INVENTOPIA 2025

FBM-SEREMBAN INTERNATIONAL INNOVATION COMPETITION (FBM-SIIC)

INNOVATION IN ACTION: TURNING IDEAS INTO REALITY

Chapter 54
Non-Suitable Area Detection for Ports and Harbour Construction Alongside Coastal Water Using Remote Sensing Approach

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ABSTRACT
The intertidal zone, being an interface between terrestrial and marine environments, is very susceptible to environmental changes like sea level rise, coastal erosion, and human activities. They have direct repercussions on biodiversity, marine ecosystems, and socio-economic activities, mainly for the locals who depend on tourism and fishing. Through an understanding of the spatial and temporal intertidal zone variations, this study also hopes to enlighten us about the degree of coastal transformation with time. The aim of this study is to identify changes in the intertidal zone that is unsuitable to be constrycted as port or harbour using satellite remote sensing data between 2016 and 2023 in the Perlis coastal area.

Key Words: intertidal zone, remote sensing, area detection, marine environment

1. INTRODUCTION

Malaysia is an ocean nation with a beautiful coastline that attracts tourists from both domestic and international travel. Highly productive habitats like mangroves, coral reefs, seaweed, and marine ecosystems can be found in the nearby coastal areas. Because of the coastal area's diversity and richness, addressing difficult environmental concerns requires an integrated strategy in order to build a place that is sustainable and well-preserved. The evaluation of the current intertidal zone including ecology, biodiversity, marine life habitat and so on becomes a reference to evaluate changes over time. The trends and patterns of sea level rise involve the use of data from tide gauges as well as satellite observations and further sea level rise over the intertidal zone may increase erosion, changes in sedimentation patterns, subsidence of low areas within habitat boundaries. Thus make this area not suitable to be choose as port or harbour.

Tides in port have a significant impact on fishing vessels. Among them is experiencing problems during the voyage when the tide is low, the water level drops and the depth in the port decreases. This makes it difficult for ships to navigate, especially large ships that need greater water depth and are easy to enter and leave the port. Furthermore, ships sailing in or out of port at low tide have a greater risk of running aground due to the reduced water depth. This can cause damage to the ship and requires more intensive precaution & security aspect. Research objectives:

i. To identify the location of the intertidal zone at coastal area using remote sensing approach.
ii. To analyse the intertidal zone between two different years to see the changes in term of it size.

2. LITERATURE REVIEW

Different geomatic techniques are employed to locate and chart the intertidal regions. For examples, multispectral satellite imagery, like Landsat or Sentinel satellites enables comprehensive surveillance of intertidal regions by examining the spectrum of light reflected from the Earth's surface allows for the classification of intertidal zones according to spectral variations, like the differentiation between areas covered by water and land. Mao et al. (2022) has employed the Normalized Difference Water Index (NDWI), which aids in distinguishing water-covered regions from land, rendering it especially beneficial for evaluating intertidal zones during different tidal stages. This information also enables spectral analysis of regions revealed at low tide and regions submerged at high tide. On the other hand, Sentinel-2 provides excellent spectral resolution through bands like red, green, blue, and infrared, which aid in recognizing various vegetation types and intertidal environments like mangroves and seagrass (Muir et al., 2024).

In unsupervised image classification, the process involves identifying each image in a dataset as belonging to one of the natural categories found within the image collection, without the use of labelled training samples. Unsupervised image categorization depends on the application of unsupervised machine learning algorithms. This article recognizes clustering algorithms and dimension reduction algorithms as two essential types of unsupervised machine learning methods required for unsupervised image categorization, along with how these methods are applied in notable implementations of unsupervised image classification techniques. Because unsupervised image categorization can facilitate classification without training samples, it has been recognized as a method for enhancing visualization and retrieval efficiency in image retrieval (Datta, et al, 2008; Datta, Ghosh & Ghosh, 2015). It has also been recognized as a method for correlating low-level features with high-level semantics, particularly in applications driven by learning (Huang & Zhang, 2012). These attributes render unsupervised image classification a plausible approach for closing the semantic gap in image retrieval (Wang, Mohamad & Ismail, 2010).

Extraction of water bodies has been performed employing numerous spectral-based indices for water and vegetation, such as the Automatic Water Extraction Index (AWEI) (Feyisa et al., 2014; Kareem, Attaee & Osman, 2024), Normalized Difference Water Index (NDWI) (Xu,2006), Modified Normalized Difference Water Index (MNDWI) (Xu, 2006;

Amoroso & Figliomeni, 2023). Nonetheless, particularly in estuaries or bays, this metric does not reflect tidally flooded salt marsh plant life. To reduce this effect, Zou et al. (2017) developed a technique incorporating vegetation and water indices, which was subsequently utilized by Chang et al. (2022) to monitor tidal flat alterations each year on a national scale.

3. METHODOLOGY

This research employs a quantitative method utilizing satellite images to examine alterations in the intertidal area along the Perlis shoreline. The approach consists of three key phases: obtaining data, processing data, and performing analysis with ArcGIS Pro and Erdas Imagine 2014.

3.1. Data acquisition and Processing

This research utilizes three datasets of Sentinel-2 satellite images captured during high tide in January 2016, March 2023, and April 2023 to investigate temporal changes in the intertidal zone. These datasets enable us to examine long-term variations (2016 and 2023) and explore short-term variations (March 2023 and April 2023), providing insight into both gradual and recent shifts along the coastline. The high spatial and multi-spectral resolution of Sentinel-2 allows for precise identification of water coverage, making it suitable for observing tidal variations, sea level increase, and coastal degradation. Through the examination of these datasets, the research will determine the degree of tidal expansion, possible environmental effects, and factors like climate change, extremeweather occurrences, and sediment realignment that affect coastal dynamics and the stability of intertidal habitats.

The data processing procedure in this research intends to methodically identifying the intertidal zone in the Perlis coastal region utilizing ArcGIS Pro and Erdas Imagine 2014 software. This data processing includes several key steps executed in order to guarantee the accuracy and dependability of the analysis outcomes. Data from the Sentinel-2 satellite is analyzed to derive information on high water zones and low water zones, and tidal data is utilized to aid analysis to fulfill specified criteria. The steps for data processing encompass image filtering, classification, water index computation, along with digitization and overlay for the comparative analysis of the intertidal zone across different timeframes, specifically in January 2016, March 2023, and April 2023.

3.2. Unsupervised Classification Using ISO Clustering

Unsupervised classification is a key step in processing satellite image data to identify the intertidal zone. In this research, the ISO Cluster method, an automated classification technique that requires no user intervention, is employed to analyze complex spectral data for the Perlis coastal region. Data from Sentinel-2 satellite images, which have undergone the Layer Stacking process, serves as the primary input. Important spectral bands, including the green and near infrared (NIR) bands, were selected due to their sensitivity to water characteristics and wetland regions. These bands assist in differentiating land regions, water, and the intertidal zone according to their reflectance values. A suitable unsupervised classification algorithm is chosen to group image pixels according to their spectral values. Two frequently utilized algorithms are K-Means Clustering and ISO Clustering (ISODATA). K-Means Clustering divides the image into multiple clusters according to spectral similarity, aggregating pixels with alike spectral characteristics into the same group. After identifying the intertidal zone, a map of this area is created utilizing Geographic Information System (GIS) tools to examine shoreline alterations, tidal influences, and their effects on the marine ecosystem.

4. RESULT, DISCUSIION AND CONCLUSION

The intertidal zone, which lies between high tide and low tide, is represented with a hatch pattern on the map (Figure 1), signifying areas that have experienced tidal changes over time.

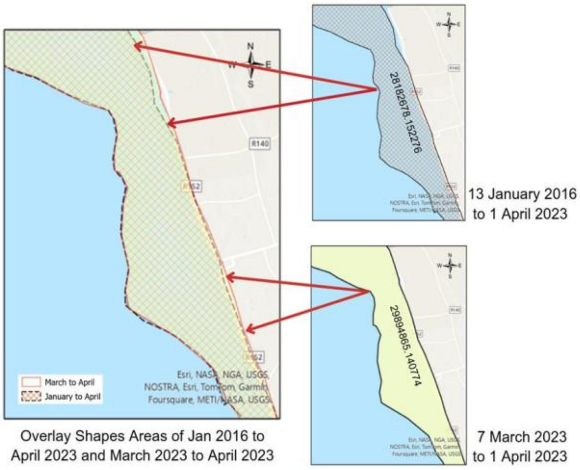

Figure 15: Result of unsuitable area for port and harbour construction classifed by remote sensing approaches

The differences in the size of the intertidal zone might result from various factors, including coastal erosion, sediment build-up, or changes to the shoreline from human actions and natural events like storms and increasing sea levels. Regarding the connection between natural factors and human activities, the research effectively correlated hanges in the intertidal zone with elements like coastal erosion, sediment deposition, and rising sea levels. Tidal data gathered indicated a drop in high tide measurements from 2.87m in 2016 to 1.84m in 2023, offering proof of shifts in hydrodynamic patterns. The effects of lunar gravity and the northeast monsoon season were also recognized as factors contributing to the phenomenon of stranded ships, providing a practical aspect to this research. The drying height area (green) serves as a critical transition zone between land and sea, acting as a buffer that protects the coastline from erosion. In this image, the drying high can be identified as mudflats or sandbanks near the boundary between the light green (intertidal zone) and yellow (land). This area also acts as a primary pathway for sediment transport from land to sea, influencing coastal dynamics.

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