University of Wollongong

Research Online

Faculty of Science, Medicine and Health -
Papers: part A

Faculty of Science, Medicine and Health

1-1-2016

Identifying spatial variability and complexity in wetland vegetation using an object-based approach

Christopher Owers

University of Wollongong, cjo766@uowmail.edu.au

Kerrylee Rogers

University of Wollongong, kerrylee@uow.edu.au

Colin D. Woodroffe

University of Wollongong, colin@uow.edu.au

Follow this and additional works at: <https://ro.uow.edu.au/smhpapers>

Part of the [Medicine and Health Sciences Commons](#), and the [Social and Behavioral Sciences Commons](#)

Recommended Citation

Owers, Christopher; Rogers, Kerrylee; and Woodroffe, Colin D., "Identifying spatial variability and complexity in wetland vegetation using an object-based approach" (2016). *Faculty of Science, Medicine and Health - Papers: part A*. 4229.

<https://ro.uow.edu.au/smhpapers/4229>

Research Online is the open access institutional repository for the University of Wollongong. For further information contact the UOW Library: research-pubs@uow.edu.au

---

Identifying spatial variability and complexity in wetland vegetation using an object-based approach

Abstract

Coastal wetland vegetation is complex in form and function. Accurately mapping the spatial variation of vegetation complexity within these ecosystems is important for identifying areas of high conservation value that provide essential ecosystem services. In this study we delineate wetland vegetation, particularly mangrove and saltmarsh, to a vegetative morphological level that identifies spatial complexity in vegetation structure. This was achieved by integrating light detection and ranging (Lidar) and aerial imagery with an object-based approach. The results demonstrate that this is an effective methodology to identify vegetation complexity, with all study sites having greater than 90% classification accuracy. These high classification accuracies were underpinned by the use of Lidar data that provide detailed structural information about vegetation that is not captured with aerial imagery. This research highlights the importance of identifying spatial variability in vegetation structure when considering the value of coastal ecosystems and the services they provide.

Disciplines

Medicine and Health Sciences | Social and Behavioral Sciences

Publication Details

Owers, C. J., Rogers, K. & Woodroffe, C. D. (2016). Identifying spatial variability and complexity in wetland vegetation using an object-based approach. *International Journal of Remote Sensing*, 37 (18), 4296-4316.

**Identifying spatial variability and complexity in wetland vegetation
using an object-based approach**

Christopher J. Owers ^{a*}, Kerrylee Rogers ^a and Colin D. Woodroffe ^a

*^a GeoQuEST Research Centre, School of Earth and Environmental Sciences, University
of Wollongong, Wollongong, Australia*

e-mail for the corresponding author: cjo766@uowmail.edu.au

co-author emails: kerrylee@uow.edu.au, colin@uow.edu.au

This work was supported by the Australian Research Council under grant FT130100532

Identifying spatial variability and complexity in wetland vegetation using an object-based approach

Coastal wetland vegetation is complex in form and function. Accurately mapping the spatial variation of vegetation complexity within these ecosystems is important for identifying areas of high conservation value that provide essential ecosystem services. In this study we delineate wetland vegetation, particularly mangrove and saltmarsh, to a vegetative morphological level that identifies spatial complexity in vegetation structure. This was achieved by integrating Light detection and ranging (Lidar) and aerial imagery with an object-based approach. The results demonstrate that this is an effective methodology to identify vegetation complexity, with all study sites having greater than 90% classification accuracy. These high classification accuracies were underpinned by the use of Lidar data that provides detailed structural information about vegetation that is not captured with aerial imagery. This research highlights the importance of identifying spatial variability in vegetation structure when considering the value of coastal ecosystems and the services they provide.

Keywords: coastal wetlands; mangrove; saltmarsh; object-based; vegetation structure; ecosystem services; Lidar

1. Introduction

Coastal ecosystems, particularly mangrove and saltmarsh, provide a range of ecosystem services including coastal protection for infrastructure, water purification, erosion control, and maintenance for commercial fisheries resources (Barbier et al. 2011). Ecosystem services are receiving considerable attention as they justify the value of ecosystems and their continuing need for conservation and restoration (Boyd and Banzhaf 2007). Ecosystems are underpinned by components, which are the abiotic and biotic characteristics associated with ecosystem structure; and processes which are the result of complex interactions between these components (de Groot, Wilson, and Boumans 2002; Boyd and Banzhaf 2007; Barbier et al. 2011; Hermann, Schleifer, and Wrbka 2011). Together components and processes perform functions, for example

1
2
3
4
5
6
7
8
9
10
11
12
13
14
15
16
17
18
19
20
21
22
23
24
25
26
27
28
29
30
31
32
33
34
35
36
37
38
39
40
41
42
43
44
45
46
47
48
49
50
51
52
53
54
55
56
57
58
59
60

carbon sequestration, that contribute to important ecosystem services such as climate change mitigation (Figure 1).

Ecosystem services provided by coastal ecosystems are spatially and temporally variable (Ewel, Twilley, and Ong 1998; Barbier et al. 2011). Remote sensing is commonly used to analyse this variability; however, this has largely focused on mapping the distribution of vegetation communities through time, and rarely to species or genera level (Adam, Mutanga, and Rugege 2009). Previous mapping of vegetation communities using remote sensing focuses on the components of an ecosystem. This results in having only tenuous links to the ecosystem services they provide due to the lack of information about the processes contributing to ecosystem function. More information about the function of ecosystems, and the interaction of ecosystem components and processes, is required to determine the spatial distribution of ecosystem services and to enable more accurate assessment of the value of coastal ecosystems.

Evaluating ecosystem processes using remote sensing is challenging; however, ecosystem components can be used as a proxy to infer processes that cannot be easily measured, as some processes correlate with aspects of components. The level of detail in which ecosystem components are mapped limit their use as a proxy for processes. Delineating ecosystem components at a vegetative morphological level that identifies vegetation structure within vegetation communities provides additional information that relates to ecosystem processes (Figure 1). For example mangrove communities have higher soil carbon sequestration rates compared to saltmarsh communities (Chmura et al. 2003; Livesley and Andrusiak 2012). Although the spatial variation of some processes can be differentiated on the basis of mapping vegetation communities, others require detailed mapping of the vegetative morphology within communities or genera. For example mangrove communities have different vegetation heights and densities

1
2
3 which define the ecosystem functions, such as habitat suitability for water birds (Noske
4
5 1995, 1996). Capturing this level of vegetative morphological detail will enable a more
6
7 informed understanding of the variability in ecosystem functions and ultimately the
8
9 value of ecosystem services in coastal wetlands.
10

11
12 [insert Figure 1 here]
13
14
15

16
17 The aim of this study is to delineate wetland vegetation, particularly mangrove
18
19 and saltmarsh, at a vegetative morphological level that identifies spatial complexity in
20
21 vegetation structure. This will provide further information on the spatial and temporal
22
23 variability of ecosystem components and correlations to ecosystem processes. Detailed
24
25 delineation of vegetation structure has been limited in previous research due to spatial
26
27 complexity of wetland vegetation and the inability of traditional remote sensing data
28
29 and approaches to identify important structural features. A common methodology for
30
31 producing fine scale wetland vegetation mapping is using aerial imagery to manually
32
33 delineate vegetation communities in a geographic information system (GIS) with expert
34
35 knowledge (CSIRO 1994; Chafer 1998; Saintilan and Wilton 2001; Oliver et al. 2012).
36
37 Other approaches include using satellite imagery with automated classification
38
39 methodologies such as spectral unmixing, decision tree classifiers, and support machine
40
41 vectors (see reviews by Ozesmi and Bauer 2002; Kuenzer et al. 2011). These traditional
42
43 methodologies have been unable to identifying structural features to a higher degree of
44
45 detail or accuracy (see reviews by Adam, Mutanga and Rugege 2009). This study
46
47 overcomes these limitations by combining aerial imagery with Lidar point cloud data.
48
49 Lidar data enables detailed structural information about vegetation to be obtained that is
50
51 not possible with imagery (see review by Heumann 2011). Previous research has
52
53 demonstrated higher classification accuracies when utilising Lidar data coupled with
54
55
56
57
58
59
60

multispectral imagery to aid classification of spectrally similar species that have different structural morphologies (Chust et al. 2008; Ke, Quackenbush and Im. 2010).

Furthermore an object-based image analysis (OBIA) approach is utilised in this study. The OBIA methodology achieves high classification accuracies of remotely-sensed data as it incorporates both spectral and spatial properties of the data (Vo et al. 2013). Comparative studies of OBIA and traditional pixel-based image analysis (PBIA) demonstrate the advantages of the OBIA methodology as well as higher accuracies in classification (Kamal and Phinn 2011; Ouyang et al. 2011; Dronova et al. 2012). Detailed structural characteristics have been investigated and proven useful for identifying ecological complexity, such as mangrove forest morphology and stand density (Kim et al. 2011; Rokitnicki-Wojcik, Wei, and Chow-Fraser 2011; Vo et al. 2013), saltmarsh genera (Ouyang et al. 2011), and vegetation health after storm events (Liu et al. 2014). Research by Dronova et al. (2012) was the first to use OBIA classification to delineate C3 and C4 metabolic pathways in vegetation using structural characteristics that correlated with these processes. In Australia, research by Kamal and Phinn (2011) used hyperspectral imagery to classify wetland vegetation at a community level, inclusive of mangrove and saltmarsh communities. More recent research delineated mangrove forest type, including open scrub, low-close forest and high close forest (Kamal et al. 2014) with a high degree of accuracy. Previous research demonstrates the utility of OBIA in delineating structural variation in wetland vegetation, however the link to ecosystem services has not been considered in sufficient detail.

This research provides a rapid assessment methodology for identifying spatial complexity in wetland vegetation structure. It also provides a platform to examine the spatial variability of ecosystem processes associated with vegetation composition and

structure, such as carbon sequestration potential and current carbon store. This will facilitate a more informed understanding of the variability in ecosystem functions and ultimately the value of ecosystem services in coastal wetlands.

2. Methods

2.1 Study Area

The south-east coast of New South Wales, Australia is a wave-dominated coastline. Saline coastal wetlands are restricted to estuaries and embayments along the coast where low energy hydrodynamic conditions occur (Roy et al. 2001). The temperate climate of south-eastern New South Wales supports mangrove and saltmarsh communities which occur along intertidal shorelines. Mangroves are typically positioned lower within the tidal frame and saltmarsh is typically positioned higher in the tidal frame. Two species of mangrove are present in this region; predominantly *Avicennia marina* and also *Aegiceras corniculatum*. Commonly present saltmarsh species include *Sporobolus virginicus*, *Samolus repens*, *Juncus kraussii* and *Sarcocornia quinqueflora* (Clarke 1993). To assess the replicability of the approach in this study, three sites with similar geomorphic setting and tidal range (approximately 2 m) within the study region were selected; Minnamurra River, Cararra Inlet and Currambene Creek (Figure 2). However they differ in environmental influences, such as catchment size, substrate type, and hydrodynamics.

[insert Figure 2 here]

2.2 Remote Sensing Data

The remote sensing data used in this study included readily available aerial imagery and

Lidar data provided by the Land and Property Information, NSW. The aerial imagery consisted of red, green and blue (RGB) spectral bands and was captured in 2009 using an ADS40 instrument mounted on a light aircraft. Data were obtained as an ortho-rectified GeoTIFF with a spatial resolution of 0.5 m. The Lidar data was obtained as a C3 classified LAS file point cloud with a footprint size of 0.62 m². The Lidar data were captured in 2010-2011 using an ALS50-II laser scanner mounted on a light aircraft. Upon receipt, both data types did not require further pre-processing or correcting. Table 1 summarises the technical specifications of the remote sensing data used in the study.

[insert Table 1 here]

2.3 Field Data

Preliminary reconnaissance at each site identified suitable vegetation structural classifications. Vegetation morphology was characterised as one of eleven dominant structural vegetation forms (Table 2, Figure 3). Mangroves were classified as tall mangrove, shrub mangrove, or dwarf mangrove. Tall mangroves were typically larger than 3 m in height with a diameter at breast height (DBH) greater than 15 cm. Shrub mangroves were defined as a height range between 3 m and 1.3 m with a DBH less than 15 cm. Dwarf mangroves were less than 1.3 m in height and therefore DBH was not measured. The distribution and function of mangrove structural classes were similar to those described by Lugo and Snedaker (1974) and further by Woodroffe (1992). Tall mangroves had characteristics of fringe and river forests, shrub mangroves had similar characteristics to basin forests, and dwarf mangroves similar to dwarf forests, or scrub forests (Twilley et al. 1998). The two species of mangrove, *A. marina* and *A. corniculatum*, were not separated when defining mangrove morphology due to similar growth in each structural form. Saltmarsh communities were classified as reed, rush,

1
2
3 *Tecticornia*, or herbs, grasses and sedges. Ecotone communities of mangrove and
4
5 saltmarsh species were classified as mixed. Sparse vegetation areas were defined as
6
7 areas with sparse vegetation growth, often ecotone communities, which had a sandy
8
9 surface substrate. Inundated areas were defined as permanent or semi-permanent areas
10
11 of water that were unvegetated. Mapped *Casuarina glauca* woodlands were classified
12
13 as *Casuarina*.
14
15

16 Each study site was ground-truthed to obtain data to train and validate the
17
18 vegetative classification. All sites were ground-truthed between December 2014 and
19
20 January 2015. Although there was a considerable time difference between remote
21
22 sensing data capture and ground-truthing this was deemed largely insignificant as
23
24 previous vegetation mapping at the study sites by Oliver et al. (2012) at Minnamurra
25
26 River and Saintilan and Wilton (2001) at Currumbene Creek and Carama Inlet was
27
28 consistent with preliminary reconnaissance. However problems may arise due to
29
30 spectral characteristics of vegetation, particularly saltmarsh, due to seasonal changes
31
32 and variable hydrological conditions. This may affect the spectral dissemination of the
33
34 aerial imagery for species that may appear similar at certain times of the year. The
35
36 location of the ground-truthed point was recorded with a Trimble real-time kinematic
37
38 GPS (error, horizontal: 8 mm vertical: 15 mm). Photos were also taken at each ground-
39
40 truthed location. As the ground-truthed data was used to train and validate the
41
42 classification, a substantial coverage of ground-truthed points was required for each
43
44 site; 134 ground-truthed points were collected for Minnamurra River, 186 for Carama
45
46 Inlet, and 148 for Currumbene Creek. Figure 4 illustrates the extent of ground-truthed
47
48 points collected for Minnamurra River.
49
50
51
52
53

54
55 [insert Table 2 here]
56

57
58 [insert Figure 3 here]
59
60

2.4 Image Analysis

All image segmentation in this study utilised the multiresolution segmentation algorithm (MRSA) in the eCognition Developer 8.7 image analysis software. The MSRA was used as it is a simple and often more effective segmentation algorithm compared to other approaches (Dronova et al. 2012). Several user inputs were required to define the parameters of the algorithm. These include scale parameter, which is the threshold for image object growth, shape, a ratio defining the influence of spectral and shape homogeneity, and compactness, a ratio for optimising object compactness and smoothness (Ke, Quackenbush, and Im 2010). Moffett and Gorelick (2013) demonstrate that the scale parameter is the most important variable to optimise for segmentation, and therefore shape and compactness values remained the default setting throughout this study (shape: 0.1, compactness: 0.5). The estimation of scale parameter (ESP) tool was used in eCognition to quantitatively approximate appropriate scale parameter thresholds for each image segmentation (Drăguț, Tiede and Levick 2010). The algorithm also required input of remote sensing data layers, such as aerial imagery, from which the image objects were created. All data layers in this study had the same weighting when used in segmentation. An example of the MRSA for Minnamurra River is given in Figure 4.

[insert Figure 4 here]

This study uses a hierarchical approach (Figure 5). For initial segmentations across all study sites, the inputs were the three spectral bands of the aerial imagery and the entire Lidar point cloud. The initial segmentation was to enable the user to manually

1
2
3 select out the wetland area of interest from the surrounding environments that were not
4 to be classified. For the proceeding segmentations and classifications in the hierarchical
5 approach, layer metrics were derived from the aerial imagery and Lidar point cloud. A
6 hydrological model; a spatial layer representing distance to water across each study site,
7 was also developed to identify inundation dynamics of vegetation. A total 45 layers,
8 including the original datasets and derived datasets, were available for segmentation and
9 classification. All layers are given in Table 3.

10
11
12 [insert Figure 5 here]

13
14
15 [insert Table 3 here]

16
17
18
19
20
21
22
23
24
25
26 The second stage of segmentation and classification, hereafter known as the
27 community level classification, delineated the wetland area of interest to mangrove,
28 saltmarsh, *Casuarina*, mixed, sparse vegetation, or inundated (Figure 5). This approach
29 differed from the initial segmentation and classification of the wetland area of interest.
30 Table 4 gives detailed information about the parameters and layers used for each
31 segmentation at each study site. The segments were classified using the standard nearest
32 neighbour supervised classification algorithm. Sample image objects for each class were
33 required to train the algorithm. The ground-truthed data was randomly divided into
34 training and validation data with less than 30% in total used as training data. The feature
35 optimisation tool in eCognition Developer 8.7 was utilised to input all available data
36 layers and compute the optimal number and combination of layers required for
37 differentiating the user-defined classes. After all image objects were classified,
38 incorrectly classified segments were manually edited with reference to the ground-
39 truthed data using expert image interpretation. This was necessary to ensure that the
40 scene was near 100% correct for the following structural classification.

The final stage of segmentation and classification was completed for mangrove and saltmarsh independently. The community level image objects were further segmented and classified to delineate the structural vegetation classes. Some sites did not contain all structural forms and where this occurred the absent class was excluded. The classifications were finalised by executing a rule process that altered a segment if it was different from all surrounding segments that were classified as the same class. This was important to ensure that the final maps demonstrated the major spatial distribution of structural classes.

[insert Table 4 here]

Validation of the final classification for each study site was completed using ground-truthed data. Ground-truthed data that was included to train the classification were excluded from the validation data. Pairwise error matrices were used to identify misclassification between classes and estimate user’s accuracy, producer’s accuracy and overall accuracy (see supplementary material). The kappa coefficient (κ) of agreement was calculated for each classification to demonstrate agreement between the data (a unitless value ranging from 1 for perfect agreement, to -1 for complete disagreement) (Congalton 1991).

3. Results

The classification maps for each study area demonstrate the spatial variability in vegetation component morphology that can be identified using this methodology (Figures 6–8). All classifications had an accuracy greater than 90% with κ coefficients indicating good agreement between the classification and ground-truthed data (Table 5). Minnamurra River recorded the highest map accuracy with 96%. Both Minnamurra

1
2
3 River and Cararma Inlet had higher accuracies for the mangrove classification than the
4
5 saltmarsh classification.
6
7

8 [insert Figure 6 here]
9

10 [insert Figure 7 here]
11

12 [insert Figure 8 here]
13

14 [insert Table 5 here]
15
16
17
18
19

20
21 The feature optimisation statistics demonstrate that the majority of variance in
22
23 all vegetation classifications was explained by less than 10 layers, with only minimal
24
25 reductions in variance when additional layers were included (Figure 9). The layers
26
27 utilised for describing 70% of the variance for each classification are provided in Table
28
29 6. We found that the dominant variance was explained by both spectral and Lidar
30
31 derived metrics, and that hydrological distance was an important layer, being
32
33 incorporated in eight of the nine classifications (Table 6).
34
35
36

37 [insert Figure 9 here]
38

39 [insert Table 6 here]
40
41
42
43

44 Each site demonstrated differences in the spatial distribution of vegetation
45
46 classes as well as vegetation groups present. Minnamurra River was the only site that
47
48 contained the saltmarsh vegetation class of reeds, namely *Phragmites australis*.
49
50 Similarly Cararma Inlet was the only site to contain *Tecticornia arbuscular*. Both
51
52 vegetation classes occupied areas in the upper intertidal. Currambene Creek and
53
54 Cararma Inlet had areas of sandy substrate with sparse vegetation throughout that was
55
56 not present at Minnamurra River.
57
58
59
60

Vegetation class statistics were derived using the final classification maps and the Lidar data (Figure 10), which highlight similar variation in structural communities across all study sites. Although a range of layers were utilised to classify variation in vegetation structure, it is evident that other factors that have not been modelled may be influencing hydrodynamics. For example, very low soil salinities and almost continuous inundation in the Reed saltmarsh at Carama Inlet indicates that groundwater contributions to hydrodynamics may be a significant control on saltmarsh distributions (Figure 10 c). The vegetation height statistics demonstrate expected trends that correlate with idealised dominant structural vegetation forms (Figure 10 a). Although the first returns indicate a high precision of the Lidar data, other derivatives such as the DEM, indicate the inability of Lidar to penetrate vegetation canopies; particularly at Minnamurra River (Figure 10 b).

[insert Figure 10 here]

4. Discussion

Capturing wetland vegetation structure identifies vegetation complexity that is not demonstrated in previous mapping. A common methodology for producing fine scale vegetation mapping is using aerial imagery to manually delineate vegetation communities in a geographic information system (GIS) with expert knowledge. This was completed for sites used in this study by Chafer (1998) and Oliver et al. (2012) at Minnamurra River, and CSIRO (1994) and Saintilan and Wilton (2001) at Carama Inlet and Currambene Creek. These studies use similar methodologies to delineate vegetation communities to major vegetation groups; mangrove, saltmarsh, *Casuarina* and mixed (ecotone of mangrove and saltmarsh communities). The methodology presented in this study delineates the structural forms of these vegetation communities, identifying

1
2
3 spatial variability that cannot be identified accurately using these previous approaches,
4
5 as demonstrated through comparisons of equivalent mapped vegetation extent using
6
7 different techniques at Minnamurra River (Table 7). Capturing the extent of vegetation
8
9 structural forms provides additional information about the complexity of vegetation
10
11 communities.
12

13
14
15 [insert Table 7 here]
16
17

18
19 Identifying structural complexity demonstrates the spatial variation of wetland
20
21 vegetation within these ecosystems. The zonation of mangroves at Minnamurra River
22
23 and Cararma Inlet show similarities in hydrological distance to water, with tall
24
25 mangroves closest to the water's edge followed by shrub mangrove and then dwarf
26
27 mangrove. At Currumbene Creek, a larger extent of tall mangrove fringe the river
28
29 channel with shrub and dwarf mangrove higher in the intertidal but not conforming to a
30
31 similar zonation as at the other sites. This spatial variability is likely a factor of the
32
33 interaction between surface elevation and hydrodynamics, and could be identified
34
35 because mangrove communities were delineated to vegetative morphological forms.
36
37 Similarly identifying structural complexity of saltmarsh demonstrates variation in
38
39 distribution. Cararma Inlet has an extensive distribution of saltmarsh for areas that are
40
41 less frequently inundated from the tide, such as Rush saltmarsh. Coupled with the
42
43 presence of inundated pools, that were not present at Minnamurra River or Currumbene
44
45 Creek, indicates the importance of groundwater contributions to hydrodynamics on
46
47 saltmarsh compositional distribution that have not been incorporated into the
48
49 classification model.
50
51
52

53
54 Capturing this variability and complexity in wetland vegetation is important for
55
56 delineating differences in distribution of ecosystem services. This is particularly useful
57
58
59
60

for directing management to areas that could be considered for conservation. For example, carbon storage dynamics have been demonstrated to be variable across wetland vegetation (Chmura et al. 2003). In this study we found that the distribution of tall mangrove, which have the highest above-ground carbon storage (Clough, Dixon, and Dalhaus 1997; Saintilan 1997), occurred in different positions on each estuary. At Minnamurra River, tall mangrove were associated with cut-off embayments, while they were restricted to the inside of meanders at Currumbene Creek and along the tidal channel of Cararma Inlet. Similarly, identifying vegetation morphologies of saltmarsh may enable more robust calculations for below-ground carbon storage. Choi and Wang (2004) demonstrate substantial differences in below-ground carbon storage for saltmarsh species depending on their hydrological position in the intertidal zone. Previous mapping that does not delineate morphological forms within saltmarsh vegetation would not be able to upscale these estimates without compromise. This is because the mapped vegetation would not capture the vegetative morphological information required to upscale the discrete measures of carbon storage. Identifying spatial variability of vegetation structure could provide greater confidence when estimating landscape scale carbon storage.

Using an object-based approach provides advantages over traditional pixel-based image analysis, resulting in higher map accuracies (Kamal and Phinn 2011; Ouyang et al. 2011; Dronova et al. 2012). All sites had an overall map accuracy of greater than 90%, providing similar accuracies to previous studies that captured vegetation complexity in coastal wetlands (Heumann 2011a; Kim et al. 2011; Ouyang et al. 2011; Vo et al. 2013; Kamal, Phinn, and Johansen 2015). Although 45 derived layers were input into the nearest neighbor algorithm, significantly less layers were required for classification. Both Lidar derived layers and spectrally derived layers were

important for differentiating vegetation classes, however the mangrove classifications relied substantially on the Lidar derived layers (Table 6). The use of Lidar point cloud data underpinned the high accuracies of classification in this study. Lidar data enables detailed structural information about vegetation to be obtained that is not possible with imagery. This is particularly useful when mapping spectrally similar vegetation that may be distinguished by structural differences through Lidar metrics (Heumann 2011b; Rokitnicki-Wojcik, Wei, and Chow-Fraser 2011), as was the case with our results. Lidar has been used in other studies; however, these studies have not taken advantage of the depth of information that this can add to wetland vegetation classification (Moffett and Gorelick 2013). Deriving several specific layers from the Lidar point cloud, rather than using the entire point cloud or only selecting the DEM, provided a more effective use in classification.

5. Conclusions

Ecosystem services provided by coastal wetlands are spatially and temporally variable. Capturing information about ecosystem function, the interaction of ecosystem components and natural processes, is required to determine the spatial distribution of ecosystem services and enable a more accurate assessment of the value of coastal ecosystems. Delineating ecosystem components at a morphological level that identifies vegetation structure within vegetation communities provides additional information about ecosystem processes. This research provides a rapid assessment methodology to identify spatial complexity in wetland vegetation structure with a high degree of accuracy. This facilitates a more informed understanding of the variability in ecosystems functions and ultimately the value of coastal ecosystems and the services they provide.

Acknowledgements

This research was supported by a UOW postgraduate scholarship awarded to C. Owers. K. Rogers receives funding from the Australian Research Council (FT130100532). Aerial imagery and Lidar data were provided by Land and Property Information, NSW. T. Oliver kindly provided areal extents for mapped vegetation presented in Oliver et al. (2012). The authors would like to thank Daniel Owers, Steven Brooks, Kathryn Owers and Kirti Lal for fieldwork assistance.

References

Adam, E., O. Mutanga, and D. Rugege. 2009. "Multispectral and hyperspectral remote sensing for identification and mapping of wetland vegetation: A review". *Wetlands Ecology and Management* (18): 281–296.

Barbier, E.B., S.D. Hacker, C. Kennedy, E.W. Koch, A.C. Stier, and B.R. Silliman. 2011. "The value of estuarine and coastal ecosystem services." *Ecological Monographs* (81): 169–193.

Boyd, J., and S. Banzhaf. 2007. "What are ecosystem services? The need for standardized environmental accounting units." *Ecological Economics* (63): 616–626.

Chafer, C.J. 1998. *A spatio-temporal Analysis of estuarine vegetation change in the Minnamurra River, 1938-1997*. Minnamurra Estuary Management Committee: Wollongong, Australia.

Chmura, G.L., S.C. Anisfeld, D.R. Cahoon, and J.C. Lynch. 2003. "Global carbon sequestration in tidal, saline wetland soils". *Global Biogeochemical Cycles* (17): 1–12.

Choi, Y., and Y. Wang. 2004. "Dynamics of carbon sequestration in a coastal wetland

1
2
3 using radiocarbon measurements.” *Global Biogeochemical Cycles* (18): 1–12.

4
5
6 Chust, G., I. Galparsoro, A. Borja, J. Franco, and A. Uriarte. 2008. “Coastal and
7
8 estuarine habitat mapping, using LIDAR height and intensity and multi-spectral
9
10 imagery.” *Estuarine, Coastal and Shelf Science* (78): 633–643.

11
12
13 Clarke, P.J. 1993. “Mangrove, saltmarsh and peripheral vegetation of Jervis Bay.”
14
15 *Cunninghamia* (31): 231–253.

16
17
18
19 Clough, B.F., P. Dixon, and O. Dalhaus. 1997. “Allometric relationships for estimating
20
21 biomass in multi-stemmed mangrove trees.” *Australian Journal of Botany* (45): 1023–
22
23 1031.

24
25
26 Congalton, R.G. 1991. “A review of assessing the accuracy of classifications of
27
28 remotely sensed data.” *Remote Sensing of Environment* (37): 35–46.

29
30
31 CSIRO. 1994. *Jervis Bay baseline studies: Final Report*. CSIRO Division of Fisheries:
32
33 North Beach, W.A., Australia.

34
35
36
37 de Groot, R.S., M.A. Wilson, and R.M.J. Boumans. 2002. “A typology for the
38
39 classification, description and valuation of ecosystem functions, goods and services.”
40
41 *Ecological Economics* (41): 393–408.

42
43
44
45 Drăgut, L., D. Tiede, and S.R. Levick. 2010. “ESP: a tool to estimate scale parameter
46
47 for multiresolution image segmentation of remotely sensed data.” *International Journal*
48
49 *of Geographical Information Science* (24): 859–871.

50
51
52 Dronova, I., P. Gong, N.E. Clinton, L. Wang, W. Fu, S. Qi, and Y. Liu. 2012.
53
54 “Landscape analysis of wetland plant functional types: The effects of image
55
56 segmentation scale, vegetation classes and classification methods.” *Remote Sensing of*
57
58
59
60

Environment (127): 357–369.

Ewel, K.C., R.R. Twilley, and J.E. Ong. 1998. “Different kinds of mangrove forest provide different goods and services.” *Global Ecology and Biogeography Letters* (7): 83–94.

Heumann, B.W. 2011a. “An object-based classification of mangroves using a hybrid decision tree-support vector machine approach.” *Remote Sensing* (3): 2440–2460.

Heumann, B.W. 2011b. “Satellite remote sensing of mangrove forests: Recent advances and future opportunities.” *Progress in Physical Geography* (35): 87–108.

Hermann, A., S. Schleifer, and T. Wrbka. 2011. “The concept of ecosystem services regarding landscape research: A review.” *Living Reviews in Landscape Research* (5): 1–37.

Kamal, M., and S. Phinn. 2011. “Hyperspectral data for mangrove species mapping: A comparison of pixel-based and object-based approach.” *Remote Sensing* (3): 2222–2242.

Kamal, M., S. Phinn, and K. Johansen. 2014. “Characterizing the spatial structure of mangrove features for optimizing image-based mangrove mapping.” *Remote Sensing* (6): 984–1006.

Kamal, M., S. Phinn, and K. Johansen. 2015. “Object-based approach for multi-scale mangrove composition mapping using multi-resolution image datasets.” *Remote Sensing* (7): 4753–4783.

Ke, Y., L.J. Quackenbush, and J. Im. 2010. “Synergistic use of QuickBird multispectral imagery and LIDAR data for object-based forest species classification.” *Remote Sensing*

1
2
3 of *Environment* (114): 1141–1154.
4

5
6 Kim, M., T.A. Warner, M. Madden, and D.S. Atkinson. 2011. “Multi-scale GEOBIA
7
8 with very high spatial resolution digital aerial imagery: scale, texture and image
9
10 objects.” *International Journal of Remote Sensing* (32): 2825–2850.
11

12
13 Kuenzer, C., A. Bluemel, S. Gebhardt, T.V. Quoc, and S. Dech. 2011. “Remote Sensing
14
15 of Mangrove Ecosystems: A Review.” *Remote Sensing* (3) 878-928.
16
17

18
19 Liu, K., L. Liu, H. Liu, X. Li, and S. Wang. 2014. “Exploring the effects of biophysical
20
21 parameters on the spatial pattern of rare cold damage to mangrove forests.” *Remote*
22
23 *Sensing of Environment* (150): 20-33.
24
25

26
27 Livesley, S.J., and S.M. Andrusiak. 2012. “Temperate mangrove and salt marsh
28
29 sediments are a small methane and nitrous oxide source but important carbon store.”
30
31 *Estuarine, Coastal and Shelf Science* (97): 19–27.
32
33

34
35 Lugo, A.E., and S.C. Snedaker. 1974. “The Ecology of Mangroves.” *Annual Review of*
36
37 *Ecology and Systematics* (5): 38-64.
38

39
40 MEA. 2005. *Ecosystems and Human well-being: Multiscale Assessment, Millennium*
41
42 *Ecosystem Assessment Series*. Washington, DC: Island Press
43
44

45
46 Moffett, K.B., and S.M. Gorelick. 2013. “Distinguishing wetland vegetation and
47
48 channel features with object-based image segmentation.” *International Journal of*
49
50 *Remote Sensing* (34): 1332–1354.
51

52
53 Noske, R.A. 1995. “The ecology of mangrove forest birds in peninsular Malaysia.” *IBIS*
54
55 (137): 250–263.
56
57
58
59
60

1
2
3
4
5
6
7
8
9
10
11
12
13
14
15
16
17
18
19
20
21
22
23
24
25
26
27
28
29
30
31
32
33
34
35
36
37
38
39
40
41
42
43
44
45
46
47
48
49
50
51
52
53
54
55
56
57
58
59
60

Noske, R.A. 1996. “Abundance, zonation and foraging ecology of birds in mangroves of Darwin Harbour, Northern Territory.” *Wildlife Research* (23): 443-474.

Oliver, T.S.N., K. Rogers, C.J. Chafer, and C.D. Woodroffe. 2012. “Measuring, mapping and modelling: an integrated approach to the management of mangrove and saltmarsh in the Minnamurra River estuary, southeast Australia.” *Wetlands Ecology and Management* (20): 353–371.

Ouyang, Z., M. Zhang, X. Xie, Q. Shen, H. Guo, and B. Zhao. 2011. “A comparison of pixel-based and object-oriented approaches to VHR imagery for mapping saltmarsh plants.” *Ecological Informatics* (6): 136–146.

Ozesmi, S.L., and M.E. Bauer. 2002. “Satellite remote sensing of wetlands.” *Wetlands Ecology and Management* (10): 381-402.

Rokitnicki-Wojcik, D., A. Wei, and P. Chow-Fraser. 2011. “Transferability of object-based rule sets for mapping coastal high marsh habitat among different regions in Georgian Bay.” *Wetlands Ecology and Management* (19): 223–236.

Roy, P.S., R.J. Williams, A.R. Jones, I. Yassini, P.J. Gibbs, B. Coates, R.J. West, P.R. Scanes, J.P. Hudson, and S. Nichol. 2001. “Structure and function of south-east Australian estuaries.” *Estuarine, Coastal and Shelf Science* (53): 351–384.

Saintilan, N. 1997. “Above-and below-ground biomasses of two species of mangrove on the Hawkesbury River estuary, New South Wales.” *Marine and Freshwater Research* (48): 147-152.

Saintilan, N., and K. Wilton. 2001. “Changes in the distribution of mangroves and saltmarshes in Jervis Bay, Australia.” *Wetlands Ecology and Management* (9): 409–420.

1
2
3 Twilley R.R., V.H. Rivera-Monroy, R. Chen, and L. Botero. 1998. "Adapting an
4
5 Ecological Mangrove Model to Simulate Trajectories in Restoration Ecology." *Marine*
6
7 *Pollution Bulletin* (37): 404-419.
8
9

10
11 Vo, Q., N. Oppelt, P. Leinenkugel, and C. Kuenzer. 2013. "Remote sensing in mapping
12
13 mangrove ecosystems — an object-based approach." *Remote Sensing* (5): 183–201.
14

15
16 Woodroffe, C.D. 1992. "Mangrove Sediments and Geomorphology" in *Robertson, A.,*
17
18 *and D. Alongi (eds.), Tropical Mangrove Ecosystems* (2): 7-41. American Geophysical
19
20 Union, Washington.
21
22
23
24
25
26
27
28
29
30
31
32
33
34
35
36
37
38
39
40
41
42
43
44
45
46
47
48
49
50
51
52
53
54
55
56
57
58
59
60

Table 1. Technical specification of aerial imagery and Lidar data.

Aerial imagery		Lidar	
Sensor	ADS40	Sensor	ALS50-II
Time of capture	February 2009	Time of capture	December 2010 – April 2011
Data type	Orthorectified GeoTIFF	Data type	LAS
Spatial resolution	0.5 m	Footprint size	0.62 m ²
Spectral resolution	3 bands red (608–662 nm) green (533–587 nm) blue (428–492 nm)	Intensity wavelength	1064 nm
Radiometric resolution	12 bits/band	Accuracy	H: 0.8 m, V: 0.3 m

Table 2. Structural vegetation class definitions for classification.

Structural form	Species/description	Vegetation height (m)	Hydrological position
Tall mangrove	<i>A.marina</i>	>3.0	Lower intertidal
Shrub mangrove	<i>A.marina, A.corniculatum</i>	1.3-3.0	
Dwarf mangrove		<1.3	
Reed saltmarsh	<i>Phragmites australis</i>	0.5-2.0	Upper intertidal
Rush saltmarsh	<i>Juncus krausii</i>	0.3-1.0	
Herbs, grasses and sedges	<i>Sporobolus virginicus, Samolus repens, Sarcocornia quinqueflora</i>	0-0.3	
<i>Tecticornia</i>	<i>Tecticornia arbuscular</i>	0.1-1.0	
Inundated area	Permanent or semi-permanent areas of water that were unvegetated	-	
Mixed vegetation	Ecotone communities of mangrove and saltmarsh species	-	
Sparse vegetation	Areas with sparse vegetation growth, often ecotone communities, that had a sandy surface substrate	-	
<i>Casuarina</i>	<i>Casuarina glauca</i>	>3.0	

Table 3. Derivative layers of aerial imagery, Lidar point cloud data and hydrological distance to water model (DEM; digital elevation model, DSM; digital surface model, DTM; digital terrain model, CHM; canopy height model, IDM; Intensity difference model).

Aerial imagery 3 band (red, green, blue)	Lidar point cloud*	Lidar point cloud intensity*	Lidar layer ratio	Hydrologic distance to water model
Mean of each band	DEM, DSM, DTM, CHM	Intensity average of all returns	All returns of high height vegetation : All returns of medium height vegetation	Mean of layer
Standard deviation of each band	All vegetation returns	Intensity average of first returns	All returns of high height vegetation : All returns of low height vegetation	Standard deviation of layer
Brightness	All returns of high height vegetation	Intensity maximum of first returns	All returns of medium height vegetation : All returns of low height vegetation	
Hue	All returns of medium height vegetation	Intensity minimum of last returns	All ground returns : All vegetation returns	
Intensity	All returns of low height vegetation	IDM		
Saturation	All ground returns			
Maximum Difference	All returns elevation average			

* all derived layers include mean and standard deviation

Table 4. Parameters and layers used for each segmentation at each study site (SP; scale parameter).

	Input data and scale parameter			
	Initial segmentation	Community segmentation	Mangrove segmentation	Saltmarsh segmentation
Minnamurra River	Blue, green, red, lidar SP = 200	Blue, green, red, lidar SP = 100	CHM, DEM, DSM, all vegetation points, high vegetation points, medium vegetation points, low vegetation points, ground points SP = 25	Blue, green, red, CHM, DEM, DSM, all vegetation points, high vegetation points, medium vegetation points, low vegetation points, ground points SP = 50
Currambene Creek	Blue, green, red, lidar SP = 200	Blue, green, red, lidar SP = 100	CHM, high vegetation points, medium vegetation points, low vegetation points, ground points SP = 25	Blue, green, red, CHM, DEM, DSM, all vegetation points, high vegetation points, medium vegetation points, low vegetation points, ground points SP = 25
Cararma Inlet	Blue, green, red, lidar SP = 200	Blue, green, red, lidar SP = 75	CHM, high vegetation points, medium vegetation points, low vegetation points, ground points SP = 15	Blue, green, red, CHM, DEM, DSM, all vegetation points, high vegetation points, medium vegetation points, low vegetation points, ground points, Average intensity of all returns SP = 25

Table 5. Classification accuracies for each study site. n = number of classes.

Note: error matrices are presented in supplementary material.

		Community classification	Mangrove classification	Saltmarsh classification	Overall map accuracy
Minnamurra River	%	99	96	93	96
	κ	0.99	0.94	0.89	0.96
	n	3	3	3	3
Currambene Creek	%	99	92	92	95
	κ	0.99	0.86	0.81	0.93
	n	5	3	2	8
Cararma Inlet	%	97	98	93	95
	κ	0.98	0.97	0.89	0.95
	n	6	3	3	10

Table 6. Feature optimisation statistics for community (com), mangrove (man), and saltmarsh (sm) classifications at each study site. Greyed out boxes indicate layers used to explain 70% or greater variance associated with each classification. For a complete table of all layers required for each classification refer to supplementary material.

Layers	Minnamurra River			Currambene Creek			Caramba Inlet		
	com	man	sm	com	man	sm	com	man	sm
Red band									
Green band									
Blue band									
Brightness									
Hue									
Intensity									
Saturation									
Maximum Difference									
DEM									
All returns of high height vegetation									
All returns of medium height vegetation									
All returns of low height vegetation									
All ground returns									
All Lidar returns elevation average									
Intensity average of first returns									
Intensity maximum of first returns									
Lidar layer ratio (medium : low vegetation)									
Mean Hydrologic distance to water model									

Table 7. Comparison of delineated wetland vegetation extent at Minnamurra River from Oliver et al. (2012) to the results presented in this study.

Vegetation community (ha)	Oliver et al. (2012)	This study	This study (structural form)
Mangrove (ha)	22	18.3	Tall mangrove – 5.2 Shrub mangrove – 8.6 Dwarf mangrove – 4.5
Mixed (ha)	2.3	5.5	
Saltmarsh (ha)	4.5	4.5	Reed saltmarsh – 0.15 Rush saltmarsh – 1.35 Herbs, grasses and sedges saltmarsh – 3.0

Figure 1. Hierarchical figure demonstrating ecosystem services as elements of components and natural processes. Dashed line indicates potential proxy. Adapted from Barbier et al. (2011), de Groot, Wilson, and Boumans (2002), Hermann, Schleifer, and Wrška (2011).

Figure 2. Location of study sites in New South Wales, Australia. Data source: Imagery © ESRI Basemaps.

Figure 3. Field photo examples of structural morphologies of vegetation a) Tall mangrove b) Shrub mangrove c) Dwarf mangrove d) Reed saltmarsh e) Rush saltmarsh f) Herbs, grasses and sedges saltmarsh g) *Tecticornia* saltmarsh h) Ephemeral inundated area i) *Casuarina* j) Mixed k) Sparse vegetation.

Figure 4. Multiresolution segmentation example (left) and recorded ground-truthed data (right) for Minnamurra River. Data source: Imagery © Land and Property Information [2009].

Figure 5. Hierarchical OBIA approach completed in eCognition (diamond = data input, oval = process, square = classes).

Figure 6. Structural classification for Minnamurra River. Data source: Imagery © Land and Property Information [2009].

Figure 7. Structural classification for Currumbene Creek. Data source: Imagery © Land and Property Information [2009].

Figure 8. Structural classification for Cararra Inlet. Data source: Imagery © Land and Property Information [2009].

Figure 9. Feature optimisation statistics for number of layers required explain the variance associated with the community classification (blue), mangrove classification (red), and saltmarsh classification (green) for a) Minnamurra River, b) Currumbene Creek, and c) Cararra Inlet.

Figure 10. Mean a) vegetation height, b) elevation and c) hydrological distance to water for each structural vegetation class for Minnamurra River (blue), Currumbene Creek (red) and Cararra Inlet (green).

Figure 1. Hierarchical figure demonstrating ecosystem services as elements of components and natural processes. Dashed line indicates potential proxy. Adapted from Barbier et al. (2011), de Groot, Wilson, and Boumans (2002), Hermann, Schleifer, and Wrbka (2011).
209x297mm (300 x 300 DPI)

Figure 2. Location of study sites in New South Wales, Australia. Data source: Imagery © ESRI Basemaps.
297x210mm (300 x 300 DPI)

Figure 3. Field photo examples of structural morphologies of vegetation a) Tall mangrove b) Shrub mangrove c) Dwarf mangrove d) Reed saltmarsh e) Rush saltmarsh f) Herbs, grasses and sedges saltmarsh g) Tecticornia saltmarsh h) Ephemeral inundated area i) Casuarina j) Mixed k) Sparse vegetation. 209x297mm (300 x 300 DPI)

Figure 4. Multiresolution segmentation example (left) and recorded ground-truthed data (right) for Minnamurra River. Data source: Imagery © Land and Property Information [2009].
210x296mm (300 x 300 DPI)

Figure 5. Hierarchical OBIA approach completed in eCognition (diamond = data input, oval = process, square = classes).
209x297mm (300 x 300 DPI)

Figure 6. Structural classification for Minnamurra River. Data source: Imagery © Land and Property Information [2009].
210x296mm (300 x 300 DPI)

Figure 7. Structural classification for Currumbene Creek. Data source: Imagery © Land and Property Information [2009].
210x296mm (300 x 300 DPI)

Figure 8. Structural classification for Carama Inlet. Data source: Imagery © Land and Property Information [2009].

210x296mm (300 x 300 DPI)

Figure 9. Feature optimisation statistics for number of layers required explain the variance associated with the community classification (blue), mangrove classification (red), and saltmarsh classification (green) for a) Minnamurra River, b) Currumbene Creek, and c) Caramba Inlet.
190x275mm (96 x 96 DPI)

Figure 10. Mean a) vegetation height, b) elevation and c) hydrological distance to water for each structural vegetation class for Minnamurra River (blue), Currumbene Creek (red) and Carama Inlet (green).
190x275mm (96 x 96 DPI)

1
2
3
4
5
6
7
8
9
10
11
12
13
14
15
16
17
18
19
20
21
22
23
24
25
26
27
28
29
30
31
32
33
34
35
36
37
38
39
40
41
42
43
44
45
46
47
48
49

Supplementary Material

Table S1. Pairwise error matrix for structural classification and ground-truthed data at Minnamurra River (HGS = Herbs, grasses and sedges). Note: class *Casuarina* has only 4 replicates and may not be statistically significant.

		Ground-truthed data									
Classification		Tall mangrove	Shrub mangrove	Dwarf mangrove	Mixed	<i>Casuarina</i>	Reed	Rush	HGS	Total	Error of commission (%)
	Tall mangrove	7	0	0	0	0	0	0	0	7	0
	Shrub mangrove	0	31	0	0	0	0	0	0	31	0
	Dwarf mangrove	0	2	15	0	0	0	0	0	17	12
	Mixed	0	0	0	32	0	0	0	0	32	0
	<i>Casuarina</i>	0	0	0	0	4	0	0	0	4	0
	Reed	0	0	0	1	0	10	0	0	11	9
	Rush	0	0	0	0	0	0	10	2	12	17
	HGS	0	0	0	0	0	0	1	19	20	5
	Total	7	33	15	33	4	10	11	21	134	
	Error of omission (%)	0	6	0	3	0	0	9	10		

Table S2. Pairwise error matrix for structural classification and ground-truthed data at Currumbene Creek. Note: classes *Casuarina* and Rush have only 4 replicates each and may not be statistically significant.

	Ground-truthed data										
		Tall mangrove	Shrub mangrove	Dwarf mangrove	Mixed	<i>Casuarina</i>	Sparse vegetation	Rush	HGS	Total	Error of commission (%)
Classification	Tall mangrove	39	1	1	1	0	0	0	0	42	7
	Shrub mangrove	0	14	1	0	0	0	0	0	15	7
	Dwarf mangrove	0	2	8	0	0	0	0	0	10	20
	Mixed	0	0	0	29	0	0	0	0	29	0
	<i>Casuarina</i>	0	0	0	0	4	0	0	0	4	0
	Sparse vegetation	0	0	0	0	0	15	0	0	15	0
	Rush	0	0	0	0	0	0	3	0	3	0
	HGS	0	0	0	0	0	0	1	9	10	10
	Total	39	17	10	30	4	15	4	9	128	
	Error of omission (%)	0	18	20	3	0	0	25	0		

1
2
3
4
5
6
7
8
9
10
11
12
13
14
15
16
17
18
19
20
21
22
23
24
25
26
27
28
29
30
31
32
33
34
35
36
37
38
39
40
41
42
43
44
45
46
47
48
49

Table S3. Pairwise error matrix for structural classification and ground-truthed data at Carama Inlet. Note: class Inundated has no replicates and may not be statistically significant.

1
2
3
4
5
6
7
8
9
10
11
12
13
14
15
16
17
18
19
20
21
22
23
24
25
26
27
28
29
30
31
32
33
34
35
36
37
38
39
40
41
42
43
44
45
46
47
48
49

Classification

Ground-truthed data												
	Tall mangrove	Shrub mangrove	Dwarf mangrove	Mixed	<i>Casuarina</i>	Sparse vegetation	Inundated	Rush	HGS	<i>Tecticornia</i>	Total	Error of commission (%)
Tall mangrove	21	0	0	0	0	0	0	0	0	0	21	0
Shrub mangrove	0	18	0	0	0	0	0	0	0	0	18	0
Dwarf mangrove	0	1	13	0	0	0	0	0	0	0	14	7
Mixed	0	0	0	30	1	0	0	0	0	0	31	3
<i>Casuarina</i>	0	0	0	0	7	0	0	0	0	0	7	0
Sparse vegetation	0	0	0	0	0	12	0	0	0	0	12	0
Inundated	0	0	0	0	0	0	1	0	0	0	1	0
Rush	0	0	0	1	0	0	0	26	0	1	28	7
HGS	0	0	0	1	0	0	0	0	22	1	24	8
<i>Tecticornia</i>	0	0	0	0	0	0	0	2	0	8	10	20
Total	21	19	13	32	8	12	1	28	22	10	166	
Error of omission (%)	0	5	0	6	13	0	0	7	0	20		

Table S4. Complete feature optimisation statistics for community (com), mangrove (man), and saltmarsh (sm) classifications at each study site. Greyed out boxes indicate layers used to explain variance associated with each classification (SD; standard deviation).

Layers	Minnamurra River			Currambene Creek			Cararma Inlet		
	com	man	sm	com	man	sm	com	man	sm
Red band (mean)									
Green band (mean)									
Blue band (mean)									
Red band (SD)									
Green band (SD)									
Blue band (SD)									
Brightness (mean)									
Hue (mean)									
Intensity (mean)									
Saturation (mean)									
Maximum Difference (mean)									
DEM (mean)									
DSM (mean)									
DTM (mean)									
CHM (mean)									
DEM (SD)									
DSM (SD)									
DTM (SD)									
CHM (SD)									
All vegetation returns (mean)									
All returns of high height vegetation (mean)									
All returns of medium height vegetation (mean)									
All returns of low height vegetation (mean)									
All ground returns (mean)									
All returns elevation average (mean)									
All vegetation returns (SD)									
All returns of high height vegetation (SD)									
All returns of medium height vegetation (SD)									
All returns of low height vegetation (SD)									
All ground returns (SD)									
All Lidar returns elevation average (SD)									
Intensity average of all returns (mean)									
Intensity average of first returns (mean)									
Intensity maximum of first returns (mean)									
Intensity minimum of last returns (mean)									
IDM (mean)									
Intensity average of all returns (SD)									
Intensity average of first returns (SD)									
Intensity maximum of first returns (SD)									
Intensity minimum of last returns (SD)									
IDM (SD)									
Lidar layer ratio (high : medium vegetation)									
Lidar layer ratio (high : low vegetation)									
Lidar layer ratio (medium : low vegetation)									
Lidar layer ratio (ground : all vegetation)									
Hydrologic distance to water model (mean)									
Mean Hydrologic distance to water model (SD)									