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Authors: Hoang, Tin, Garcia, Rodrigo, O'Leary, Michael, and Fotedar, Ravi

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Identification and Mapping of Marine Submerged Aquatic Vegetation in Shallow Coastal Waters with WorldView-2 Satellite Data

Tin Hoang[†‡*], Rodrigo Garcia[††§], Michael O'Leary[†], and Ravi Fotedar[†]

[†]Department of Environment and Agriculture, Faculty of Science and Engineering, Curtin University, Bentley, Perth, Western Australia 6102, Australia

[‡]Center for Coastal Management and Development Studies, Hue University of Sciences, Thua Thien Hue, 8454, Vietnam

[††]Remote Sensing and Satellite Research Group, Department of Physics and Astronomy, Curtin University, Bentley, Perth, Western Australia 6102, Australia

[§]School for the Environment, University of Massachusetts Boston, Boston, Massachusetts 02125, USA

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ABSTRACT

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Marine submerged aquatic vegetation (MSAV) naturally occurs on rubble and dead coral substrates in temperate and tropical coastal regions. During the growing season, MSAV develops to form dense canopy seaweed beds that play a vital role in coastal marine ecosystems and offer great potential to chemical, pharmaceutical, and bio-energy industries. At present, the total biomass and the distribution of the MSAV beds along the coast of Western Australia (WA) are not fully identified and quantified. Therefore, the application of satellite remote sensing data with high spatial resolution for examining the MSAV beds is required. The main objective of the present study was to assess and map the distribution of MSAV at two sites; Rottnest Island and Point Peron, Rockingham, WA, using WorldView-2 (WV2) satellite data. These study sites are important marine protected areas in WA waters with extraordinary documented biodiversity. By means of quantitative quadrat techniques, the MSAV canopy covers and fresh biomass data from the ground truth observations were assessed from September 2012 to December 2014. At Point Peron, the fresh biomass of *Sargassum* in the inter-tidal zone reached 5651.7±754.5, 5218.9±192.6, 1136.6±526.4, and 3472.2±434.2 g m^{-2} for spring, summer, fall, and winter, respectively. The overall accuracy of the minimum distance method was employed and yielded the highest accuracy rates of 90.93% (Kappa coefficient, $\kappa = 0.96$) and 97.13% ($\kappa = 0.96$) for Rottnest Island and Point Peron, respectively. The Mahalanobis classification with overall accuracy yielded 90.66% ($\kappa = 0.88$) and 94.16% ($\kappa = 0.85$) for Rottnest Island and Point Peron, respectively. The study results revealed that WV2 satellite data provided evidence of the high accuracy of MSAV classification.

ADDITIONAL INDEX WORDS: *clear shallow waters, marine habitat mapping, satellite remote sensing.*

INTRODUCTION

High spatial resolution satellite remote sensing is an effective tool for monitoring, evaluating and mapping biodiversity and natural resources in coastal areas (Green *et al.*, 1996; Gibbons *et al.*, 2006). There are numerous studies that have used high-resolution satellite images for identifying and mapping coastal habitats such as coral reefs (Benfield *et al.*, 2007), sea grass meadows (Guimarães *et al.*, 2011), mangroves (Heenkenda *et al.*, 2014; Ibrahim *et al.*, 2015), macroalgae (Garcia *et al.*, 2015; Tin, O'Leary, and Fotedar, 2015), and freshwater/ salt marsh (Carle, Wang, and Sasser, 2014). However, these studies mostly utilized sensors with fewer than four spectral bands in the visible domain, which limited the detailed classification of vegetation (Feilhauer *et al.*, 2013). To overcome the limitations, in October 2010, a WV2 satellite was successfully launched into orbit and began to acquire high spatial resolution images, 0.5-m for panchromatic and 2-m for multispectral images, and high spectral resolution (eight bands) including four additional spectral bands with additional near-infrared, coastal-blue, yellow, and red-edge bands (Updike and Comp, 2010).

Evaluation and validation of the feasibility of the new spectral bands of WV2 satellite data on identifying and mapping MSAV in coastal habitats are a necessity. This work not only contributes to scientific research but also provides useful information for managers, conservationists, and coastal planners, and is particularly relevant for marine conservation parks' authorities. The main objectives of the present study were: 1) validating the feasibility of the WV2 satellite data for identifying and mapping MSAV in coastal habitats; 2) evaluating three machine learning algorithms/classification methods, Mahalanobis distance (MDiP), supervised minimum distance (MiD), and spectral angle mapper (SAM), for mapping the diversity of MSAV.

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*Corresponding author: tin.hoangcong@postgrad.curtin.edu.au

METHODS

In this section, we present a description of the study area, spectral reflectance measurements, WorldView-2 images acquired, processing methods, and the accuracy assessment used in this study.

Study area

Rottnest Island and Point Peron, Rockingham are recognized as biodiversity hotspots of the WA coast and have been selected as pilot study sites for the region. The tidal range of the WA coast is relatively low (± 1 m). Rottnest Island is located off the WA coast approximately 19 km from the port of Fremantle, while Point Peron is a large limestone region at Shoalwater Islands Marine Park on the Rockingham coast (Figure 1). The study sites are dominated by canopy forming macroalgae such as *Sargassum* sp., *Ecklonia* sp., sea grass (*Amphibolis* sp., *Posidonia* sp.), and other associated MSAV species such as *Ballia* sp., *Metagoniolithon* sp., *Asparogopsis* sp., *Gracilaria* sp., and *Ulva* sp.

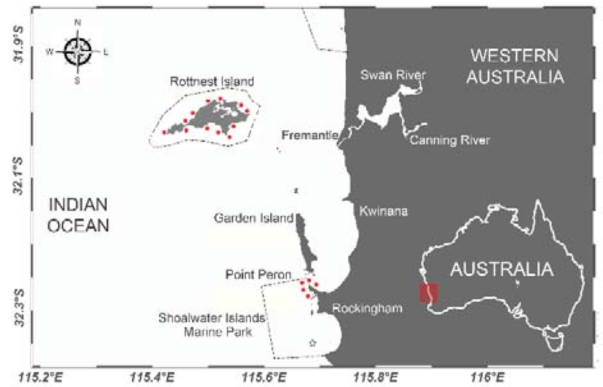

Figure 1. Map showing the selected study locations along the Western Australian coast, Australia. The dashed lines symbolize marine protected areas' boundaries.

Field surveys and vegetation classes

The purpose of mapping mainly focuses on the abundance of habitats. Consequently, broad-scale field surveys were conducted as much as possible. We used a combination of both scuba and free diving methods to collect ground truth data of the dominant habitat types. Ten and three survey transects were carried out at Rottnest Island and Point Peron, respectively (Figure 1). Along the transects, MSAV samples, in the depth range between 0.2 and 3.5 m, were collected and underwater photographs taken.

The classification of benthic habitats at the two study sites was based on a hierarchal classification scheme that included three levels and five classes (Figure 2). Classification at level 1 was based on the pixel reflectance value that best separated vegetated and non-vegetated benthos. The non-vegetated level 1 substrates were subdivided into sandy and limestone substrates by means of reflectance characteristics. Likewise the vegetated level 1 substrates were classed as either macroalgae and sea grass by means of spectral reflectance and the ground truthing from the field survey data. Level 3 classification, including five different habitat classes, largely depended on the characteristics of spectral reflectance to divide them into two groups of canopy algae and algae turf. The group of sea grass, sand, and limestone was also similar to level 2.

Spectral reflectance measurement and processing

Twenty-two MSAV samples that included macroalgae, sea grass, sand and limestone substrates were collected at Point Peron (32.2715 ºS, 115.6865 ºE), WA on August 22, 2014. The MSAV samples were preserved in cold containers and transported to the Curtin Aquatic Research Laboratory within four hours of collection. The samples were then identified to species level and their spectral reflectance was measured by an ASD Hi-Res FieldSpec® 4 portable spectroradiometer (1-nm resolution, 350−2500 nm coverage). All samples were placed on a non-reflective black tray and measured from nadir position (~10º). Thirty replicates were measured for each sample.

WorldView-2 image acquistion

Two WV2 scenes covering the Rottnest Island and Point Peron, Rockingham regions were acquired for study areas in WA coastal waters. The selected WV2 were captured on February 7 and October 28, 2013 for Point Peron, Rockingham and Rottnest Island, respectively. The captured time of the satellite corresponds to Australian mid-spring and late summer, coinciding with the most dominant MSAV habitat development, particularly the canopy macroalgae such as *Sargassum* and *Ecklonia* (Tin, O'Leary, and Fotedar, 2015; Kendrick and Walker, 1994).

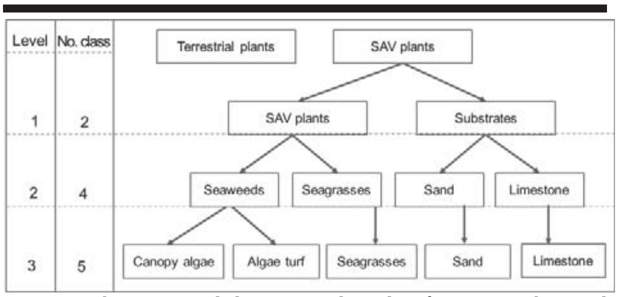

Figure 2. The conceptual diagram used to classify marine submerged aquatic vegetation habitats in clear shallow coastal waters.

Remote sensing image processing

The WV2 digital numbers were first converted to top of atmosphere surface reflectance values with the procedure given by Updike and Comp (2010). The FLAASH algorithm in ENVI 4.7 was then used for atmospheric correction. High-resolution panchromatic data (0.5-m) were fused with the lower resolution multispectral bands (2-m) to create a colorized high-resolution dataset.

Accuracy assessment

Overall classification accuracy was calculated by dividing the total number of calculated pixels by the total error pixel in the classification process; overall classification accuracy was measured in units of percent. Index error (error matrices) was used to calculate the user's and producer's accuracy. In particular, the error matrix (user's accuracy) was used to determine the accuracy of the object's classification and Kappa coefficient index (κ) of n parameter estimation.

RESULTS

In this section, we describe the marine submerged aquatic vegetation types, spectral reflectance characteristics, mapping MSAV distribution, and results of accuracy assessment.

Marine submerged aquatic vegetation distribution substrates

According to field surveys, the distribution area of MSAV at selected sites in WA coast is mainly distributed on the limestone substrates within depths ranging from 0.2 to 3.5 m. The major subtrates are sandy and limestone rock.

Spectral reflectance characteristics

The results of the PCA analysis measuring the surface spectral reflectance of 19 MSAV groups and three substrate types showed that all MSAV groups in shallow coastal waters (<3 m) can be divided into four main groups: brown macroalgae, red macroalgae, green macroalgae, and benthic substrate groups. The sea grass group has two dominant species, *Posidonia* sp. and *Amphibolis* sp. The results from in-air spectral measurements showed that the sand and limestone substrates were completely different from the reflectance spectra of the other MSAV species (Fearns *et al.*, 2011). The peak spectral reflectance values of brown macroalgae species were usually at 550 nm. Brown and red macroalgae usually have longer wavelengths and could have more than one maximum point (580 and 650 nm) (Figure 3). Regression between in situ and WV2 satellite-derived spectral reflectance, based on the classification results PCA and we found that all species of MSAV and substrates can be classified into/divided into four main groups. Therefore, in this present study, four major substrate habitats including sea grass, mixed MSAV, turf algae, canopy algae, and two main benthos substrate types including bare limestone and sand were selected for habitat mapping.

Mapping the distribution of MSAV

The results of the MDiP, MiD and SAM classification methods revealed that the distribution area differed with each method (Figures 4 and 5). The MDiP classifier showed that the mixed SAV was in deep waters. Sea grasses were identified as the dominant habitat and were usually distributed in the shallow waters where a sandy bottom is the most dominant. With the MiD classifier, sea grass was also identified as the highest distributed habitat that included the deep water areas. Canopy algae, algae turf, and sand were also interpreted similarly to the results of the MDiP method. Likewise, the SAM classifier expressed the sketchy interpretation results and unclear pattern of some sea grass, mixed SAV, and sand. Canopy algae and algae turf were not presented clearly either. At Point Peron, fresh biomass of *Sargassum* at the inter-tidal zone reached 5651.7±754.5, 5218.9±192.6, 1136.6±526.4, and 3472.2±434.2 gram per square meter (g m^{-2}) for spring, summer, fall, and winter, respectively.

Accuracy assessment

In Rottnest Island, the confusion matrix showed that the highest overall accuracy was achieved with the MiD classification method (90.93%), followed by the MDiP classification method (90.66%). The lowest overall accuracy was found in the SAM classification method with a value of 49.93%. In particular, the MiD classification methods had user's accuracy ranging from 86.9% for mixed MSAV to 100% for the bare limestone class. In the MiD classification methods, all identified classes had a user's accuracy greater than 70%.

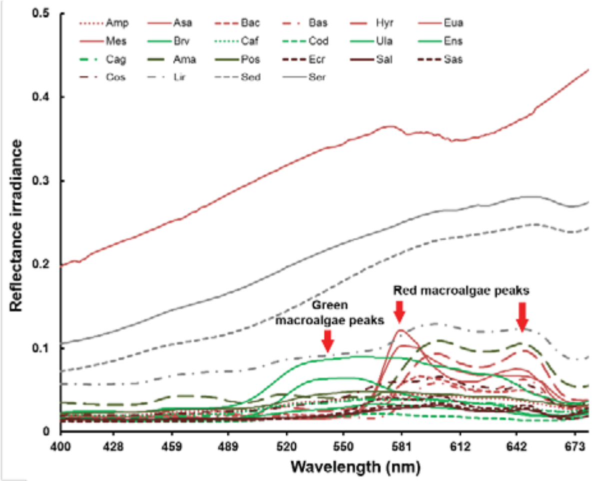

Figure 3. The in-air spectral signatures of the main inter-tidal submerged aquatic vegetation species and substrates in WA. Note: Sal = *Sargassum linearifolium*, Sas = *S. spinuligerum*, Ecr = *Ecklonia radiata*, Cos = *Colpomenia sinuosa*, Asa = *Asparagopsis armata*, *Hyr* = *Hypnea ramentacea*, Bas = *Ballia* sp., Amp = *Amphiroa anceps*, Eua = *Euptilota articulata*, Bac = *Ballia callitrichia*, Mes = *Metagoniolithon stelliferum*, *Ula* = *Ulva australis*, *Ens* = *Entermorpha* sp., Cod = *Codium duthieae*, Cag = *Caulerpa germinata*, Caf = *C. flexis*, Brv = *Bryopsis vestita*, Ama = *Amphibolis antartica*, Pos = *Posidonia* sp., Sed = Sediment, Ser = Sediment/Rubble, Lir = Limestone rocks with red coralline algae covering.

Producer's accuracy ranged from 43.8% for the canopy algae class and 100% for both sea grass and sand classes. Five out of six classes had a producer's accuracy greater than 70%, excluding the canopy algae class with 43.8%. User's accuracy of the MDiP classifier gave only the sea grass class less than 70% (66.6%), while the remaining classes were greater than 70%. Producer's accuracy of canopy algae was 45.7%, while the remaining classes had values greater than 70%. The user's accuracy of SAM had an accuracy value greater than 70%. Two out of the six classification classes had producer's accuracy of less than 70%, including canopy algae and sand.

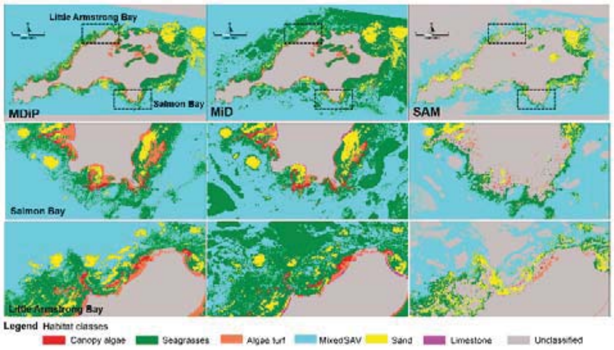

Figure 4. Comparison of classification results from three different classifier methods, MDiP, MiD, and SAM, at Rottnest Island study sites.

At Point Peron, the overall accuracy of the MiD classifier also reached the highest value of 97.13% (coefficient κ = 0.94). The MDiP classifier with general accuracy value reached 94.16% (κ = 0.88), and the lowest value SAM classifier a value of 88.43% (κ coefficient = 0.74). In the classification results of the MiD classifier, only the producer's accuracy of the bare limestone class was 68.58%' none of the classes had classification results less than 70% in terms of both user's and producer's accuracy. Similarly to the MDiP classifier, only the user's accuracy of the canopy algae class was valued at 66.7%; the remaining classes in terms of both user's and producer's accuracy were greater than 70%. The SAM classifier gave two out of six classes user's accuracy values lower than 70% including canopy algae and sand. The remaining results for both user's and producer's accuracy were above 70%.

DISCUSSION

Rehabilitation and development of MSAV habitats is currently one of the priority activities in ecosystem conservation, including freshwater ecosystems (Harwell and Havens, 2003; Herrera-Silveira and Morales-Ojeda, 2009; Yuan and Zhang, 2008). However, assessing the growth and mapping the current state of distribution of MSAV on a large scale is very time-consuming and labor-intensive not only because of geographical issues but also because of seasonal and weather variations (Yuan and Zhang, 2008). The results of this study can be compared with those of the recent studies that used high-resolution satellite imagery for mapping of shallow coastal vegetation. Fearns (2011) used HICO hyperspectral images in mapping marine vegetation that showed the optical model could classify 80% of the image pixels. Of those, approximately 50% of pixels were distinguished as sea grass and sand and 90% were classified as macroalgae (Fearns *et al.*, 2011). Regarding the optimum depth for classification satellite remote sensing imagery, this present study showed a similar trend to that of Reshitnyk and colleagues (2014) as results suggested that WV2 imagery can provide the finest interpretation of eelgrass, and brown and green macroalgae habitats at depths above <3.0 m.

The overall accuracy of the classification outcomes in the present study is higher than that of the study by Kumar and colleagues (2015) when using support vector machine (SVM), artificial neural network (ANN), and SAM classification methods for classifying crop and non-crop canopy in India. The highest overall accuracy found in SVM and ANN algorithms was 93.45% and 92.32%, respectively. Likewise, the SAM method has low accuracy among the classification methods (74.99%) (Kumar *et al.*, 2015). In this study, MDiP and MiD methods demonstrated potential for identifying and mapping MSAV with WV2 multispectral high-spatial resolution (MHSR) satellite imagery. This was validated by the highest overall accuracy (greater than 90%) for both study sites in WA. The MDiP method showed that mixed MSAV was in deep waters rather than shallow coastal waters.

This study supports the feasibility of previous studies suggesting that MHSR satellite data (*e.g.* QuickBird, WV2) would be suitable for mapping benthic macroalgae cover in regions of very high heterogeneity (Vahtmäe and Kutser, 2007). In addition, the MHSR imagery data combined with field surveys in coastal shallows are a perfect fit. However, hyperspectral airborne imagery (HAI) is an advantageous imagery source which have the abundantly information to assess coastal marine habitats due to its hyperspectral characteristic bands, regardless data acquire price. HAI is still very expensive compared with MHSR as it is collected by separate regions for each study purpose (Yuan and Zhang, 2008).

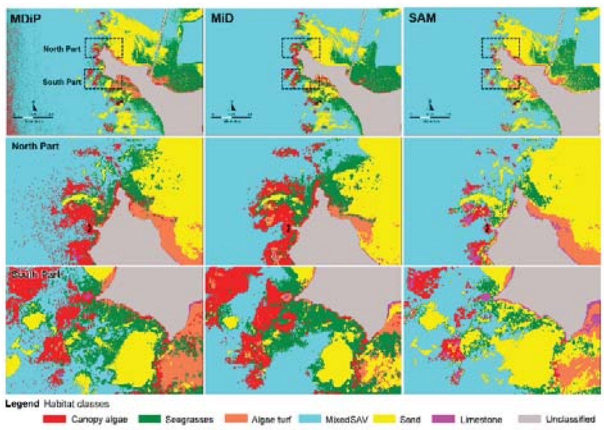

Figure 5. Comparison of classification results of three different classifier methods, MdiP, MiD, and SAM, at Point Peron study sites.

The similarity of reflectance spectra of sea grass species to those of other macroalgae groups is owed to their biological characteristics. A study of sea grass distribution by remote sensing in Bourgneuf Bay (France) for *Zostera marina* and *Z. noltii* species showed reflectance spectra distinct from micro and macroalgae, particularly in the wavelength used NIR band (Barillé *et al.*, 2010). Our results for in-air measurement and reflectance spectra of 22 MSAV species showed that two sea grass species, *Posidonia* sp. and *Amphibolis* sp., had reflectance spectra characterized by green and red macroalgae groups, respectively. As either they can have many different emphytes algae on the leaves' surface or they were on older stages in the life cycle when the leaves' pigments was changing. A similar pattern was found by Yuan and Zhang (2008), who found that the spectral reflectance ratios of submerged aquatic species decreased with the aging MSAV species (Yuan and Zhang, 2008). This can be explained by the aging vegetation, decaying, and appearing of emphytes organisms on their leaves, branches, thallus' surface. Therefore, spectral reflectance not only reflects the host species but is also affected by many other fouling organisms.

CONCLUSIONS

This work demonstrates a case study using high spatial resolution satellite images in evaluating MSAV identification and distribution in shallow coastal waters. The major advantages of increasing the number of spectral bands and spatial resolution are better detection ability and MSAV distribution map with clear water column as WA coastal waters. The results revealed that both MDiP and MiD classification methods showed better evidence for the greater accuracy of MSAV classification results than the SAM classification method. Classification results also showed a full representation of the distribution of MSAV groups in shallow coastal areas.

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