MONITORING SHORELINE CHANGES IN WEST COAST OF PENINSULAR MALAYSIA USING STATISTICAL ANALYSIS TECHNIQUES

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ABSTRACT: Coastal zone monitoring provides information about conditions of coastal areas whether affected by natural or human activities. Monitoring coastal zones could be applied by monitoring shoreline which is an important criterion to measure boundary of a country. Unlike traditional ground survey technique that consume time and cost, remote sensing provides alternative in fast way. In this research, satellite image classification using simple machine learning algorithms was employed to classify land and water classes. Then, historical shorelines of Langkawi island, located at north west coast of Peninsular Malaysia are extracted as vector GIS files after performing raster to vector operation. The shoreline changes for 43 years between from 1973 until 2016 is assessed using analysis techniques such as End Point Rate and Linear Regression Rate. The result of shoreline change envelope shown that the major change of shoreline effected on south and west areas of Langkawi while the east area recorded the smallest change.

1. INTRODUCTION

A shoreline is a boundary that physically separates between the land and the water (Boak & Turner, 2005). Shoreline changes can be the result of numerous causes, both natural and anthropogenic, can lead to both erosion and accretion (Yu, et al., 2011).

Many techniques have been employed to extracting shorelines from medium resolution satellite images. Yu et al. (2011) used 9 scenes of Landsat TM images from 1987 to 2008 using the same acquisition time with the tide observation time. They utilized Band 5 because water absorbs strongly shortwave infrared light while performing six-classes ISODATA classification that resulting classification results were merged into two distinct land and sea categories. Feng et al. (2014) proposed a new cellular automata approach by considering the edge directional information of the imagery to extract the shoreline information from multi-temporal Landsat TM images of Shanghai from 1979 to 2008. Addo & Kodzo (2013) utilized mid infrared (band 5) and the green (band 2) using band ratio technique to identify water-land boundary for the pan-sharped Landsat images which employed by Gram-Schmidt algorithm for Landsat images from 1986 to 2011. While machine learning also used to classify land and water classes such as Maximum Likelihood (Rokni, et al., 2015), Mahalanobis Distance (Sekovski et al., 2014), Minimum Distance (Sekovski et al., 2014), Neural Network (Rokni et al., 2015) and Support Vector Machines (Yousef & Iftekharuddin, 2014).

To quantify shoreline changes over time, Yu et al. (2011) examined the changed classes from the land and sea classes over time, from time t to time t + 1, and counted the number of pixels associated with each change. Addo & Kodzo (2013) calculated historic rates of shoreline change using end point rate (EPR) and weighted linear regression (WLR) with 200m interval transects. Dewidar & Frihy (2010) analyzed erosion and accretion pattern along the northeastern coastline of Nile Delta, from Gamasa to Port Said for 35-year period between 1972 to 2007 using EPR, WLR and Jackknife Rate (JKR).

This research aims to monitor the shoreline changes using the multi-temporal medium resolution satellite images acquired in the North West Coast of Peninsular Malaysia from 1973 and 2016. First, the satellite images were classified to generate land and water classes maps. Then the shorelines were generated from each classified map through the post-processing raster to vector and polygon to line operations. Finally, the shoreline changes were assessed using the checkpoints set in the study area.

2. MATERIALS AND METHODS

In this study, the method used to extract shoreline from satellite image and monitor its changes consists of four phases. The four phases are pre-processing, classification, accuracy assessment and change analysis as shown in Figure 1.

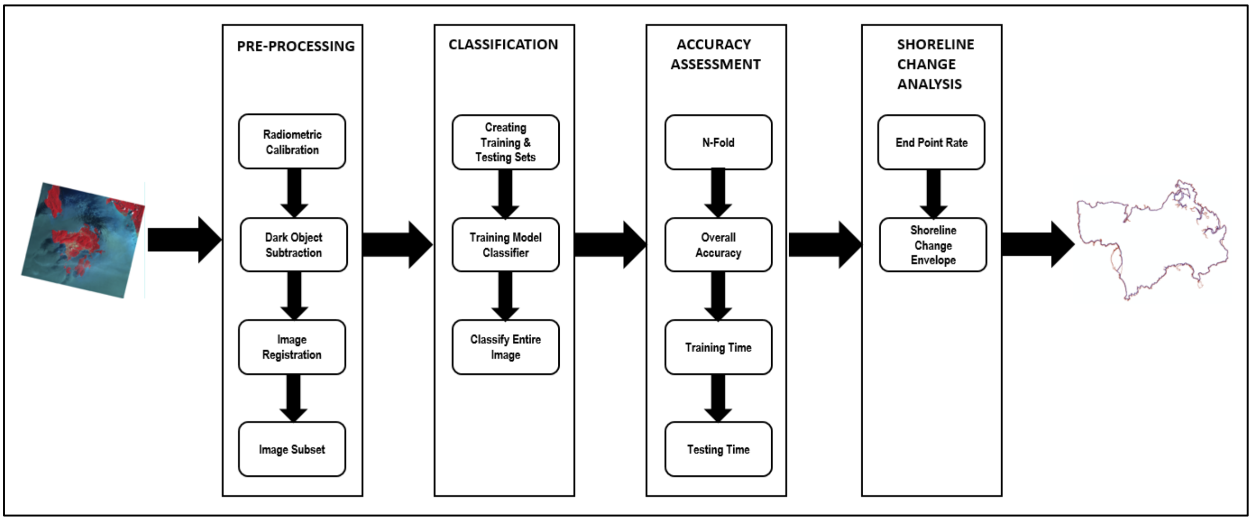

Figure 1. Methodology of this study

2.1 Study Area

The chosen study area was in the Langkawi Island, which located at the North West coast of Peninsular Malaysia, as shown in Figure 2. Specifically, this island is located between 6º 15'N and 6º 29'N latitude and 99º 37'E and 99º 57'E longitude. The total area of Langkawi Island is about 47,848 ha. The island comprises many small islands, however only the main landmass was considered in this study.

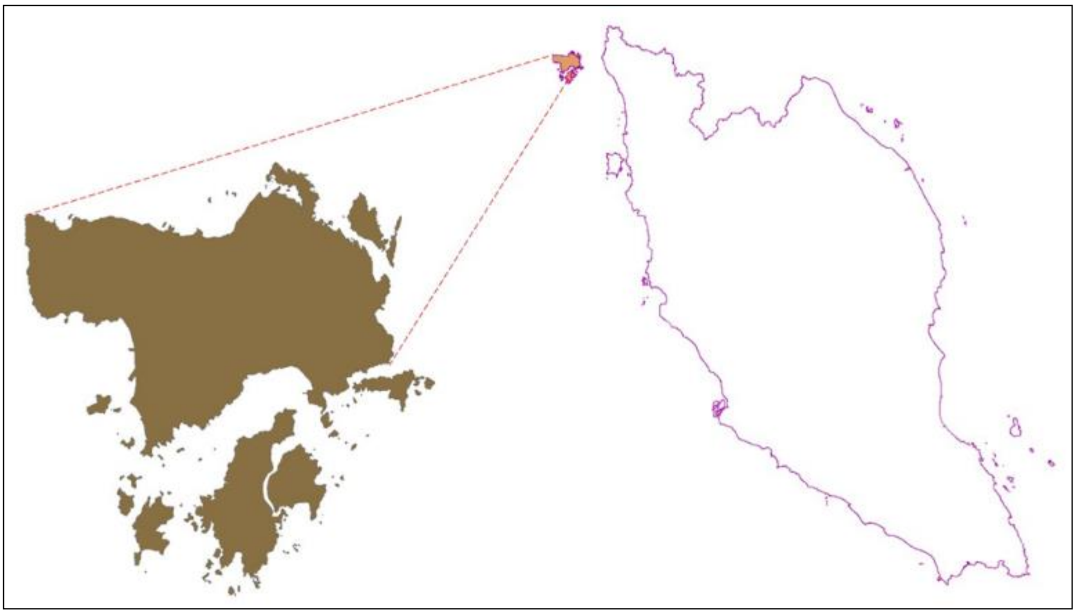

Figure 2. Study area of the research

2.2 Data Acquisition

The data used in this research consisted of five scenes of multispectral Landsat data. The scenes were acquired on five different days as shown in Table 1.

Table 1. Data Used in This Study

No	Satellite Image Data	Date	Resolution (m)
1	Landsat 1 MSS	06/01/1973	60
2	Landsat 7 ETM+	06/03/2002	30
3	Landsat 5 TM	14/12/2009	30
4	SPOT MS	20/02/2013	10
5	Landsat 8 OLI	23/01/2016	30

2.3 Pre-processing

The main aim of the pre-processing phase was to clean satellite images from errors caused by satellite sensors in term of atmospheric, radiometric and geometric corrections. Once cleaned, the images were used in the classification phase. After the study area and image data were established, atmospheric correction using dark subtraction method was applied to remove atmospheric scattering effects of the image data. Geometric correction was performed using image-to-image with RMS value of 0.457. Later, West Peninsular Malaysia Rectified Skew Orthomorphic (RSO) Kertau was chosen to project the image data onto a local projection system. Finally, the image sub-setting was performed to fit the image to study area.

2.4 Satellite Image Classification

Supervised classification was used to classify land and water classes of satellite images. Training set was created to build the model, while testing set was produced to measure its performance. For this study, only one set of training and testing was created in the form of polygons. There were 260 polygons for land classes and 65 polygons for land water classes. For this study, there were 3 simple machine learning techniques considered for satellite image classification, namely Decision Tree (DT), k-Nearest Neighbor (k-NN) and Linear Discriminant Analysis (LDA). The assessment for performance measurement of the satellite image classification was based on the overall accuracy, training time, and testing time.

2.5 Accuracy Assessment

The purpose of perform accuracy assessment was to identify the most accurate classifier to separate land and water classes. The assessment for accuracy of the satellite image classification was based on the overall accuracy, training time, and testing time. To ovoid overfitting, K-fold cross-validation method was used and only one set training and testing set used.

2.6 Shoreline Change Analysis

In this study a Digital Shoreline Analysis System (DSAS) version 4.3 software developed by Thieler et al., (2009) was used to calculate rate of shoreline changes. This system requires user data to meet specific field requirements. These field requirements include field name, data type, properties of geographic features.

3. EXPERIMENTAL RESULTS

3.1 Image Classification Results

Table 2 summarizes the results of image classification of the satellite images. LDA was the most effective simple machine learning technique, recording the highest overall accuracy at 99.21% with the lowest training and testing time with 0.060 and 0.534s respectively. In contrast, k-NN achieved 99.21% of overall accuracy, the highest training and testing time with 0.378s and 8.210s respectively, relegating it to the last place for this performance measure.

Table 2. Machine Learning Used in Satellite Image Classification

No	Machine Learning Techniques	Overall Accuracy (%)	Training / Testing Time (s)
1	Decision Tree	99.28	0.098 / 0.576
2	k-Nearest Neighbor	99.21	0.378 / 8.210
3	Linear Discriminant Analysis	99.30	0.060 / 0.534

In this case, the classified image by LDA was chosen to extract shoreline because of the highest performance in terms of accuracy and time. Later, the classified image underwent a raster image to vector GIS output. Finally, in order to ensure the output vector was in line format, the polygon to line conversion process was carried out as shown in Figure 3.

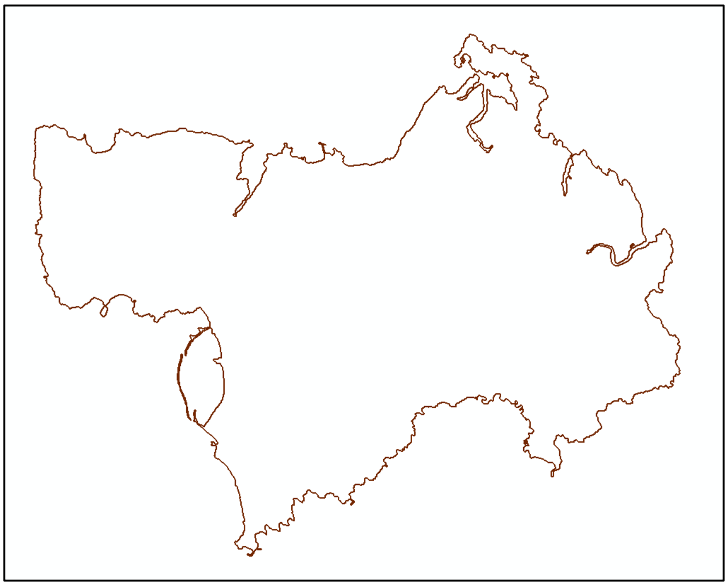

Figure 3. The extracted shoreline

3.2 Shoreline Change Analysis Result

Based on our setting, DSAS program generates 3354 transects that are oriented perpendicular to the baseline at a 100m spacing alongshore (Figure 4). These transects span the entire study along coastline of Langkawi island (~180 km length). The measured distance between the fixed baseline point and the shoreline positions generated by the program provides a reliable record for monitoring the changes of shoreline positions over the 43 years' time frame of the generated vectors.

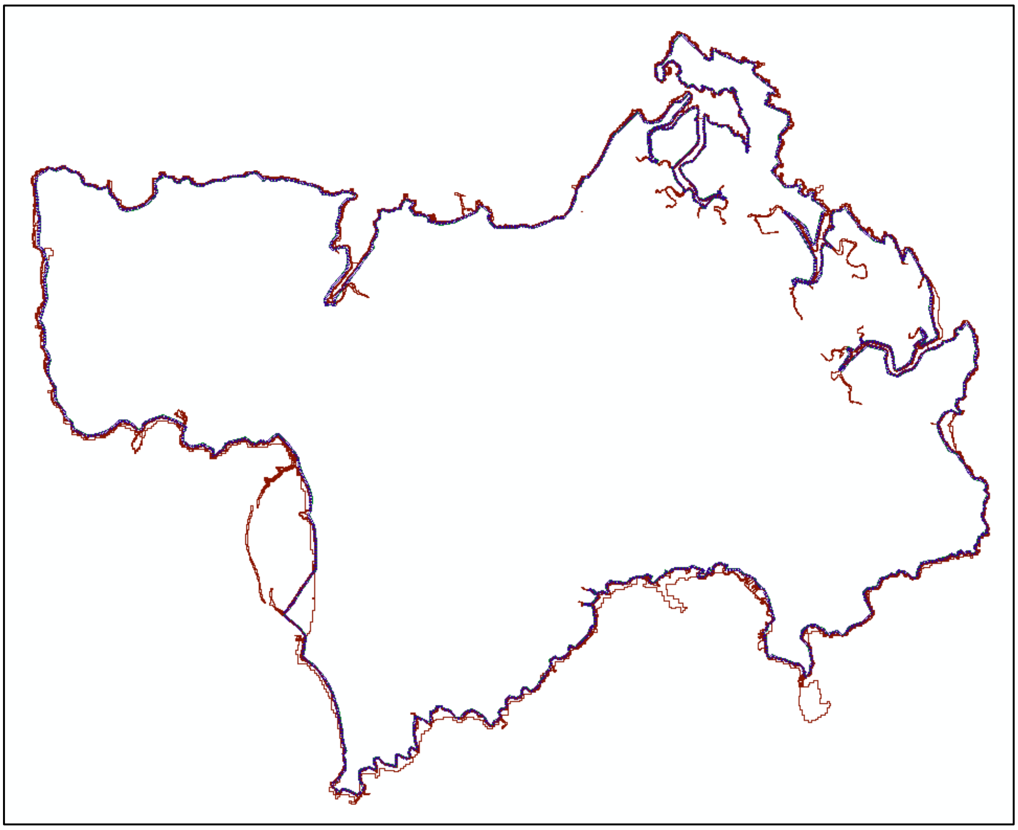

Figure 4. DSAS transects output

For the shoreline change envelope, it can be shown that the major change of shoreline effected on south and west areas of Langkawi while the east area recorded the smallest change as depicted in Figure 5.

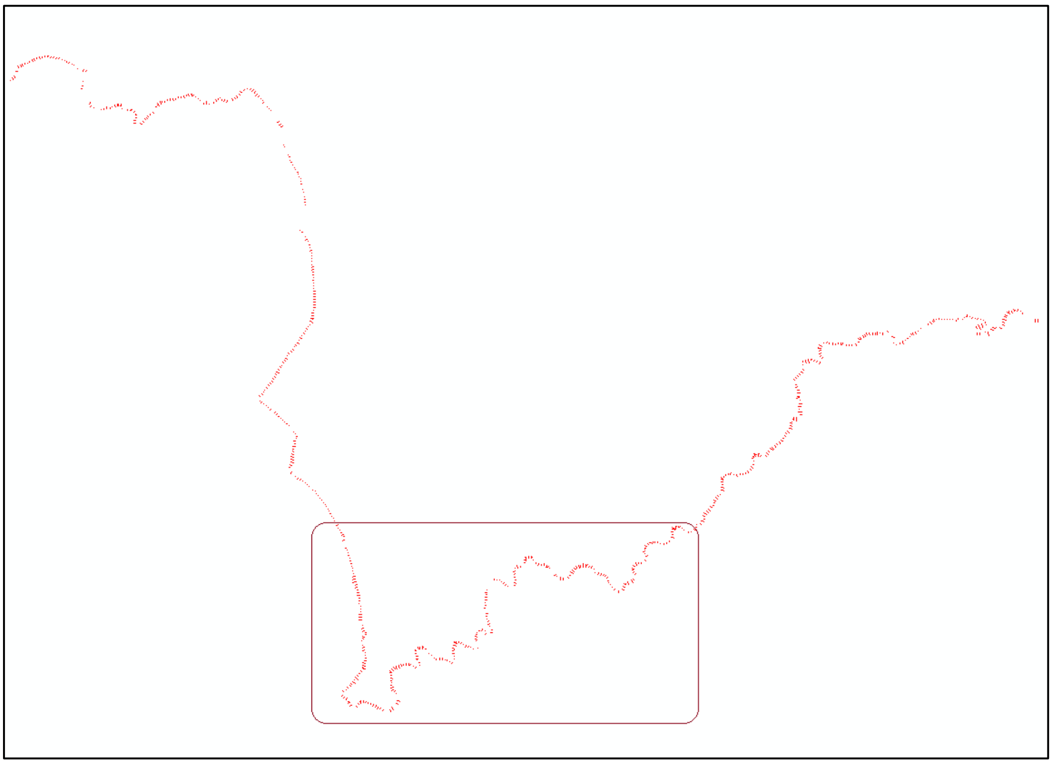

Figure 5. Shoreline change envelope result

4. ACKNOWLEDGMENTS

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