

SATELLITE-BASED MAPPING OF ABOVE-GROUND BLUE CARBON STORAGE IN SEAGRASS HABITAT WITHIN THE SHALLOW COASTAL WATER

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ABSTRACT:

These Mapping and estimation of seagrass total above-ground carbon (STAGC) using satellite-based techniques are required to fast-track the achievement of the 2020 agenda on Sustainable Development Goals (SDG) 14th. This attainment is possible as seagrass habitats provide a critical coastal ecosystem for storing blue carbon stock, sediment accumulation, fisheries production and stabilisation of coastal environment. However, seagrasses are generally declining across the globe due to anthropogenic disturbance, resulting in a prolonged growth rate of seagrasses that varies according to the species compositions. Therefore, this study aims at mapping and estimation of seagrass total above-ground carbon (STAGC) using Landsat ETM+ in the coastline of Penang. These satellite images were calibrated with Bottom Reflected Index (BRI) and Depth Invariant Index (DII) to compare the estimate of the STAGC for more accuracy. The leaving radiances of the seagrass were correlated with the corresponding in-situ measurements to predict seagrass carbon. This established relationship with BRI image shown a healthy correlation with STAGC ($R^2 = 0.992$, $p \leq 0.001$). Whereas the STAGC versus DII relationship has less accuracy ($R^2 = 0.955$, $p \leq 0.01$), adjusted $R^2 = 0.980$ and 0.978 were recorded for both BRI and DII STAGC estimate using the logistic model. Therefore, careful management of blue carbon stock is essential, as this study shall contribute to achieving targets 14.2 and 14.5 of SDG 14th by the United Nations.

1. INTRODUCTION

1.1 Background of the Study

Satellite-based mapping and estimation of seagrass total above-ground carbon (STAGC) are crucially required. With seagrass habitats as coastal flowering vegetation, which holds essential ecological roles in coastal ecosystems. The seagrasses are considered essential ecosystem due to the extensive meadows they form, which support high biodiversity. These habitats also provide a critical coastal ecosystem for storing blue carbon stock, sediment accumulation, fisheries production and stabilisation (Traganos *et al.*, 2018). They generally contribute to the ocean ecosystems services by providing a vital nursery area for several species that support fisheries and adjacent habitats (Tan *et al.*, 2016).

The seagrass meadows ecosystem functions comprise genetic variability maintenance, coastal environment resilience by protecting from erosion, as well as carbon sequestration via removing carbon dioxide (CO₂) from the atmosphere and storing it as an organic matter (Misbari and Hashim, 2016). Their higher productivity qualifies them a disproportionate impact on ocean great primary productivity, usually producing substantially more organic carbon (OC) than the seagrass habitat requires (Hossain *et al.*, 2015). Seagrass carbon storage is effective removal of CO₂ from the atmosphere and ocean pools, which plays an essential role in climate change mitigations (Sani and Hashim, 2018).

However, seagrasses are mainly declining due to anthropogenic disturbance, resulting in a prolonged growth rate that varies according to the species compositions. The 20th century, and

primarily since the 1940s, the seagrass habitats losses have been detected in various realms across the globe as a result of industrial impacts, boating, construction, dredging, overfishing, mining, and rising sea levels. In Malaysia sixteen widely distributed seagrass species exists in both subtidal and intertidal environment, shoals and semi-enclosed lagoons along the coastline of Malaysia. They are providing massive ecosystem services, while frequently experiencing a gradual decline as at the global level. This continued deterioration of local seagrass is due to growth in population and economic advancements.

Currently, studies on seagrass blue carbon stock mapping and estimations of STAGC using satellite-based remote sensing (RS) are limited (Hashim *et al.*, 2014). Therefore, an urgent need for regional and continental mapping and estimation of seagrass carbon stock is required. Indeed, this habitat may perhaps function as an indicator for climate change mitigation, offering valuable information that will be useful for coastal health management. It also provides conservations of related habitats within the investigated sites such as coral reefs and mangrove forest (Sani and Hashim, 2018).

Hence, cost-effective techniques for seagrass blue carbon stock mapping and estimation is required, to replace conventional methods and overcome the confines available researchers and resources for such evaluation. Satellite remotely sensed data had been employed successfully, to detects, map, and estimate seagrass above-ground biomass (Misbari and Hashim, 2016). Percentage cover (Kovacs *et al.*, 2018) and change detection in seagrass above-ground biomass estimation (Misbari and Hashim, 2014). Single species of seagrasses have similarly been spectrally detected and mapped by employing

hyperspectral RS data (Lyons *et al.*, 2011). RS seagrasses maps of large-scale areas with high accuracy has been realised within less cleared and cleared water via Depth Invariant Index (DII) and Bottom Reflected Index (BRI) (Misbari and Hashim, 2016; Poursanidis *et al.*, 2018; Traganos, *et al.*, 2018).

Despite the efforts invested by researchers, however, there are no documented studies on the seagrass total above-ground carbon stock using the satellite-based approach in the entire Penang coastline and these results to a vacuum in complying with United Nation’s convention on climate change. Therefore, this study employed the satellite-based RS techniques to mapped and estimated seagrass total above-ground carbon stocks using BRI and DII in Penang coastline of Peninsula Malaysia (PM). Similarly, the STAGC quantified from BRI and DII were compered for more accuracy. The estimate was successfully achieved using Landsat ETM+, which was realised by upscaling the study sample sites. It is crucial to report the seagrass total above-ground carbon stock for supporting the realisation of sustainable developments goal’s targets 14.2, and 14.5 establish by the United Nations.

2. MATERIALS AND METHOD

Seagrass total aboveground carbon data was obtained from the seagrass habitats occurring in the coastline Penang of PM. The study area covers about 131,590 km² of the total land area, as presented in Figure 1. Penang state is in the north-western coastline of PM, to the northern and eastern part bounded by Kedah state. The southern part is boarder by Perak state, similarly at the western side by the Straits of Malacca, as well as Sumatra of Indonesia. Penang encompasses the Penang Island, which has an area coverage of approximately 285km², and a coastal strip in the mainland known as Province Wellesley. Gazumbo Island is sandbank located in the eastern coastline (5°21’N, 100°19’E), near the Penang Bridge where the in-situ seagrass samples were collected, up-scaled to map the seagrass total aboveground biomass of the entire Penang coastline.

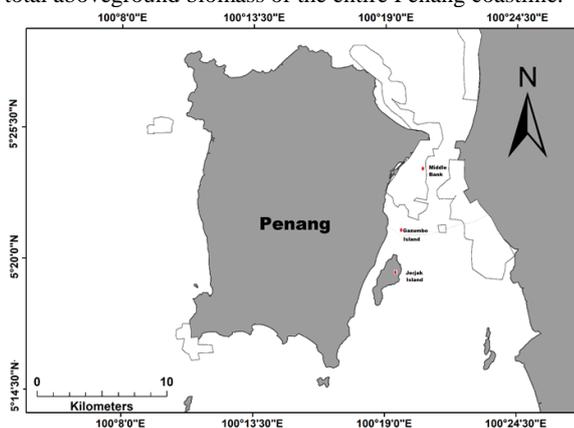


Figure 1. Seagrass boundaries along the study area.

2.1 Materials

Two principal material sets were employed in this study, precisely the satellite-based RS data and field measurements via in-situ observations utilised for ground-truthing. This ground-truthing is divided into two independent mutual sets for induction and deduction of the seagrass modelling. The Landsat 7 ETM+ data were used to estimate STAGC. The image was enclosed with minimum cloud cover inclined by monsoon seasons (see Table1). The field samples gathering in

2017 was performed in Gazumbo Island, which was extended to cover the whole seagrass meadows occurring within the coastline of Penang state. Furthermore, hydrographical charts obtained from the “Malaysian National Hydrographic Centre” was used for getting the depth.

Table 1. Description of the information on Landsat 7 ETM+ images employed for this study

No.	Scene ID	Date of Acquisition	Location	Monsoon	Cloud Coverage (%)
1.	LE71280 56201701 OEDC00	2017-01-10	Penang	NE*	6

Note: *seagrass possibly not affected by monsoon

2.2 Data Processing

The two major stages (as shown in Figure 2) comprise three data processing phases were observed in this study. These phases involve a) pre-processing of data comprising geometric correction, radiometric correction, and atmospheric correction of satellite image; b) seagrass occurrence mapping; and c) estimation of STAGC from the derived seagrass boundary (distribution map). Figure 2 demonstrates the flowchart of the entire three data processing phases. The tasks involved in data processing were achieved through processing software of digital image ArcMap version 10.4 and ENVI version 5.0.

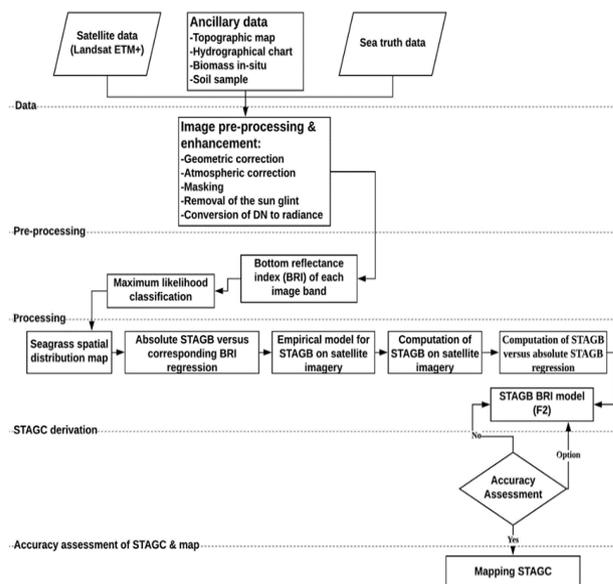


Figure 2. STAGC estimation flow chart employing BRI.

To achieve the estimate of seagrass carbon in any of its biophysical components precisely STAGC using satellite images. Specific processes were observed, starting from in-situ seagrass measurements to satellite data acquisition. Similarly, pre-processing and processing of the satellite imageries, biomass estimation, and biomass to carbon conversion using 0.34 an existing conversion factor was also observed. Those mentioned above were well explained in a publication that estimates the seagrass biomass changes along Straits of Johor, in Merambong, PM (Misbari and Hashim, 2016). Although this study only used two seagrass retrieval after the water column corrections using BRI and DII, which are needed for understanding the dynamics of seagrass carbon stocks estimation.

2.3 Seagrass in-situ Sampling Method

Seagrasses occurrences around the study location were observed according to the tidal height, considered a challenges task in seagrass data gathering. Thirty (30) transects were established randomly in the sample locations (Gazumbo island Penang state), precisely within the shoal as well deep-water border. Similarly, quadrates were linearly placed and moved in every 5m along a 50 to 100m transects line, placed in the seagrass meadows. The entire location of the sample points was marked on the images of ETM+. GPS (Garmin) handheld was employed for recording each point, most significantly at the starting as well as the ending points of the overall transect lines. For estimating seagrass mixed species, 72 STAGB samples were harvested within the sample location via a 0.25m² quadrate, representing one-quarter of a full quadrate, which ranges from 100% to < than 10% quadrate coverage of seagrass. These samples were cleaned by applying the formalin solution together with clean water before proceeding to dry via oven for about a minimum of 48 hours and at 900C, till no more weight loss was documented. STAGC samples were weighed using an electronic scale. Therefore, the samples recorded were correlated with the corresponding BRI for mapping and estimation of STAGC.

2.4 Applying Water Column Correction Methods to Improve Accuracy in Seagrass Model

It is necessary to measure light attenuation and correct the effects of the water column on benthic reflection utilised in applications, which encompass the SAV production and mapping of seagrass ecosystem (Klema, 2013a, 2013b). The most common method used for water column correction is that of the Lyzenga's (Lyzenga, 1981; Maritorena, 1996). Lyzenga (1978), this conveyed the correlation amongst radiance with bottom reflectance via the following equation:

$$L_i = L_{d,i} + a_i r_i \exp(-K_i g Z), \quad (1)$$

where

L_i describes the radiance within band i . $L_{d,i}$ stands for the radiance average, which was recorded in deep-water in band i (meaning external reflection obtained from the surface of water and scattering from the atmosphere). a_i always constant, comprise of solar irradiance, atmospheric transmittance, water surface, and the radiance reduction. All mentioned occurred as a result of refraction in the water surface. r_i stands for bottom surface reflectance, whereas, K_i refers to the efficient water attenuation coefficient (m⁻¹) of band i . g implies the geometric factor accounting for the path length via the water, Z stands for the water depth (m), and \exp indicate the exponential. As further suggested by Lyzenga (1978) that a depth-invariant index (DII) calculation should be enabled to remove scattering of light. Absorption effects in both water body and atmosphere can also be calculated, as expressed in equation (2):

$$DII_{ij} = \frac{K_j \ln(L_i - L_{d,i}) - K_i \ln(L_j - L_{d,j})}{\sqrt{K_i^2 + K_j^2}} \quad (2)$$

where subscripts of i and j correspond to two distinct satellite bands and refer to the natural logarithm. This DII is recognised to be effective in correcting less turbid water (clear water) such as type I and II waters (Bukata *et al.*, 2018), however inefficient when there is less clarity of the water (Sagawa *et al.*, 2010). Hence, to improve the accuracy of coastal mapping Sagawa *et*

al. (2010) suggested for an alternative model as "bottom reflectance index (BRI)", which can be expressed through the following equation:

$$BRI = \frac{(L_i - L_{si})}{\left[\exp(-K_i g Z) \right]} \quad (3)$$

Through substituting the numerator of equation (3) via $a_i r_i \exp(-K_i g Z)$ of equation (1), therefore, the BRI could be re-arranged as equation (4):

$$BRI_{ij} = a_i r_i \quad (4)$$

Where a and r refer to as in equation (1), with this development, BRI can proficiently be used in type II and III coastline. This achievement enables the comparison of more than only the proportions in reflectance distinction.

2.5 Seagrass Total Blue Carbon Stock Derivation Using Satellite-based and In-Situ Data

The STAGC was derived using BRI and DII models for retrieving submerged seagrass. The utilisation of these two models is to prove their efficiency in carbon stock estimation. Therefore, the most effective model for seagrass assessment is BRI; with that reason, the model is expressed as followed:

The model BRI was termed f_j , which was produced from the values of BRI on the satellite imagery. This model was used for estimating the STAGC by establishing a relationship between the BRI values and STAGB in-situ measurement using the logistic model. The new extracted values of the image were derived through applying the STAGB model with the STAGB in-situ, were employed for accuracy assessment (RMSE). The accuracy was achieved to ensure the precise measurement of the STAGC within the study site.

$$\text{Seagrass STAGB} = f_j (BRI) \times C. \quad (5)$$

where:

$STAGB$ = seagrass total above-ground biomass,
 $f_j (BRI)$ = function of STAGB in term of BRI, and
 C = a conversion factor of 0.34 (34 % of the biomass in seagrass is carbon) to convert biomass to carbon,

Therefore, STAGC is the function of BRI.

3. RESULTS AND DISCUSSION

The main results presented by this study comprised a) mapping the spatial extent of seagrass meadows and b) quantification of the total aboveground seagrass carbon using BRI and DII in the coastline of Penang. The motivation that triggered the seagrass carbon estimation is to comply with the UNFCCC conversion, which mandates all member state to report the inventory of their carbon stocks.

3.1 Mapping the Spatial Extent of Seagrass Aboveground Carbon

Before the estimation of seagrass blue carbon stored in aboveground, the mapping of the spatial extent, it is necessary

to identify the boundaries of the seagrass occurrence within the study area. Carbon stocks estimation is generally measured as the percentage of carbon stores in blue carbon habitats. This proportion is typically described in metric tonnes of carbon per hectare (Mt/ha^1) of an identified depth (Kroeger *et al.*, 2017). Hence, the seagrasses in the study location were spatially mapped, and their proportion was estimated. The said tasks were realised via selecting a suitable logistic model, which was employed for establishing a relationship between BRI and STAGB. The correlations were successfully achieved, and carbon contents of the STAGC, as well as mapping, were realised.

The spatial extent of the seagrass meadows was mapped, and their boundaries were identified based on the sample point of in-situ measurement. Likewise, the seagrass presence through utilising maximum likelihood classification was detected (Table 2). In Gazumbo the sample area, 1,342.17ha of STAGC were discovered, whereas 0.4 MtC/ha^1 was recorded as the contents of STAGC in aboveground seagrass pools. The predicted and derived carbon contents were correlated to ensure accuracy and for validating the seagrass results.

Table 2. Summary of seagrass locations using MLC.

Classes	Gazumbo	Proportion of extent (%)
Deepwater	181845	38
Mud	126862	27
Seagrass	163528	35
Total extent =	472235	

For determining the seagrass occurrences, values of pixel were converted into BRI. The Landsat ETM+ 2017 corrected water column's bands were classified for spatially mapping the distribution of seagrass meadow. MLC was employed for supervised classification due to the well-distribution and adequate sampling data for training and assigning individual pixel into the possible corresponding substrate classes according to probability density function. The classification method is proven as the best in categorically classifying underlying substrate features. Before this classification exercise, training areas, for mud/sand, seagrass as well as deep water were generated based-on in-situ observations. The overall classification accuracy with the interaction of inter-classes is demonstrated in Table 3.

Table 3. Confusion matrix for classification of coastal features with BRI on Landsat ETM+ using MLC. The training samples set of an individual class derived from in-situ data were assigned for classifying the BRI layer.

Classification Data	Reference Data (Pixel)			User Accuracy
	Seagrass	Mud/Sand	Row Total	
Landsat ETM+				
Seagrass	64	12	76	84.15
Mud/Sand	36	67	85	78.8%
Column total	100	79	161	
Producer accuracy	64.0%	84.8%		
Overall accuracy			55.45	
Kappa coefficient			%	0.5547

The most suitable Landsat band, which demonstrated robust compliance between in-situ data and result of seagrass delineation is the blue and red band ($BRI_{b,r}$) combination. This evidence proved that the combination has higher accuracy (Table 3) when compared with $BRI_{g,r}$ or $BRI_{b,g}$. Before conducting such assessment, verification of in-situ data was implemented. The blue band demonstrated the most suitable band within shallow for detection of substrate feature precisely seagrass with changing density classes.

3.2 Logistic Models used for Deriving Above-ground Seagrass Total Carbon Stock

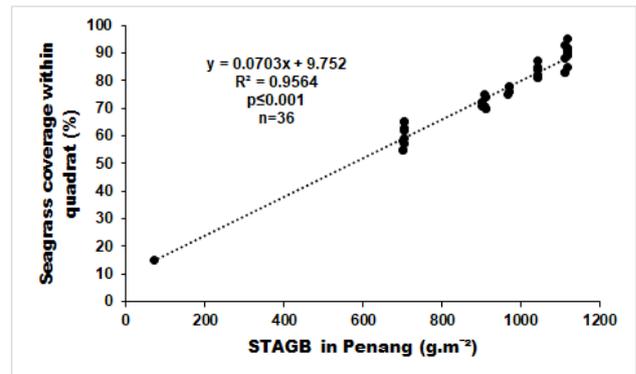


Figure 3. Correlation between STAGB acquired from in-situ measurement with the seagrass proportion of seagrass coverage in Penang.

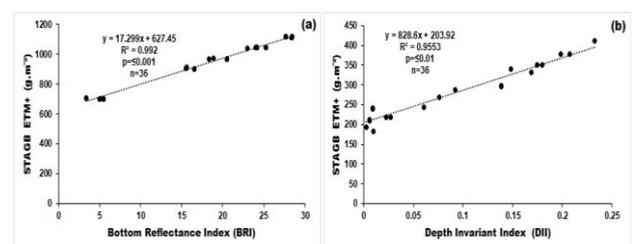


Figure 4. The established relationship between seagrass indexes with STAGB quantified empirically from the Landsat ETM+ imageries of a) STAGB vs BRI_b and b) STAGB against DII acquired after water column correction in 2017.

To perfectly reporting the results of STAGC within the study location, the relationship between STAGB attained from in-situ observation with the percentage of seagrass coverage was performed (see Figure 3). Similarly, ground-based in-situ measurement in STAGB and derived STAGB from BRI via prediction were compared. This process was also applied to DII for ensuring accuracy and comparing of the output (Figure 4). It connoted that BRI_b values are higher compared to DII that it is less than 1% of the BRI values attained from Landsat ETM+. These variations in proportion could be as results of the impact in-depth, which is only present in BRI model, even though the DII model has no depth variable. Additionally, it gives the impression that STAGC quantified from RS-based data over-calculated the biomass matrices when compared with the manual STAGB measurement. Figure 5 shows the coefficient determination of R^2 obtained through establishing a relationship between STAGB ground-based measurements against STAGB estimated via Landsat ETM+. Therefore, R^2 0.99 and 0.98, with respective RMSE $\pm 0.90 g.m^{-2}$ and $\pm 0.62 g.m^{-2}$ for only 30 m pixel resolution were realised.

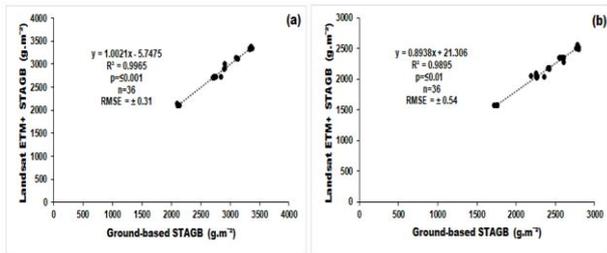


Figure 5. The in-situ-based seagrass biomass versus satellite-based estimation in the corresponding point locations using 36 inductive sites as well as 36 deductive sites.

Individual single plotted marker denotes seagrass sampling quadrats selected by 0.5 x 0.5 m scale, which were up-scaled to the size of 30 x 30 m Landsat pixel. Table 4 shows the logistic models employed to establish an association between STAGB against BRI and STAGB versus DII obtained both from ETM+. In this regards, the most suitable logistic model was used for the STAGB estimation.

Table 4. Logistic models established on STAGB versus BRI and STAGB against DII acquired with Landsat ETM+.

State	Regression Model	Equation	R ²
Penang BRI	Exponential **	STAGB = 651.97e ^{0.0194(BRI)}	0.986
	Linear ***	STAGB = 17.299BRI + 627.45	0.992
	Logarithmic **	STAGB = 208.26ln(BRI) + 379.87	0.934
	Polynomial (second-order) *	STAGB = 0.0229BRI ² + 18.042BRI + 623.32	0.992
	Power *	STAGB = 489.31BRI ^{0.2372}	0.956
Penang DII	Exponential ***	STAGB = 207.53e ^{2.9386x (DII)}	0.942
	Linear **	STAGB = 828.6DII + 203.92	0.955
	Logarithmic **	STAGB = 39.617ln(DII) + 405.48	0.799
	Polynomial (second-order) *	STAGB = 1173.2DII ² + 590.81DII + 208.23	0.960
	Power *	STAGB = 429.57DII ^{0.1444}	0.833

Note: significant levels: * $p \leq 0.05$; ** $p \leq 0.01$; *** $p \leq 0.001$. In the selection of the best applicable logistic model to quantify STAGC, determination of coefficient via regression analysis was applied as per the prime indicator. Thus, several logistic models were used on the Landsat images, where the linear model was found the most suitable in deriving STAGC contents in the study location. The linear model employed in both images of BRI and DII can be expressed as follows:

$$\text{STAGB} = 17.299\text{BRI} + 627.45 \quad (1)$$

where a) = 17.299; and b) 627.45 = 0.986.

$$\text{STAGB} = 828.6\text{DII} + 203.92 \quad (2)$$

where a) = 828.6; and b) 203.92 = 0.955.

As the model (R²), coefficient correlation demonstrated a high percentage of relationship with BRI (R²0.986) on the satellite-based image after processing, compared with the DII, which revealed R² = 0.955. The STAGC estimate from seagrass meadow is regarded as suitable with Landsat 7 ETM+ of 30 m resolution. Therefore, the results of this study and some reported publications on seagrass biomass mapping and estimation (Hashim, *et al.*, 2014; Misbari and Hashim, 2016; Sagawa, *et al.*, 2010), it can be revealed that Landsat 7 with a high radiometric-resolution possess an excellent compliance using BRI than DII for estimating STAGC.

3.3 Mapping and Estimation of Seagrass Blue Carbon Aboveground Carbon Component

Blue carbon component is regarded as a pool where carbon is captured and, which are usually documented in MtC /ha¹ in a specific carbon pool (Kroeger, *et al.*, 2017). The determination of carbon contents in the STAGC were realised after selecting the most suitable association between STAGB against BRI_b and STAGB versus DII_b. These developed models (linear regression) were applied through band-mask on the satellite image for obtaining the STAGB. Similarly, to derive the STAGC contents, a conversion factor of 0.34 was utilised (Sani *et al.*, 2019).

The STAGC mapping of Penang Straits was achieved (Figure 6). BRI_b pixels were summed to 191,928, and where for a single pixel is 900 m². This pixels proportion resulted in the realisation of the total area of 17,273.52ha covered by STAGC. The amounted carbon confirmed that the STAGC derived from BRI image is higher than the contents obtained using DII image, as shown in Table 5 (the estimation of STAGC with BRI recorded 80% while, DII 20% carbon contents). These differences in carbon contents from the two models (Figure 7) can be because of the depth values that exist only in BRI. These depth values enable the BRI to be applied for detecting submerged seagrass species in both clear (type A) and less clear water (type B).

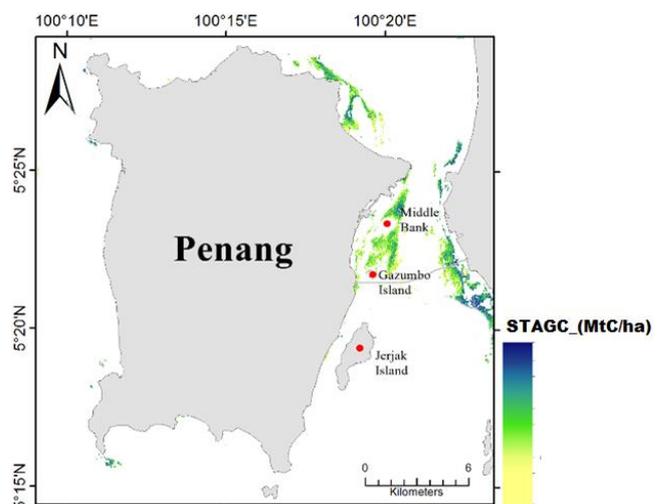


Figure 6. The total aboveground seagrass blue carbon spatial extent in Penang coastline.

Table 5. The proportion of STAGC of both western and eastern Johor.

Model type	Seagrass total area (ha)	Carbon stock (MtC/ha ¹)	STAGC (%) out of STAGB	Accuracy assessment (RMSE)
BRI	17,273.52	0.44	0.45	+0.31
DII	17,273.52	0.11	0.35	+0.54

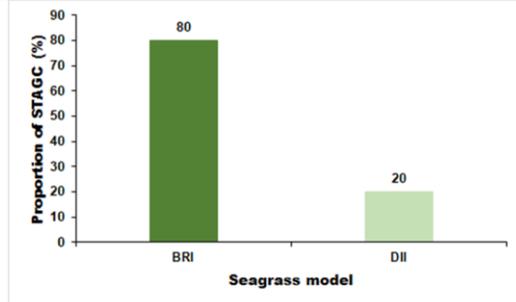


Figure 5. The differences between the proportions of STAGC estimated using BRI and the other with DII model.

As revealed earlier, the bands blue and red were employed in this study was due to the better capability of the blue band in penetrating water when compared with other bands. Whereas, the green band functionality is similar to that of the blue band, not as excellent as a blue band. This study is, therefore, essential to convey substantial impacts to four key sectors such as society, related industry, economy and environment. It will be vital to the inhabitant of coastal environment who solemnly relied on the coastal resources comprising mangrove forest, fisheries. Similarly, the coastal management authority could adopt this study on issues related to the coastal environment as well as the marine life biodiversity. To know how to tackled ocean health and food security.

Furthermore, it will assist in making a critical decision by related industry such as ‘National Department of Fisheries Board’, principally on fish abundance within seagrass species along the coastline of Penang. Economically, fisheries, tourism, and aquaculture activities will be benefited from this study, as they significantly relied on coastal health. Hence, reinstating the ocean resilience via protection of seagrass spatial extents and STAGC is the focal point of this study. Generally, adapting these results as measures will assist in fast-tracking the realisation of targets 14.2, 14.5 of United Nations sustainable development Goal 14th, which is scheduled to be terminated in the year 2020.

3.4. Accuracy Assessment

Several accuracy assessments were conducted to ensure precise mapping and estimation of STAGC. The statistical assessments include RMSE applied to confirm the agreement between in-situ STAGB and the predicted STAGB. Whereas the overall accuracy of intertidal and submerged seagrass detection on 30m resolution of Landsat ETM+ was conducted, both user’s and producer’s accuracy of seagrass were also applied (Table 3). STAGB correlated with in-situ seagrass coverage within the quadrat was reported. Also, for more conformation of the accuracy, t-test and khat statistic were observed (Table 6).

Area	Khat statistic	t-test
Penang	0.15	≤0.01

Table 6. Accuracy assessment of seagrass

4. CONCLUSIONS

This study has effectively used satellite-based RS to demonstrate the mapping and estimation of STAGC by using a suitable logistic model and processing methods in a complex seagrass habitat. The robustness of DII and BRI on a Landsat ETM+ imagery is confirmed. BRI and DII images were used to allow the mapping of seagrass spatial distribution and estimation of STAGC contents of the study area. The estimate realised by the seagrass retrieval models (BRI and DII) were compared for more precise STAGC measurement. Information on sea truth was employed for training datasets used in the MLC and validation of the features. Consequently, this study is needed, as to provide initiatives for STAGC mapping and quantification within the coastline of Penang state. The results provided by this study will assist in coastal management as it gives awareness on STAGC dynamics, which can help speed up the realisation of SDGs’ targets 14.2 and 14.5 of the United Nations.

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