A unique Ruleset for Saltmarsh and Mangrove monitoring using Sentinel-2

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Abstract

Mangrove and saltmarsh vegetation are two important communities in the wetland ecosystem that require continuous monitoring considering their ecological threats and status. Remote Sensing observation is one of the tools to monitor this community. However algorithms are also important for the best sensor to map it accurately. Although there is some research about eCognition-based mapping, a unique rule set is important to monitor this community. Considering this research gap, a unique threshold-based ruleset has been generated in the Random Forest Model environment. A range of vegetation indices, individual bands of Sentinel 2 and Digital Elevation Model (DEM) data were tested in the feature selection method to find the best features for a Random Forest (RF) model. Top three variables were selected and those are (a) reNDVI_A, (b) VIRE_A, and (c) SWIR1 which gave 98.37% accuracy for the test data. A similar trend was found for the other three sites when they were compared with observed data. For site 1, Mangrove was 84.73%, Saltmarsh was 60.19%, and Mixed was 70.12% accurate. A similar trend was found for other three sites with overall accuracy 87.74 % for site-2, 66.23% for site 3, and 72.98% for site 4. A unique ruleset for wetland extent estimation will help to map a wide range of areas with a very minimum level of fieldwork. It will also reduce the cost of mapping done by visual observation, measurement and extensive fieldwork. The results of this work will provide the necessary insight and motivation for ecologists, and environmentalists.

1. Introduction

1.1 Introduction

Mangroves are evergreen woody plants and grow in the inter-tidal region in the tropics and subtropics, with a total global area of about 137,760 km2 (Giri et al. 2011). Saltmarsh is an intertidal plant community dominated by herbs and low shrubs (Adam 1993). Although Saintilan (2009) treated them not as exclusively intertidal, he defined a special characteristic that apart them from mangroves. Mangroves and saltmarsh both play an important role in the coastal biodiversity and maintenance of ecological balance (Rasel et al 2019). However, global mangrove forests declined by 35% from 1980 to 2000 due to conversion to agricultural land, aquaculture ponds, and construction land (Giri 2016). Similarly, saltmarshes have suffered a long history of reclamation for coastal development, being vulnerable to temperature change, sea-level rise and associated geomorphic and vegetation transitions (Saintilan and Rogers 2013). This degradation of saltmarshes wetlands could increase net global atmospheric CO2 inputs by approximately 6% per year(Hopkinson et al. 2012). Hence wetland ecosystems including mangrove and coastal saltmarshes have been targeted for greenhouse gas (GHG) offset programs, carbon trade and habitat restoration (Emmett-Mattox et al. 2010; Mcleod et al. 2011). It is crucial, therefore, to monitor the extent of mangrove and saltmarsh against land use change and wetland ecosystem degradation.

Remote sensing is one of the options to identify vegetation and monitor land cover changes that provides an accurate, efficient, and repetitive method of mapping and evaluating mangroves. Olmsted and Armentano (1997) mentioned the need for monitoring wetland vegetation and its distribution to detect changes in the terrestrial aquatic landscape transition. Wetland classification is challenging due to the fluctuation of water and is further complicated by the need for frequent data collection and high spectral and spatial resolution imagery. Because coarse spatial resolution images captured by satellite missions may produce lower image classification accuracy, especially in wetland areas. It is well acknowledged that due to the narrow spectral gap within the electromagnetic spectrum of hyperspectral data, there is a redundancy of information within a similar spectral channel. Although Sentinel-2 is not a hyperspectral sensor, however, there are three additional red edge bands within a very narrow spectral gap. In addition, two NIR and two SWIR bands are also within the narrow spectral channel. So, it is very important to check the multicollinearity (variables are highly correlated) within the bands. Variable selection is a crucial issue in machine learning (RF) dealing with applied classification and regression problems (Hastie et al. 2001). The RF itself provides three independent variable importance measures, Mean Decrease Accuracy (MDA) measure, the Gini Purity Index, and the number of times each variable is selected (Mansour et al. 2012)

1.2 Aim and prospect of the study.

Based on the above circumstances, our primary objective of this study were to develop a ruleset derived from a new Sentinel 2 MSI that would accurately extract the area of saltmarsh and mangrove. A range of vegetation indices, individual bands of Sentinel 2 and Digital Elevation Model (DEM) data were tested in the feature selection method to find the best features for a Random Forest (RF) model. The selected variables were used in eCognition to set a threshold for each class. Imagery collected from four sites had different dates of acquisition, hence the reflectance value for each class also differed. Thus, a unique ruleset was developed from one study site (study site-1) and applied it to the remaining three sites to determine performance.

A unique ruleset for wetland extent estimation will help to map a wide range of areas with a very minimum level of fieldwork. It will also reduce the cost of mapping done by visual observation, measurement and extensive fieldwork associated with it. The results of this work will provide the necessary insight and motivation for ecologists, wetland groups, environmentalists, and remote sensing groups to shift toward the most affordable and freely accessible satellite imagery necessary for reliable mangrove and saltmarsh area estimation for wetland management.

2. Data and Methodology

2.1 Study site

The four sites are located in Port Stephens, NSW, Australia (Fig. 1), a tidally dominated drowned river within the Port Stephens-Great Lakes Marine Park. Three sites are situated around the main estuaries that feed into Port Stephens (Myall River, Karuah River, Tillegery Creek), with the forth situated around north Arm Cove (Fig. 1). The dominant intertidal wetland species are *Avicennia marina* (Grey mangrove), and numerous small saltmarsh species including *Sporobolus virginicus* (Saltwater couch), *Juncus kraussii*, *Sarcocornia quinqueflora* (Samphire) and *Phragmites australis* (Common reed). Mapping, did not, however, discriminate among species and instead classified only mangrove and saltmarsh habitats.

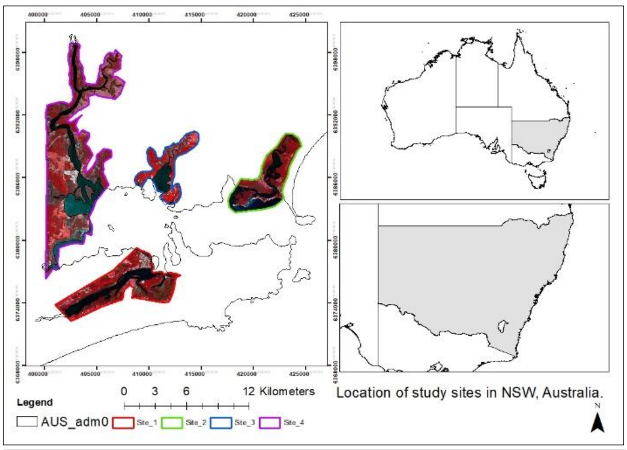


Figure-1: Study site map: Australia country boundary and map of New South Wales (NSW) state (Clockwise). The main view picture shows the locations of four study sites in NSW. An RGB composite of Sentinel-2A for each study location is overlaid to the study sites (site1-4) vector polygon.

2.2 Satellite imagery

High-resolution and cloud-free satellite images from the Sentinel 2 (10 m spatial resolution) from 2015 to 2023 and 30 m spatial resolution Landsat 5, 7 and 8 imagery from 1985 to 2014 were obtained and processed in the Google Earth Engine (GEE) cloud computing environment.
Description of the dataset available in the GEE platform that are used to generate MaxNDVI seasonal irrigation area raster for 35 years' time series.

2.3 Digital Elevation Model (DEM)

Elevation data was downloaded from the ELVIS - Elevation and Depth - Foundation Spatial Data site, http://elevation.fsdf.org.au as 1 m DEM tiles. These tiles were then combined into a mosaic using the "Mosaic to New Raster" tool in ArcGIS 10.6.1.

2.4 List of variables and vegetation indices:

The vegetation indices that are selected for this study are mainly focused on NIR, SWIR and Rededge bands of Sentinel 2 data. Some of the indices have been modified due to the presence of three red edges and two SWIR bands in Sentinel-2 data (Table 2)

Table 2: Description of different variables

Serial No	Variables	Description	References
1 -10	Spectral Bands	10 Bands of Sentinel (10m resolution)	
11	MNDW-1	Modified Normalized Water Index-1 (Green-SWIR1)/(Green +SWIR1)	(Ji et al. 2009)
12	MNDWI -2	Modified Normalized Water Index-2 (Green-SWIR1)/(Green +SWIR2)	
13	NDRE-1	Normalized Difference RedEdge Index-1 (NIR1-Rededge1)/(NIR+Rededge 1)	(Eitel et al. 2011; Ramoelo et al. 2015)
14	NDRE-2	Normalized Difference RedEdge Index-2 (NIR1-Rededge1)/(NIR+Rededge 2)	
15	NDRE-3	Normalized Difference RedEdge Index-3 (NIR1-Rededge1)/(NIR+Rededge 3)	
16	SAVI	Sentinel Improved vegetation Index (NIR2-R)/(NIR+R)	(Ng et al. 2017)
17	RVI	Ratio Vegetation Indices NIR1/R	(Heuman n 2011)
18	VIRE-1	Vegetation Indices Ratio Based on RedEdge-1 10-NIR1/(Rededge1)^2	(Xie et al. 2008)
19	VIRE-2	Vegetation Indices Ratio Based on RedEdge-2 10-NIR1/(Rededge2)^2	
20	VIRE-3	Vegetation Indices Ratio Based on RedEdge-3 10-NIR1/(Rededge3)^3	
21	VIRE-A	10-NIR2/Rededge1	(Xie et al. 2008)
22	VIRE-B	10-NIR2/Rededge2	
23	VIRE-C	10-NIR3/Rededge3	
24	reNDVI-A	(NIR2-Rededge1)/(NIR+Rededge 1)	(Wolf 2012)
25	reNDVI-B	(NIR2-Rededge2)/(NIR+Rededge 2)	

26	reNDVI-C	(NIR2-Rededge3)/(NIR+Rededge 3)	
27	DEM	1 meter resolution DEM	

2.5 Extracting Image Spectra for Model Calibration.

To apply the random forest (RF) supervised classification algorithm, training data for seven types of image spectra were collected from 70% of the pixels in Site 1. These seven classes are Mangrove, Saltmarsh, Mixed, Forest, Water, Grass, and Urban . As our classification method followed a step-by-step elimination strategy to map only the target three classes, we combined some similar non-target classes within a broad general category. For example, water and mudflat were considered in the same class, water. Due to the similar spectral properties, sand and urban structure were grouped in the same class, urban. The remaining 30% of pixels in Site 1 were used to validate the model.
Three wetland vegetation classes identified in the study are Mangrove, Saltmarsh and mixed. Some of the terrestrial plant species (termed as Forest spectra) in the area have similar spectral properties as mangrove species based on age and abundance. However in most of the cases plant species (Forest) spectra have significantly different spectral properties, and it was an issue at level 2 (Table 3) classification when all non-target (including forest and grass) vegetation and other abundance (i.e. water, mudflat and sand/soil) were separated from the target classes (mangrove, saltmarsh and mixed).

2.6 Random Forest model

This study uses the application of the predictive model Random Forest (RF). Although RF models are presented in this study, it should be mentioned that the mapping and feature selection tool presented here applies the predictive models using the R package caret. This allows the flexibility of from several classifier-based algorithms with a range of feature selection method.

2.6.1 Parameter optimization for random forest model

RF works based on two tuning parameters, the number of trees in the ensemble (ntree), and the number of variables randomly sampled at each node to be considered for splitting (mtry) (Peters et al. 2002). In principle one should simultaneously optimize both parameters before applying them for a model development. However, this computation process is intractable. We used the ‘randomForest’ library for RF classification, and Classification and Regression Training (Caret) packages (Kuhn 2008) for feature selection. R statistical software (R development core team 2016) was used to tune the parameters, variable selection and execute the Random Forest Classification method.

2.6.2 Random Forest variable selection

Mean Decrease Accuracy: It gives a rough estimate of the loss in prediction performance when that particular variable is omitted from the training set. If two variables are somewhat redundant, then omitting one of them may not lead to massive gains in prediction performance, but would make the second variable more important. The Mean Decrease Accuracy measure is computed from permuting OOB data: For each tree, the prediction error on the out-of-bag portion of the data is recorded (error rate for classification, MSE for regression). Then the same is done after permuting each predictor variable. The difference between the two is then averaged over all trees, and normalized by the standard deviation of the differences.

Mean Decrease Gini: GINI is a measure of node impurity, i.e. . If this feature is used to split the data, it will tell how pure the nodes will be. Highest purity means that each node contains only elements of a single class. Assessing the decrease in GINI when that feature is omitted leads to an understanding of how important that feature is to split the data correctly. This GINI measure is the total decrease in node impurities from splitting on the variable, averaged over all trees. For classification, the node impurity is measured by the Gini index. For regression, it is measured by the residual sum of squares.

2.7 Threshold for wetland feature extraction

Individual spectral were examined to allow a threshold for each class using the top-ranked features selected in the feature selection process. At level 1, only DEM data (Table 3) were used to separate wetland from the upland area. Besides the top-ranked features, other features were also applied to remove non-target classes at level 2. However, top-ranked features were only applied for the level 3 classification step to develop a unique threshold for salt marsh and mangrove area extent calculation.

Table 3: Three level classification in the eCognition using threshold-based approaches.

<table>
<tr><td>Level 1</td><td>Upland (elevation)</td><td colspan="4">Wetland (separated based on elevation)</td></tr>
<tr><td colspan="2">Level 2</td><td>Wetland Non-target class (remove grass, mudflat , water and other forest within wetland)</td><td colspan="3">Wetland Target Class (Class-1:Mangrove Class-2:Saltmarsh Class-3: Mixed</td></tr>
<tr><td colspan="3">Level 3</td><td>Mangrove</td><td>Saltmarsh</td><td>Mixed</td></tr>
</table>

2.8 Model validation and accuracy assessment

Object-based accuracy: The Intersect tool of ArcGIS calculates the geometric intersection of any number of feature classes and feature layers. The features, or portion of features, that are common to all inputs (that is, they intersect) will be written to the output feature class. Polygon inputs and polygon output approach of intersecting was used in ArcGIS 10.5 to assess object based accuracy. Threshold-based classification object derived from eCognition and microphytes dataset (polygon shape file) were used as inputs for every three classes (level 3). The output intersected layer was considered as the correct area for each class. In this way, individual objects were intersected with the microphytes data to calculate the model performance (under/over estimation), subsequently area was calculated for each class to randomly distributed within a threshold based output map to generate a thematic confusion matrix to calculate the model performance (under and over estimation) subsequently area was calculated for each class to compare the results.

Confusion matrix from the test sample: 30 % test data randomly distributed within a threshold based output map to generate a thematic confusion matrix to calculate the overall accuracy of the classified map

3. Results and Discussion

3.1 Identification of Image Spectra for Wetland Mapping

Spectral profiles for Tilligery Creek (Site-1) showed that buildings, water and grass had highly distinctive spectral features compared to the other habitats (Figire 2). The Mangroves were clearly distinguishable species using spectra within the range of Rededge 2 to SWIR 2. The spectral profile of Saltmarsh’s is confusing with the mixed’s profile, however, they are still clearly separable with the spectrum of SWIR (Figure 2). Mangroves were only distinguishable when using bands 5-9

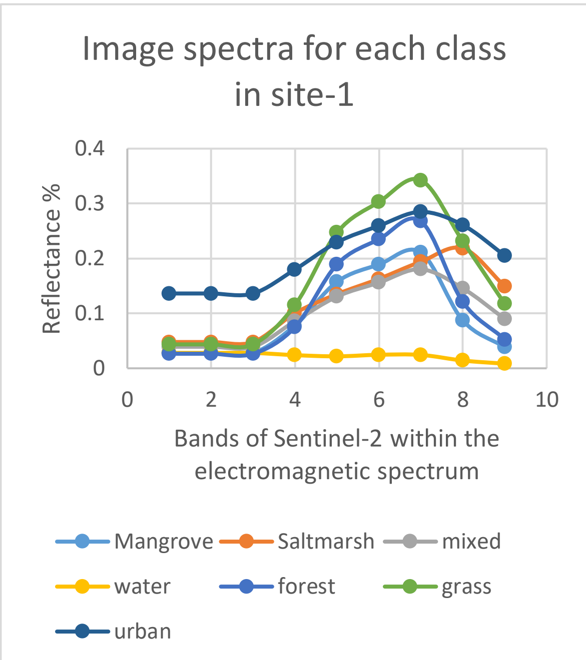


Figure 2. The spectral profile of different classes derived from the calibration sample points of site-1 (Tilligerry creek).

3.2 Optimum parameter of the random forest (RF) algorithm for wetland mapping

Instead of default (1/3 of the total number of variables), mtry, lowest Out-Of-Bag (OOB) error rate was used to determine the best value of mtry (Figure 3). In the OOB method, some of the training data are excluded for each classification tree generation, and the errors for these data can be used to inform the RF of the relative strength (Dube and Mutanga 2015).

From figure 3, it is clear that mtry and ntree has a very minimal effect on the results of accuracy. We can see that the most accurate value for ntree was 1500 and mtry was 13 with accuracy 0.988. Based on the cross-validation result, mtry value =13 and ntree = 1500 were used in the variable selection model assessment.

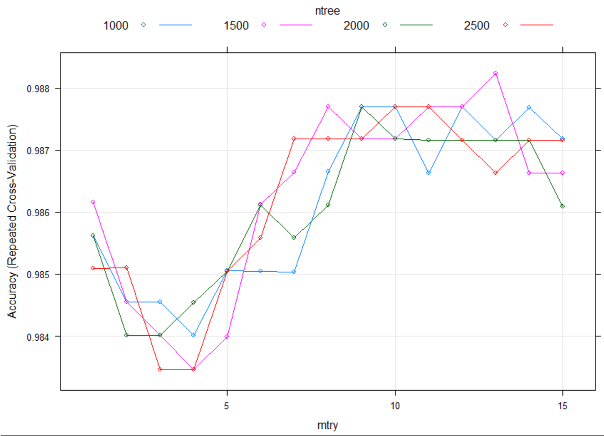


Figure 3. Optimization of random forest parameters (mtry and ntree) using training data.

3.3 Variable Selection in Random Forest

Random Forest feature importance method was able to identify the smallest number of explanatory variables that would offer the best predictive ability of the random forest (Figure 4). Here top three variables were selected and those are (a) reNDVI_A, (b) VIRE_A, and (c) SWIR1.

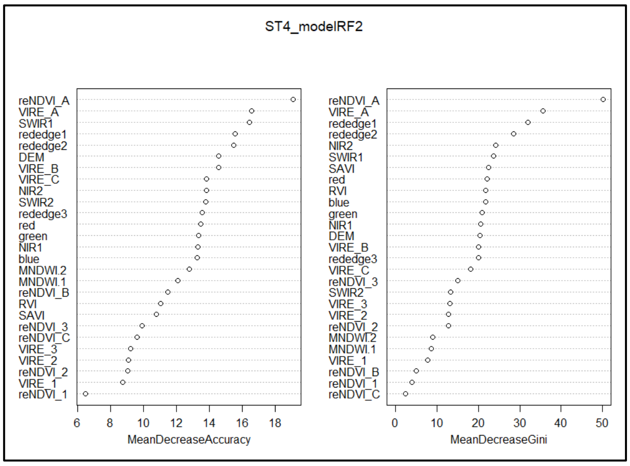


Figure 4: Shows the number of top-ranked variables to classify wetland area.

Out of Bag (OOB) error rate increased from 1.28 % to 1.61% when all 27 variables were added to the model (Table 4 a and b)

Table 4a: Confusion matrix derived from 27 variables from site 1 calibration data set. (Key: Mangrv= Mangrove, Salt=Saltmarsh).

	Man grv	Sa lt	M ix	Wa ter	For est	Gr ass	Urb an	Accur acy
Man grv	68	0	0	0	0	0	0	100%
Salt	0	55	2	0	0	0	0	96.00
Mix	1	5	36	0	0	0	0	85.71
Wat er	0	0	0	107	0	0	0	100
Fore st	0	0	0	0	198	0	0	100

Grass	0	0	0	0	0	65	0	100
Urban	0	0	0	0	0	0	86	100
Total	69	60	38	107	198	65	86	623 (98.72%)

Table 4b: Confusion matrix derived from *reNDVI_A, VIRE_A, and SWIR1*s from Site 1 calibration data set. (Key: Mangrv= Mangrove, Salt=Saltmarsh).

	Mangrv	Salt	Mix	Water	Forest	Grass	Urban	Accuracy
Mangrv	67	0	0	1	0	0	0	98.52
Salt	0	55	2	0	0	0	0	96.00%
Mix	1	5	36	0	0	0	0	85.71%
Water	0	0	0	107	0	0	0	100%
Forest	0	0	0	0	198	0	0	100%
Grass	0	0	0	0	0	65	0	100%
Urban	0	0	0	0	0	0	86	100%
Total	68	60	38	107	198	65	86	623(98.39%)

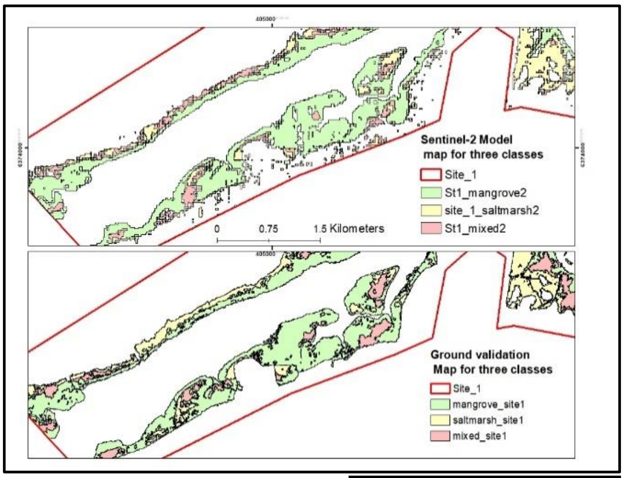
3.4 Threshold-based classification for wetland feature extraction:

The three top-ranked variables were applied at level 3 classification to extract mangrove, saltmarsh and mixed classes. From the threshold value, it is clear that there is a sharp boundary between two classes to automate the process in eCognition. For example, SWIR1 value is similar between saltmarshes and mixed classes but there is a clear boundary for reNDVI value. Similarly, VIRE_A feature value for saltmarsh and mangrove are similar but SWIR1 and reNDVI value make a clear boundary between these two classes. This value resulted from a long trial and error method and worked for site -2 imagery as well. Because both study sites covered by the same Sentinel-2 imagery and there is a similarity of reflectance value for each class. For study site-3 and 4 were covered by different date of Sentinel-2 image and have different reflectance value. That's why for study site 3 and 4 there was a slight modification within the value of these three features. For more details, readers are requested to look at the supplementary data provided online for site-3 and 4.

Table 5: Threshold for wetland classification

Mangrove	Saltmarsh	Mixed
ReNDVI_A $\geq$ 0.32 to $\leq$ 0.50	**ReNDVI_A $\geq$ 0.17 to < 0.31**	**ReNDVI_A$\geq$ 0.32 to $\leq$ 0.41**
VIRE_A $\geq$ 1400 $\leq$ 2500	VIRE_A$\geq$ 500 $\leq$ 1700	VIRE_A $\geq$ 1000 $\leq$ 1900
SWIR1 $\leq$ 0.12	SWIR1 $\geq$ 0.15 $\leq$ 0.25	**SWIR1 > 0.12 $\leq$ 0.21**

3.5 Performance of Sentinel-2 derived variables for wetland extent map for site -1



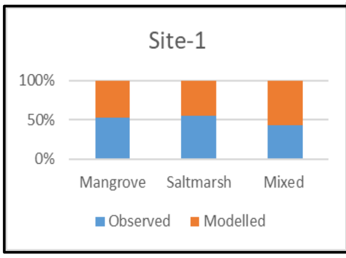


Figure 5: Comparison of (a Figure 5: Comparison of (a) Sentinel-2 and (b) manual visual interpretation based on field survey using near map imagery for

Figure 5 Comparison of Sentienl-2 wetland mapping to the manually drawn, field-validate map for Site 1

The wetland extent maps of the study site-1 derived from the three Sentinel variables depicted the extent of habitats well compared to the field-vaildated manual-produced map (Figure 5(a, b)). The wetland extent map produced by means of field survey and manual visual interpretation in 7.5 cm pan-sharpened near map imagery is presented in Figure 5(b), which is used as a reference map. However, there were some clear discrepancies, with the Using visual overview, Sentinel-2 including dispersed scattered misclassified mangrove patches

A sub-section of Site 1 is shown in Figure 6 to depict highlight the misclassification issue. In both maps, mangrove is well defined as the mangrove area is homogenous. But some pixels are bare (Red rectangle in figure 6a) in Sentinel-2 map as there no mangrove more than 50% within 10m pixel. But it was not an issue for near map visual map as it delineated small patches using high spatial resolution (6c). In addition, a mixed class of visual map (the black circle in 6c) was divided into saltmarsh and mixed two categories (the black circle in 6a) in Sentinel-2 map. It was clear that high-resolution manual delineated map could better render the creeks within the mangrove forest (Blue triangle, 6c), but it overestimated by Sentinel-2 data (Blue triangle, 6a).

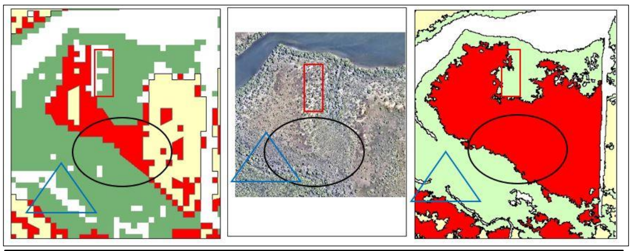


Figure 6: Shows how Sentinel-2 mapping accuracy deviated from the observed microphytes map data for site-1 where (a) Sentinel-2 model map (b) nearmap imagery for that site and (c) High resolution manually delineated map.

3.6 Comparison of modelled and observed area for three wetland features

3.6.1 Accuracy assessment for site 1

Objet based accuracy: When individual objects were intersected with the reference map, only 392.12 ha mangrove area were overlayed with the reference map. And this area for saltmarsh and mixed were 138.29 ha and 87.46 ha for mixed class (Table 6).

Table 6: Observed and modelled areain Site-1

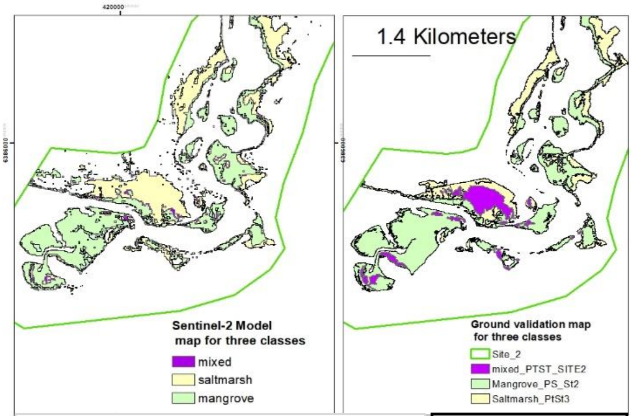
Site-1	Observed (ha)	Modelled (ha)	Accurate (ha)
Mangrove	462.740083	419.045006	392.12 (84.73%)
Saltmarsh	229.737205	185.505018	138.29 (60.19%)
Mixed	124.720018	163.220034	87.46 (70.12%)
Total	817.19	767.765	617.87 (75.60%)
When individual object was tested for each respective classes	Difference	=817.19 - 617.87 =199.32 ha	= 651.82/817.19*100 = **75.60 %**

Confusion matrix from the test data: Within 129 randomly generated mangrove points, 123 points were accurately overlayed to the reference map. And for saltmarsh and mixed category this percentage was 87.03% and 88.00% respectively (Table 7). Compare to the polygon intersection method, this thematic matrix method provided higher accuracy for each class.

Table 7 : Confusion matrix

Class name	Sample no	Mangrove	Saltmarsh	Mixed	Accuracy (%)
Mangrove	129	**126**	0	3	97.67
Saltmarsh	108	2	**94**	12	87.03
Mixed	50	1	4	**44**	88
Total	287	129	98	59	91.98 Overall accuracy

3.7 Wetland extent map for site-2 (Myall River estuary)



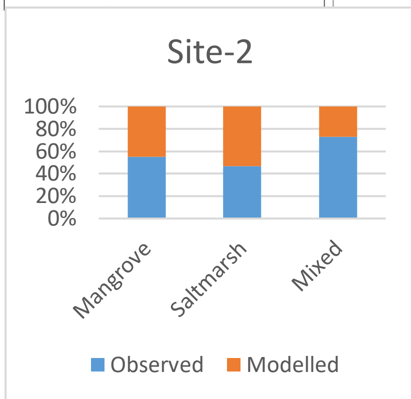


Figure 7: Comparison of (a) Sentinel-2 and (b) manual visual interpretation based on field survey using near map imagery for mangrove and saltmarsh classification.

The wetland extent maps of the study site-2 produced from Sentinel-2 is shown in Figure 7(a) and manual visual interpretation map came from near map imagery is presented in Figure 7(b). Like as site-1, Sentinel-2 data extracted the mangrove extent very well (7c). Within Myall River Estuary, the Sentinel-2, and manual classifications precisely extracted the mangrove areas, with an area of 269.45 ha, and 331.06 ha, respectively. The saltmarsh area produced by the visual interpretation is 206.17 ha and 237.58 ha is by Sentinel-2 (Figure 7c). This over estimation (7c) of saltmarsh from Sentinel-2 is very clear at the centre part of the map that is zoomed in figure 7.

Major discrepancy raised from the definition of the mixed class followed by area calculation under this category. A large portion of mixed class category has been identified as saltmarsh and zoomed in figure 8.

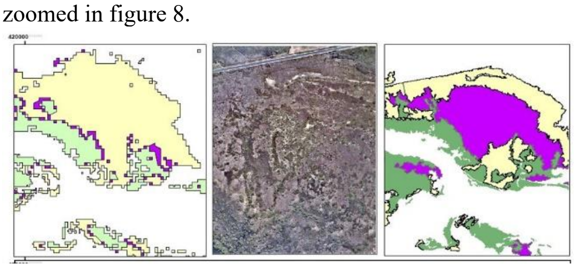


Figure 8: Shows how Sentinel-2 mapping accuracy deviated from the observed microphytes map data for site-2 where (a) Sentinel-

2 model map (b) near map imagery for that site and (c) High resolution manually delineated map.

3.8 Wetland extent map for site-3 (Bundabah Creek):

Within the four sites, Bundabah creek is the smallest and very uneven sites in terms of scattered distribution of mangrove and saltmarsh. There are very few areas of homogenous mangrove that are along the creek. Due to the effect of water in 10 m pixel, extraction of homogenous mangrove pixels was severely impacted and very clear from figure 9 . Considering the creek and narrow water channel, high-resolution manual delineated map better rendered the creeks within the mangrove forest but this mangrove area was not well depicted in Sentinel-2 data due to impure pixels in terms on water. Delineation of saltmarsh and mixed was still an issue for study site three. According to the manually delineated map, mangrove, saltmarsh and mixed areas are with an area of 80.06 ha, 63.17 ha and 88.14 ha, respectively. The mangrove, saltmarsh and mixed area produced by the Sentinel-2 map are 80.62 ha, 60.59 and 78.55 ha respectively. Although from figure 9c it looks like almost 50:50 ratio, accuracy was severely affected due to the above reasons and will be discussed in the accuracy assessment section.

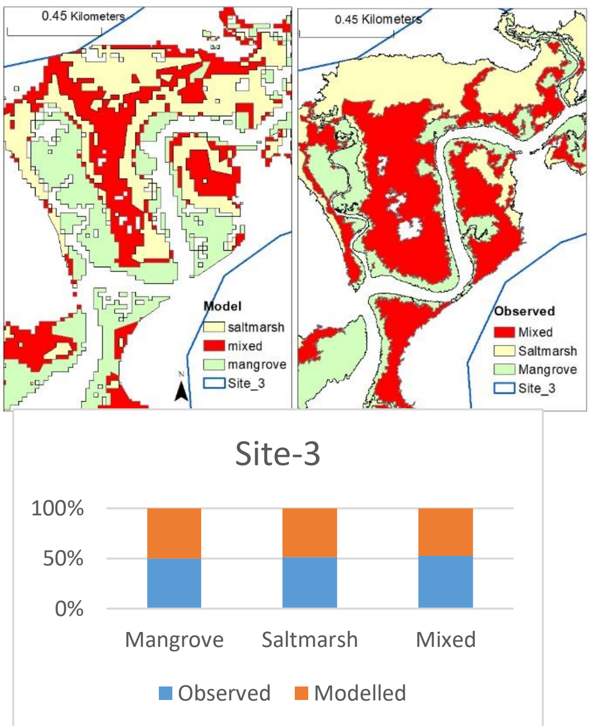


Figure 9: Comparison of (a) Sentinel-3 and (b) manual visual interpretation based on field survey using near map imagery for mangrove and saltmarsh classification.

3.9 Wetland extent map for site-4 (Correebah Island and Swan Island):

This is the largest site among the four and has total 1820.23 ha area of wetland along the Karuah River. According to the manually delineated map, mangrove, saltmarsh and mixed areas are with an area of 868.84 ha, 425.83 ha and 525.55 ha, respectively. The mangrove, saltmarsh and mixed area produced by the Sentinel-2 map are 620.02 ha, 258.99 ha and 679.97 ha respectively. Using visual overview, Sentinel-2 data extracted the mangrove extent less (10) compare to the visual map, a similar trend was for saltmarsh. But it was reverse for mixed were mixed was overestimated (15-20% more). One of the important features of this site is it has a major part covered by mudflat or muddy area within mangrove. This is the most important reason that effects on mangrove area estimation. In the manual delineation map this muddy area was included within a habitat either mangrove or mixed. But in Sentinel-2 this area has been removed at layer 2 mapping stage in eCognition when all non-target area has been excluded from the target features.

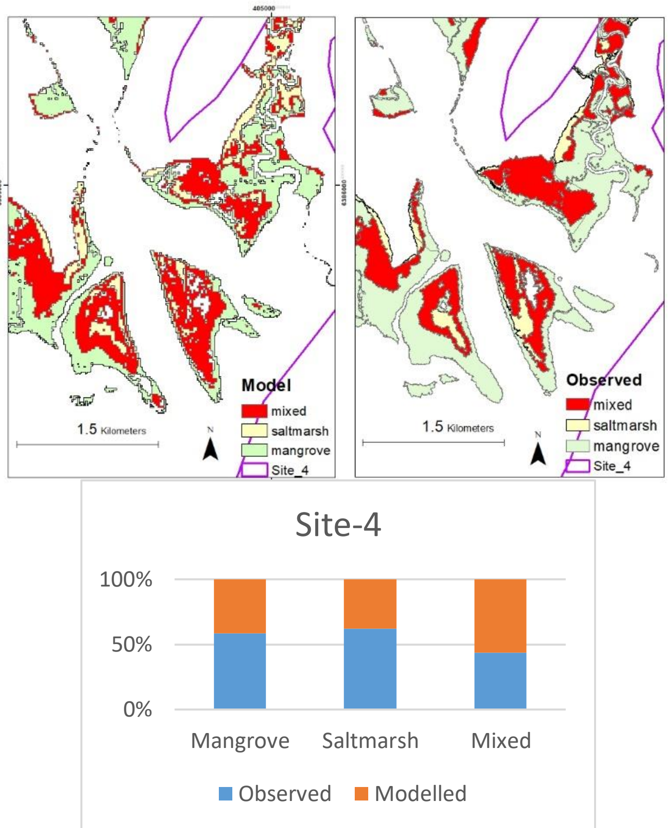


Figure 10: Comparison of (a) Sentinel-2 and (b) manual visual interpretation based on field survey using near map imagery for mangrove and saltmarsh classification.

3.10 Performance of threshold based technique for wetland extent mapping

Developing an efficient framework for mapping mangroves is tricky due to their growth behavior and requires a deep understanding of the spectral, physical, and spatial distribution characteristic of the mangroves and surrounding wetland covers (Valderrama-Landeros et al. 2017; Wang et al. 2004). There is no universal framework for different imagery and sites for a specific vegetation map. In the study, we used a unique threshold-based approach for mangrove extent and it is reproducible. In general, a framework developed for a specific sensor cannot directly transferred to other sites because of different ecological characteristics of mangrove system, climate and solar altitude angle (Wang et al. 2018). However, in this study the unique ruleset was replicated to the other three sites with a very minor changes that asserts the ability of this framework for a state-wide mangrove mapping scheme.

The only uncertainties introduced in the accuracy comparison were attributed.

(1) No clear definition of mixed, saltmarsh and mangrove classes during the mapping process from near map data with ground truth validation where we applied a clear definition to separate each class from others.
(2) Bare land/ mudflat was not removed in the reference map when it was developed in 2014/2015 (ongoing process). Masking of this bare and mudflat area from the model map effects on area estimation.

4. Conclusion and recommendation

A rule-based algorithm has been presented to map wetland and monitor mangrove and saltmarsh extent using open source satellite platform. Our analysis has shown that, a rule-based thresholding and variable selection method improve the accuracy of wetland mapping. Subsequently, we discuss how data provided by satellite remote sensing could be most effectively leveraged to support mangrove and saltmarsh monitoring. Although it was tested sperate three sites as a pat of validation, application of this rule for other sites can confirm the reliability and robustness of the rule-based model.

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