MULTI-SENSOR MAPPING AND ESTIMATION OF SEAGRASS ABOVEGROUND BLUE CARBON STOCKS USING LANDSAT OLI AND ETM+ ALONG MERAMBONG COASTAL WATER

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ABSTRACT: Multi-sensor mapping and estimation of aboveground seagrass blue carbon stocks are essential to address the extreme deterioration of seagrass meadows. Resulting from climatic fluctuation and related anthropogenic activities throughout the globe. However, the critical role played by seagrass blue carbon pool in the ocean carbon cycle makes it crucial in fast-tracking sustainable development goal (SDG) 14th. Therefore, this study used multi-spectral sensors of Landsat OLI and ETM+ to derive seagrass total aboveground carbon (STAGC) in seagrass meadows of Merambong coastal water along Peninsula Malaysia (PM). A logistic model was employed to establish a relationship between the bottom reflectance index (BRI) with in-situ of seagrass total aboveground biomass (STAGB). The revelation of this developed model proved an agreeable correlation (R^2 0.96, p=≤0.001 and 0.60% STAGC per hectare (MtC/ha^1)). Equally, accuracy assessment revealed an excellent RMSE +- 0.62 result. Hence, this study shall support the realisation of SDG 14th targets 14.2 and 14.5 established by United Nations (UN), to prompt the success of the 2020 agenda.

KEYWORDS: blue carbon, satellite remote sensing, STAGB, BRI, SDG 14th

1. INTRODUCTION

Multi-sensor mapping and estimation of aboveground carbon within seagrass meadows are crucial for solving the declining of the ecosystem. This important coastal habitat sequesters and emits a substantial amount of carbon through its biophysical component (Sani et al., 2019). As discovered in 2009 report by the "United Nations Environmental Programme's" (UNEP) that "Blue Carbon" plays an essential role in oceans health for carbon binding, also > 50% of atmospheric carbon dioxide (CO_2) has been captured and stored by the marine vegetations. Therefore, the initiatives on blue carbon are appreciated globally due to their efforts in climate change mitigation through the restoring and conserving coastal ecosystems. It offers to mobilise finances and revenues via a grouping of the utmost practices on coastal conservation and restoration (Hossain and Hashim, 2019; Wilson and Forsyth, 2018).

In Malaysia there exist sixteen seagrass species (Hashim et al., 2017; Misbari and Hashim, 2016), which are broadly distributed within the subtidal and intertidal regions, semi-enclosed lagoons as well as shoals in the shoreline of Malaysia (Hossain *et al.*, 2015a; Sani and Hashim, 2018), providing numerous ecosystem services (Martínez-Crego et al., 2016), however, they are experiencing a gradual deterioration (Hashim, et al., 2017). If this important habitat continued with the losses, it would eventually result in the emissions of greenhouse gas, losses of ecosystem services and biodiversity (Duarte et al., 2013). Ecosystem services are recently reviewed by Hossain and Hashim (2019). Consequently, reporting the inventory on seagrass blue carbon occurring in the shorelines of the Malaysian Peninsula could address the issues on climate change mitigation, predicting the possible carbon emissions through detection of seagrass cover changes (Lundquist *et al.*, 2018; Misbari and Hashim, 2016). Also, it allows the integration of seagrasses carbon management together with oceanic management strategies. The satellite-based sensor can only detect vegetation the surface due to its constraints and inherent of instruments (Hashim *et al.*, 2014). Ultimately, the precise estimate of underground carbon remains a challenging issue. However, "seagrass total above-ground carbon (STAGC)" and other biophysical components in seagrass meadow can be quantified through indirect measurements using remotely sensed model to overcome the limitations of the satellite sensor.

Previous researches have been investing efforts using satellite-based remote sensing to mapping and estimation above-ground biomass in seagrass meadows (Ferwerda et al., 2007; Koedsin et al., 2016; Kovacs et al., 2018). However, knowledge gaps still exist in the spatial distributions and extents of the meadows. Similarly, seagrass total above-ground carbon (STAGC) estimation has also not been adequately reported. Other important gaps include (Sani, et al., 2019) a) seagrass and marshes' conversion factors for converting biomass to carbon, using a geospatial method are lacking, b) and b) seagrass blue carbon hábitat drivers associated to losings/degradation, of meadows are equally lacking. Furthermore, international collaborations on regional seagrass blue carbon derivation, dynamics, as well as threats remain unaddressed. Hence, this study complemented other scientists, to investigate the STAGC contents in seagrass meadow using satellite images within Merambong shoreline Johor, Peninsular Malaysia.

2. METHODOLOGY

2.1 Description of Study Area

This study was conducted in Merambong Shoal, which is situated within the "mouth of Sungai Pulai estuary", Johor Straits, Peninsular Malaysia, as demonstrated in Figure 1. Widespread seagrasses mixed species composition are occurring in the muddy estuary water (Barrell *et al.*, 2015). Furthermore is surrounded by the dominant 15 *Enhalus acoroides* as well as *Halophila ovalis* species. Seagrasses naturally grow in shallow water with less than 4 meters of depth (Baird *et al.*, 2016; Eisemann *et al.*, 2019). Seagrass, seaweed, coral, and several benthic organism's co-occurrences have required an estuary motivating site for marine researches.

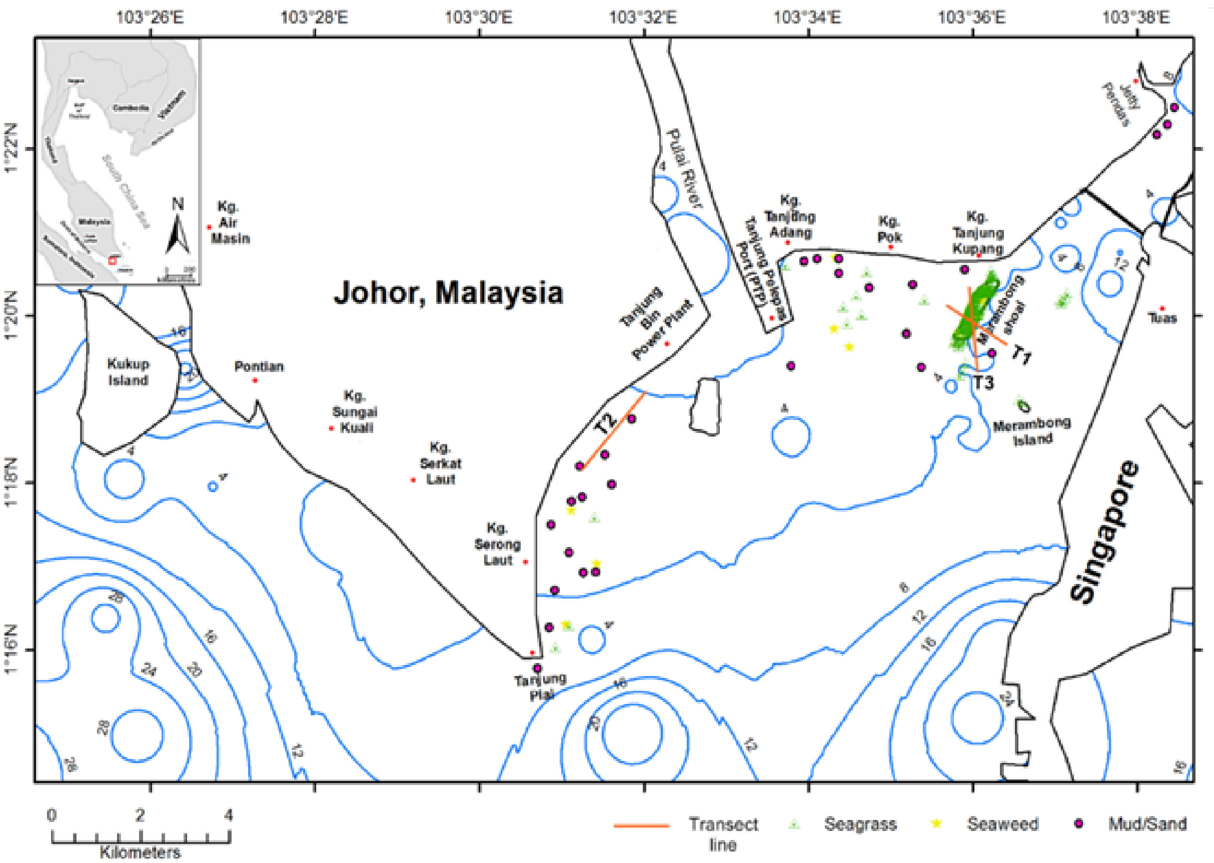

Figure 1. Location of the in-situ samples at the study site (Misbari and Hashim, 2016)

2.2 Materials

There are two main material sets used in this study, precisely the satellite-based images and field samples of STAGB obtained through measurements observations. The samples obtained were divided into independent two mutual sets, namely induction (for seagrass modelling) and deduction. The medium-resolution Landsat 8 Operational Land Imager (OLI) and Landsat 7 Enhanced Thematic Mapper Plus (ETM+) images were utilised to derive the STAGC contents in the study site (Figure 2 demonstrates their viewed). This image contains minor cloud cover due to monsoon seasons, Table1 demonstrates the information on the description. The in-situ samples gathered in 2017 was realised in Merambong coastline. Furthermore, the hydrographical charts were acquired from the "Malaysian National Hydrographic Centre" which were employed for obtaining information on the water 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	LE71250592017245EDC00	2017-09-02	Johor	Post-SW**	54

Note: *seagrass possibly not affected by monsoon

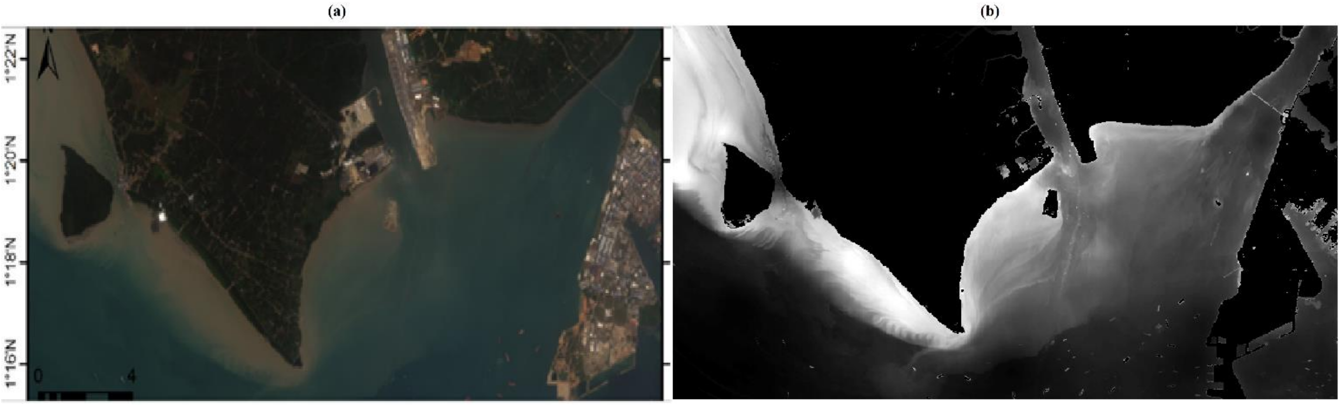

Figure 2. The viewed study site from (a) Landsat ETM+ and (b) OLI

2.3 Data Processing

The two main steps (Figure 3) encompass three phases of data processing, comprise 1) pre-processing of satellite images such as geometric, radiometric as well as atmospheric corrections; b) seagrass spatial extent mapping; and c) STAGC quantification using the derived seagrass boundary. Figure 3 shows a general flowchart of the whole data processing phases. This exercise involved in the data processing was attained using ENVI version 5.0 and ArcMap version 10.4 digital processing software's environment. To accomplish the estimation of carbon contents in any biophysical components of seagrass (STAGC) using satellite images. Precise procedures were observed, beginning from in-situ seagrass sampling to satellite data acquirement. Equally, image pre-processing and processing, estimation of biomass, and biomass conversion to carbon via a conversion factor (0.34) were likewise observed. For more detailed information on seagrass preprocessing refer to (Misbari and Hashim, 2016). Even though the study only utilised a single seagrass retrieval model (BRI) after the water column corrections, which is required for comprehending the seagrass carbon dynamics.

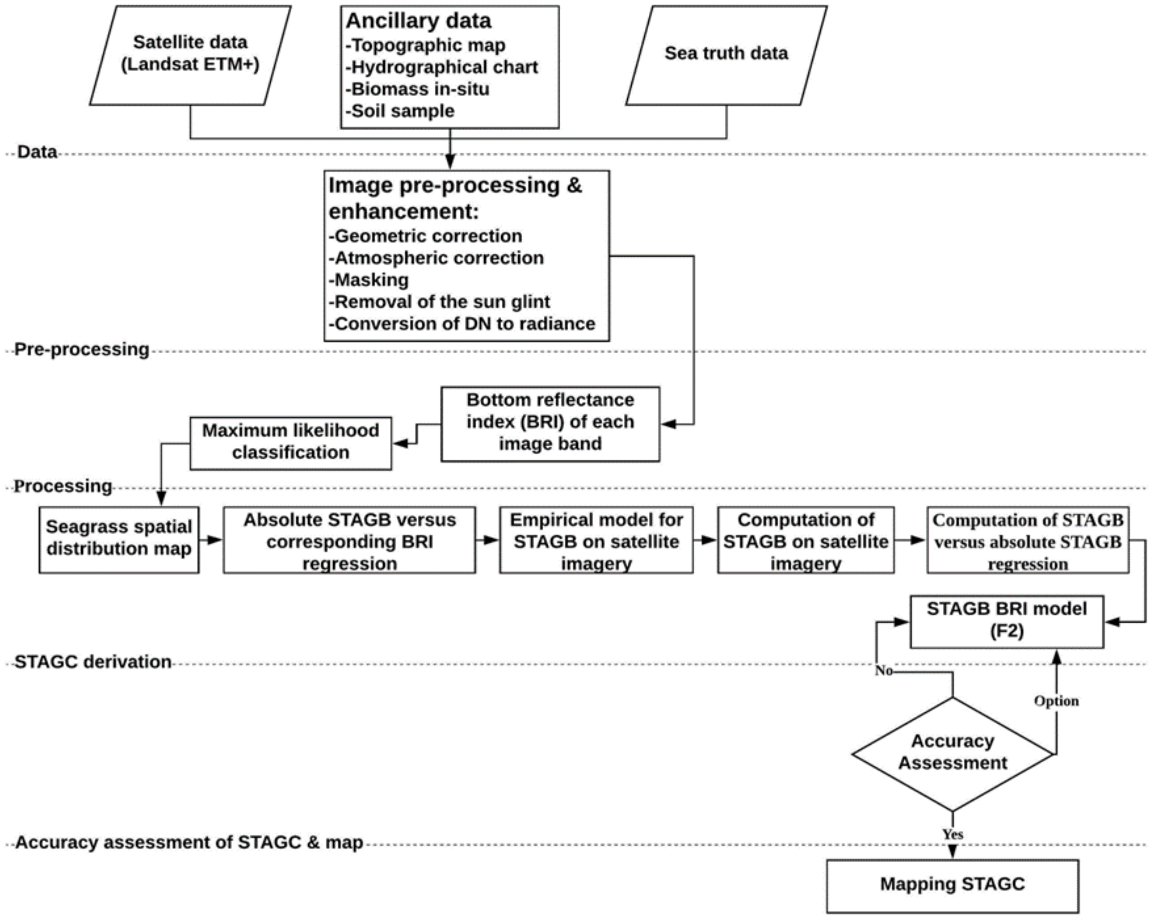

Figure 3. Flowchart Employed for this Study

24 Seagrass in-situ Gathering

Seagrasses cover extents within the study location were observed by utilising the tidal height that is identified as a challenging work in seagrasses in-situ measurement. Transects (thirty) were placed randomly in the sample locality (Merambong), specifically in the shoal border and deeper waterside. Likewise, quadrates were established in a linear structure and transferred in each 5m in transects line with 50 -100m, set in the seagrass meadows. The entire samples points collected within the location was identified in the Landsat ETM+ images. A handheld Garmin GPS was employed for registering a single point, most significantly at the starting and ending points of all the entire observed transect lines. For estimating mixed species of seagrasses, seventy-two STAGB samples were harvested through a 0.25m^2 quadrate. The obtained sample is considered as one-quarter of the complete quadrate ranging between 100 to lee than 10% seagrass coverage of within a quadrate. The STAGB samples were cleaned by using a formalin solution and freshwater before proceeding with the drying method via the oven for approximately 48 hours on 900C. This method continued until none weight losses were recorded. An electronic scale weighed the in-situ samples. Thus, recorded samples were correlated with the corresponding BRI-based point for seagrass above carbon derivation.

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

It is fundamental to measure light attenuation plus correction of water column influences on a benthic reflection used in applications, which include mapping and SAV production of seagrass meadows (Klemas, 2013a, 2013b; Sani et al.). The most basic technique employed for a "water column correction" is Lyzenga's (Lyzenga, 1981; Maritorena, 1996; Misbari and Hashim, 2016). Lyzenga (1978), this indicated the association of radiance versus bottom reflectance via the following equation (1)

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

where

L_i terms as the radiance in band$_i$. $Ld_{,i}$ represent a radiance average recorded for the deep-water in bandi (this means external reflection acquired via the water surface that scattered from the atmosphere). a_i is permanently constant, encompass of atmospheric transmittance, solar irradiance, radiance reduction and water surface. The entirely mentioned happened because of refraction from the water surface. r_i represents the reflectance from the bottom surface, while, K_i stands for bandi effectual water attenuation coefficient (m^{-1}). g entails the geometric factor revealing the path length through the water, Z indicates the depth of water (m), and exp show the exponential. Furthermore, (Lyzenga (1978)) suggested that the depth-invariant index (DII) estimation should facilitate the removal of light scattering. The effects of absorption from both atmosphere as well as water body could similarly be estimated, as expressed in equation (2) below:

$$\mathrm{DII}_{ij} = \frac{K_j \mathrm{In}(L_i - L_{d,i}) - K_j \mathrm{In}(L_i - L_{d,i})}{\sqrt{K_i{}^2 + K_i{}^2}} \quad (2)$$

where

subscripts in i and j relate to two different satellite bands and denote to a natural logarithm. The DII model is approved to be more active in correcting less clear water (less turbid water) include type (1 and 2) waters (Bukata *et al.*, 2018; Hossain *et al.*, 2015b). Though it is ineffective if the water is less clear (Sagawa *et al.*, 2010). Therefore, to increase the coastal mapping accuracy, Sagawa et al. (2010) proposed for a substitute model term "bottom reflectance index (BRI)", which could be expressed using the following equation (3):

$$BRI = \frac{(Li - Lsi)}{\left[\exp(-KigZ)\right]} \quad (3)$$

By replacing equation (3) numerator through $a_i r_i$exp $KigZ$ of the equation (1), thus, the BRI can be re-arranged as the following equation (4):

$$\mathrm{BRI}_{ij} = a_i r_i, \quad (4)$$

where

a with r stands for as in equation (1), by this improvement, BRI could competently be utilised within type 1 to III coastal water. This attainment allows a comparison > the only proportions of reflectance distinction.

2.6 Satellite-Based Seagrass Total Blue Carbon Stock Derivation Technique

The Landsat ETM+ and OLI (Figure 2) obtained in 2017 were the satellite images employed. Pre-processing, processing procedures, ground-truthing and hydrographical chart were also applied for STAGC mapping and derivation in seagrass meadow of Merambong shoal (see Figure 3). The pre-processing of the satellite images observed in the article involve, radiometric, geometric, atmospheric as well as water column correction on the images. A correlation was proved on absolute STAGB collected by up-scaling a quadrat in a pixel area of 30 m by 30 m resolution (Hashim, *et al.*, 2014). The above-ground carbon contents were obtained by multiplying the biomass in gram values ($g.m^2$) using existing conversion values of 0.34 (Sani, *et al.*, 2019). The carbon contents were converted to metric tons of carbon per hectare (MtC/ha). The following expressed equation (5) were used in quantifying the STAGC.

$$\mathrm{STAGB} = f_1\ (BRI)\ X\ 0.34 \quad (5)$$

where
STAGB = "seagrass total above-ground biomass"
f_1 *(BRI)* = function one rely on bottom reflectance index
X 0.34 = carbon conversion values

Consequently, seagrass total of above-ground carbon is the function of bottom reflectance index.

3. RESULTS AND DISCUSSION

The main outcomes exhibited by this article involved i) mapping the seagrasses spatial extents (refer to Figure 4) with meadows and ii) derivation of the total upper seagrasses carbon utilising DII and BRI in the shoreline of Merambong. The urge that trigged the assessment of seagrasses carbon is complying by the UNFCCC resolution, which required the entire member states to inform inventory of the carbon contents there have. The information revealed by this study could be used in updating the status of seagrass carbon contents of the Malaysian Peninsula in the global database. These revelations will also fast-track the achievements of "Sustainable Development Goal" 14 on targets 14.2 as well as 14.5 set by the United Nations. To attain the STAGC stocks derivation, "seagrass total above-ground biomass" STAGB was associated with BRI (see Figure 5) via logistic regression model that proved an agreeable correlation, prior to the developed model coverage of seagrass (%) in the quadrate against the STAGB were likewise related (Figure 6 and 7) using both OLI and ETM+, this processes were required to ensure precise estimation.

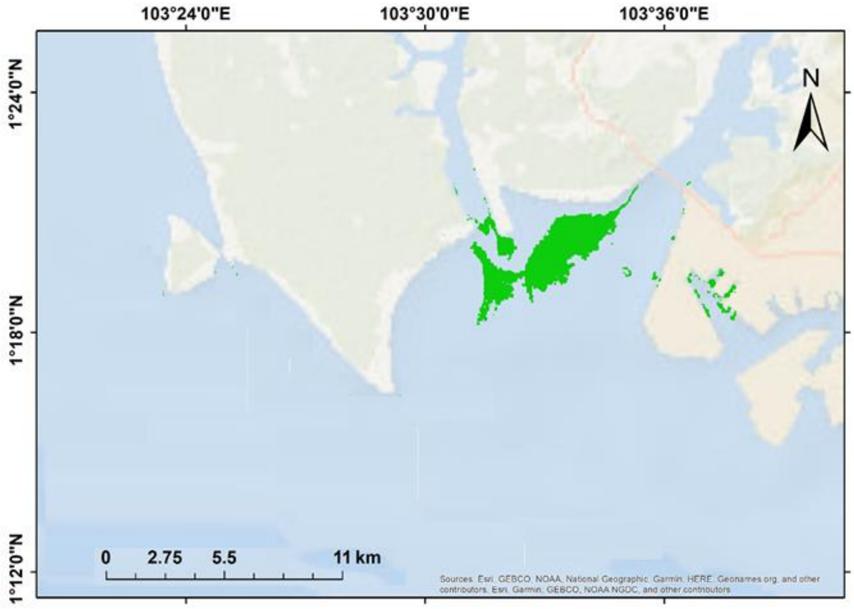

Figure 4 Spatial Distribution of STAGC in Merambong Coastline

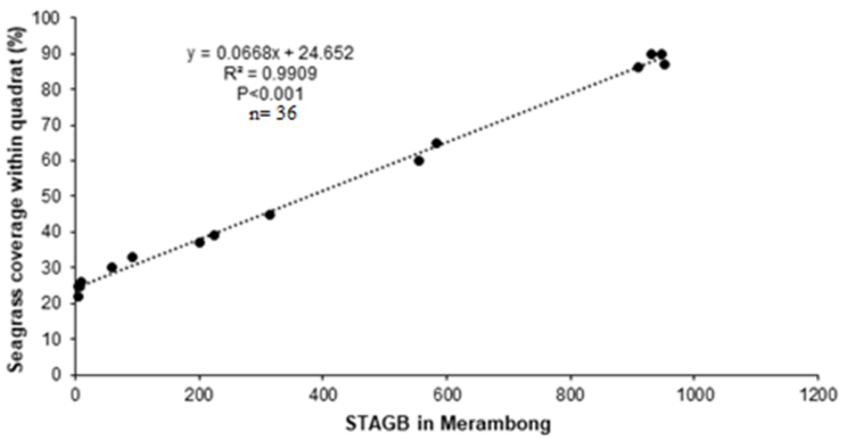

Figure 5. Correlation of Seagrass Coverage within the Quadrat against STAGB

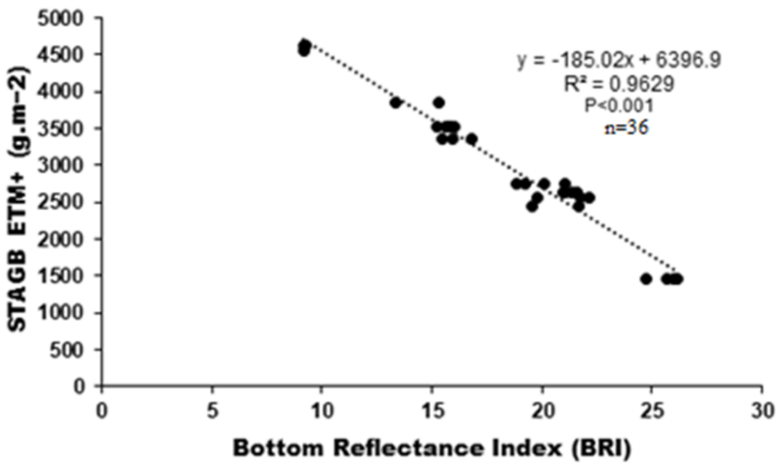

Figure 6. Relationship of BRI_b versus STAGB Empirically Quantified from Satellite Imagery

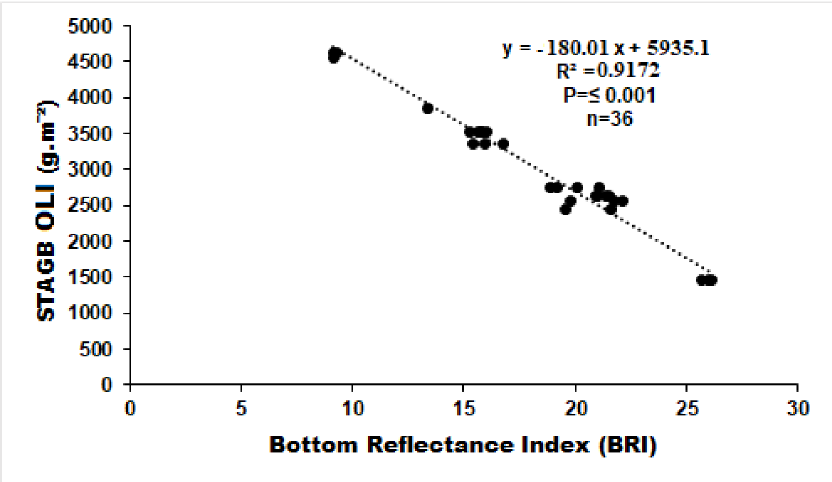

Figure 7. Relationship of BRI_b versus STAGB Empirically Quantified from Satellite Imagery

The STAGB quantified from the ground with the predicted STAGB from BRI image were analysed; this was realised to assure the precision of STAGC estimate. Moreover, the STAGB determined from satellite-based imagery overestimated compared to the manual STAGB estimation. The coefficient R2 determination using the regression plot, correlated between in-situ STAGB derivation with STAGB obtained from ETM+ and OLI scenes, 0.99, 0.97 and RMSE +-0.90 g.m-2, 0.80g.m-2 respectively for 30 m pixel resolution.

3.1 The STAGC Carbon Stock Derivation

Blue carbon stock is measured as the quantity of organic carbon stored in a blue carbon pool or component, commonly described as organic carbon's metric tons per hectare (Mt /ha1) within an identified soil depth (Kroeger *et al.*, 2017). The stock in STAGC was estimated after spatially mapping the pixel areas containing seagrass on a BRI image, presenting the seagrass boundary covering about 1,342.17 hectares and each includes 0.60 MtC/ha[1] with 0.60% of seagrass total blue carbon of the study area (Table 2).

3.2 Mapping the Spatial Extent of Aboveground Seagrass Carbon

Before the estimate of seagrasses carbon trapped in the aboveground, mapping of the seagrass spatial extents was done; this is essential to detect the boundaries were seagrasses exist in the study location. Estimation of carbon stocks is usually measured using the carbon stores percentage within a blue carbon habitat. This carbon proportion is generally expressed in "metric tonnes of carbon per hectare" (Mt /ha^{1}) using a recognised depth (Kroeger, *et al.*, 2017). Therefore, the seagrass occurring in the study location was mapped spatially, and their carbon contents were estimated. The stated tasks were accomplished through choosing the suitable logistic model to establish a correlation among BRI and STAGB. The relationships were effectively realised, and the carbon stocks of the STAGC and mapping were also achieved. The presence of seagrasses occurrence was detected by using maximum likelihood classification techniques (Table 2). In Merambong, 1,342.17ha of STAGC were observed (Table 3), while 0.60 MtC/ha^{1} (0.60%) was reported as the total stocks of STAGC pool (out the total proportion of the entire seagrass stocks). The prophesied and derived carbon stocks were compared to ensure agreement and for precise seagrass results.

Table 2. Classification (MLC) Confusion Matrix for Coastline Features with BRI employing Landsat Imagery. Training Samples Fixed for Particular Class Acquired through in-situ Measurements were Specified for Classifying the BRI Layer

Classification Data	**Reference Data (Pixel)**			**User Accuracy**
	Seagrass	**Mud/Sand**	**Row Total**	
Landsat ETM+				
Seagrass	294	40	334	88.0%
Mud/Sand	20	60	80	75.0%
Column total	314	100	414	
Producer accuracy	93.6%	60.0%		
Overall accuracy			79.2%	
Kappa coefficient			0.7965	
Landsat OLI				
Seagrass	250	50	300	83.3%
Mud/Sand	10	50	82	60.0%
Column total	260	100	382	
Producer accuracy	96.1%	50.0%		
Overall accuracy			75.9%	
Kappa coefficient			0.7104	

Table 3. Seagrass Total Aboveground Blue Carbon Stock

Sample area	Sensor	Seagrass total area (ha)	Carbon stock (Mt /ha-^{1})	Percentage (%)	Accuracy assessment (RMSE)
Merambong	ETM+	1,342.17	0.60	0.60	+- 0.62
	OLI		0.40	0.40	+-0.76

3.3 Accuracy Assessment

Various accuracy assessments were conducted to facilitate precise mapping and derivation of seagrass upper carbon. These evaluations involve the used of RMSE for proving the correlation between STAGB obtained via in-situ measurement and the STAGB predicted from the satellite. These overall accuracies for intertidal and submerged seagrasses detections on both ETM+ and OLI of 30m resolutions were conducted. Additionally, the producer's, as well as the user's accuracy on meadows, were also employed (Table 3). Moreover, for more accuracy validation, khat statistic and t-test were observed (Table 4).

Table 4. Accuracy Assessment Conducted for Seagrass

Area	Sensor	Khat statistic	t-test, *p*
Merambong	ETM+	0.15	≤0.001
	OLI	0.18	≤0.01

3.4 Discussion

This study is required as it will crucially be impacted on the environment, related industry, economy, and the coastal inhabitants. It highlighted the precise estimations of biomass and seagrass aboveground carbon contents (STAGC) occurring within seagrass meadow. These revelations can work as a basis for a better comprehension of the ocean carbon cycle at the global level. More so, information about STAGC seagrass carbon component is expected to aid in sustainable marine resource management. Likewise, it will be helpful for scientists, coastal managers, as well as coastal dwellers who relied on tidal resources. More significantly, the "United Nations 2020 agenda for SDG 14th" could be Fasttrack. These results give a holistic view of the dynamics in seagrass carbon stored in aboveground biomass, which influences critical ecosystem services.

4. CONCLUSION

This article proved the combination of in-situ measurement and satellite-based (ETM+ and OLI) for deriving STAGC contents. Although the results of the study is a just prefatory portion of our major leading research on seagrasses total carbon stocks derivation using satellite-based (STAGC, STBGC, and soil organic carbon (SOC))within the shoreline of Peninsula Malaysia. Water column correction was applied on two satellite images of ETM+ and OLI for mapping seagrass spatial extents. These discovered boundaries were used for STAGC estimation with satisfactory accuracy. The seagrass mapping and quantification method used here will support the coastal biodiversity conservations. More crucially it will support the accomplishment of 2020 agender set by the United Nations to realised targets 14.2 as well as 14.5 of "Sustainable Development Gold" 14.

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