

Change analysis on historical shorelines extracted from medium resolution satellite images: a case study on the southern coast of Peninsular Malaysia

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Abstract. Information on changes of coastal zones such as erosions and accretions can be monitored by identifying conditions of shorelines. Shorelines provide the boundary information of land and water, which can be performed by using satellite images rather than by using traditional ground survey, which is known as laborious and expensive. In this study, the historical satellite images of Landsat sensors were gathered from year 1977 to 2017. Additionally, one image of SPOT-5 was also included to get more data for analysis. For each satellite image acquired, supervised machine learning techniques were used to classify the image into land and water classes. Then, the shoreline GIS vector were extracted after locating boundaries of both classes and applying post-processing stages on the classified images. The historical shorelines extracted were used to do further change analysis using End Point Rate method to examine the differences between the older shorelines and the newer shorelines. At this stage, two baselines were created for inner and outer baselines to control the analysis boundary limit. Then, transects of the historical shorelines were created for every 50 m interval. The rate of change statistics represent a cumulative summary of the processes affected during the observation duration. The research findings observed that the southern region of Peninsular Malaysia which known as Tanjung Piai was affected mostly by erosion while the western coast was affected by accretion. The erosion regions were affected by the living population along the coastal areas while the accretion was caused by land reclamation against erosion or built-up area expansion. This study was conducted to observe the most affected areas in the southern Peninsular Malaysia for more than 30 years' duration, potentially due to sea level rises besides natural processes and anthropogenic activities.

1. Introduction

Over the years, natural process and man-made activities are the most contributed activities towards changing the nature of coastal areas. Naturally, coastal changes are largely due to a host of factors, such as tides, winds, waves, water currents, sediments, and oceanic temperatures, among others being categorized as highly dynamic processes caused the changes [1]–[3]. In contrast, the anthropogenic or man-made activities are the results from the heavy concentration of people along the coastal areas because in recent years, most newly developed towns and cities, are located along the coastal areas.



Inevitably, anthropogenic activities resulting from the heavy concentration of people has adversely affected the coastal areas by bringing socio-economic activities together. Without redress, such activities can significantly change the coastlines of countries, which can occur unpredictably. Moreover, the changes are affected by several factors caused by hydrodynamic changes (e.g., river cycles, sea level rises), geomorphological changes (e.g., barrier island formation, split development) and other factors (e.g., sudden and rapid seismic, storms). Therefore, monitoring of coastlines is needed to provide important information about prevailing conditions of coastal areas of a country by examining changes that are taking place along its borders.

According to [4], such border is commonly referred to a 'coastline' or a 'shoreline'. A shoreline is defined as a physical line that acts as an interface that separates land and water, thus creating a boundary between the two [5], [6]. As such, shoreline extraction provides important information of the boundary between land and water, which can help detect and monitor any signs of coastal erosions or accretions. Currently, coastline monitoring can be performed using several techniques, such as remote sensing, aerial photography, and field survey. Given that it uses satellite images that can cover vast land areas, remote sensing is deemed as the most accurate and the fastest technique among the three. Moreover, this technique can extract important boundary information from satellite images using appropriate image analyses. In contrast, the techniques based on traditional field survey or airborne aerial photography are relatively time-consuming, laborious, and imprecise. By monitoring shoreline using rate of change statistics would represent a cumulative summary of the processes that have affected the coast [5].

The works are based on empirical observation to analyze changes along the coast and to predict future positions. [7] calculated rate of change statistics at 200 m interval of 283 transects using End Point Rate (EPR) and Weighted Linear Regression (WLR) methods for 5 shoreline positions covering a medium term of 25 years period. [8] analyzed at 1 km interval of 67 transects for Balasore coast using linear regression (LR) and EPR methods for 8 shoreline positions covering a high term of 38 years from 1975 to 2013. [9] calculated rates of shoreline change at 50 m interval of approximately 16,000 transects along the entire mainland coastline and major islands using EPR method in Digital Shoreline Analysis System (DSAS) for shoreline positions covering 20 years period from 1989 to 2009. [10] calculated rate of change of Songkhla coast using EPR method of aerial photographs and satellite images for 7 shoreline positions covering 45 years observation from 1967 to 2011.

For the local study, impact assessment study on coastal and marine resources have been conducted by NAHRIM on two pilot studies, in Chenang beach at the west coast of Langkawi, and Tanjung Piai at the south coast of Johor. From the study by [11], an estimated 148 ha of Chenang beach and 1,820 ha of Tanjung Piai coastal land will be inundated by the seawater for the worst-case global projected sea level rise (SLR) at 10 mm/year. The affected areas include mudflats, mangroves and riverbanks. However, the local projected SLR for both area is 1.3 mm/year. Therefore, this study was conducted to observe the most affected areas in the southern Peninsular Malaysia, particularly in Tanjung Piai for more than 30 years' duration, which was affected might be due to sea level rises, natural processes and anthropogenic activities.

2. Methodology

The method used to extract shorelines from satellite images and apply change analysis on historical shoreline data consisted of four phases, namely pre-processing, shoreline extraction, validation assessment, and shoreline change analysis, as depicted in Figure 1.

2.1. Study area

The chosen area of this study was the southern region of Pontian coast. This study area is located at 1°23' N and 1°15' N latitudes and 103°25' E and 103°34' E longitudes, covering a total distance of coastline about 37.65 km stretch from Sungai Permas on the west to Sungai Karang at the east. From Figure 2, Tanjung Piai located at the south while Kukup and Tanjung Bin located at the west and the east areas respectively. Among the three, Tanjung Piai is the most popular because it is located at the southern-most point of continental Asia as well as Peninsular Malaysia [12]. Tanjung Piai is abundant with commercially valuable species, where it consists of coastal mangroves and intertidal mudflats.

Furthermore, Tanjung Piai has been designated internationally as an important wetland protected by Ramsar site starting on 31st January 2003. Kukup on the other hand is a unique fishing town with its on-stilt coastal water community including Kukup Island, another Ramsar site which is the largest inhabitant mangrove island in Asia. Iskandar Malaysia spanning 2,217 km², is an integrated development in Johor with five strategically planned flagship zones with designated economic activities. Tanjung Piai Maritime Industrial Park falls within Flagship Zone C under Iskandar Malaysia, also known as the Western Gate Development focusing on development of maritime centre. Tanjung Bin is known as the largest power station in the south west of Malaysia, which is one of the four coal power plants in Malaysia, comprising three plants of 700 megawatts each. Under Iskandar Malaysia, Tanjung Bin Petrochemical and Maritime Industries is another key development projects falls under the same flagship with Tanjung Piai.

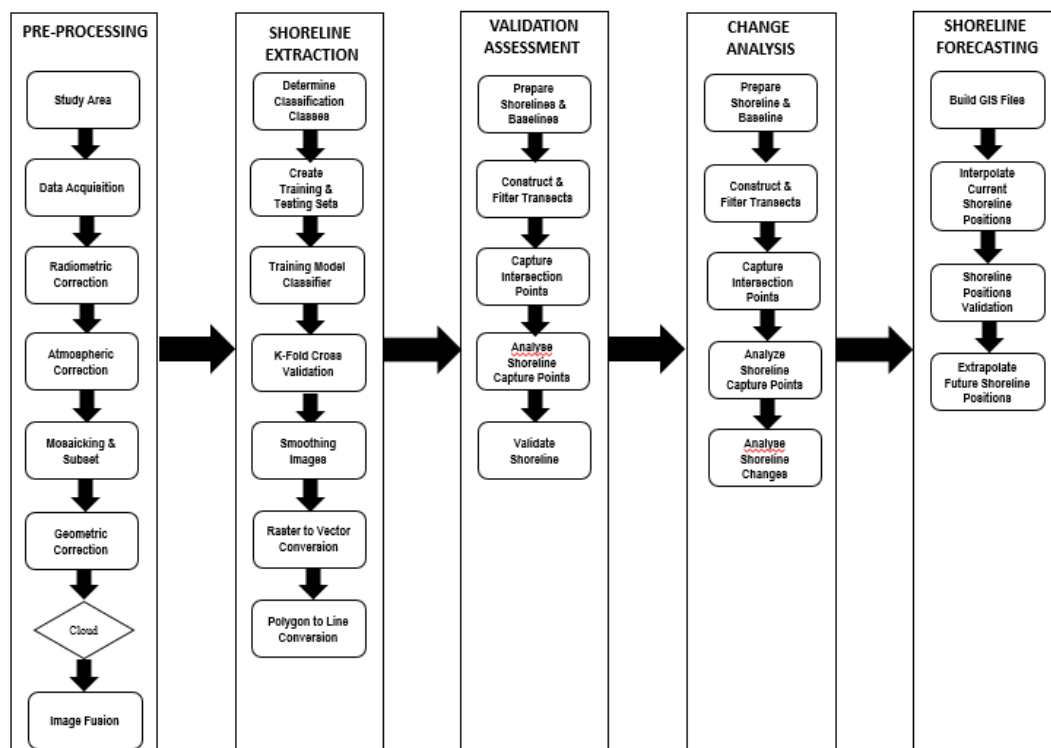


Figure 1. Methodology of this research.

2.2. Data acquisition

Multi-temporal satellite images data of Landsat and Satellites Pour l'Observation de la Terre (SPOT) sensors were used in this study. The duration covered for this study were 40 years, from 1977 to 2017. Total of only 7 scenes multispectral satellite images consisted of 5 scenes Landsat sensors, 1 scene of SPOT-5 sensor and 1 scene of TerraSAR-X sensor were used as the research data due to unavailability of many cloud free images during the chosen period. Therefore, the images could not be collected in regular interval. Additionally, TerraSAR-X image was used to fuse SPOT-5 image that contained clouds and shadows. Therefore, only six scenes were considered for the analysis. However, the number of scenes chosen would sufficiently covered the study area and the observation duration. Table 1 summarizes the data of the all six scenes.

From Table 1, all of the images were formalized to the same spatial resolution (in m) for further analysis. In order to do that, images from both Landsat 2 Multi Spectral Scanner (MSS) and Landsat 4 MSS sensors were up-sampled to 30 m while SPOT 5 image was down-sampled to 30 m to match the spatial resolution of other Landsat sensors [13][8]. On the other hand, the remaining Landsat 5 Thematic Mapper (TM), Landsat 7 Enhance Thematic Mapper Plus (ETM+) and Landsat 8 Operational Land Manager (OLI) images used the original 30 m resolution.

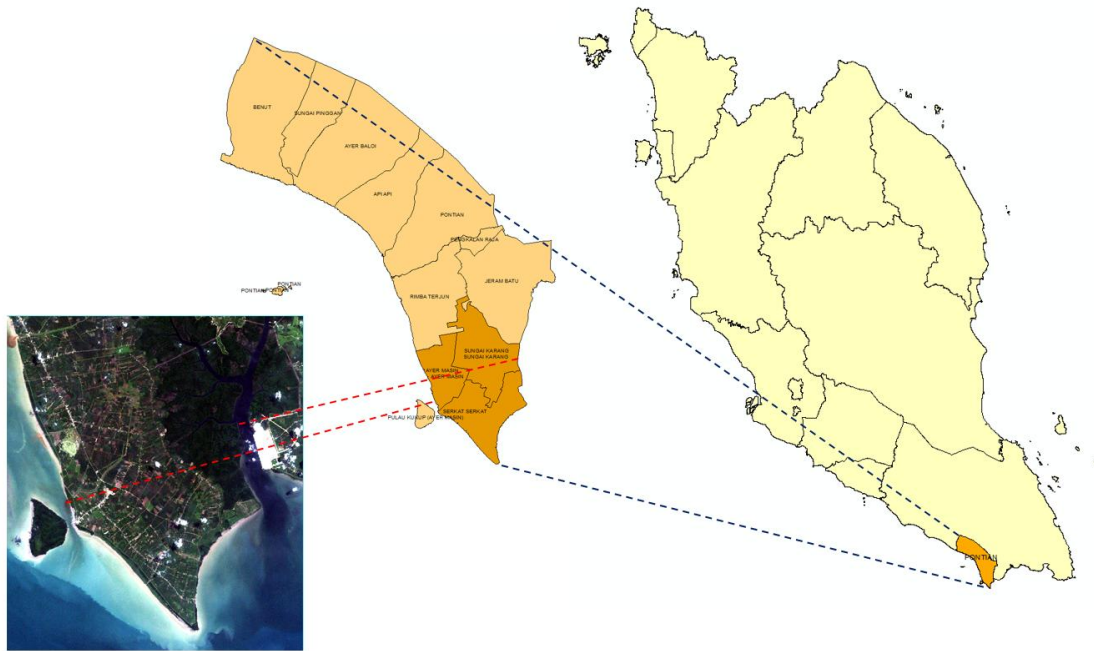


Figure 2. Study area of research.

Table 1. Description of the satellite images data.

Satellite Sensor	Path/Row	Acq date	Acq time (GMT)	Spatial res (m)	Resample to (m)
Landsat 2 MSS	134/059	21/03/1977	02:19:34	60	30
Landsat 4 MSS	125/059	08/11/1989	02:49:03	60	30
Landsat 7 ETM+	189/024	28/04/2000	03:24:09	30	-
Landsat 5 TM	125/059	29/06/2008	03:03:42	30	-
SPOT-5	274/347	14/04/2014	02:44:43	10	30
TerraSAR-X	ScanSAR 008 HH	09/03/2014	22:53:40	18.5	30
Landsat 8 OLI	125/059	08/07/2017	03:16:25	30	-

2.3. Data pre-processing

The pre-processing phase involved identifying a specific study area geographically and suitable data before performing series of error cleaning processes, such as radiometric, atmospheric and geometric corrections as in the first phase of Figure 1. Radiometric calibration was performed on the images to convert the satellite images to radiance (L_λ) images, as expressed by Equation 1.

$$L_\lambda = Gain \times Pixel\ value + Bias \quad (1)$$

The pixel value is a digital number (DN) that ranged from “0” to “255”, and the radiance of each image band depends on the gain and the bias values. Then, dark object subtraction (DOS) method was applied to the radiance image to remove haze components caused by the additive atmospheric scattering effects of the image data [14]. Then, image registration process was performed using image-to-image geometric correction process with Root-Mean-Square (RMS) value of 0.457 for 30 Ground Control Points (GCPs). The explanation of three stages cleaning processes in the pre-processing stages has been explained in more details in [14][15]. Mosaicking process was applied by combining more than one images to cover area of study due to cloud cover or incomplete study area for one scene.

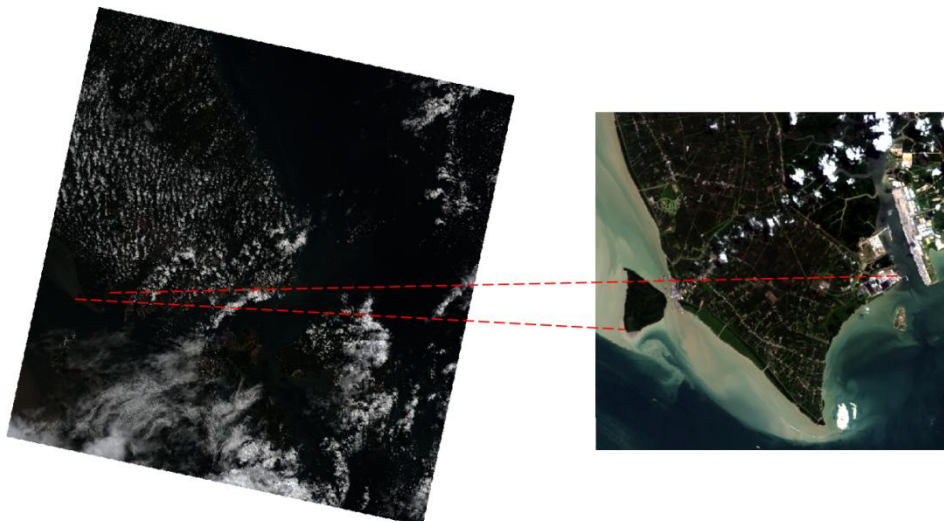


Figure 3. Landsat 8 data

Finally, image subset was performed on the acquired image to form a specific and small area to cover the study area instead of the large whole area. Landsat 8 image data are shown clearly in Figure 3, which the raw image contains dense cloud. However, after performing series of pre-processing stages and locating the study area free from cloud, the output image can be seen clearly.

Nevertheless, typical satellite images contain noise consisting of clouds, shadows and haze which lead to difficulty in extraction. Atmospheric correction can remove haze, not the other two. However, the problem becomes more intense if the clouds and shadows are located at the boundary areas of land and water regions. Moreover, the regions cannot be masked out to do analysis because important boundary information may have been removed. As such, the fusion of multispectral and SAR images, which can retain important spatial boundary information, can help extract shorelines with higher accuracy. Thus, the Intensity, Hue and Saturation (IHS) technique was applied for the fusion of SPOT-5 multispectral and TerraSAR-X images to produce synthetic fusion images that can be as accurate as the original images by previous study [16] as shown in Figure 4.

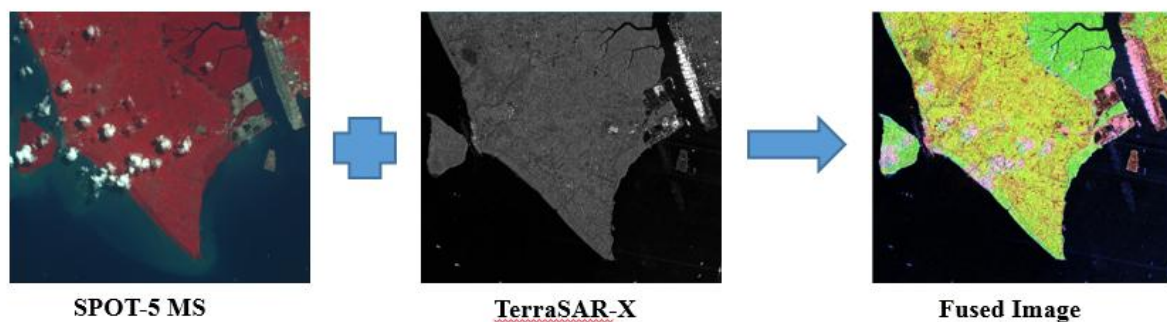


Figure 4. Fusion of multispectral and SAR

2.4. Shoreline extraction

In the satellite image classification stage, supervised classification using machine learning was chosen using pixel-based approach as in second phase of Figure 1. For this study, Multilayer Perceptron (MLP), K-Nearest Neighbour (kNN) and Support Vector Machine – Linear kernel (SVM-L) were used to classify land and water classes as in previous study [14]. In order to perform machine learning classification, a training set in the form of polygon was created to build the model. In this case, there were 200 and 100 polygons generated for land and water classes respectively.

In the accuracy assessment stage, the 10-fold cross validation method was used to test the model by using the same training set, but the analysis was performed on one subset while validation on the other nine subsets used totally 10 different partitions. In this process, the overall classification accuracy was used as measurement indicators.

In the last stage, the smoothing processes (e.g., sieve and clump) were performed to generalize the classified images data, such that the resultant polygons would be smooth. Then, the resultant classified images underwent a conversion process, through which the original raster images were converted to a vector GIS format. Then, the polygon-to-line conversion process was carried out on the vector GIS files to ensure the extracted shorelines files would be in the lines format. Finally, line smoothing using Polynomial Approximation with Exponential Kernel (PAEK) method was applied on the extracted shorelines data after all erroneous data were removed.

2.5. Validation assessment

In the validation phase (third phase of Figure 1), Analysing Moving Boundaries Using R (AMBUR) [17] software was used to validate the extracted shoreline from Landsat 8 OLI which was acquired in 2017 against a reference shoreline (acquired in 2016 from the local authority) using line analysis. Accordingly, the extracted shorelines data were merged with the reference shoreline to form a single shoreline data. The assessment was considered only the extracted shoreline data of Landsat 8 OLI image from three Machine Learning (ML) classifiers with the reference data. The result of this analysis was elaborated more details in the previous work [18].

2.6. Change analysis

The historical shorelines were compiled in GIS vector format and managed in ArcGIS 10.3. The AMBUR [17] was used for rate estimation of change analysis (fourth phase of Figure 1). The AMBUR uses measurement two baselines (i.e. inner and outer baselines) method to calculate rate of change statistics for a time series of shorelines. The baselines were constructed to serve as the starting point for all transects cast by the AMBUR application.

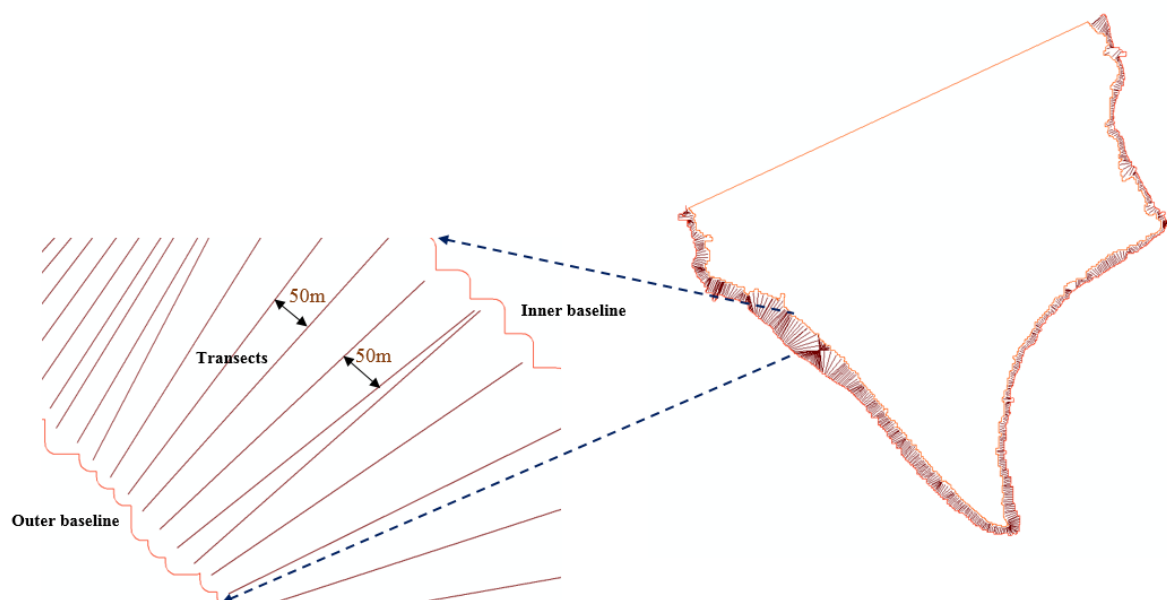


Figure 5. Transects along baselines

In fact, buffering was used instead of screen digitizing to create two baselines that covered both the interior and the exterior of the shorelines because the shapes of baselines are important for the calculations of changing shorelines that will influence transects orientation [17]. Both transects and shorelines containing the required fields were then set up to run analysis functions. Transects were

casted between the inner and the outer baselines at 50 m intervals as in Figure 5. Historic rates of shoreline change were then calculated at each transect using End Point Rate (EPR). The EPR was employed where only two shoreline positions were available for the period between 1977 and 2017. The EPR was calculated by dividing the distance between the shorelines by the number of years that have elapsed, as in Equation 2. Furthermore, the EPR method uses only two data points to delineate a change rate, the earliest and most recent shoreline positions. Given that only the end data points are used, the information contained in the other data points entirely omitted, preventing the observation of variations in rate through time.

$$EPR = \frac{Y_2 - Y_1}{X_2 - X_1} \quad (2)$$

where Y_1 , and Y_2 are shoreline positions and X_1 , X_2 are time differences.

3. Results and Discussion

The analysis of the experimental data was carried out on a high-performance workstation, namely Dell Precision 3620 machine, which was equipped with 3.4GHz Intel i7-6700 Quad Core Processor and 64 GB RAM, running on Microsoft Windows 7 (a 64-bit operating system) to support the ML classifier and change analysis. In order to extract shoreline from satellite images in raster format, the shoreline extraction stages required high-performance workstation with fast CPU and high memory. In the shoreline change analysis, it does not required as high-performance workstation as in shoreline extraction stage, it was sufficient enough to use any computer. However, using the same computer would fasten the analysis process.

3.1. Shoreline extraction result

Shoreline extraction phase comprised of four main stages; pre-processing, satellite image classification, accuracy assessment and post-processing. Three machine learning (ML) classifiers namely MLP, kNN and SVM-L were assessed in term of overall accuracy (OA). Generally, for all three classifiers, the latest sensor recorded the highest OA with 99.60%, in contrast with the earliest sensor recorded the lowest OA with 90.00%. Moreover, the increasing in accuracy was due to the increasing number of spectral bands used in the latest sensor. Finally, MLP was chosen to extract shorelines as it proved the highest accuracy [14] among the three methods .

3.2. Shoreline extraction validation assessment result

The researchers carried out validation assessments of extracted shorelines of Landsat 8 (2017) using MLP classifier with reference shoreline provided by local authority (2016). The extracted shoreline also performed with PAEK algorithm to help smoothen as well as improve the extraction process. Furthermore, the findings showed that the accuracy of the extracted shoreline was directly proportional to the accuracy of the image classification with smoothing operation by using PAEK, hence affected the quality of extracted shorelines.

3.3. Shoreline change analysis result

There were six shoreline vectors from different dates considered for the analysis. For the study area, Pontian coast faced with changes whether erosion or accretion processes. Overall, the results showed that the Pontian coast is a highly dynamic feature with an average rate of accretion estimated to be about 2.42 m/year comprising of mean erosion rate estimated about -2.2 m/year while mean accretion rate estimated about 4.6 m/year. The findings generally confirm the high rates of erosion as high as -8.99 m/year reported for Tanjung Piai estuary located at the most southern of the Pontian coast as National Hydraulic Research Institute of Malaysia (NAHRIM) has highlighted it as sea level rise prone. In contrast, the accretion along Kukup coast to Tanjung Piai was due to land reclamation activities to build Tanjung Piai Maritime Industrial Park.

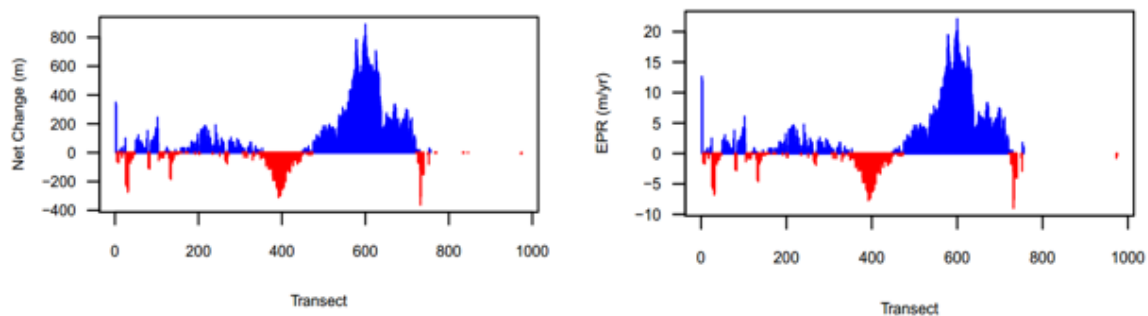


Figure 6. Net change (m) and EPR (m/y) results

Figure 6 shows the net change and the EPR results of Pontian coast for 40 years' duration, for the detailed analysis. From the net change result, it can be seen clearly the accretion occurred in three main transect groups ; i) 50 to 100 m, ii) 180 to 350 m, and iii) 450 to 680 m. Among the three groups, the third group is considered as the longest transects and the first group is the shortest one. From the figure, the third group achieved the maximum net change with more than 800 m. However, the second group achieved the shortest net change even with the long transect. For the erosion, the sequential transect cannot be seen clearly as in accretion, except in the transect 350 to 450 m. The net change for that group recorded approximately 350 m and almost reached the highest at transect 680 to 700 m (almost 400 m). As summary, the accretion occurred more than erosion along the coast.

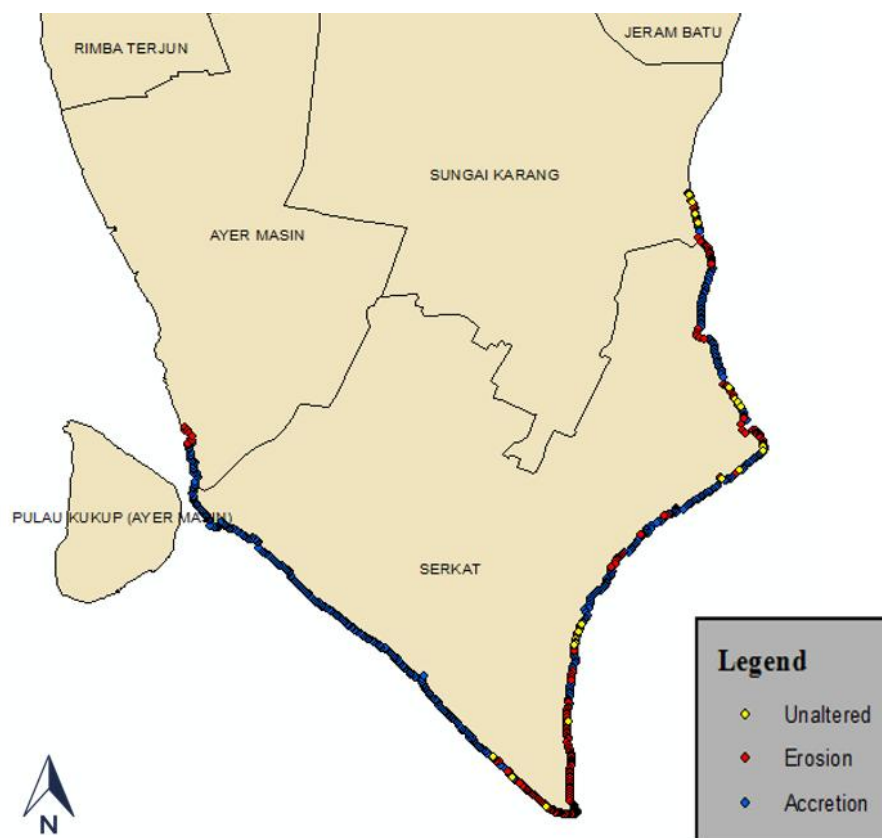


Figure 7. Change analysis map

From the EPR result (also similar with the net change analysis), it can be seen clearly the accretion occurred in three main transect groups; i) 50 to 100 m, ii) 180 to 350 m, and iii) 450 to 680 m. From the three groups, the third group is considered as the longest transects and the first group is the shortest one. From the figure, the third group achieved the maximum EPR with more than 20 m/y. However, the second group achieved the shortest EPR even with the long transect. For the erosion, the sequential transect cannot be seen clearly as in accretion, except in transect 350 to 450 m. The EPR for that group recorded approximately 5 m/y and almost reached the highest at transect 680 to 700 m (almost 10 m/y). As summary, the accretion occurred more than the erosion along the coast.

The results of the two previous analyses can only depicted which transect was affected by erosion and accretion. However, the location can be depicted more clearly if displayed on the map. The output of net change result was reclassified into three classes, namely erosion (red color), accretion (blue color) and unaltered (yellow color) instead of two classes as depicted in Figure 7. To find out which region in Pontian coast involved for this analysis, Pontian map was overlaid with the change analysis map. From the map, all coasts along Serkat were involved in this analysis while only small area along Ayer Masin and Sungai Karang coasts were involved. From the figure, transect starts at the east to the west areas via the south area. From the map shown, Tanjung Piai, which located at the most southern area, was recorded with the erosion while the west coast from Tanjung Piai to Kukup coast was recorded with the accretion. However, few parts along the coast were left unaltered.

4. Conclusion

Results of this study reveal the trends in shoreline changes along the southern coast of Malaysia for 40 years' period of observation. During this period, the changes were not only affected by natural processes and anthropogenic activities, but also by the sea level rise. With the advancement of satellite sensors and big data, spatio-temporal data from the satellite images can be used to find trends in shoreline changes of this coast. This approach could also be replicated along the entire Malaysia's coast. The findings along Pontian coast show that the most southern region faced erosion while the west region stretching from Kukup to Tanjung Piai faced accretion.

For the future works, the details of accretion and erosion occurred need to be reclassified further into more classes, so that types of both accretion and erosion can be analyzed more detailed, from light to severe, etc. Moreover, the change analysis can be implemented between acquisition times of each satellites being observed.

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