed. Table 3.1 below show the parameter used for both years which is 2019 and 2022 to do segmentation.

Table 3.1: Segmentation Parameter.

Parameter	Value
Shape	0.4
Scale	300
Compactness	0.8

From the table 3.1 above, the shape parameter of 0.4 indicates that the segmentation process will consider the geometric properties of objects in the image. A lower shape parameter value suggests that the segmentation algorithm will prioritize objects with more irregular or complex shapes. Then, the scale parameter of 300 indicates that the segmentation process will consider objects at various sizes within the image. This is crucial in capturing the multiscale nature of mangrove ecosystems, which consist of vegetation patches of different sizes and densities. By incorporating multiple scales, the segmentation algorithm can effectively identify mangrove objects at different resolutions, accounting for both larger dominant patches and smaller, more intricate structures. Lastly, the compactness parameter of 0.8 signifies that the segmentation algorithm will prioritize objects with higher spatial coherence or compactness. This parameter controls the smoothness or fragmentation of the generated segments. A higher compactness value indicates that the algorithm will tend to produce more compact and cohesive objects. Figures 4.1 and 4.2 below show the result of segmentation generated from parameter used.

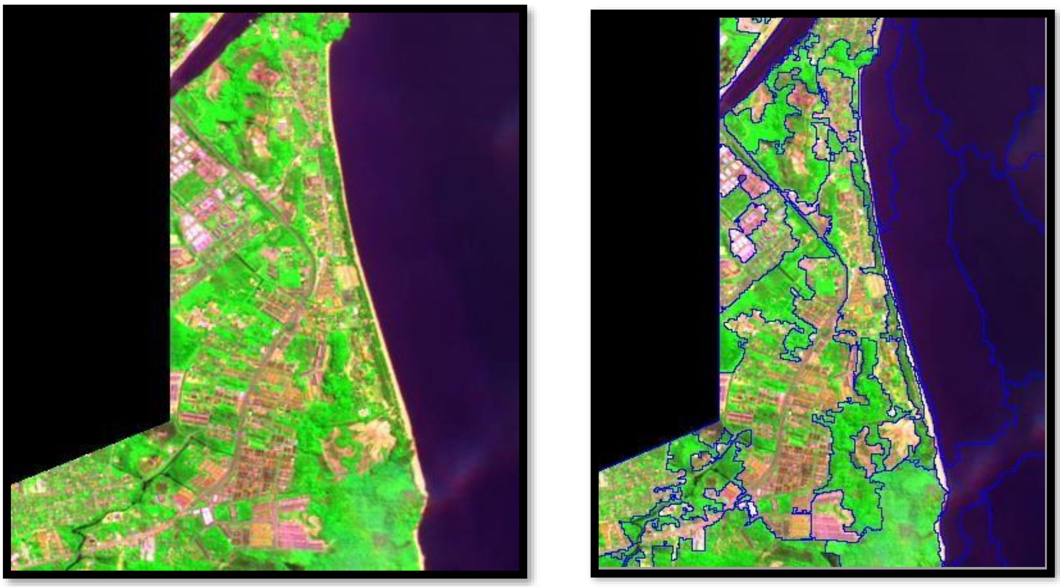

Figure 4.1: Segmentation Image 2019.

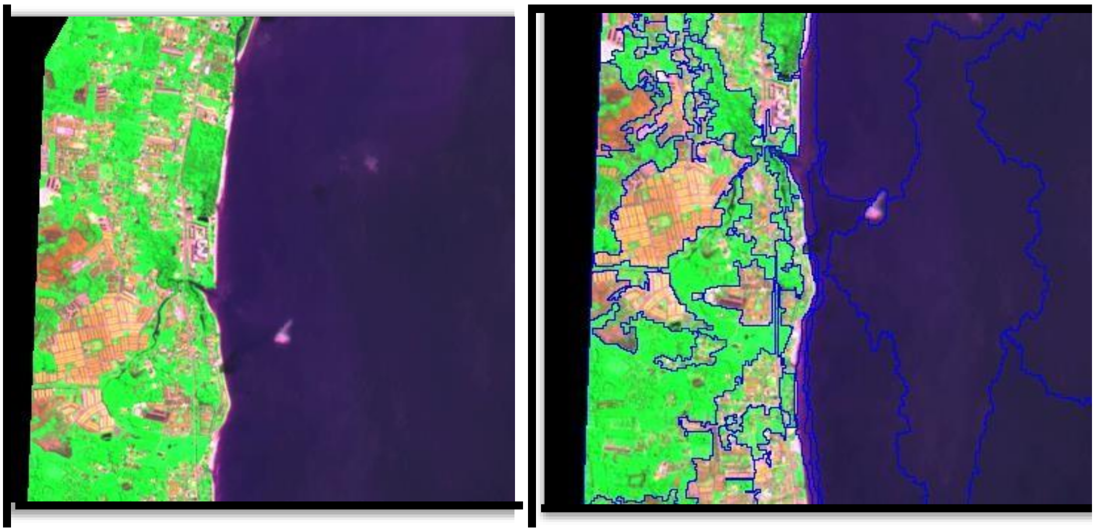

Figure 4.2: Segmentation Image 2022.

4.4 Land Use Land Cover (LULC) Classification

The classified map makes it possible to visualize and evaluate the distribution of mangrove habitats throughout Pahang coastal. It gives information on the spatial size, position, and trends of mangrove forests in the region. Mangrove dominant areas, distance from water, and distribution across topography and landform types can all be determined using this approach. Figure 4.3 below show the differences land use land cover of mangrove between year 2019 and 2022.

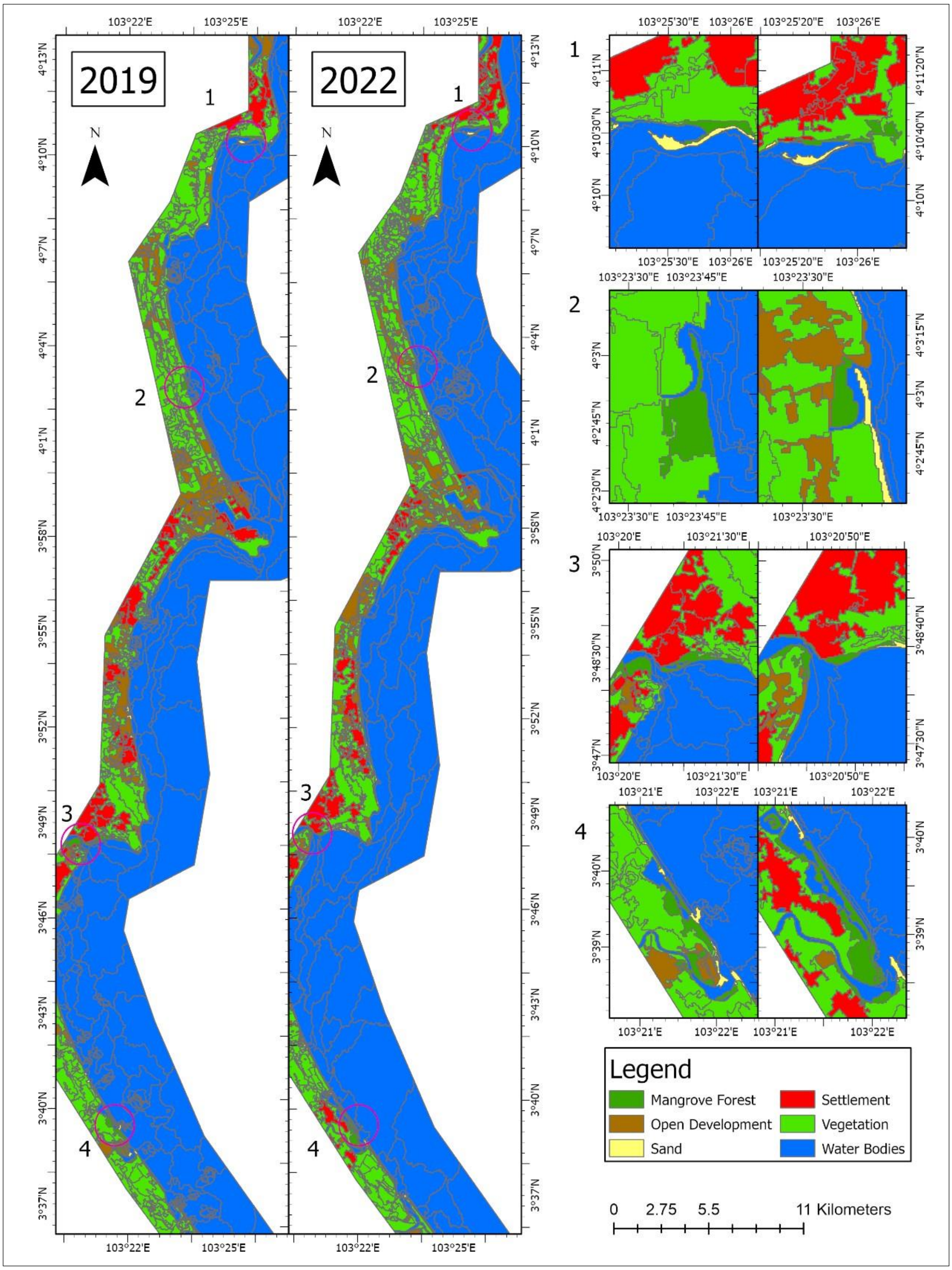

Figure 4.3: Land Use Land Cover (LULC) Classification for 2019 and 2022.

By comparing labelled maps from different time periods, changes in the size and location of mangrove areas can be seen over time. This research makes it possible to track the evolution of mangrove dynamics through time, such as their expansion, contraction, or degeneration. Understanding temporal variations in mangrove cover is critical for analyzing the effects of natural and manmade variables and directing conservation and management efforts. Table 3.2 below show the attribute table of land use land cover.

Table 3.2: Attribute Table of Land Use Land Cover.

Features	Area (ha)		Area Change (ha)	Percentage (%)	Remarks
	2019	2022			
Coastal Forest	1.629	1.860	0.177	5	Increase
Open Development	24.363	27.455	3.092	6	Increase
Sand	2.693	2.306	-0.386	-8	Decrease
Settlement	22.930	24.035	1.105	2	Increase
Vegetation	104.196	101.129	-3.067	-1	Decrease
Water Bodies	359.711	358.825	-0.886	0	Decrease

Analysis of the land use land cover (LULC) changes in mangrove areas in Pahang from 2019 to 2022 reveals both positive and negative trends. Firstly, there was a noteworthy increase in the area of coastal forest, indicating potential conservation efforts and the expansion of mangrove habitats. This 5% increase reflects positive growth and suggests a focus on preserving these valuable coastal ecosystems. Additionally, open development areas experienced a 6% increase, implying human activities and infrastructure development encroaching on mangrove areas. This trend highlights the need for careful planning and sustainable land use practices to balance development with mangrove conservation.

On the other hand, there were decreases in certain land cover classes. The area of sand decreased by 8%, which may be attributed to natural erosion processes or human activities impacting the coastal sediment dynamics. Furthermore, there was a 1% decrease in vegetation, indicating potential changes in vegetation composition, loss of mangrove trees, or shifts in land use practices. These changes emphasize the importance of monitoring and managing the ecological health of mangroves to ensure their long-term sustainability.

Interestingly, the areas of settlement and water bodies experienced relatively small changes, with a 2% increase in settlement areas and a negligible decrease in water body areas. The increase in settlement areas suggests urbanization or population growth near the mangrove regions, while the minor decrease in water bodies may be attributed to natural variations in water levels or changes in hydrological dynamics

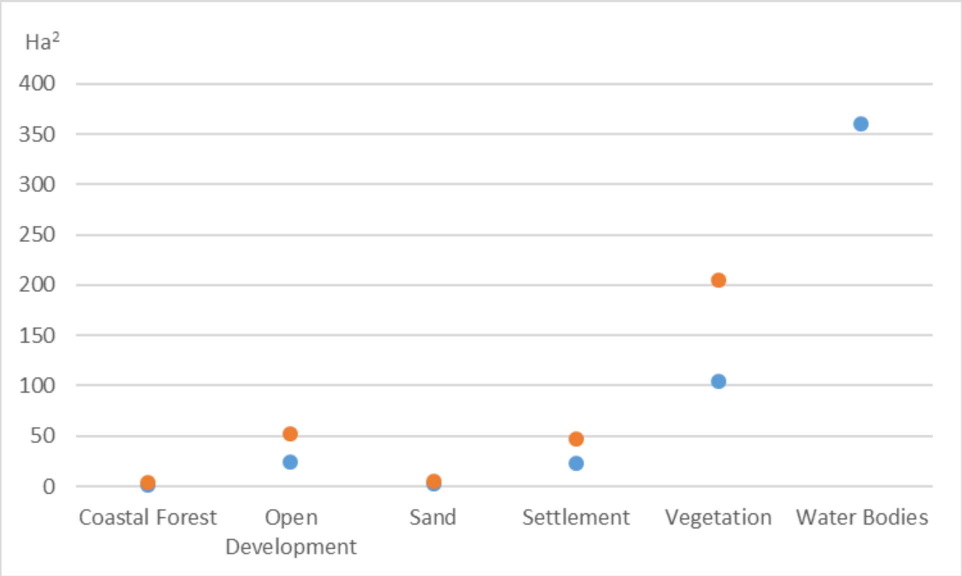

Table 4.4: Graph of LULC Feature Changes from 2019 to 2022.

4.5 Accuracy Assessment

When assessing accuracy, results from an analysis are compared to a reference dataset to gauge their quality. For measuring general performance, result-based assessment uses numbers like accuracy, precision, recall, and error rates. By examining the causes of the results using methods like confusion matrices, error analysis, feature importance, and sensitivity analysis, analysis-based assessment probes deeper. By combining both methodologies, result acquire a thorough picture of the analysis's reliability and limitations, allowing next party to make educated decisions about changes or future actions. Table 3.3 below show the accuracy assessment of the land use land cover classification for the mangrove for year 2019 and 2022.

Table 3.3: Accuracy Assessment of LULC Classification for 2019.

2019	Mangrove Forest	Open Development	Sand	Settlement	Vegetation	Water Bodies	Total (User)
Mangrove Forest	7	0	0	0	1	1	9
Open Development	0	83	0	10	1	1	95
Sand	0	5	13	3	0	0	21
Settlement	0	2	3	55	0	0	60
Vegetation	1	1	0	5	286	8	301
Water Bodies	1	1	0	0	9	250	261
Total (Producer)	9	92	16	73	297	260	747

Producer Accuracy	User Accuracy
Mangrove Forest: 78%	Mangrove Forest: 78%
Open Development: 90%	Open Development: 87%
Sand: 81%	Sand: 62%
Settlement: 75%	Vegetation: 95%
Vegetation: 96%	Settlement: 92%
Water Bodies: 96%	Water Bodies: 96%
Overall Accuracy: 93%	Kappa Coefficient: 0.86

The study of the table 3.3 above demonstrates an overall accuracy of around 93%, showing that the categorization model correctly predicted the land cover categories. There is a wide range of class-specific accuracy, with Coastal Forest having achieved 77.8%, Open Development having achieved 87.4%, Sand having achieved 61.9%, Settlement having achieved 91.7%, Vegetation having achieved 95.0%, and Water Bodies having achieved 95.8%. These specific precisions demonstrate the model's performance for each land cover type. The analysis demonstrates that the model has a high degree of precision for categories such as Vegetation and Water Bodies, but a lower degree of precision for categories such as Sand. The Kappa coefficient of 0.86 signifies a substantial level of agreement between the predicted and actual classifications that exceeds what would be expected by chance alone. This indicates a strong level of consistency in the model's predictions, showcasing its reliability in accurately categorizing the land cover. The overall analysis provides valuable insights into the accuracy and performance of the classification model for various land cover categories, allowing for additional enhancements and adjustments to increase its consistency and reliability.

Table 3.4: Accuracy Assessment of LULC Classification for 2022.

2022	Mangrove Forest	Open Developm ent	Sand	Settle ment	Vegeta tion	Water Bodies	Total (User)
Coastal Forest	7	0	0	0	1	0	8
Open Development	0	104	0	1	0	0	105
Sand	0	0	20	5	0	2	27
Settlement	0	4	4	33	0	0	41
Vegetation	1	2	0	3	295	7	308
Water Bodies	0	2	2	0	6	165	175
Total (Producer)	8	112	26	42	302	174	664

Producer Accuracy	User Accuracy
Coastal Forest: 88%	Coastal Forest: 88%
Open Development: 99%	Open Development: 93%
Sand: 74%	Sand: 77%
Settlement: 80%	Settlement: 79%
Vegetation: 96%	Vegetation: 98%
Water Bodies: 94%	Water Bodies: 95%
Overall Accuracy: 94%	Kappa Coefficient: 0.92

The overall accuracy is estimated to be around 94%. This shows a good level of precision in predicting the land cover categories for the given cases. When we look at each class separately, we find that the accuracy varies quite a little. The accuracy of the Coastal Forest metric is 87.5%, whereas the accuracy of the Open Development metric is 99.0%, the accuracy of the Sand metric is 74.1%, the accuracy of the Settlement metric is 80.5%, the accuracy of the Vegetation metric is 95.8%, and the accuracy of the Water Bodies metric is 94.3%. The data shows that most classes perform well, with Open Development achieving the best accuracy. Sand and Settlement, on the other hand, have lesser accuracies the. The Kappa coefficient, a measure of agreement beyond chance, is reported at 0.92. This signifies a substantial level of agreement between the predicted and actual classifications that exceeds what would be expected by chance alone. The high Kappa coefficient suggests a strong level of consistency and reliability in the model's predictions, highlighting its effectiveness in accurately categorizing the land cover.

4.6 Mangrove Healthiness Using Normalized Difference Vegetation Index (NDVI)

The analysis of mangrove healthiness using the Normalized Difference Vegetation Index (NDVI) provides valuable insights into the condition and distribution of mangrove ecosystems. By calculating NDVI values and analyzing their patterns and variations, it is possible to assess the overall health status of mangroves. Higher NDVI values typically indicate healthier vegetation and better photosynthetic activity. By establishing thresholds and classifying different levels of healthiness based on the observed NDVI values, it becomes possible to identify areas of concern and prioritize conservation efforts. The visual representation of NDVI values on maps helps to detect spatial patterns and variations, enabling effective monitoring and decision-making for the management and protection of mangrove habitats. The figure 4.5 below shows the value NDVI of the Mangrove.

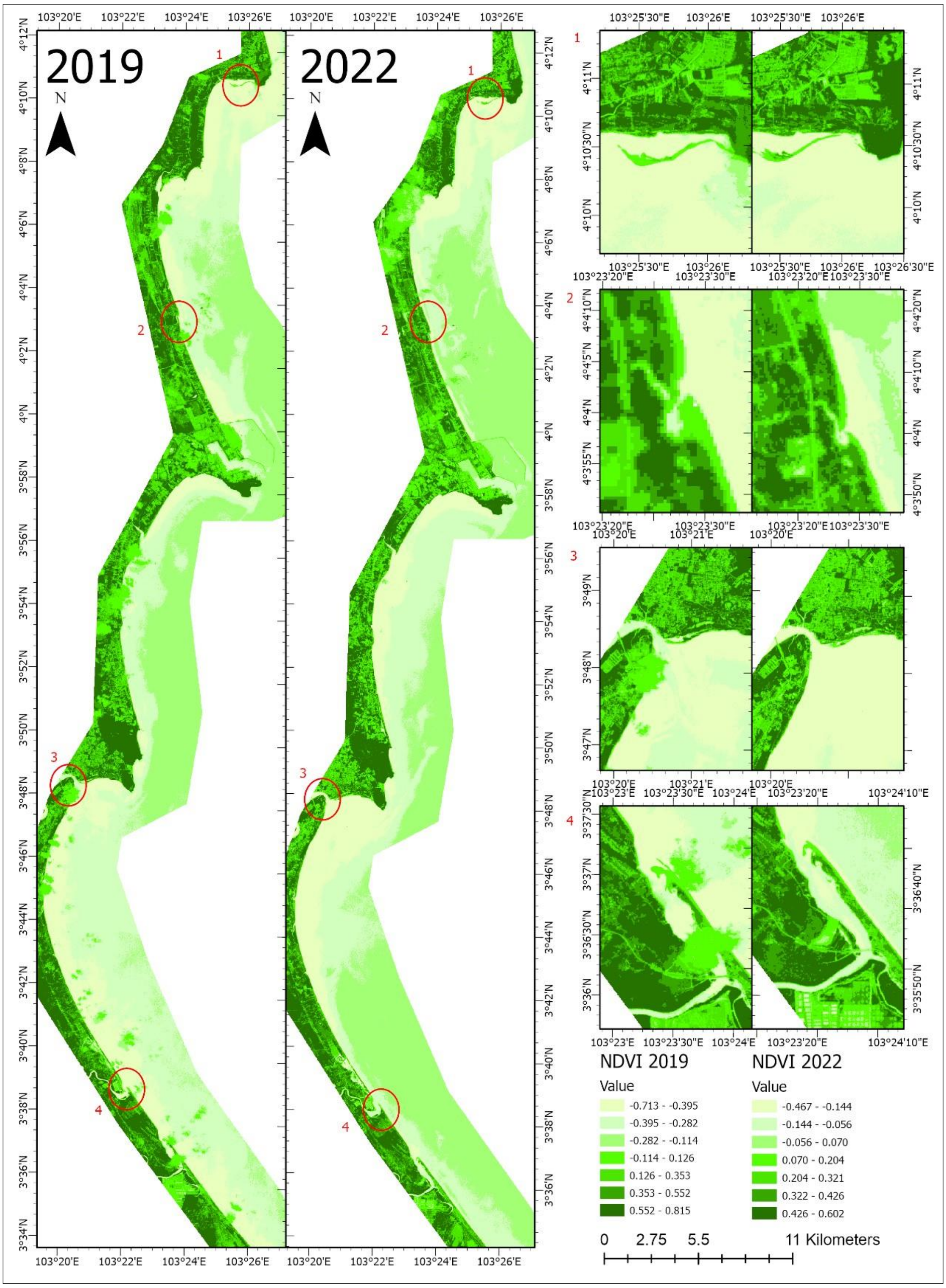

Figure 4.5: Distribution of NDVI at Pahang Coastal for 2019 and 2022.

Table 3.5: NDVI Value for Mangrove in 2022.

Sample	Latitude (N)	Longitude (E)	NDVI Value	Health Condition
1 (A)	4°10’44’’	103°25’33’’	0.621	Medium
1 (B)	4°10’38’’	103°25’32’’	0.409	Medium
1 (C)	4°10’36’’	103°25’38’’	0.207	Low
2(A)	4°03’55’’	103°23’24’’	0.671	High
2(B)	4°03’56’’	103°23’27’’	0.559	Medium
2(C)	4°03’58’’	103°23’29’’	0.147	Low
3(A)	3°48’21’’	103°20’17’’	0.614	Medium
3(B)	3°48’29’’	103°20’21’’	0.605	Medium
3(C)	3°48’29’’	103°20’17’’	0.236	Low
4(A)	3°36’34’’	103°23’17’’	0.563	Medium
4(B)	3°36’45’’	103°23’20’’	0.677	High
4(C)	3°36’46’’	103°23’23’’	0.336	Medium
A – Near Land B – Mid Area C – Near Water				

In the "Near Land" category, Sample 1 (A) exhibits a relatively high NDVI value of 0.621, indicating a medium health condition. This suggests that the vegetation in this area is relatively healthy. Similarly, Sample 2 (A) has an even higher NDVI value of 0.671, indicating a high health condition. These findings suggest that areas near land, as categorized in this analysis, generally show healthier vegetation with higher NDVI values.

Moving on to the "Mid Area" category, both Sample 1 (B) and Sample 2 (B) have lower NDVI values compared to the "Near Land" category. Sample 1 (B) has an NDVI value of 0.409, while Sample 2 (B) has an NDVI value of 0.559. Both samples are classified as having a medium health condition. These results indicate that the vegetation in the mid areas, as categorized in this analysis, shows relatively lower health compared to the areas near land.

Lastly, in the "Near Water" category, both Sample 1 (C) and Sample 2 (C) display the lowest NDVI values among the three categories. Sample 1 (C) has an NDVI value of 0.207, while Sample 2 (C) has an even lower NDVI value of 0.147. Both samples are classified as having a low health condition. These findings suggest that vegetation near water, as categorized in this analysis, exhibits poorer health conditions compared to the areas near land and in the mid areas.

Table 3.6: NDVI Value for Mangrove in 2019

Sample	Latitude (N)	Longitude (E)	NDVI Value	Health Condition
1 (A)	4°10’43’’	103°25’06’’	0.456	Medium
1 (B)	4°10’38’’	103°25’12’’	0.372	Medium
1 (C)	4°10’38’’	103°25’18’’	0.322	Low
2(A)	4°04’00’’	103°21’21’’	0.430	Medium
2(B)	4°03’58’’	103°23’26’’	0.396	Low
2(C)	4°04’02’’	103°23’27’’	0.212	Low
3(A)	3°48’22’’	103°20’19’’	0.460	Medium
3(B)	3°48’26’’	103°20’14’’	0.381	Medium
3(C)	3°48’38’’	103°20’24’’	0.271	Low
4(A)	3°36’33’’	103°23’22’’	0.500	Medium
4(B)	3°36’38’’	103°23’25’’	0.427	Medium
4(C)	3°36’46’’	103°23’23’’	0.148	Low
A – Near Land B – Mid Area C – Near Water				

In the "Near Land" category, Sample 1 (A) exhibits a relatively high NDVI value of 0.621, indicating a medium health condition. This suggests that the vegetation in this area is relatively healthy. Similarly, Sample 2 (A) has an even higher NDVI value of 0.671, indicating a high health condition. These findings suggest that areas near land, as categorized in this analysis, generally show healthier vegetation with higher NDVI values.

Moving on to the "Mid Area" category, both Sample 1 (B) and Sample 2 (B) have lower NDVI values compared to the "Near Land" category. Sample 1 (B) has an NDVI value of 0.409, while Sample 2 (B) has an NDVI value of 0.559. Both samples are classified as having a medium health condition. These results indicate that the vegetation in the mid areas, as categorized in this analysis, shows relatively lower health compared to the areas near land.

Lastly, in the "Near Water" category, both Sample 1 (C) and Sample 2 (C) display the lowest NDVI values among the three categories. Sample 1 (C) has an NDVI value of 0.207, while Sample 2 (C) has an even lower NDVI value of 0.147. Both samples are classified as having a low health condition. These findings suggest that vegetation near water, as categorized in this analysis, exhibits poorer health conditions compared to the areas near land and in the mid areas.

4.7 Category Level of Mangrove Healthiness

The categorization of green, yellow, and red can be used to represent different levels of mangrove healthiness. The green category indicates a high level of health with thriving vegetation, while the yellow category represents a moderate level of health with some signs of stress or degradation. The red category signifies a low level of health with significant degradation and loss of biodiversity. These categories provide a simplified framework to assess and understand the condition of mangrove ecosystems, considering factors such as vegetation density, vitality, and NDVI values. However, it's important to note that a comprehensive evaluation of mangrove health should consider multiple criteria and factors to capture the complexity and nuances of these vital coastal ecosystems.

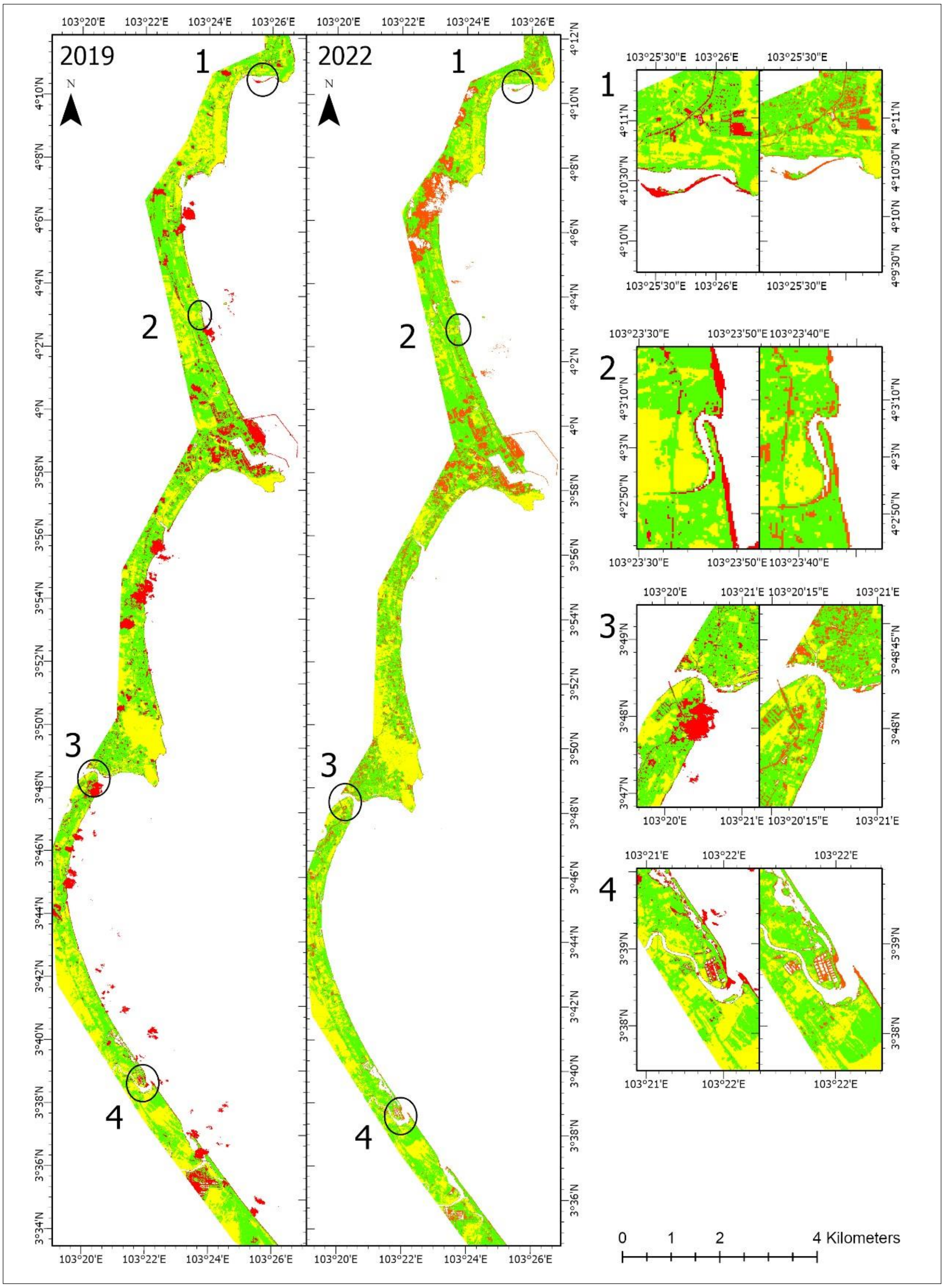

Figure 4.6: Map Ranking of Category Healthiness.

CHAPTER FIVE

CONCLUSION AND RECOMMENDATION

5.1 Introduction

This chapter summarised the overall review of the study. The conclusion was based on the findings of the related field surveys and research. The methodology, research background, problem statement, result, and analysis of this study were all completed. Furthermore, this chapter contained a recommendation on the benefits acquired from this study as well as improvements for future research.

5.2 Conclusion

In conclusion, all the objective in this study had been achieved, referring to the first objective which is to classify the mangrove classification using satellite imagery on Pahang by using Object Based Image Analysis (OBIA). There are 3 parameters that had been found for this classification which is shape, scale and compactness. OBIA improves accuracy by considering the spatial context and characteristics of objects, enabling more precise and detailed results compared to pixel-based methods. It allows for the integration of ancillary data, enhancing the analysis and providing a comprehensive understanding of the study area. The second objective is to determine the healthiness of mangrove habitat using vegetation index. By calculating and analyzing NDVI values, it is possible to assess the health status of mangroves, detect areas of stress or degradation, and monitor changes over time. This information is crucial for conservation efforts, sustainable management practices, and informed decision-making to protect and preserve the health and biodiversity of mangrove habitats. Based on the final result which is map of the mangrove healthiness show that the mangrove at Pahang is at good condition. The map has been created to depict the ultimate result as third objective based on outcome from the first and second objective. The mapping of mangrove healthiness using ArcGIS software allows us to see this goal.

5.3 Recommendation

There are several improvements to the study that might be suggested based on the findings. In this research, the OBIA method are used to classify the mangrove and NDVI are used to determine the mangrove healthiness. For the OBIA method, the data or image satellite used are need to have high spatial resolution because the parameter in OBIA is quite good for high spatial resolution. This allows for better object segmentation, as smaller and more intricate objects can be accurately delineated. This level of detail helps in capturing the complex spatial patterns and characteristics of objects within the image, including mangrove stands, water bodies, and other land cover features. It also reduces the chances of misclassification and improves the discrimination between different land cover classes, including mangroves and other vegetation types. The higher level of detail aids in differentiating between closely related features, such as mangroves and other types of forests, and helps to capture more specific characteristics of each class. Then, it allows for a more accurate assessment of mangrove health, extent, and changes over time, which can aid in setting conservation priorities, planning restoration efforts, and evaluating the effectiveness of management interventions. Overall, the use of high spatial resolution data in OBIA enables more accurate and detailed analysis of mangroves, facilitating better understanding, monitoring, and decision-making for the conservation and sustainable management of these vital ecosystems.

REFERENCES

Lombard, F., & Andrieu, J. (2021, May 18). Mapping Mangrove Zonation Changes in Senegal with Landsat Imagery Using an OBIA Approach Combined with Linear Spectral Unmixing. *Remote Sensing*, 13(10), 1961. https://doi.org/10.3390/rs13101961

Bunting, P., Rosenqvist, A., Hilarides, L., Lucas, R. M., Thomas, N., Tadono, T., Worthington, T. A., Spalding, M., Murray, N. J., & Rebelo, L. M. (2022, July 30). Global Mangrove Extent Change 1996–2020: Global Mangrove Watch Version 3.0. *Remote Sensing*, 14(15), 3657. https://doi.org/10.3390/rs14153657

Hamzah, M. L., Amir, A. A., Abdul Maulud, K. N., Sahadev Sharma, S., Mohd, F. A., Selamat, S. N., Karim, O., Ariffin, E. H., & Begum, R. A. (2020, July 30). Assessment of The Mangrove Forest Changes Along the Pahang Coast Using Remote Sensing and GIS Technology. *Journal of Sustainability Science and Management*, 15(5), 43–58. https://doi.org/10.46754/jssm.2020.07.006

Valderrama-Landeros, L., Flores-de-Santiago, F., Kovacs, J. M., & Flores-Verdugo, F. (2017, December 14). An assessment of commonly employed satellite-based remote sensors for mapping mangrove species in Mexico using an NDVI-based classification scheme. *Environmental Monitoring and Assessment*, 190(1). https://doi.org/10.1007/s10661-017-6399-z

Zhang, T., Hu, S., He, Y., You, S., Yang, X., Gan, Y., & Liu, A. (2021, February 20). A Fine-Scale Mangrove Map of China Derived from 2-Meter Resolution Satellite Observations and Field Data. *ISPRS International Journal of Geo-Information*, 10(2), 92. https://doi.org/10.3390/ijgi10020092

Khairul Abdullah Halim, M., Hidayah Halid, N., Ahmad, A., Mohd Suhaimi, H., & Hidayat Jamal, M. (2019, February 21). Monitoring mangrove forest cover declination at kilim karst geoforest park, Langkawi from 2005 to 2017 using geospatial technology. IOP Conference Series: *Earth and Environmental Science*, 220, 012059. https://doi.org/10.1088/1755-1315/220/1/012059

Baishya, S., Banik, S. K., Choudhury, M. D., Das Talukdar, D., & Das Talukdar, A.

(2020). Therapeutic potentials of littoral vegetation: an antifungal perspective. Biotechnological Utilization of Mangrove Resources, 275–292. https://doi.org/10.1016/b978-0-12-819532-1.00011-1

Topah @ Apandi, E. B., Salleh, S. A., Rahim, H. A., & Adnan, N. A. (2022, October 1). Mapping of Coastline Changes in Mangrove Forest using Digital Shoreline Analyst System (DSAS). IOP Conference Series: *Earth and Environmental Science*, 1067(1), 012036. https://doi.org/10.1088/1755-1315/1067/1/012036

Idris, N. S., Mustapha, M. A., Sulaiman, N., Khamis, S., Husin, S. M., & Darbis, N. D. A. (2021). The dynamics of landscape changes surrounding a firefly ecotourism area. *Global Ecology and Conservation,* 29, e01741. https://doi.org/10.1016/j.gecco.2021.e01741

Wang, D., Wan, B., Qiu, P., Su, Y., Guo, Q., Wang, R., Sun, F., & Wu, X. (2018, September 14). Evaluating the Performance of Sentinel-2, Landsat 8 and Pléiades-1 in Mapping Mangrove Extent and Species. *Remote Sensing*, 10(9), 1468. https://doi.org/10.3390/rs10091468

Kamal, M., & Phinn, S. (2011, October 20). Hyperspectral Data for Mangrove Species Mapping: A Comparison of Pixel-Based and Object-Based Approach. *Remote Sensing*, 3(10), 2222–2242. https://doi.org/10.3390/rs3102222

Mokhtar, E. S., Majid, M. A. A. A., Norman, M., Roslani, M. A., Nasirun, N., & Mohammad, Z. (2022, April 1). Mangrove Area Delineation using Object-Based Classification on Sentinel-2 Imagery: Tuba Island, Langkawi. IOP Conference Series: *Earth and Environmental Science*, 1019(1), 012019. https://doi.org/10.1088/1755-1315/1019/1/012019

Yunus, M. Z. M., Ahmad, F. S., & Ibrahim, N. (2018). Mangrove vulnerability index using GIS. AIP Conference Proceedings. https://doi.org/10.1063/1.5022901

Ellison, J. C. (2014, December 31). Vulnerability assessment of mangroves to climate change and sea-level rise impacts. Wetlands Ecology and Management, 23(2), 115–137. https://doi.org/10.1007/s11273-014-9397-8

Donato, D. C., Kauffman, J. B., Murdiyarso, D., Kurnianto, S., Stidham, M., & Kanninen, M. (2011, April 3). Mangroves among the most carbon-rich forests in the tropics. *Nature Geoscience*, 4(5), 293–297. https://doi.org/10.1038/ngeo1123

Jia, M., Wang, Z., Zhang, Y., Mao, D., & Wang, C. (2018, December). Monitoring loss and recovery of mangrove forests during 42 years: The achievements of mangrove conservation in China. *International Journal of Applied Earth Observation and Geoinformation*, 73, 535–545. https://doi.org/10.1016/j.jag.2018.07.025

Walters, B. B., Rönnbäck, P., Kovacs, J. M., Crona, B., Hussain, S. A., Badola, R., Primavera, J. H., Barbier, E., & Dahdouh-Guebas, F. (2008, August). Ethnobiology, socio-economics and management of mangrove forests: A review. Aquatic Botany, 89(2), 220–236. https://doi.org/10.1016/j.aquabot.2008.02.009

Carugati, L., Gatto, B., Rastelli, E., Lo Martire, M., Coral, C., Greco, S., & Danovaro, R. (2018, September 5). Impact of mangrove forests degradation on biodiversity and ecosystem functioning. Scientific Reports, 8(1). https://doi.org/10.1038/s41598-018-31683-0

Wan Mohd Khalik, W. M. A., & Wahizatul Afzan, W. A. (2020). Sustainable Development Through Science, Technology and Innovation. *Journal of Sustainability Science and Management*, 15(4). https://doi.org/10.46754/jssm.2020.06.01

Ottinger, M., Clauss, K., & Kuenzer, C. (2016, January). Aquaculture: Relevance, distribution, impacts and spatial assessments – A review. Ocean & Coastal Management, 119, 244–266. https://doi.org/10.1016/j.ocecoaman.2015.10.015

Omar, H., Afizzul Misman, M., & Musa, S. (2019, November 13). GIS and Remote Sensing for Mangroves Mapping and Monitoring. Geographic Information Systems and Science. https://doi.org/10.5772/intechopen.81955

Ahmad, Z., Mohamad Suharni, M. L., Taib, S. N. A., & Shammodin, M. S. (2019, June 25). Impact of coastal development on mangrove distribution in Cherating Estuary, Pahang, Malaysia. *Malaysian Journal of Fundamental and Applied Sciences*, 15(3), 456–461. https://doi.org/10.11113/mjfas.v15n3.1091

Nalawade, P. M., Gadakh, B. L., & B., K. A. (2022, August 12). Vegetation Change Detection using Remote Sensing and GIS, 2001-2021 – A Case Study of Nashik City, Maharashtra. Ecology, Environment and Conservation, S233–S237. https://doi.org/10.53550/eec.2022.v28i04s.035

Ofosu Anim, D., Kabo-bah, A. T., Nkrumah, P. N., & Murava, R. T. (2013, May 16). Evaluation of NDVI Using SPOT-5 Satellite Data for Northern Ghana. *Environmental Management and Sustainable Development*, 2(1). https://doi.org/10.5296/emsd.v2i1.3709

Donoghue, D. (2001, October 31). Remote Sensing and Image Interpretation edited by Thomas M. Lillesand and Ralph W. Kiefer, John Wiley, New York, 2000. No. of pages: 736. Price £29.95. ISBN 0 471 25515 7. Earth Surface Processes and Landforms, 26(12), 1361–1361. https://doi.org/10.1002/esp.267

Muhsoni, F. F. (2020, December 18). Estimation Model of Mangrove Carbon Stock Using LDCM Imagery. *International Journal of Science, Engineering and Information Technology*, 5(1), 239–244. https://doi.org/10.21107/ijseit.v5i1.9116

Rivera-Monroy, V. H., Lee, S. Y., Kristensen, E., & Twilley, R. R. (Eds.). (2017). Mangrove Ecosystems: A Global Biogeographic Perspective. https://doi.org/10.1007/978-3-319-62206-4

Abd. Shukor, A.H. (2004). The use of mangroves in Malaysia. In: Promotion of mangrove-friendly shrimp aquaculture in Southeast Asia (pp. 136-144). Tigbauan, Iloilo, Philippines: Aquaculture Department, Southeast Asian Fisheries Development Center

Asri, N. A., & Musa, F. (2021). Tourists' Attitudinal Factor Towards Mangrove Conservation: A Case Study of Kilim Karst Geoforest Park, Langkawi, Malaysia. In UMS Colloquium on Fundamental Research and Application (Vol. 8, Issue 2). UMS Co-FA2020.

Alongi, D. M. (2020, September 10). Carbon Cycling in the World's Mangrove Ecosystems Revisited: Significance of Non-Steady State Diagenesis and Subsurface Linkages between the Forest Floor and the Coastal Ocean. Forests, 11(9), 977. https://doi.org/10.3390/f11090977

Aluri, J. S. R., & Karyamsetty, H. J. (2018, March 1). Reproductive Ecology of Bruguiera cylindrica (L.) Bl. (Rhizophoraceae), A True Viviparous Mangrove Tree Species in Coringa Mangrove Forest, Andhra Pradesh (India). Transylvanian Review of Systematical and Ecological Research, 20(3), 31–38. https://doi.org/10.2478/trser-2018-0017

Dahdouh-Guebas, F., Jayatissa, L., Di Nitto, D., Bosire, J., Lo Seen, D., & Koedam, N. (2005, June). How effective were mangroves as a defence against the recent tsunami? *Current Biology*, 15(12), R443–R447. https://doi.org/10.1016/j.cub.2005.06.008

Foody, G., & Mathur, A. (2004, June). A relative evaluation of multiclass image classification by support vector machines. IEEE *Transactions on Geoscience and Remote Sensing*, 42(6), 1335–1343. https://doi.org/10.1109/tgrs.2004.827257

Blaschke, T. (2010, January). Object based image analysis for remote sensing. ISPRS *Journal of Photogrammetry and Remote Sensing*, 65(1), 2–16. https://doi.org/10.1016/j.isprsjprs.2009.06.004

Hilmi, E., Kusmana, C., Suhendang, E., & Iskandar. (2017, October 31). Correlation Analysis Between Seawater Intrusion and Mangrove Greenbelt. Indonesian Journal of Forestry Research, 4(2), 151–168. https://doi.org/10.20886/ijfr.2017.4.2.151-168

Efriyeldi, E., Mulyadi, A., & Samiaji, J. (2020, January 1). Condition of Mangrove Ecosystems in Sungai Apit Siak Distric Based on Standard Damage Criteria and Quality Indicators Mangrove Environment. IOP Conference Series: *Earth and Environmental Science*, 430(1), 012013. https://doi.org/10.1088/1755-1315/430/1/012013

APPENDICES

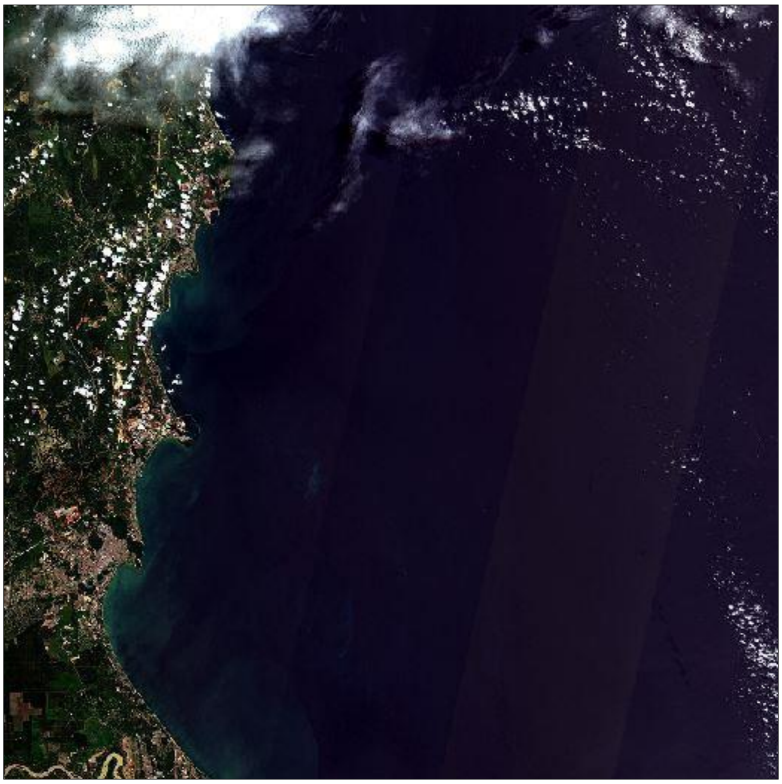

Image Satellite Sentinel for Year 2019 Along Pahang Coastal

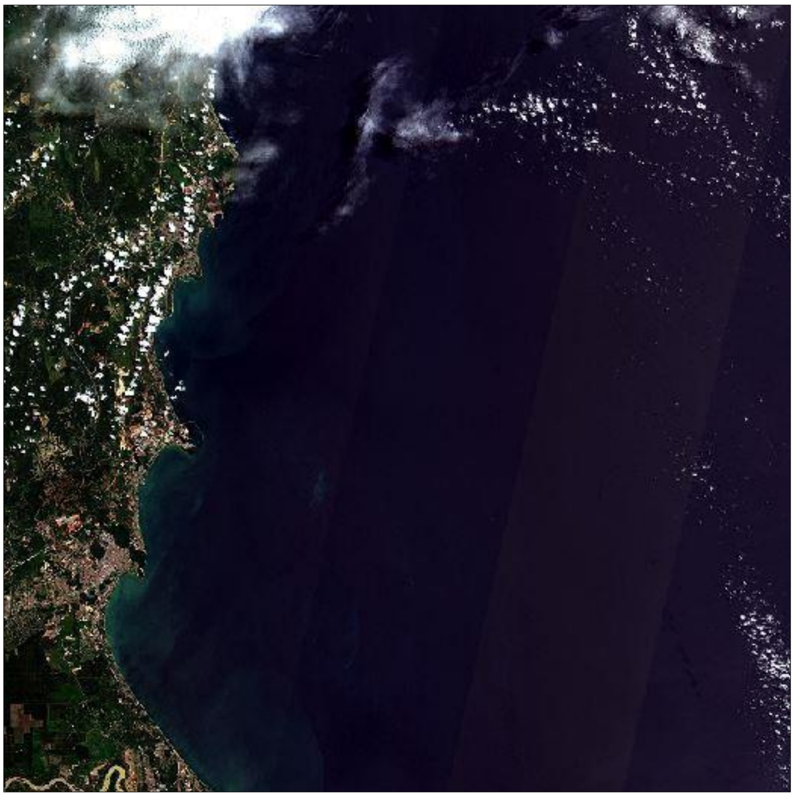

Image Satellite Sentinel for Year 2022 Along Pahang Coastal

Introduction to Mangrove Leave

Introduction to Mangrove Root

AUTHOR'S PROFILE

NAME	AHMAD KAMIL BIN MAT NAWI
AGE	25
ADDRESS	LOT 1293, KG BENDANG KERIAN, 16200 TUMPAT, KELANTAN
NATIONALITY	MALAYSIAN
EDUCATION	• 2019 – 2023 BACHELOR OF GEOMATIC SCIENCE (AP220) UITM ARAU PERLIS • 2016 – 2019 DIPLOMA IN POLYMER TECHNOLOGY (AS113) UITM ARAU PERLIS