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# ASSESSMENT OF THE MANGROVE FOREST CHANGES ALONG THE PAHANG COAST USING REMOTE SENSING AND GIS TECHNOLOGY

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**Abstract:** Mangrove forests provide vital ecosystem services to the surrounding communities. Despite their importance, development in coastal areas impose a direct impact on reducing area cover. It is an important topic to understand the effect of coastal development on the carbon storing capacity of mangroves. This study aimed to examine the rate of erosion and accretion and estimate the amount of carbon stock change along the Cherating - Pekan coastline in Pahang, Malaysia. The rate of erosion and accretion from 2006 to 2014 was determined by using SPOT 5 satellite images. The normalised difference vegetation index (NDVI) was modelled to estimate carbon stock specific to the mangrove forest. Results from the study reveal that mangroves grew at only four locations along the 87 km Cherating–Pekan shoreline. Difference analyses unveil that the coastline had undergone erosion and accretion processes, with Cherating River and Penor River showing the most rapid change of 10.31 and 18.17 m/year, respectively, using the end point rate (EPR) method. Ular River and Kuantan River have been identified as areas prone to moderate erosion. The total carbon stock of mangroves in 2006 and 2014 was estimated at 499.78 and 520.48 t/ha, respectively. This finding provides the baseline information which would be helpful and should be considered when planning the future development as well as in the management of resources along the Pahang coastline.

Keywords: Carbon stock, erosion and accretion, NDVI, climate change, GIS.

## Introduction

Mangroves are valuable, unique in structure, and have a special ecological function while they are also ecologically vulnerable to environmental changes. Mangrove ecosystem is an important natural resource that provides multiple ecosystem services for the local communities. A comprehensive assessment of natural resources can provide important information required for the planning, management, and conservation of mangroves. Amir (2018) asserted that there is a need to improve the weaknesses in the planning, approval, and implementation processes of mangrove-related projects to ensure the sustainability of their resources. Mangrove forests provide a wide range of products and services such as food sources for the coastal community, nursery habitats, biodiversity conservation, water filtration, shoreline stabilisation, storm protection, flood control, recreation, and tourism (McIvor *et al.*, 2012; Rahman *et al.*, 2013; Spalding *et al.*, 2014; Sandilyan & Kathiresan, 2015; Giri *et al.*, 2015).

Mangrove protection is increasingly believed to be crucial in terms of climate change mitigation and adaptation by virtue of the large amount of carbon available in the above and below ground biomass. Donato *et al.* (2011) estimated that mangroves store the larger amount of carbon than any other types of forest, with a storage capacity of between 990 and 1074 t/ha. These forests have been recognised as highly productive and carbon sequester (Kauffman *et al.*, 2011; Adame *et al.*, 2013; Costanza *et al.*, 2014).

Despite their values, these ecosystems continue to shrink in area cover and are being degraded and converted for various reasons such as urban, aquaculture, and agriculture development (Giri *et al.*, 2011; Richards & Friess, 2016; Madihah *et al.*, 2018). In Malaysia, most of the mangrove habitat loss is due to the change in land cover as a result of agricultural expansion as well as aquaculture and urban coastal development (Richards & Friess, 2016). Polidoro *et al.* (2010) predicted that the impacts of future anthropogenic activities on coastal ecosystems would only worsen as the population in the coastal regions continues to increase. As a result, the pressures exerted by humans have been shown to be a major threat to the mangrove ecosystem. Ottinger *et al.* (2016) have found that the fastest growing animal-producing sectors, i.e., the aquaculture industry also poses a serious threat to the mangroves.

One of the main factors that have been decreased of the mangrove distribution along the Pahang coastline is coastal development. Ahmad *et al.* (2019) mentioned that these mangrove areas have been cleared to give space for developments such as human settlements, aquaculture farm, small markets, parking area, and others. Furthermore, Dasgupta & Shaw (2013) mentioned that the land near river and shoreline are low in value and affordable, therefore attracting developers to develop the area and causing severe destruction to the mangroves**.** The Malaysian mangroves provide multiple ecological, economical, and social benefits to the coastal population (Kanniah *et al.*, 2015).

The ability of remote sensing to estimate mangrove cover and biomass has improved significantly over time (Sharma *et al.*, 2009; Kuenzer *et al.*, 2011). GIS and remote sensing are acceptable methods to evaluate the impact of the sea level rise, coastal erosion, and land use changes near the coastal area (Maulud & Rafar, 2015). Satellite remote sensing can give a more comprehensive and rapid assessment of coastal and mangrove area covers (Bandyopadhway *et al.*, 2009; Sharma *et al.*, 2012). Proisy *et al.* (2007) reported that the advancement in technology has not only improved the accuracy of remote sensing for mapping and detecting change, but it also improved the ability to predict standing biomass. Kuenzer *et al.* (2011) described that remote sensing as a very consistent and reliable method for measuring and monitoring large forested areas. Therefore, this study aimed to assess the land use cover changes and estimate the aboveground carbon stock changes in the mangrove forest along the Pahang coastal area using the satellite remote sensing technique.

## Methodology

### *Study area*

The study was conducted in the low lying Cherating-Pekan shoreline of the Pahang state, which is located in the East Coast of Peninsular Malaysia, facing the South China Sea (between 04° 07' 38'' and 03° 32' 05'' N; 103° 23' 45'' and 103° 27' 41'' E). The Cherating-Pekan coastal area is nearly to 84-km long sandy shoreline. The mangroves areas are located at Cherating River, Ular River, Kuantan River and Penor River. The National Coastal Erosion Study (NCES) (1985) shows that these areas are a major resource for the local fishing industry as well as important spawning and feeding areas for many marine and intertidal species.

### *Data*

The data used in this research were obtained from both *in-situ* observation and satellite images. Two series of optical satellite images were used to determine the coastal land use cover change and mangroves aboveground carbon stock. The cloud free satellite images (SPOT 5) for 2006 and 2014 were obtained

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from the Earth Observation Centre at Universiti Kebangsaan Malaysia. SPOT 5 has a 2.5-m pixel spatial resolution and four spectral bands, i.e., band 1- green (0.50–0.59 μm), band 2- red (0.61–0.68 μm), band 3- near infrared (NIR) (0.79–0.89 μm), and band 4-short wave infrared (SWIR) (1.57–1.75 μm). These optical satellites were selected because they allowed the vegetation indices to be determined by using the red and NIR spectral bands. The SPOT 5 images were corrected by atmospheric and radiometric processes to obtain synchronised images with true surface reflectance values. The SPOT 5 images were selected because of ~~its~~ their high spatial and spectral resolutions, and many researchers have used the normalised difference vegetation index (NDVI) for land use cover to monitor large vegetation area change along the shoreline (Munyati & Mboweni, 2013). Table 1 summarises the criteria of potential data for AGB stock changes and Table 2 enlists the characteristics of SPOT 5 satellite information.

Table 1: Overview of satellite used for carbon stock mapping.

| No | Elements | Optical Remote Sensing | Radar Remote Sensing | LiDAR |
|---|---|---|---|---|
| 1 | Satellite types | Quickbird, Worldview, SPOT, Sentinel, Landsat and MODIS | Space-borne systems such as Terra-SAR, ALOS and PALSAR have become available since 2000 | Light Detection and Ranging, a few LiDAR instruments currently operating from satellite platforms |
| 2 | Advantages | the best alternative to biomass estimation through field sampling due to its global coverage, repetitiveness and cost-effectiveness.<br><br>Spatial resolution less than one metre to hundreds of metres | this has enabled repetitiveness and cost-effectiveness.<br><br>SAR sensors can operate day or night while penetrating through haze, smoke, and clouds. | relatively new technology that has found favour in biomass estimation.<br>It has the ability to sample the vertical distribution of canopy and ground surfaces, providing detailed structural information about vegetation.<br><br>This leads to more accurate estimations of basal area, crown size, tree height and stem volume |
| 3 | References | (Hyde *et al*., 2006), (li *et al*., 2008), (Rahman *et al*., 2005) | (Castel *et al*., 2002), (Sarker *et al*., 2013), (Le Toan *et al*., 2011) | (Saremi *et al*., 2014), (Lim & Treitz, 2004), (Garcia *et al*., 2002) |

Table 2: Satellite images data acquisition information and characteristics

| Type of data | Date | Time | Event | Tidal Height | Spatial resolution |
|---|---|---|---|---|---|
| SPOT 5 | 2/7/2006 | 11.49 am | High Tide | 2.5 m | 2.5 m |
| SPOT 5 | 22/8/2014 | 11.00 am | High Tide | 2.2 m | 2.5 m |
| SPOT 5 | 20/7/2006 | 11.49 am | Low Tide | 1.9 m | 2.5 m |
| SPOT 5 | 5/8/2014 | 11.03 am | Low Tide | 1.8 m | 2.5 m |

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### *Flowchart*

The method of carbon stock assessment in this research which involved field surveys, image analysis, model development, and quantifying AGC stocks is shown in Figure 1. These procedures are described in the subsequent sub-sections.

### *Land Use and Land Cover (LULC) Classification*

In this study, the LULC of the area were classified into six categories: (1) coastal forest (mangrove), (2) other vegetation, (3) open development areas, (4) water bodies, (5) land, and (6) sand. The changes were determined in one kilometre buffer zone. This approach utilises a supervised classification by selecting homogeneous signatures of pixel classes which overlap with other classes and combining them to categorise the full extent of the original images by using the maximum likelihood algorithm (Misra & Balaji, 2015). Change difference analyses were carried out to estimate the changes in the study area that were identified by comparing the results of two time date categories (Hamdan *et al.*, 2013). In this study, the spectral characteristics of mangroves appeared darker on satellite images because they grew in wet coastal regions, and used the combinations of bands 4, 3 and 2 of the SPOT 5 images for the selection of training area (Hamzah & Omar, 2009). The verification of land use and land cover categories was done through an extensive fieldwork observation. Prior knowledge and published data of several locations also helped in the result verification process (Kanniah *et al.*, 2015).

### *Accuracy Assessment*

Accuracy assessment is an important part of classification. This technique is determined by comparing the image of LULC classification result with reference data such as field data, topographic map, and others. The kappa accuracy provides a statistically valid assessment of the quality of classification and was used to assess the overall class accuracy as shown in Equation 1:

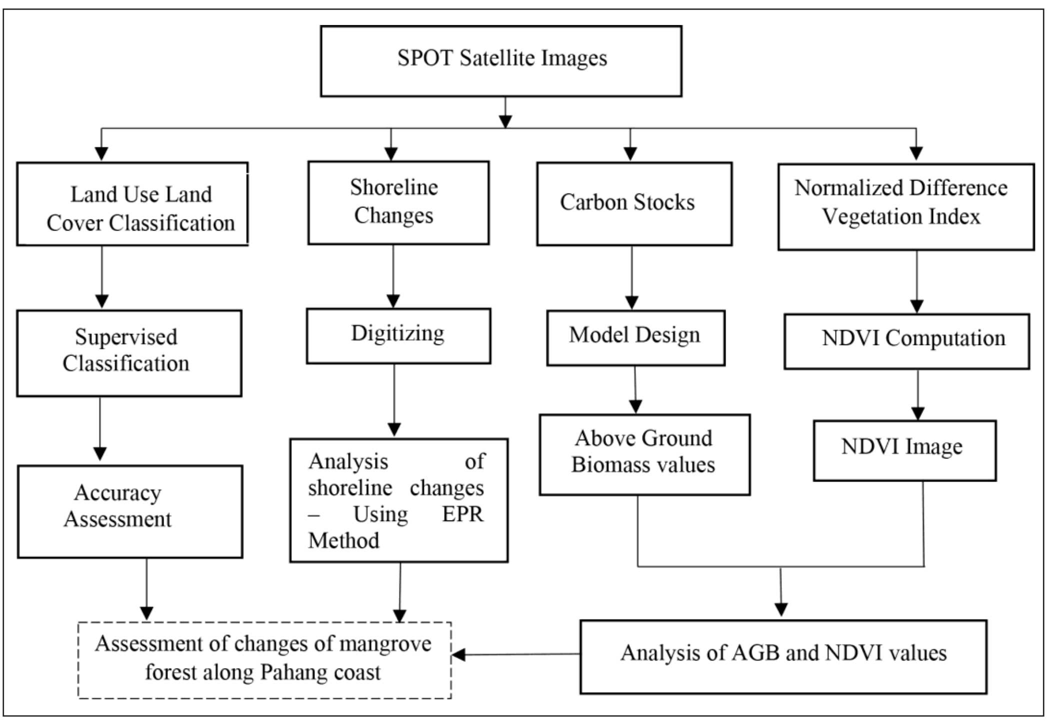


Figure 1: Flowchart of research

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

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 observations

### *Shoreline Extraction*

The shoreline is defined as the physical interface between land and water (Dolan *et al.*, 1980; Zakaria *et al.*, 2006). The determination of shoreline position in satellite data is very subjective. Previous researchers used various indicators for shoreline positioning, such as high tide mark (Fisher & Overton, 1998; Stockdon *et al.*, 2002), high water level (Fenster & Dolan, 1999), wet-dry mark (Overton *et al.*, 2011), vegetation line (Zarillo *et al.*, 2008), dune line (Stafford, 1971), berm of the beach (Norcross *et al.*, 2002), cliff base or top (Moore *et al.*, 1999), mean high water (MHW) level (Kankara *et al.*, 2015), etc. Thus, by considering these factors, the high water line (HWL) (i.e., the effective shoreline is equivalent to the wet/dry line of the previous tide), which is clearly recognisable in all images was the most appropriate shoreline for monitoring the changes (Chenthamilselvan *et al.*, 2014; Kankara *et al.*, 2015). Manual digitisation of shoreline is a time-consuming process and its accuracy is subjected to the knowledge of the interpreter; hence, it is very important that the interpreter is able to duplicate the results (Kankara *et al.*, 2015). The shoreline features were determined based on the differences in the colour pixels of the land and the sea. The band ratio technique was used to differentiate the land from the water pixels. A more advanced digitisation technique was used to obtain the shoreline features in the Arc-GIS software. Misra and Balaji (2015) stated that to further improve the results, a visual interpretation was done to edit the shoreline features so that they conform to the high tide line (HTL).

### *Analysis of Shoreline Changes*

The shoreline extracted from the satellite image was compiled in the ArcGIS 10.3 software. All shoreline positions were merged as a single feature on the attribute table, which allowed for the multiple coastline files to be appended into a single shapefile. Digital Shoreline Analysis System (DSAS) version 4.0, which is an extension of the ESRI ArcGIS developed by the USGS, was used to compute the shoreline change rate (Thieler *et al.*, 2009). The computation of shoreline changes was done in four steps: (1) preparation of shoreline position, (2) determination of baseline, (3) generation of transect line, and (4) computation of changes. The historical shoreline position was extracted using a digitising technique of the shoreline for 2006 and 2014. A baseline was determined to be 1 km from the shoreline by using a buffering technique and was the digitised onshore area. The baseline is located parallel to the shoreline, and the transect line was automatically generated by the DSAS tool, which produced 1068 transect lines with a 0.25-m interval between each transect line.

The computation of shoreline change for the short term analysis requires only two historical shoreline data set. The shoreline change rate was computed by dividing the distance of shoreline movement by the time elapsed between the oldest and the most recent shorelines. In this study, the digitised shoreline for 2006 and 2014 in the vector format were used as the input for the DSAS to calculate the rate of shoreline change.

The end point rate (EPR) is a simple and popular approach used to calculate the shoreline change rate. The EPR was obtained by dividing the difference of distance change by the number of years elapsed between the two shoreline positions. Linear extents with negative EPR values indicate erosion, whereas those with positive values indicate accretion (Misra & Balaji, 2015). A minimum of two shoreline dates is required for to calculate the rate, as shown in Equation 2:

$$\text{EPR (m/y)} = \frac{\text{Distance (X – Y)}}{\text{Time between latest and previous shoreline}} \quad (2)$$

### *Normalised Difference Vegetation Index (NDVI)*

Vegetation index has long been used in remote sensing application to monitor temporal changes associated with vegetation (Ofosu Anim *et al.*, 2013). The NDVI in the vegetation indices is one of the frequently used techniques in such analyses by the virtue of its strong correlation with the photosynthetic activity, which is the basis for its use in assessing the net primary production (Gadakh & Jaybhaye, 2016; Gu & Liu, 2012; Munyati & Mboweni, 2013). Hamdan *et al.* (2013) elucidated that NDVI is based on the characteristics of vegetation which has noticeable absorption in the red spectrum and very strong reflectance in the NIR spectrum. This technique has been used to monitor the greenness pattern of the natural vegetation on the earth surface. NDVI is computed using Equation 3:

$$\text{NDVI} = \frac{\text{Band NIR – Band Red}}{\text{Band NIR + Band Red}} \quad (3)$$

where band RED and NIR are the visible red and NIR reflectance value, respectively. The output of NDVI values ranges between −1 and +1. Healthy vegetation generally has high NIR reflectance and absorbs strongly in the red spectral region (Lillesand & Kiefer, 2014). Positive values indicate different vegetation classes, whereas near zero and negative values indicate non-vegetation classes, such as water, snow, urban area, and barren land (Hamdan *et al.*, *2013).*

### *Aboveground Biomass Assessment (AGB)*

The SPOT 5 satellite images were used to assess the aboveground carbon stock of the mangrove forests along the Pahang coast for the period between 2006 and 2014. In this context, remote sensing satellites provide an opportunity to monitor changes in forest carbon and able to estimate the forest carbon density over large extent in a continuous manner (Asner, 2009; Hamdan *et al.*, 2013; Kanniah *et al.*, 2015). Several researchers have used NDVI to estimate forest carbon, however in this study, the relationship between NDVI and AGB was established using the data obtained from the mangroves in Peninsular Malaysia (Figure 2). The AGB of the mangroves was estimated using Equation 4 (Shahrul, 2015) as follows:

$$\text{AGB} = 28.015e^{3.5546(\text{NDVI})} \quad (4)$$

Where, AGB is the aboveground biomass,
*exp* (….) = “raised to the power of (…)” and
*NDVI* = Normalized difference vegetation index as shown in Equation 3.

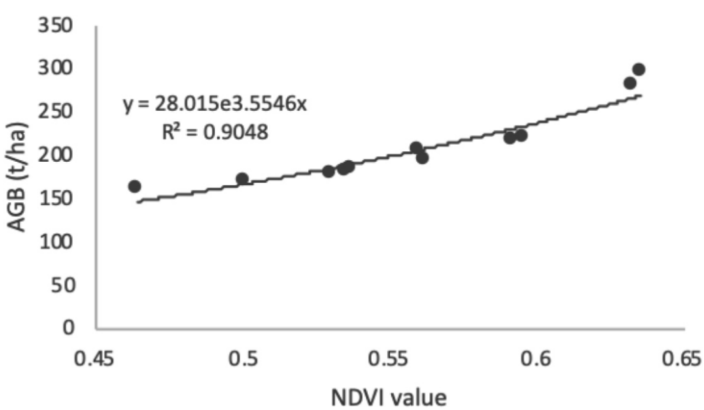


Figure 2: Relationship between AGB and NDVI value. Data obtained from the mangrove forest in Malaysia (Shahrul, 2015)

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## Results and Discussion

### *Land Use and Land Cover Classification*

The distribution of the six categories of landuse types for 2006 and 2014 (coastal forest, other vegetation, open development areas, water bodies, land, and sand) are shown in Figure 3. Table 3 shows that within eight years, Ular River ~~has~~ lost 1.36 ha (8.7%) of its coastal forest (mangrove), while Penor River shows a loss of 0.72 ha (7.2%). On the other hand, Cherating River and Kuantan River gained 0.28 ha (4.6%) and 0.95 ha (9.1%) of coastal forest (mangrove), respectively. The loss of mangroves in the study area is due to urbanisation. According to Kanniah *et al.* (2015), the fastest growing of urban development will threaten the survival of mangrove forests. Shahbudin *et al.* (2010) also identified several types of coastal developments for several purposes such as tourism (Kuantan River waterfront and several resorts), jetty for fisheries landing, and mangrove clearing for commercial purposes (mainly for commercial building and residential areas) along the Pahang coast. Therefore, there is a need to implement necessary measures to prevent further loss of the existing mangrove cover.

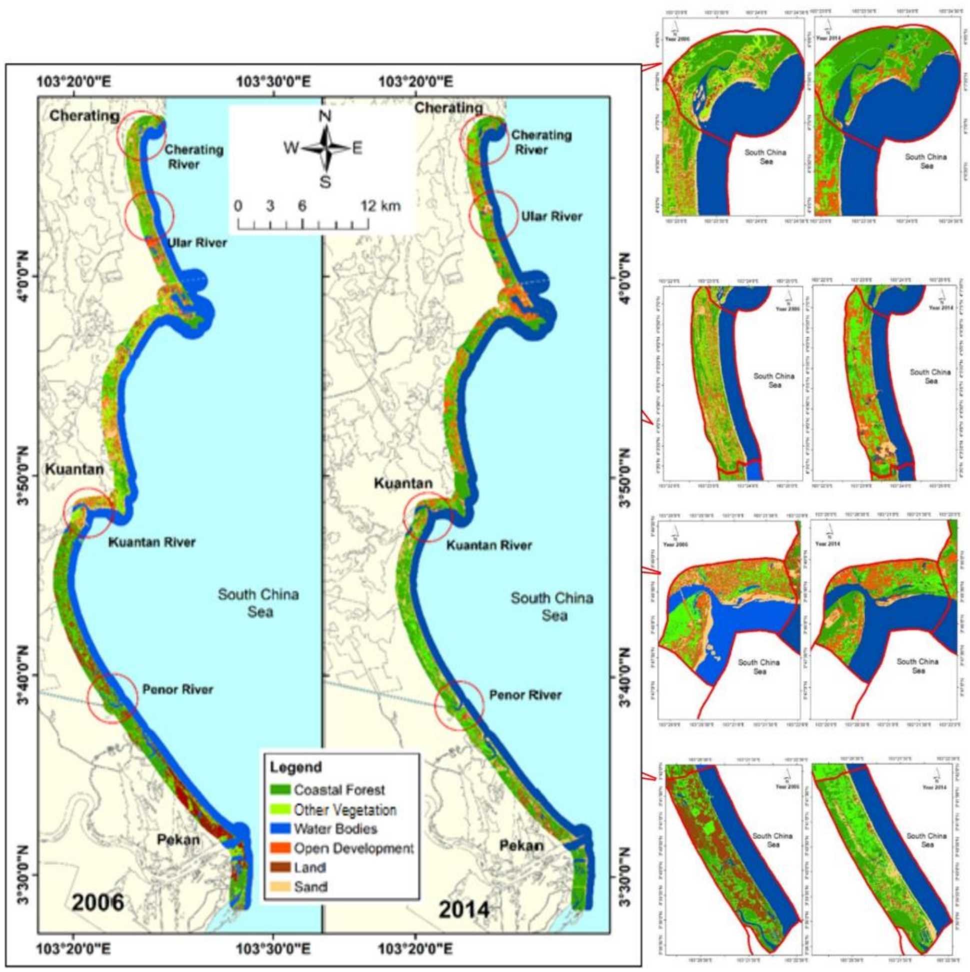


Figure 3: Land use and land cover map along the Cherating-Pekan shoreline in Pahang between 2006 and 2014

Generally, Cherating River and Ular River lost 0.26 ha (4.3%) and 0.28 ha (1.8%) of their other vegetation, respectively, during the eight years. The land category in the four locations lost from 1.8% to 8.5% (0.11 to 0.88 ha) during the same period. For the open development category, only Kuantan River remained unchanged during this period, while both Cherating River and Penor River lost as much as 0.11 ha (1.8%) and 0.02 (0.2%), respectively. The Ular River gained 2.25 ha (14.5%) of the open development area.

Table 3 also shows the changes in the land cover and land use categories for all locations of the study area. Cherating River shows that the areas for coastal forest (mangrove) and water bodies increased by about 0.28 and 0.37 ha, respectively, while the other vegetation shows a reduction of about 0.26 ha. Both the land and open development categories show a similar change of 0.11 ha. The sand category recorded a loss of 0.17 ha during this period.

Ular River shows the largest change in the coastal forest (mangrove) category. More than 1.36 ha of the total forested area was lost. The land category shows a decrease of 0.93 ha, which is the highest loss after the coastal forest category, followed by the sand and other vegetation categories. The decrease in the sand and other vegetation categories was around 0.31 and 0.28 ha, respectively. The area for the open development and water bodies categories show an increase of 2.25 and 0.63 ha, respectively.

The classification of land use and land cover for Kuantan River between 2006 and 2014 shows that the water bodies increased by about 1 ha (Table 3), while the coastal forest (mangrove) and other vegetation increased approximately 0.95 and 0.15 ha, respectively. The land and sand categories lost around 0.88 and 1.21 ha of their areas, respectively, during the study period. This is because, the attraction of living near the shoreline has increased the demand for residential areas such as near the Tanjung Lumpur area in Kuantan (Shahbudin *et al.*, 2009; Mohd *et al.* 2019).

Penor River shows a significant change in land use and land cover for the sand category, which recorded an increase of 0.87 ha in total area. The largest decrease in the area of 0.80 ha was for the land category, followed by coastal forest (mangrove) (0.72 ha), and open development areas (0.02 ha). Shahbudin *et al.* (2009), also revealed that the small scale of cage culture industries was implemented in this area, which had been built by the villagers. Most of these cage structures have been built from mangroves and illegally cut down from the nearby mangrove forest. Other vegetation and water bodies within the area ~~between~~ show an increase of 0.65 and 0.02 ha, respectively, during the study period. Ibrahim (1998) also pointed out that these mangrove forests occured in a small area and often fragmented along the six rivers in Pahang especially at Chenor River, Dua River, Kempadang River, Ular River, Balok River, and Cherating River. Ibrahim (1998) and Mohd *et al.* (2019) also stated that mangrove vegetation was mainly dominated by *Rhizophora* sp., *Avicennia* sp., and *Sonneratia* sp. along this shoreline.

Between 2006 and 2014, the land use in the area between Cherating River, Ular River, and Kuantan River was dominated by urban housing areas and forest areas, along with the development of high density urban housing near the industrial areas of Ular River in 2014. As mentioned by Hamdan *et al.* (2013), almost 31% of land use were converted for industrial and urban development. Kuantan, which is the capital city of Pahang, is located in the center between Cherating, Ular, and Penor. This could be the reason for the employment opportunity brought about by this new development. The expansion of beach resorts and tourism areas resulted in a change from a medium density to high density urban housing. In the area between Kuantan and Pekan, agricultural plantations such as coconut, paddy, rubber, oil palm, and development of new urban housing were observed to dominate the landscape. However, interestingly, this is contrary to a study conducted by Shahbudin *et al*. (2009) which showed the massive development activities in Kuantan had given enormous pressure to the coastal ecosystem. The current threats to Pahang's forest are primarily due to the residential and

Table 3: Classification of land use and land cover for Cherating River, Ular River, Kuantan River and Penor River in 2006 and 2014

| Classification | Location | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Cherating River | | | Ular River | | | Kuantan River | | | Penor River | | | Total | | |
| | 2006 (ha) | 2014 (ha) | Area Change (ha) | 2006 (ha) | 2014 (ha) | Area Change (ha) | 2006 (ha) | 2014 (ha) | Area Change (ha) | 2006 (ha) | 2014 (ha) | Area Change (ha) | 2006 (ha) | 2014 (ha) | Area Change (ha) |
| Coastal Forest (Mangrove) | 1.60 | 1.88 | 0.28 (4.6%) | 2.69 | 1.33 | -1.36 (-8.7%) | 2.63 | 3.58 | 0.95 (9.1%) | 3.17 | 2.45 | -0.72 (-7.2%) | 10.09 | 9.24 | -0.85 |
| Other Vegetation | 0.85 | 0.59 | -0.26 (-4.3%) | 3.94 | 3.66 | -0.28 (-1.8%) | 1.55 | 1.70 | 0.15 (1.4%) | 1.52 | 2.17 | 0.65 (6.5%) | 7.86 | 8.12 | 0.26 |
| Land | 0.26 | 0.15 | -0.11 (-1.8%) | 2.29 | 1.36 | -0.93 (-6.0%) | 1.85 | 0.97 | -0.88 (-8.5%) | 1.99 | 1.19 | -0.80 (-8.0%) | 6.39 | 3.67 | -2.72 |
| Open Development | 0.41 | 0.30 | -0.11 (-1.8%) | 0.35 | 2.60 | 2.25 (14.5%) | 0.00 | 0.00 | 0.00 | 0.02 | 0.00 | -0.02 (-0.2%) | 0.78 | 2.9 | 2.12 |
| Water Bodies | 2.62 | 2.99 | 0.37 (6.1%) | 4.94 | 5.57 | 0.63 (4.0%) | 3.00 | 3.99 | 0.99 (9.5%) | 3.20 | 3.22 | 0.02 (0.2%) | 13.76 | 15.77 | 2.01 |
| Sand | 0.29 | 0.12 | -0.17 (-2.8%) | 1.36 | 1.05 | -0.31 (-2.0%) | 1.37 | 0.16 | -1.21 (-11.6%) | 0.10 | 0.97 | 0.87 (8.7%) | 2.12 | 2.30 | 0.18 |
| Total area (ha) | 6.03 | 6.03 | | 15.57 | 15.57 | | 10.40 | 10.40 | | 10.00 | 10.00 | | | | |

industrial development purposes, followed by aquaculture and other related activities.

Table 4 summarises the result of correlation matrix analysis between mangroves and LULC classification. The highest correlation was observed in the open development reflectance with $r = -0.67$. The biggest area changes for all land use land cover classification can be found in open development between four study locations in 2006 and 2014 with 2.12 ha (Table 3). The changes were contributed greatly by Ular River with 14.5% of changes. Therefore, the open development is a strong indicator for causing mangrove loss. In general, other vegetation, water bodies, and sand have a low negative relationship with $r = -0.058$, $-0.112$, and $-0.158$, respectively. There was a moderate positive relationship between mangroves and land with $r = 0.455$ because both categories were reduced with 0.85 and 2.72 ha of area, respectively. Therefore, there was no significant difference between the mangrove and land categories.

### *Accuracy Assessment*

The supervised classification for land use and land cover of 2006 and 2014 were verified with topographic map, Google Earth and in-situ measurement. The accuracy assessments were accepted and the overall kappa ($\hat{K}$) for supervised classification for 2006 and 2014 images was good, as listed in Table 5. The overall kappa for supervised classification shows the value of 0.83 and 0.91 with an overall accuracy of 85.42% and 94.00%, respectively.

From Table 6, the stratified random method provided a very high accuracy assessment for the coastal forest (mangrove), other vegetation, water bodies and sand categories with kappa ($\hat{K}$) statistics of approximately 1. It also provided a high accuracy of 0.7–0.89 for the land and open development categories, respectively.

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Table 4: Correlation matrix for each class

| | **Coastal Forest (Mangrove)** | **Other Vegetation** | **Land** | **Open Development** | **Water Bodies** | **Sand** |
|---|---|---|---|---|---|---|
| Coastal Forest (Mangrove) | 1 | | | | | |
| Other Vegetation | -0.058 | 1 | | | | |
| Land | 0.455 | 0.651 | 1 | | | |
| Open Development | **-0.673** | 0.545 | -0.021 | 1 | | |
| Water Bodies | -0.112 | 0.907 | 0.435 | 0.717 | 1 | |
| Sand | -0.158 | 0.695 | 0.603 | 0.249 | 0.450 | 1 |

Table 5: Accuracy Assessment of LULC classification on years 2006 and 2014

| **No** | **Classified Image** | **Overall Kappa ($K^{\wedge}$)** | **Overall Accuracy** |
|---|---|---|---|
| 1 | SPOT 5 Image 2006 | 0.83 | 85.42 % |
| 2 | SPOT 5 Image 2014 | 0.91 | 94.00% |

Table 6: Summary of kappa ($K^{\wedge}$) statistics of Land Use Land Cover classification

| **No** | **Classification Types** | **Year 2006** | **Year 2014** |
|---|---|---|---|
| 1 | Coastal Forest (Mangrove) | 1.0 | 0.95 |
| 2 | Other Vegetation | 0.85 | 1.0 |
| 3 | Land | 0.7 | 0.68 |
| 4 | Open Development | 0.82 | 0.89 |
| 5 | Water Bodies | 0.96 | 1.0 |
| 6 | Sand | 1.0 | 1.0 |

### *Analysis of Shoreline Change*

The result of shoreline change analysis was computed by dividing the distance of shoreline between the shoreline for 2006 and the shoreline for 2014. Results show that Cherating River experienced a higher rate of erosion, while the highest rate of accretion occurred at Penor River, as shown in Table 7. Between 2006 and 2014, the 10.31 m maximum rate of shoreline change ~~of~~ as a result of erosion occurred at Cherating River, while the 18.17 m maximum rate of accretion occurred at Penor River.

On the other hand, the 0.01 m minimum rates of shoreline change due to erosion occurred at Ular River, while the 0.02 m minimum rate of shoreline change due to accretion occurred at Cherating River. The present study found that 96.2% of the Cherating River experienced erosion. This result is in consistent with the findings made by Fazly *et al.* (2018) which reported that the Cherating River is very susceptible to erosion. This is because the shoreline is facing the South China Sea, which has strong waves that eventually caused erosion in this area. Fazly *et al.* (2018) also found that Cherating is an area with very high vulnerability to erosion. Cherating River is a fragile area which could easily undergo physical changes as a result of natural and anthropogenic activities. Azid *et al.* (2015) and Fitri, Hashim, Abolfathi, & Maulud (2019), also discovered that human activities, such as beach construction, land reclamation, and port construction activities have a strong impact in the processes that occur in this area. Shahbudin *et al*. (2009) also found that Kuantan River, for example, is the main route for vessels to the South China Sea. Routine trips of these vessels along the river have generated short wave action from current wave. This may affect the mangroves especially certain species, such as Rhizophora and Sonneratia, which are at the front line of the mangroves. Erosion due to short wave action will cause the substrate to loose slowly and its roots will not be able to hold the tree and will collapse in a certain period.

### *Carbon Stock Assessment*

The NDVI value for the coastal forest (mangrove) and other vegetation categories obtained from the SPOT-5 data was from 0.28 to 0.52. The changes that occurred between 2006 and 2014 were primarily due to the loss of vegetation as a result of deforestation, reservoir construction, and cropping activities (Shahbudin *et al*., 2009; Mohd *et al*. 2019). At Cherating River, the highest NDVI values for the coastal forest (mangrove) and other vegetation categories were 0.52 and 0.49, respectively. Penor River has the lowest NDVI values for coastal forest (mangrove) and other vegetation in 2006 and 2014.

The results for carbon stock analysis for 2006 and 2014 are presented in Table 8. The carbon stocks for 2006 and 2014 ranged from 107.49 to 145.91 t/ha and 103.17 to 157.28 t/

Table 7: Rate of shoreline change determined using the EPR method

| **Study area** | **Cherating River** | **Ular River** | **Kuantan River** | **Penor River** |
|---|---|---|---|---|
| Mean shoreline change (m/year) | 2.49 | 0.63 | 0.00 | 5.05 |
| The maximum rate of shoreline change (m/year) | | | | |
| Erosion | 10.31 | 5.77 | 7.43 | 1.77 |
| Accretion | 17.93 | 2.26 | 6.28 | 18.17 |
| The minimum rate of shoreline change (m/year) | | | | |
| Erosion | 0.04 | 0.01 | 0.07 | 0.03 |
| Accretion | 0.02 | 0.1 | 0.06 | 0.1 |
| Total transect | | | | |
| Erosion | 177 | 180 | 91 | 17 |
| Accretion | 7 | 90 | 93 | 414 |
| Percentage (%) | | | | |
| Erosion | 96.2% | 66.7% | 49.5% | 3.9% |
| Accretion | 3.8% | 33.3% | 50.5% | 96.1% |

Table 8: The changes of the carbon stock

| **Area** | **Carbon stock value (t/ha)** | | **Changes** |
|---|---|---|---|
| | **2006** | **2014** | |
| Cherating River | 115.11 | 157.28 | 42.18 |
| Ular River | 145.91 | 127.79 | -18.11 |
| Kuantan River | 107.49 | 132.24 | 24.75 |
| Penor River | 131.27 | 103.17 | -28.10 |
| Total | 499.68 | 520.48 | 20.80 |

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ha, respectively. The results show that the overall carbon stocks in 2006 and 2014 were approximately 499.78 and 520.48 t/ha, respectively. Cherating River recorded the biggest change in carbon stock, followed by Kuantan River, Penor River, and Ular River. Nevertheless, these results are contrary to the findings of Hamdan *et al.* (2016) because the area factor covered by this study was only within a 1-km radius. Ular River recorded a slightly higher average carbon stock in 2006 (145.91 t/ha) than in 2014 (127.79 t/ha). This is due to the erosion phenomenon caused by wave and the monsoon season (Fazly *et al.*, 2018).

## Conclusion

The assessment of mangrove forest on the Pahang coast was done using remote sensing and GIS technology. The findings of the study are that these locations experienced higher rates of erosion and accretion, with Cherating River and Penor River showing the most rapid change of 10.31 and 18.17 m/year, respectively. Estimation of carbon stocks along the Cherating–Pekan shoreline was done using satellites images for 2006 and 2014 and the results show that the mangrove ecosystem at Cherating River, Ular River, Kuantan River, and Penor River were 107.49 to 145.91 t/ha and 103.17 to 157.28 t/ha, respectively. The determination of carbon stock associated with vegetation index distribution has become a key factor to facilitate the understanding of environmental dynamics of land use and land cover, and help in ensuring more responsible management of the resources available along the coast of Pahang. Therefore, there is a need to conduct a more in-depth study by using field measurement and high resolution satellite data for carbon stock estimation, especially along the 87-km Pahang shoreline to obtain a more accurate estimation of carbon stock. Local authority needs to implement many programmes and initiatives to increase the decline of mangrove forests as a result of rapid development in the coastal areas of Pahang. Mangrove forests are important in preventing erosion.

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