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Vegetation Biomass of *Sargassum* Meadows in An Chan Coastal Waters, Phu Yen Province, Vietnam Derived from PlanetScope Image

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Abstract: SW (Seaweed) is a valuable coastal resource for its use in food, cosmetics, medicine and other items. In this study, PS (PlanetScope) imagery was combined with field sampling to demonstrate the capability of mapping of SAV (Submerge Aquatic Vegetation) (including both SW and SG (Seagrass) beds) and biomass mapping of *Sargassum* meadows in An Chan coastal waters, Tuy An district, Phu Yen province, Vietnam. In term of SAV and *Sargassum* mapping, authors proposed an improved remote sensing technique based on Sagawa's BRI (Bottom Reflectance Index) algorithm with attention to Tassan's concept in discrimination of light attenuation coefficient K_d between shallow and deep waters. Authors' results showed high accuracy in mapping of SAV and *Sargassum* distribution with overall accuracy and Kappa coefficient of 92.52% and 0.8957, respectively. The classified class of SW (i.e. *Sargassum* sp.) then was separated absolutely from other classes in SAV map for estimation of *Sargassum* biomass. The red and green spectral pre-processed BRI channels (i.e. BRI_3 and BRI_2) of PS were used to estimate the *Sargassum* biomass using a multiple 2nd order polynomial regression model with very high accuracy (R^2 = 0.9707; RMSE = ± 109.21 g/m^2). The average total *Sargassum* biomass was 897.8 g/m^2 with total *Sargassum* yield in whole region reaching a value of 449.57 tons in cover area of 50.32 ha of *Sargassum* meadows. This result opens the great potential of biomass and yield estimation of *Sargassum* and other SW meadows in coastal waters (including enough optically deep waters) by remote sensing techniques based on PS imagery.

Key words: PS satellite image, *Sargassum* biomass, SW, BRI.

1. Introduction

SW (Seaweed) is a valuable aquatic resource for its use in food, cosmetics, medicine and other items. SW stock is one of important components of the coastal ecosystem that provides living space for mangroves and coral reefs and breeding grounds and food for several types of marine fauna (i.e. fish, shrimp, marine reptiles, shellfish and mammals,…). SW also cleans water for fish farming. The beneficial chemical properties and nutritional value of SW have made it a commercially important coastal product.

Habitat mapping is one of important issues for management, research and planning of marine resources. Mapping SW resources covering larger spatial areas using conventional methods through field investigations is capital intensive and time-consuming. Remote sensing technology has significantly been supporting the observation of the Earth's surface. Today, optical satellite imageries with high resolution can assist scientists to precisely detect the different patterns of terrestrial as well as aquatic ecosystems [1, 2]. These techniques expand its scale to underwater ecosystem and effectively create aquatic resource maps, and include SW mapping [3]. In the field of aquatic habitat mapping, water column correction is the driving factor that improves the accuracy of digitized classifications relevance to benthic substrates. Numerous researchers attempted to remove the affection of water layers to the solar radiance and

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extract the bottom reflectance spectrum from the data of hyper-spectral sensors or equivalent ones. Several models are well developed but they are mathematical comprehensive, such as semi-analytical and radiative transfer-based forward models, look-up table based spectrum matching inverse models [4-6] or require optical properties data of water environment [7-9]. These approaches can calculate quantitatively bottom reflectance of spectral bands from orbit optical data with relative high accuracy, and lead to easily estimating the biomass of SAV (Submerge Aquatic Vegetation) canopies by ordinary vegetation indies (such as NDVI—Normalization Different Vegetation Index, LAI—Leaf Area Index, GVI—Greenness Vegetation Index, …) as applied for terrestrial and forestry ecosystems. However, these techniques are complex, require hyper-spectral satellite imageries or need optical properties data of water column. Ordinary satellite imageries with four spectral bands of blue, green, red and near infra-red are still limited by these issues. On the other side, significant attention has been paid to empirical approaches for multispectral data by means of band combination algorithms. Under specific assumption, the authors attempted to simplify their model and make them more reliable, compatible with different conditions of the field sites. They assume that bottom reflectance in band i ($L_{b,i}$) is an exponential function of depth and attenuation coefficient in this band ($K_{d,i}$). Lyzenga [10] mathematically describing the relationship between the bottom reflectance and radiance values which were recorded at satellite sensor. According to Lyzenga's concept [10], the depth in a pixel is constant for all bands, he attempted to linearize the relation between radiance in pair bands and water depth. The main assumptions of Lyzenga's algorithm are that: (i) differences in radiances between different pixels for the same substrate are due to differences in depth; and (ii) K_d is constant for each band. The slope of the regression linear curve from plot ln($L_{b,i}$) vs. ln(Ln$_{b,j}$) corresponds to a proxy of the attenuation coefficient ratio $K_{d,i,}j$ that is a constant value for any substrate. As a result, a new image of depth-independent composition of corrected radiance in band pair i and j (pseudo-color band) will be generated. It becomes the base for digitized classification of benthic habitats in next steps. That explains the name of this method as DII (Depth Invariant Index). Lyzenga's algorithm [10] is relatively simple and is currently one of the most popular approaches in underwater habitat mapping [10-16]. However, those approaches need some critical assumptions, such as homogeneity of substratum and water layers [17] that may not be appropriate to several coastal lagoons [4]. The DII image that is obtained from i, j band pairs (as above mention) is independent with the depth [10], so that it is hardly used to estimate the biomass of SAV canopies. In recent years, Sagawa, et al. [18] have successfully applied a new technique which is derived from Lyzenga algorithm to detect the distribution of SG (Seagrass), namely BRI (Bottom Reflectance Index). For its application, the depth and attenuation coefficient are required. Depth data of various pixels on a homogeneous substrate (sand) allowed estimation of the attenuation coefficient. The regression between the radiance and depth of these pixels was calculated and the slope of the linear equation corresponded to the attenuation coefficients of each spectral band. This method will improve the accuracy of the underwater habitat mapping and SAV biomass estimating as well. Moreover, both DII and BRI methods applied only very well for underwater habitat mapping and biomass estimating (such as coral reef, SG beds, …) in shallow water, but they met certain errors when detecting SW meadow in deeper waters. While detecting the macroalgae meadows in deeper waters with non-uniform composition, Tassan [19] proposed a new concept on the differentiation of the attenuation coefficients in shallow water where higher brightness is and in deeper waters where lower brightness is. Tassan's algorithm is a modified DII (and BRI as well) method through numerical simulations for application in environments with important gradients in turbidity between shallow and deep waters and improves the processed results by discrimination of the attenuation coefficients between two shallow/deeper water zones.

In this paper, authors attempt to approach SW mapping and biomass estimating of *Sargassum* meadows in An Chan Coastal Waters (Phu Yen province, Vietnam), extracting from PS (PlanetScope) image. The Sagawa's algorithm with Tassan's modification is main technique for *Sargassum* distribution mapping and their biomass estimation.

2. Material and Methods

2.1 Object and Research Scope

Authors' objects are SW meadow mapping and biomass estimation of *Sargassum* canopies at coastal waters in My Quang, Hon Chua, An Chan commune Tuy An District, Phu Yen province, Vietnam (Fig. 1). This is an open coastal waters having enormous potential for developing tourism and a marine-based economy. It is also an area with high biodiversity and many rare and precious species such as turtles, squid, lobsters and sea cucumbers that have been recorded [20]. In periods when waterline reaches the lowest level, the tidal flat in fishing village in North My Quang exposed in the air with the vast SG beds with 1,000 m long and 320 m wide. In this region, *Sargassum* meadow usually grows most strongly in April-June every year. Spatial distribution and biomass of *Sargassum* meadow will be extracted and estimated from PS image base on an improved Sagawa's algorithms that will be presented in next part.

2.2 Data and Methodology

2.2.1 Satellite Image

Two image scenes of PS, level 1B, acquisition time of 28 June 2018 with code number of 20180628_024114_1004 and 20180628_024115_1004 have been ordered from PS constellation belonging to ESA (European Space Agency). PS image has the spatial resolution of 3.1 m × 3.9 m with 4 spectral bands in the visible spectral bands: blue (455-515 nm), green (550-590 nm), red (590-670 nm) and NIR (Near Infrared) (780-680 nm). These scenes were already geo-corrected by ESA in Geographic Long/Lat Projection, Datum WGS84 and then they have been re-sampled into projection of UTM, Datum WGS84, Zone 49, in spatial resolution 5 m × 5 m.

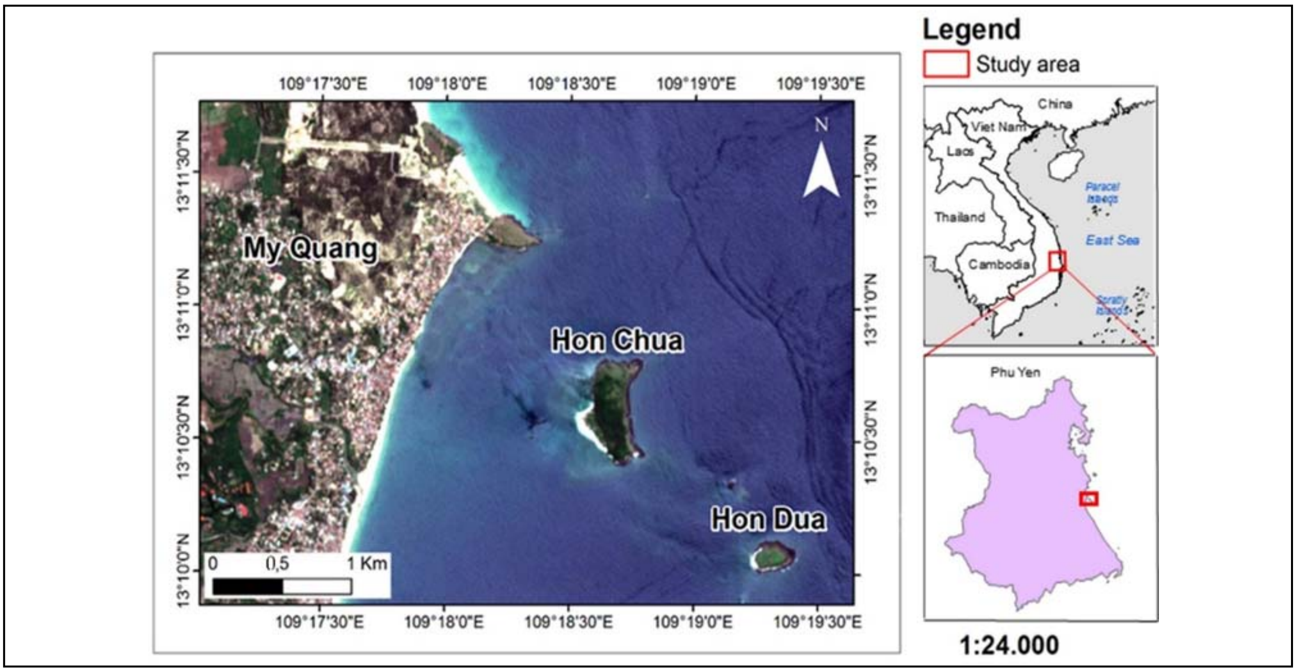

Fig. 1 Map of pilot study area, An Chan commune, Phu Yen province, central Vietnam.

2.2.2 Field Survey Data

The field data collection was carried out in June 2018 under the protocols of the Survey Manual for Tropical Marine Resource [21]. This period was chosen for field data collection because of low tide conditions. Authors utilized the boats to observe the distribution of *Sargassum* meadows and other habitats in An Chan shallow waters. Moreover, the sampling of them also was carried out along cross-sections in My Quang tidal flat when low tide by walking. Line transect and some spot check methods were used for collecting spatially referenced benthic cover of *Sargassum* meadows and other habitats. In addition, three adjacent transects from shore to 15 m in Xep beach which covers fresh homogenous sand for extracting BRI indies that will be presented in next parts.

Cross and alongshore transect lines were chosen to cover the range with differences in the biomass levels throughout the *Sargassum* area. The field data collected were used for the classification approaches and validation of the output underwater habitat maps. Digital photographs of 0.5 m × 0.5 m quadrats of the benthos (Photo-Quadrats) were captured at 20 m intervals along the sites which will estimate above-ground field biomass. The field study sites (including survey site for BRI pre-processing, SAV mapping, and Biomass estimation) were shown in Fig. 2.

2.2.3 Data Processing for Spatial Distribution Mapping of *Sargassum* Meadows

The distribution of *Sargassum* meadows and other habitats in An Chan coastal waters will be assessed by remote sensing techniques base on PS image source. All applied algorithms for extracting habitat map in this study require orbit multispectral data that have been geometrically corrected, radiometrically calibrated and masked for land and clouds. PS imageries, level 1B used in this study were already geo-corrected and atmospherically corrected into Ref_{TOA} (Reflectance in Top of Atmospheric). In practice, authors only apply a multiple factor of 0.0001 for all of four original DN (Digital Number) bands of PS image, then creating the Ref_{TOA} image. In next step, authors applied continuously atmospheric correction by Dark Subtract tool for removing atmospheric noises in optical deep water area and creating a new image of (Ref_{TOA} - $Ref_{TOA,\infty}$). And then, the step of water column correction by the improved Sagawa's algorithms will be performed.

The BRI of Sagawa's algorithm was represented by formula as:

$$BRI_i = \frac{Ln\left(Ref_{TOA,i} - Ref_{TOA,\infty,i}\right)}{e^{Kd.Z}} \qquad (1)$$

The improved Sagawa's algorithm is a BRI modified one with attention of Tassan's concept on discrimination of light attenuation coefficient K_d between shallow and deep waters. Modified BRI algorithm was represented by double formula (similar as Eq. (1)) with the seperation of attenuation coefficient K_d in two cases: $K_{d\text{-}HighAlbedo}$ in upper water layer and $K_{d\text{-}LowAlbedo}$ in lower water layer.

To define the extent of the SW (Sargassum. sp) meadows, SG beds and other subtractes, a spatial distribution map was produced using the MLC (Maximum Likelihood Classification). Five discrete classes were classified (i.e., Sargassum SW, SG, SD (Sandy), RK (Rock) and OTs (others)) by using BRI pre-prosessed bands (including both blue, green, red, NIR) as input image for the MLC algorithm.

The classified class of SW (i.e. Sargassum sp.), then was seperated absolutly from other classes (in MLC results) for estimation of Sargassum biomass in next step.

2.2.4 Methodology for Estimating of *Sargassum* Biomass from PS Data

SLR (Simple Linear Regression) and MR (Multiple Regression) models were applied to estimate *Sargassum* biomass. The BRI values from the corrected PS image were extracted for each of the biomass sample sites using all the available wavebands for this image. The 56 sample biomass values were entered as the dependent variable and the BRI pre-processed values as the independent variable for SLR analysis. Choose

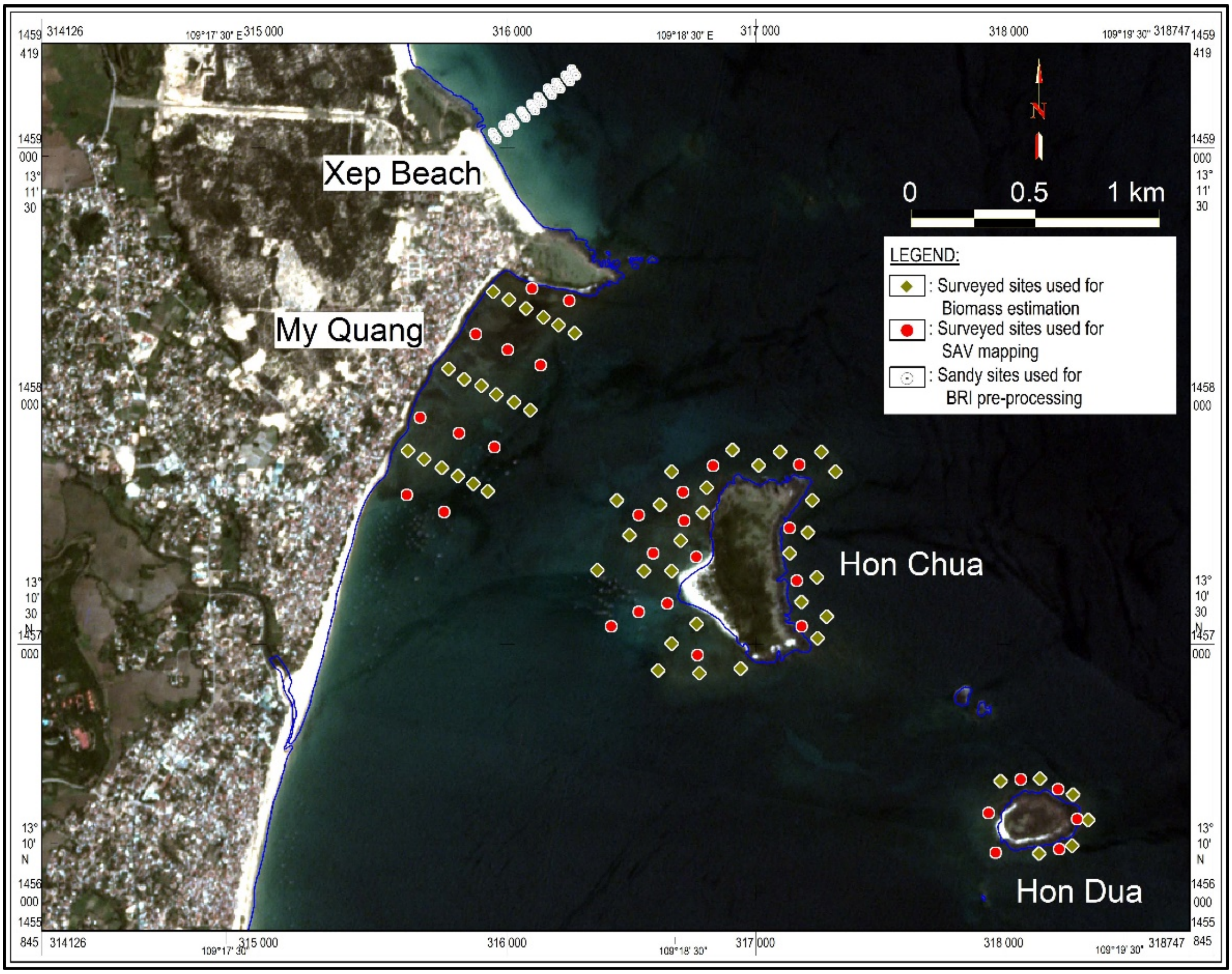

Fig. 2 Schema of field survey network in SAV mapping and *Sargassum* Biomass estimation for An Chan coastal waters by remote sensing techniques derived from PS image.

the best BRI variables with high R^2 (Coefcient of Determination) and low RMSE (Root Mean Square Error) for analysis in MR models in next step. Both MLR (Multiple Linear Regression) and MPR (Multiple Polynomial Regression) models based on the best BRI variables will be performed. Finally, the best resultant regression function was then applied to each pixel in the image for producing a map of *Sargassum* biomass.

2.2.5 Accuracy Assessment

The error assessment procedure of habitat mapping of *Sargassum* and other SAV followed standard satellite image processing protocols. The confusion matrices and summary tables containing the OA (Overall Accuracy) and kappa coefficients were generated using ENVI (ENvironment for Visualizing Images), version 5.2. The coefcient of determination values (R^2), RMSE were analyzed to evaluate the accuracy of the biomass estimation.

3. Results and Discussions

3.1 Spatial Distribution of Sargassum Meadows Derived from PS Images

3.1.1 Determining the Datasets of Attenuation Coefficients and Processing Equation Systems of the BRIs (Bottom Reflectance Indies)

Through the observed homogenous sand beds in Xep Beach and surrounding shallow waters, authors chose SD pixels along 3 adjacent cross sections from shore of Xep Beach to 15 m depth. Thanks to good overlapping between spectral image (Ref_TOA) and bathymetry one, it allows us to determine attenuation coefficients of BRI algorithms in both two cases, one in shallow waters and another in deeper ones. Based on visual observing along plot of Ref_TOA_i versus depth (Fig. 3), authors determined more concretely attenuation coefficients in each case, as:

The dataset of attenuation coefficients regarding enhanced BRI algorithm will correspond to values of -6.109, -4.61 and -4.681, respectively. These coefficients adapt in depth range from 0 to 8 m. When the depth is greater than 8 m, attenuation coefficients of enhanced BRI will be -6.628, -4.904 and -9.062, respectively. Processing equation systems of improved BRIs will be written more detailedly by:

When $H \leq 8$ m then

$$\begin{cases} \mathrm{BRI}_1 = e^{-6.109}\left(\mathrm{Ref}_{\mathrm{TOA},1} - \mathrm{Ref}_{\mathrm{TOA},\infty 1}\right) \\ \mathrm{BRI}_2 = e^{-4.610}\left(\mathrm{Ref}_{\mathrm{TOA},2} - \mathrm{Ref}_{\mathrm{TOA},\infty,2}\right) \\ \mathrm{BRI}_3 = e^{-4.681}\left(\mathrm{Ref}_{\mathrm{TOA},3} - \mathrm{Ref}_{\mathrm{TOA},\infty,3}\right) \end{cases} \quad (2a)$$

When $H > 8$ m then

$$\begin{cases} \mathrm{BRI}_1 = e^{-6.628}\left(\mathrm{Ref}_{\mathrm{TOA},1} - \mathrm{Ref}_{\mathrm{TOA},\infty,1}\right) \\ \mathrm{BRI}_2 = e^{-4.904}\left(\mathrm{Ref}_{\mathrm{TOA},2} - \mathrm{Ref}_{\mathrm{TOA},\infty,2}\right) \\ \mathrm{BRI}_3 = e^{-9.062}\left(\mathrm{Ref}_{\mathrm{TOA},3} - \mathrm{Ref}_{\mathrm{TOA},\infty,3}\right) \end{cases} \quad (2b)$$

Attentionally, the subscripts of 1, 2, 3 correspond to blue, green and red bands, respectively.

3.1.2 The Spatial Distribution of SAV and *Sargassum* Meadow Derived from Improved BRI Algorithm

Enhanced BRI images and same training points data were also applied to detect the SAV meadows and other substrates at An Chan coastal waters. The objects were chosen to classify are also similar, it means: (i) SG; (ii) SW; (iii) RK beds; (iv) SD beds; and (v) OTs.

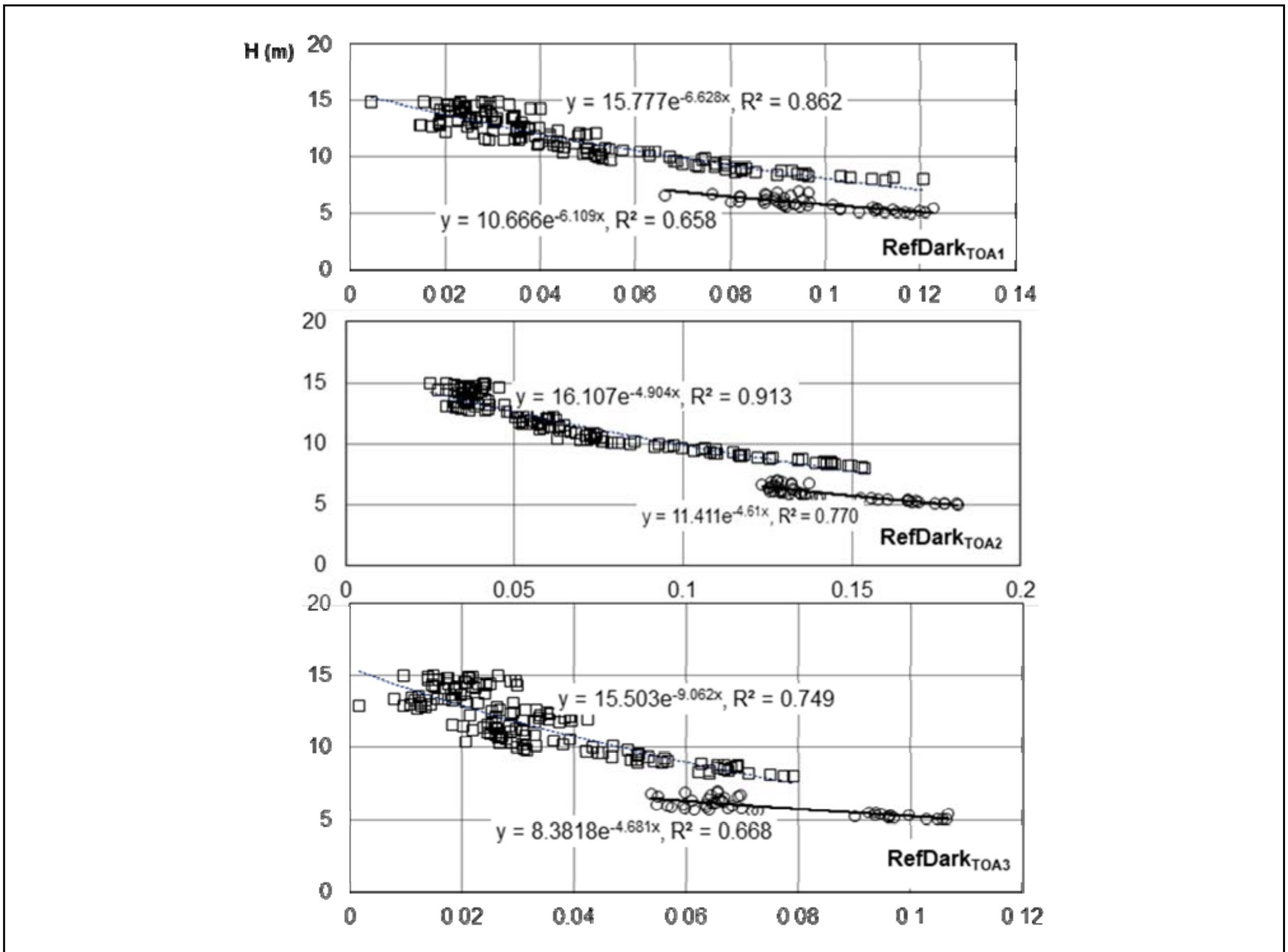

Fig. 3 The attenuation coefficients Kd_i used for estimating BRI_i extracted from PS image dated on 20 June 2018.

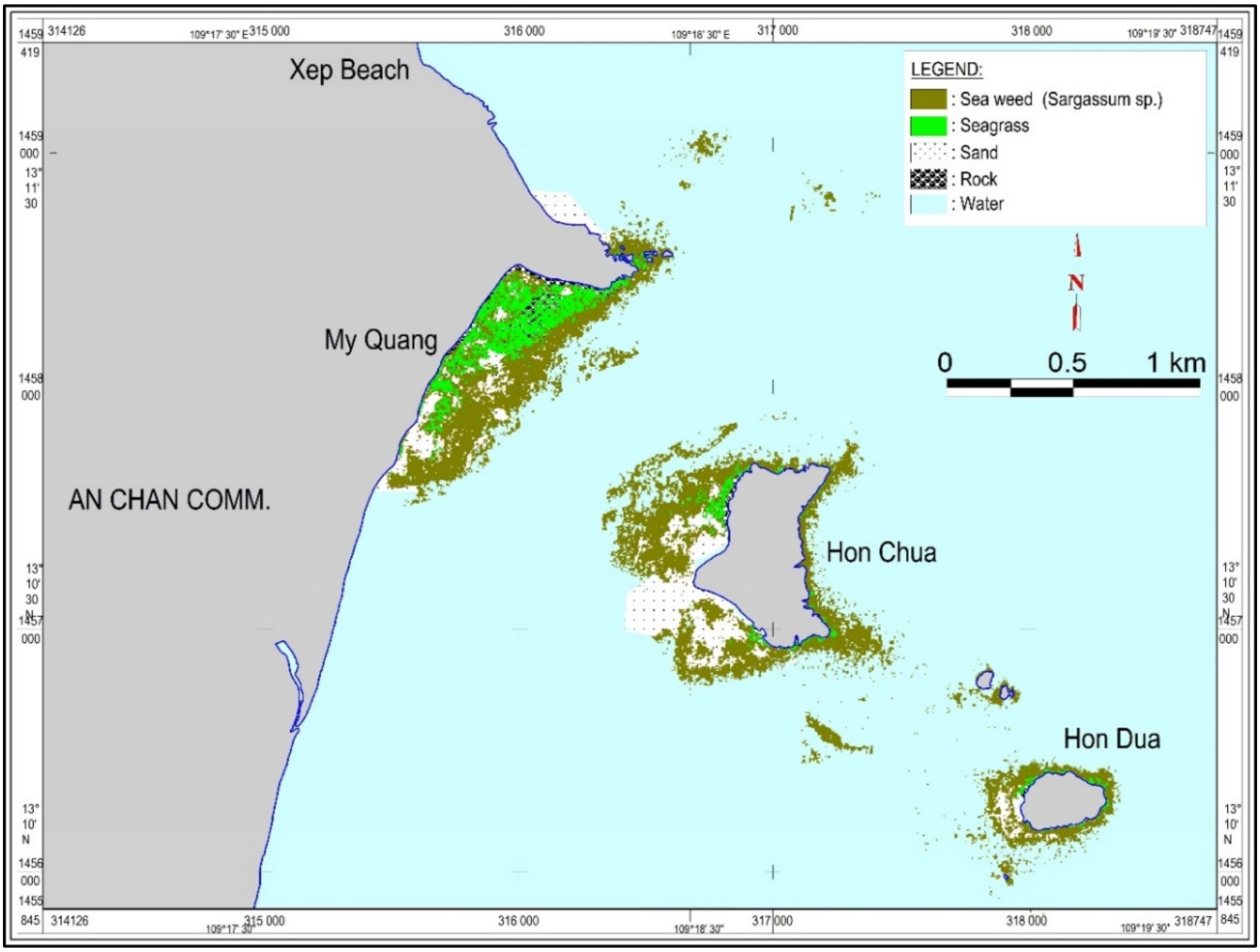

Fig. 4 Distribution of SAV canopies in An Chan, Hon Chua obtained from PS image (20th June, 2018) based on improved BRI technique.

Classification results of SAV canopies and other subtrates in An Chan coastal waters obtained from improved BRI images are shown in Fig. 4.

Classification results of *Sargassum* canopies and other substrates from PS satellite image base on enhanced BRI techniques, allow us to estimate distributed areas and scale of SAV (Submerge Aquatic Vegetation). In term of spatial distribution of *Sargassum* seaweed meadows, in My Quang coastal water include scattered seaweed patches that lie interspersed with seagrasses on dead coral reefs with distributed area of 4.25 ha and another patch was approximately 15.95 ha that located at the foot of the reefs in 3-4m deep. The seaweed meadows in Hon Chua include broad patches of *Sargassum* lie around islet and in foot of the reef in 3-4m deep with their width was 100 m wide and area were approximately 22.8 ha. The seaweed meadows in Hon Dua include broad patches of *Sargassum* lie around islet and in foot of the reef in 3-4m deep with their width was about 50 m wide and area were approximately 5.72 ha. Besides, seaweed meadows also found in underwater very small reef with area was approximately 1.60 ha. The total seaweed area in whole An Chan region (include My Quang-Hon Chua-Hon Dua) was approximately 50.32 ha.

3.1.3 The Accuracy of SAV Image Classification by BRI Techniques

The accuracies of SAV classification using different techniques are shown in Table 1. The OA and kappa coefficient of SAV classification by BRI technique were 92.52% and 0.90, respectively.

Table 1 Confusion matrix of SAV classification results in An Chan coastal waters obtained from enhanced BRI technique in PS image, date 28 June 2018.

Classes	SW	SG	RK	SD	OTs	Sum.
SW	62	65	6	4	2	139
SG	5	206	0	1	9	221
RK	23	0	0	45	0	68
SD	95	1	2	0	53	151
OTs	0	6	0	0	130	136
Sum	185	278	8	50	194	715
OA		92.52%				
Kappa coefficient		0.8957				

3.2 Biomass Estimation of SW Meadow (Sargassum. sp)

3.2.1 Regression Models with Spectral Bands of BRI as Independent Variables for Biomass Estimation

The four BRI corrected spectral bands from PS image and field biomass sampling points were used as the independent and dependent variables for linear regression analysis, respectively. For the whole linear regression models with BRI bands, the analysis revealed the two most BRI bands with the most information content to be red band—BRI_3 (R^2 = 0.9675), and then green—BRI_2 (R^2 = 0.8703) (Fig. 5); these bands were therefore used to estimate the biomass of *Sargassum* meadows.

An RMSE value of ±110.57 g/m^2 (R^2 = 0.9699) was calculated using the MLR model (Fig. 6, left) with predicted equation expressed by:

$$\text{Obs}^1 \text{ Biomass} = 1650.7 + (5103.3 \times BRI_2) - (18937 \times BRI_3) \quad (3)$$

Another RMSE value of ±109.21 g/m^2 (R^2 = 0.9707) was calculated using the multiple 2nd order polynomial regression model (Fig. 6, right) with predicted equation expressed by:

$$\text{Obs}^2 \text{ Biomass} = -3391.12 + (2866.2 \times BRI_2) + (19544.7 \times (BRI_3 - 0.513))^2 \quad (4)$$

The performance of each regression model (i.e., SLR for single BRI corrected band, MLR, and multiple 2nd order polynomial regression) is shown in Table 2.

The results in Table 2 indicated good to very good relationships (R^2 = 0.870-0.967) between BRI values of red (BRI_3), green (BRI_2) bands and field biomass. In contrast, the results showed poor relationship (R^2 = 0.396-0.569) between BRI_1 (blue band), and/or BRI_4 (NIR band) and field biomass. The brown pigment of *Sargassum* is the reason to explain the good correlation between red and green bands and field measured biomass. The BRI of these bands was therefore used to estimate the biomass of *Sargassum* meadows. The results in Table 2 also showed that, the improved performance of the predicted algorithms, multiple linear and polynomial regression models used for only these bands (i.e. red and green) needs to apply. Finally, the best predicted model of 2nd order polynomial regression (R^2 = 0.9707; RMSE = ±109.21 g/m^2) was chosen for *Sargassum* biomass estimation in our study site.

3.2.2 *Sargassum* Biomass of *Sargassum* Canopies in An Chan Coastal Waters

A *Sargassum* biomass map produced from the biomass predicted model by multiple 2nd polynomial regression algorithm was created (Fig. 7). Total *Sargassum* produce derived from resultant map of biomass distribution (as above mention) was estimated with an yield value of 449.5 in an cover area of 50.32 ha, so average biomass of whole of An Chan region is 897.8 g/m^2. The yield, cover area and average biomass of *Sargassum* meadows in An Chan according to sub-regions (i.e. My Quang, Hon Chua, Hon Dua) was also estimated more detailedly and shown in Table 3.

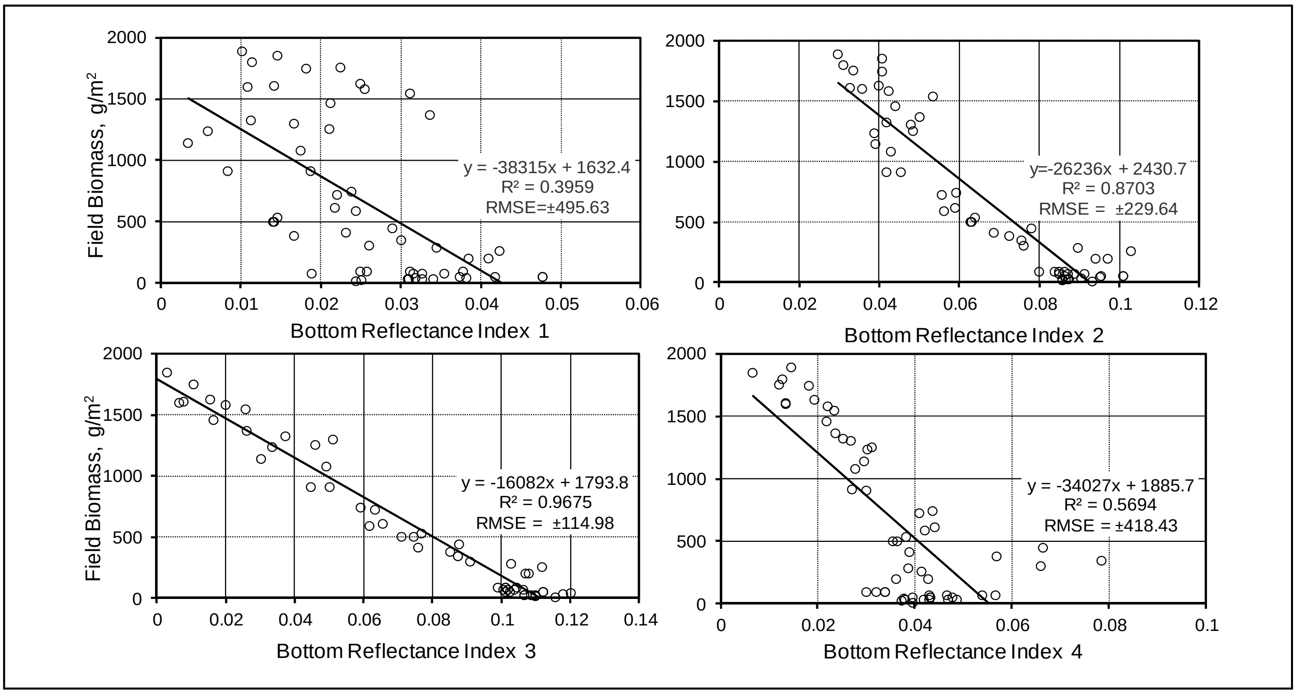

Fig. 5 Scattering plots of BRIs vs. field *Sargassum* biomass (g/m^2) using the SLR models for single BRI band algorithms.

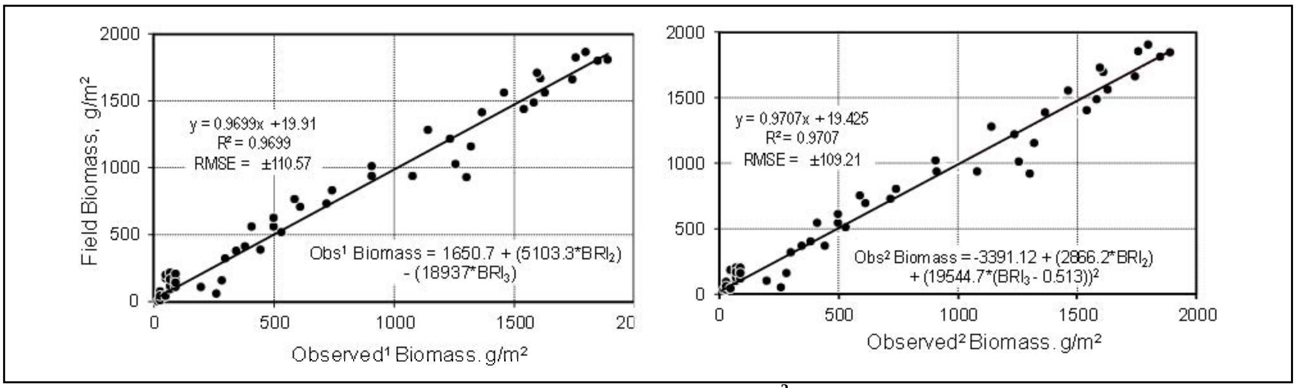

Fig. 6 Scattering plot of observed vs. estimated *Sargassum* biomass (g/m^2) using the MLR (left) and multiple 2nd order polynomial regression models (right).

Table 2 The performance of models (R^2 and Root Mean Square Error) for the biomass estimation of *Sargassum* meadows, where their biomass was estimated by BRI corrected bands (both single and multiple bands).

Bands-predicted model	R^2	RMSE (g. FW/m^2)	Bands	R^2	RMSE (g FW/m^2)
Blue (BRI_1)—simple linear reg.	0.3959	±495.63	NIR (BRI_4)—simple linear reg.	0.5694	±418.43
Green (BRI_2)—simple linear reg.	0.8703	±229.64	(BRI_2 and BRI_3)—multiple linear reg.	0.9699	±110.57
Red (BRI_3)—simple linear. reg.	0.9675	±114.98	(BRI_2 and BRI_3)— multiple polynomial reg.	0.9707	±109.21

Table 3 Total produce (t), cover area (ha), average biomass (g/m^2) of *Sargassum* meadows in An Chan coastal water, Phu Yen province, Vietnam derived from PS image.

My Quang			Hon Chua			Hon Dua			Whole of An Chan coastal water		
Total yield	Area	Avg. biomass	Total yield	Area	Avg. biomass	Total produce	Area	Avg. biomass	Total yield	Area	Avg. biomass
(t)	(ha)	(g/m^2)	(t)	(ha)	(g/m^2)	(t)	(ha)	(g/m^2)	(t)	(ha)	(g/m^2)
168.29	20.20	833.2	213.84	22.80	962.8	67.32	7.32	920.2	449.5	50.32	897.8

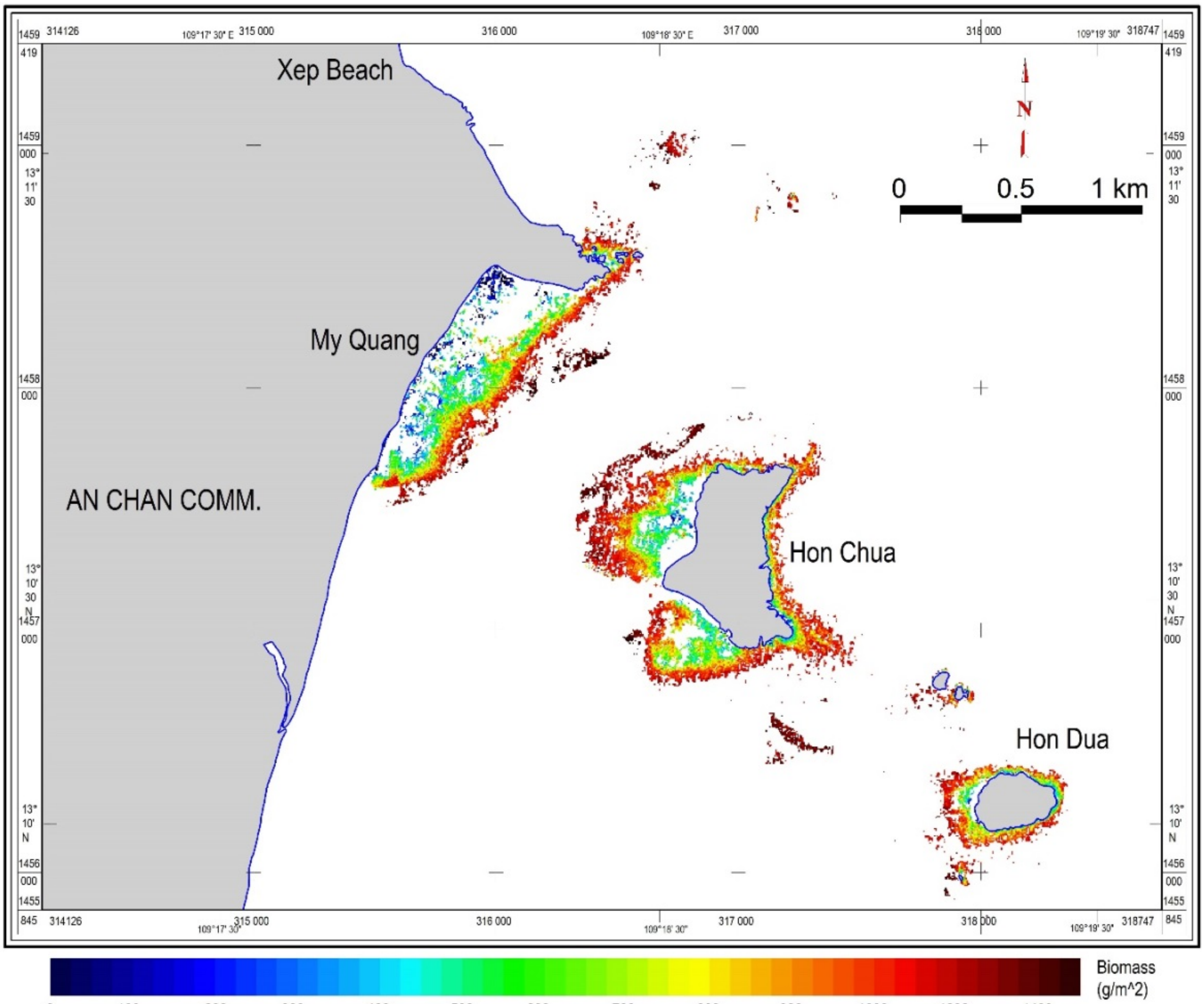

Fig. 7 ***Sargassum*** **biomass map for An Chan coastal waters derived from PS image and field data sets.**

4. Conclusion

This study confirmed the utility of PS data for mapping the spatial distribution of SAV canopies and estimation of *Sargassum* biomass in An Chan coastal waters, Tuy An district, Phu Yen province, Vietnam.

SAV (includeing *Sargassum* SW meadow) in An Chan commune, Tuy An district, Phu Yen province can be detected well and have the high level of accuracy (OA = 92.57%, Kappa coefficient = 0.90) by using improved BRI method. Total SW area in An Chan region was approximately 50.32 ha, with 20.20 ha *Sargassum* meadows in My Quang, 22.8 ha in Hon Chua, 5.72 ha in Hon Dua and a small part of 1.60 ha in underwater small reefs.

The simple linear as well as MR models that base on corrected BRI indies (including only BRI_3 and BRI_2) showed an high accuracy ($R^2 \approx 0.97$; RMSE ≈ ±109.21 g/m^2) *Sargassum* biomass estimation. A *Sargassum* biomass map in An Chan coastal waters derived from PS image was created. Spatial distribution of observed *Sargassum* biomass that is obtained from the map allowing us to estimate total yield of *Sargassum* in An Chan coastal water was about 449.5 tons in cover area of 50.32 ha, and their average biomass was about 897.8 g/m^2.

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Conflicts of Interest

The authors declare no conflict of interest.

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