Time and tide wait for no Mangroves: High resolution remotely sensed mapping of coastal saltmarsh vegetation

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Key points

- High-resolution colour-infrared aerial imagery combined with Object-Based Image Analysis (OBIA) can accurately map fine-scale saltmarsh and mangrove communities across estuarine environments.
- The OBIA workflow, integrating spectral and elevation data and informed by on-ground ecological knowledge, outperformed traditional field-based mapping in spatial detail and consistency.
- The approach successfully delineated functional saltmarsh groups and revealed distinct spatial patterns and areas of potential change, including evidence of "saltmarsh squeeze."
- The resulting high-resolution vegetation maps and reproducible workflow provide a robust, efficient tool for estuary monitoring and management.
- The methodology is transferable to other estuaries and supports short- and long-term coastal management and planning.

Abstract

Estuarine / intertidal saltmarsh communities are recognised as ecologically significant habitats, yet their fine-scale spatial distribution is often poorly mapped due to the complexity and heterogeneity of vegetation across tidal gradients. This project was initiated to test the efficacy of high-resolution, remotely sensed community-level vegetation mapping, relative to traditional on-ground methods, in accurately mapping saltmarsh type and extent across three intertidal areas in Western Port Bay, near Melbourne.

High-resolution colour-infrared aerial imagery supplied by MetroMap was used as the primary remote sensing dataset. An Object-Based Image Analysis (OBIA) workflow was developed in ArcGIS Pro to segment the imagery and classify multiple saltmarsh communities and mangroves. The approach incorporated spectral and elevation variables, with iterative rule-set development informed by on-ground ecological knowledge. Accuracy assessment was conducted using drone-imagery validation and expert interpretation.

The OBIA method successfully delineated and classified key saltmarsh functional groups and mangrove communities across the three study estuaries. The analysis produced high-resolution vegetation maps suitable for integration into existing GIS platforms, and a reproducible classification workflow. Results revealed distinct spatial patterns in vegetation composition, as well as areas of potential change including the widely reported 'saltmarsh squeeze' relevant to future management.

The improved spatial detail and community-level classification provide a robust evidence base for land managers, with the outputs informing short and long-term management planning and monitoring. The GIS workflow demonstrates the value of high-resolution aerial imagery and OBIA for coastal habitat monitoring and can be applied to other estuaries / intertidal areas where land managers are seeking efficient and repeatable mapping methodologies.

Keywords

Saltmarsh, Estuarine vegetation, Object-Based Image Analysis (OBIA), High-resolution aerial imagery, Remote sensing, Coastal wetlands, GIS mapping, Habitat monitoring.

Introduction

Object-Based Image Analysis has a well-established role in Australian estuarine vegetation mapping, particularly for mangrove, saltmarsh and seagrass habitats. However, published literature is dominated by satellite and UAV applications. Explicit applications using high-resolution aerial photography are less numerous in peer-reviewed journals, although evidence from operational mapping programs, most notably NSW DPI's statewide estuarine macrophyte mapping, indicates that OBIA based on aerial imagery has been used extensively in practice for estuarine habitat mapping. Similar application of OBIA based on aerial imagery in Victoria is less widespread.

Estuarine vegetation communities, including mangroves, saltmarshes and seagrass beds, are critical components of coastal ecosystems because they provide habitat and nursery areas for fish and other aquatic fauna, improve water quality by trapping sediments and nutrients, stabilise shorelines, sequester and store significant amounts of carbon, and support the ecological functioning and resilience of estuaries. These habitats are also highly sensitive to pressures such as coastal development, altered hydrology, pollution, invasive species, and climate change, making accurate spatial information essential for effective management, conservation and restoration programs.

Remote sensing provides a consistent, efficient and repeatable means of mapping estuarine vegetation across large and often inaccessible coastal environments, overcoming many of the limitations associated with traditional field-based surveys and manual aerial photo interpretation. Conventional mapping approaches can be time- and labour-intensive, are often constrained by site accessibility and tidal conditions, and may disturb sensitive intertidal habitats during field verification. In addition, manual interpretation can be subjective and frequently requires the simplification of complex vegetation patterns into discrete mapping units. In contrast, high-resolution remotely sensed data, such as aerial imagery and LiDAR, enable objective and spatially explicit mapping of vegetation communities, capturing fine-scale variation in habitat extent, condition and structure that may not be readily observed through field surveys alone. These approaches allow managers to monitor temporal change, quantify habitat loss or expansion, identify emerging threats, and produce standardised mapping products across broad geographic extents while significantly reducing the time, cost and disturbance associated with traditional methods. Although successful implementation relies on appropriate training data, field validation and specialised geospatial analysis techniques, the benefits of improved efficiency, consistency, spatial coverage and ecological representation make remote sensing an increasingly valuable tool for estuarine vegetation monitoring and management.

For this project, a methodology was developed and evaluated for the identification and mapping of fringing vegetation communities in a case study estuary in Western Port Bay using remotely sensed data. The approach integrated high-resolution multispectral aerial imagery with LiDAR-derived canopy height and digital elevation models within an ArcGIS Pro workflow. The analysis was supported by video from a drone flyover and results from a previous mapping exercise performed for the Victorian Index of Estuary Condition (Sinclair and Kohout, 2018; DELWP, 2021).

Applying OBIA in complex, dynamic environments like estuaries using high-resolution imagery remains at the forefront of combined remote sensing and ecological monitoring techniques.

Study area

Warringine Creek in Western Port Bay, Victoria (Figure 1) has a diversity of estuarine vegetation types that represent a good test of the method as well as previous drone imagery capture that allowed for a closer inspection of the existing vegetation communities without the need to visit the site. Index of Estuarine Condition (IEC) mapping of fringing vegetation for Warringine Creek is also available. According to Sinclair and Kohout (2020), IEC mapping for Warringine Creek only had a desktop assessment, meaning manual aerial photo interpretation was used to map the vegetation types being used to inform this project.

Figure 1 Study area location with extent of vegetation assessed outlined in black

Method

There were two key parts to the approach: (i) determining the vegetation community types that would be the focus of the mapping and (ii) determining the optimal classification method utilising the available image segmentation and classification toolset in ArcGIS Pro. The approach relied on dataset acquisition, preparation, derivation and composition and tailored workflow parameterisation.

Mapped vegetation communities

Based on the whole published dataset of vegetation communities (EVC) mapped in the Index of Estuary Condition (2021), we deliberately selected those EVC that were most dominant by area (Hectares) using the rationale that if we can accurately map these EVC remotely then this represents the bulk of the vegetation type coverage in estuaries and intertidal areas along the Victorian coast (Table 1).

Table 1 Target vegetation communities for OBIA based mapping

Intertidal EVC code	Intertidal EVC name	Area (Ha)	%	EVC description
WSH	Wet Saltmarsh Herbland	7488	22.66%	A107
MS	Mangrove Shrubland	5157	15.60%	140
WSS	Wet Saltmarsh Shrubland	3307	10.01%	A108
SAM	Saline Aquatic Meadow	2904	8.79%	842
EW	Estuarine Wetland	2734	8.27%	10
CTS	Coastal Tussock Saltmarsh	2105	6.37%	A112
		Total	**71.70%**	

ArcGIS Pro workflow

The ArcGIS Pro workflow was structured around the obligatory object-based image analysis steps of image segmentation followed by image classification. Two key source datasets were used: a high resolution (5cm spatial resolution) colour-infrared aerial image from MetroMap (17th of July 2023); and a 1m spatial resolution Digital Elevation Model (DEM) from the State Government of Victoria's Coordinated Image Program (28th of November 2017). Additional datasets were derived from these inputs, including a separate Near-Infrared (NIR) band, a Normalized Difference Vegetation Index (NDVI) and a Canopy Height Model (CHM); and from these, two final composite datasets were created as inputs: a 'for segmentation' and a 'for classification' dataset.

The 'for segmentation' dataset was segmented using the *Segment Mean Shift* tool by adjusting spatial, spectral and segment size parameters to best represent real-world expression of the vegetation communities (Figure 2). The 'for classification' dataset was classified using a comparative test of two classifiers commonly used in OBIA, Support Vector Machine (SVM) and Random Trees (RT).

The classifiers were trained with spectral signature files derived from sample points representing each vegetation community class (around 100 points per class). Points were located using a combination of the existing IEC mapping, cross-checking with the drone imagery and using results of a preliminary analysis of the available aerial imagery and LiDAR to distinguish the degree of spectral and canopy elevation difference between the vegetation types. The sample set was split 70:30 into training and validation points respectively and a Kappa coefficient confusion matrix (Table 2) was used to assess the accuracy of the classification results.

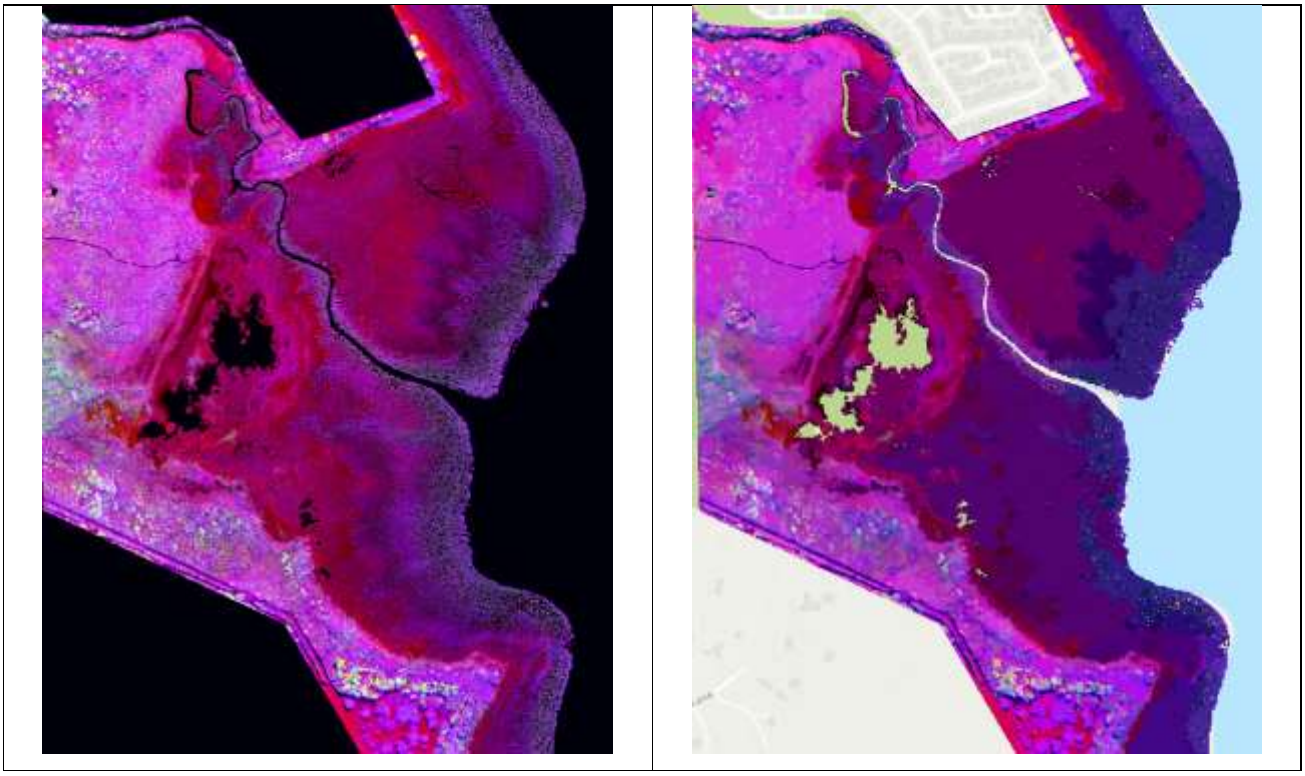

Figure 2 Sample of the pixel-based composite 'for segmentation' input dataset in false colour (left) consisting of near-infrared band, normalized difference vegetation index and a canopy height model; and the false colour object-based segmentation output (right). The black in the left-hand image is the water mask. Both images show the richness of spectral and spatial information available for analysis

Results

The RT classifier performed best and returned an accuracy of 92% which is near-perfect agreement (Table 2).

Table 2 actual classification accuracy results (refer right hand columns for the standard Kappa coefficient agreement category)

Class	C_1	C_2	C_3	C_4	Total	User Accuracy	Kappa	Kappa coefficient	Interpretation
C_1	30	0	0	0	30	1.00		0	No agreement
C_2	0	27	0	3	30	0.90		0.1-0.2	Slight agreement
C_3	0	0	30	1	31	0.96	n/a	0.21-0.40	Fair agreement
C_4	0	3	0	26	29	0.89		0.41-0.60	Moderate agreement
Total	30	30	30	30	120	n/a		0.61-0.80	Substantial agreement
Producer Accuracy	1.00	0.90	1.00	0.86	n/a	0.94		0.81-0.99	Near perfect agreement
Kappa	n/a						0.92	1	Perfect agreement

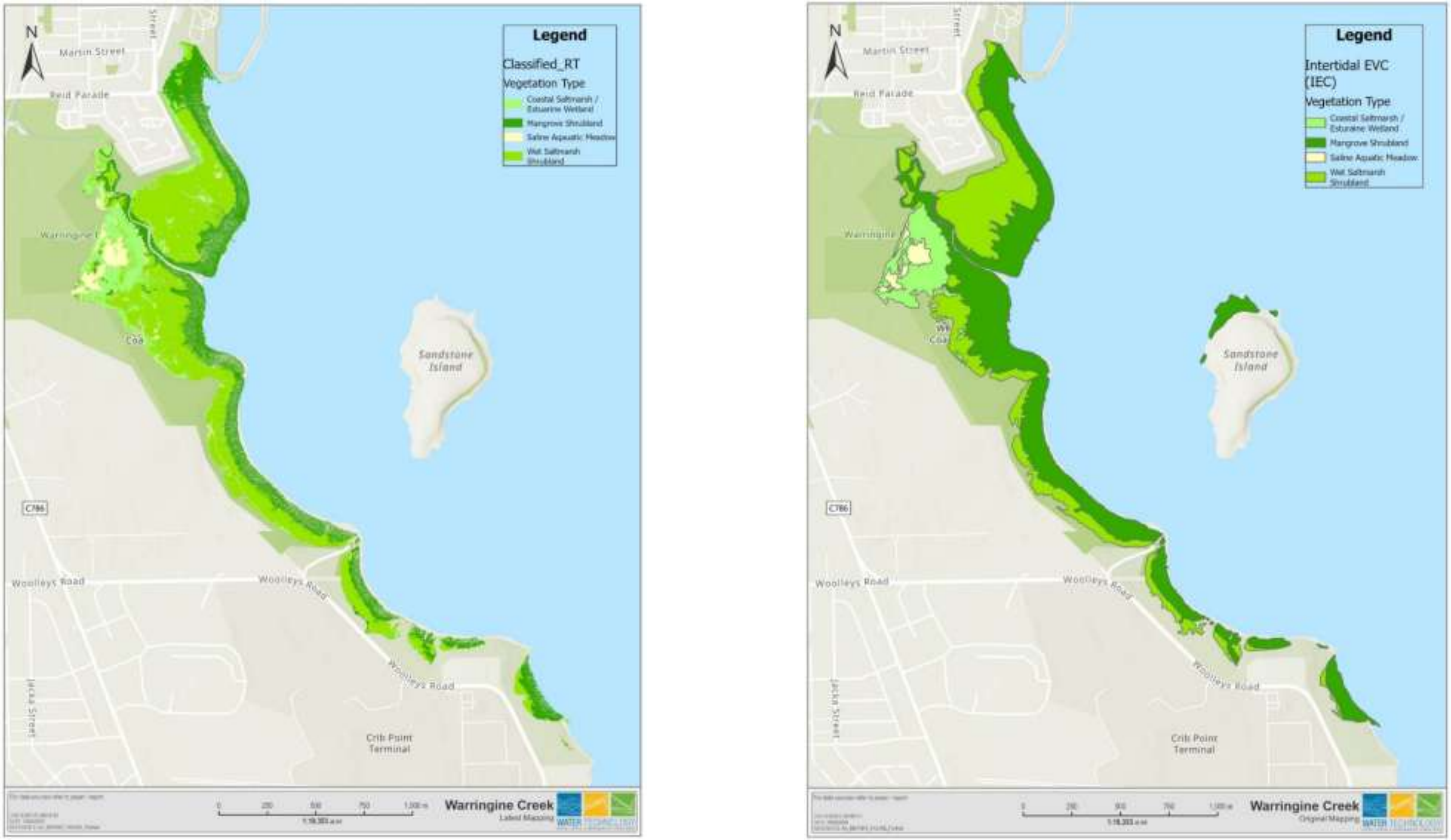

Figure 3 Study area results (left) compared to original IEC mapping (right)

Comparison of the image classification results with the original mapping

Figure 3 compares the OBIA mapping results (left panel) with the IEC mapping (right panel), highlighting the general agreement yet finer detail possible using OBIA and high-resolution imagery. IEC mapping relied heavily on desktop aerial photo interpretation supported by field mapping where access was feasible. The mapping deliberately homogenised within, and simplified boundaries between, vegetation types. Because of the high spatial resolution (30cm) our OBIA approach conversely mapped the complexity of the on-ground vegetation within patches of each vegetation type and emphasised the transitional (blended) nature of many of the boundaries. An example of where the OBIA approach excelled was within areas of Wet Saltmarsh Shrubland where intervening patches of Wet Saltmarsh Herbland and mudflat were mapped. This is commensurate with what would be expected with seasonal variability in the Wet Saltmarsh Shrubland/Herbland community.

Working at very high spatial resolution emphasised the importance of creating sufficient training data for each vegetation type and the challenge of accurately placing training points within vegetation types to ensure the point was located over a representative patch of vegetation and not over a gap in the vegetation. An example of insufficient training samples was Estuarine Scrub being mapped as Mangrove. This occurred due to the absence of a spectral signature for Estuarine Scrub and the classifier recognising the spectral similarity of *Melaleuca ericifolia* with Mangrove, even though elevation was different. Another example was areas of Estuarine Wetland being mapped in gaps within Wet Saltmarsh Shrubland, which is ecologically incorrect. Again, this occurred because of the spectral similarity of the gaps with Estuarine Wetland due to insufficient spectral information being available to the classifier.

The lessons learned from review of these pilot results confirmed the OBIA approach shows significant promise and that ecological accuracy in the mapping outputs can be optimised by refining the training points.

How the results can be used to inform potential future changes

We used the classified results of the vegetation extents to determine the present-day elevation ranges the different vegetation types were associated with and relate these to tide levels in Western Port Bay from the nearby Stony Point Tide Gauge (Ports Victoria, 2023). We were able to do this by querying the elevation range per class using the DEM and the mapped vegetation extent. All saltmarsh types were integrated because it is extremely difficult to accurately project which specific saltmarsh type(s) will successfully migrate and dominate into the future; thus, the focus of the exercise was to determine which areas of the estuary were suitable for saltmarsh (broadly) in the future. We therefore focused on defining three tide ranges that were: saltmarsh dominated, transitioning between saltmarsh and mangrove and mangrove dominated.

Utilising the worst case (SSP5-8.5) median sea level rise projections for Western Port Bay (CSIRO, 2024), future tide levels in 2050 (+0.19m) and 2090 (+0.47m) were projected across the study area using a simple bathtub model. The projected tide levels enabled us to map areas that would be suitable for saltmarsh only, either saltmarsh or mangrove or mangrove only (Figure 4).

The results showed that at Warringine, all vegetation types shift landward with sea level rise with areas of mangrove projected to increase whilst areas of saltmarsh are projected to reduce. Most of the shift is projected to occur between 2050 and 2090 so that by 2090, Warringine will be a mangrove dominated estuary with saltmarsh existing in a few remining elevation niches.

How the OBIA approach can assist estuary vegetation management

An accurate and repeatable remote mapping approach enhances the temporal frequency and spatial extent over which vegetation types of management importance can be monitored, helping to highlight change over time and reducing the need to physically assess sensitive vegetation communities. Further, the ability to simulate likely vegetation community change through mapping projections facilitates management planning and decision-making. Such mapping helps to highlight where accommodation space may or may not exist within and around the estuary and informs the likely sustainability of different vegetation communities.

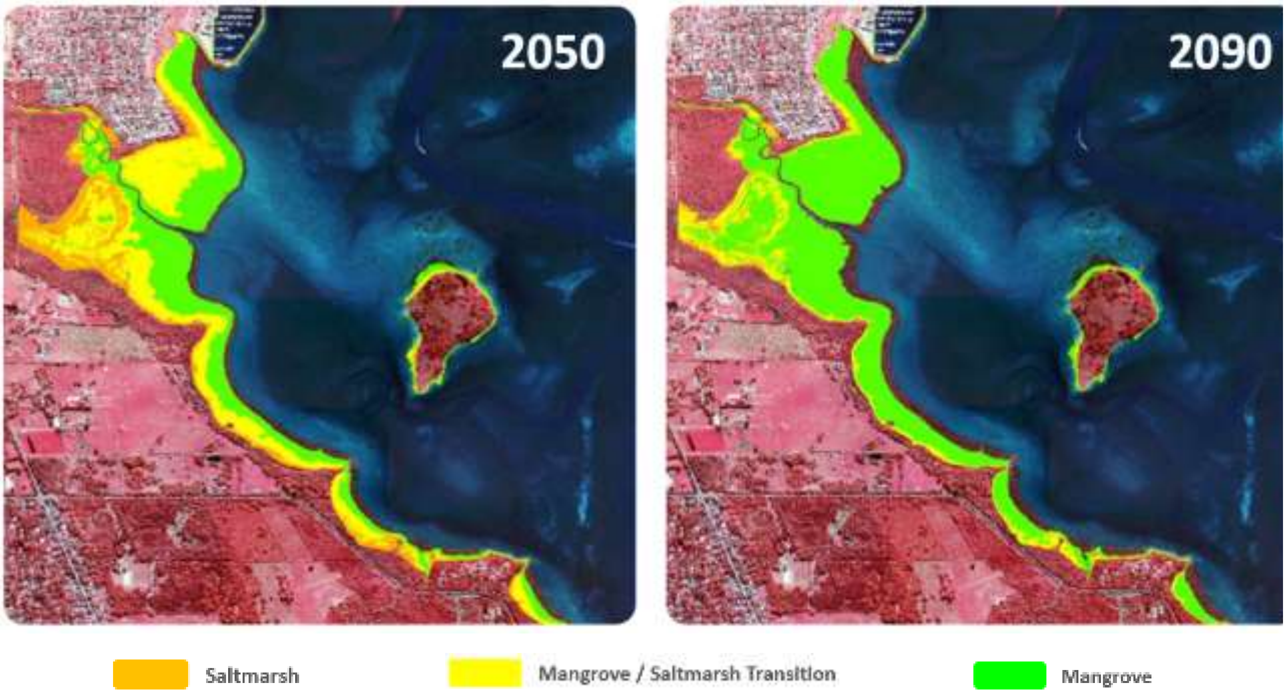

Figure 4 Sea level rise driven projections of future vegetation extents focusing on mangroves and saltmarsh

Conclusions

The project demonstrated that:

- Appropriately parameterised OBIA workflows in ArcGIS Pro can accurately map intertidal vegetation communities using a targeted set of aerially captured high-resolution elevation and spectral datasets.
- Deriving and composing the right combination of datasets being used as inputs for segmentation and for classification is a key foundational aspect for generating accurate results.
- Working at 30cm resolution, sufficient creation and careful placing of training points is critical to attain high levels of classification accuracy.
    - Testing revealed instances where the classifiers were challenged due to insufficient training points being created for vegetation communities present within the image being analysed.
    - Placing a training point on top of vegetation and not on top of another feature in the image is critical, even though the point is broadly within the extent of the target vegetation community.
- The very high spatial resolution of the results revealed plenty of real-world on-ground variation in vegetation extents which allowed for complex patterns and transitions between vegetation types to be observed. This allows for a more realistic representation of the extents of vegetation communities to be shown in mapping without the need to simplify boundaries for mapping purposes, as has been the case with traditional mapping approaches.
- Being able to accurately map intertidal vegetation communities using remote techniques allows for an increased frequency of repeat monitoring to track change over time. When combined with the projections of future vegetation extents with sea level rise, powerful insights can inform management decision-making in the short-medium term that consider current and potential future conditions.

- Compared to traditional on-ground and manual aerial photo interpretation methods, the developed approach can produce results in a matter of hours compared to days.

In summary, the developed approach is sufficiently accessible, efficient, and effective to be rolled out more broadly because it relies on readily available spatial datasets and GIS software *and* produces ecologically meaningful results. The main constraint on its applicability is the available coverage of 4-band (Red, Green, Blue and Near-infrared) aerial imagery over desired study areas. However, this type of imagery is increasingly being captured across broader areas as the demand for it increases and suppliers understand its applications and deliberately fly aircraft fitted with the required cameras.

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