# Champion Bay Habitat Mapping 2025

## Technical Report

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## Version Register

| Version | Status | Author | Reviewer | Comment | Authorised for Release (signed and dated) |
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# Acronyms and Abbreviations

| Term | Full term |
|---|---|
| AHD | Australian Height Datum |
| BCH | Benthic Communities and Habitat |
| BSS | Bed Shear Stress |
| CATAMI | Collaborative and Automated Tools for Analysis of Marine Imagery |
| DII | Depth Invariant Index |
| DMPA | Dredge Material Placement Area |
| EIA | Environmental Impact Assessment |
| EPA | Environmental Protection Agency |
| GPS | Geographic Positioning System |
| ha | hectares |
| LAU | Local Assessment Unit |
| LiDAR | Light Detection and Ranging |
| m | Meters |
| MSL | Mean Sea Level |
| MWPA | Mid West Ports Authority |
| O2M | O2 Marine |
| OBIA | Object Based Image Analysis |
| PmaxP | Geraldton Port Maximisation Project |
| RF | Random Forest |
| WA | Western Australia |

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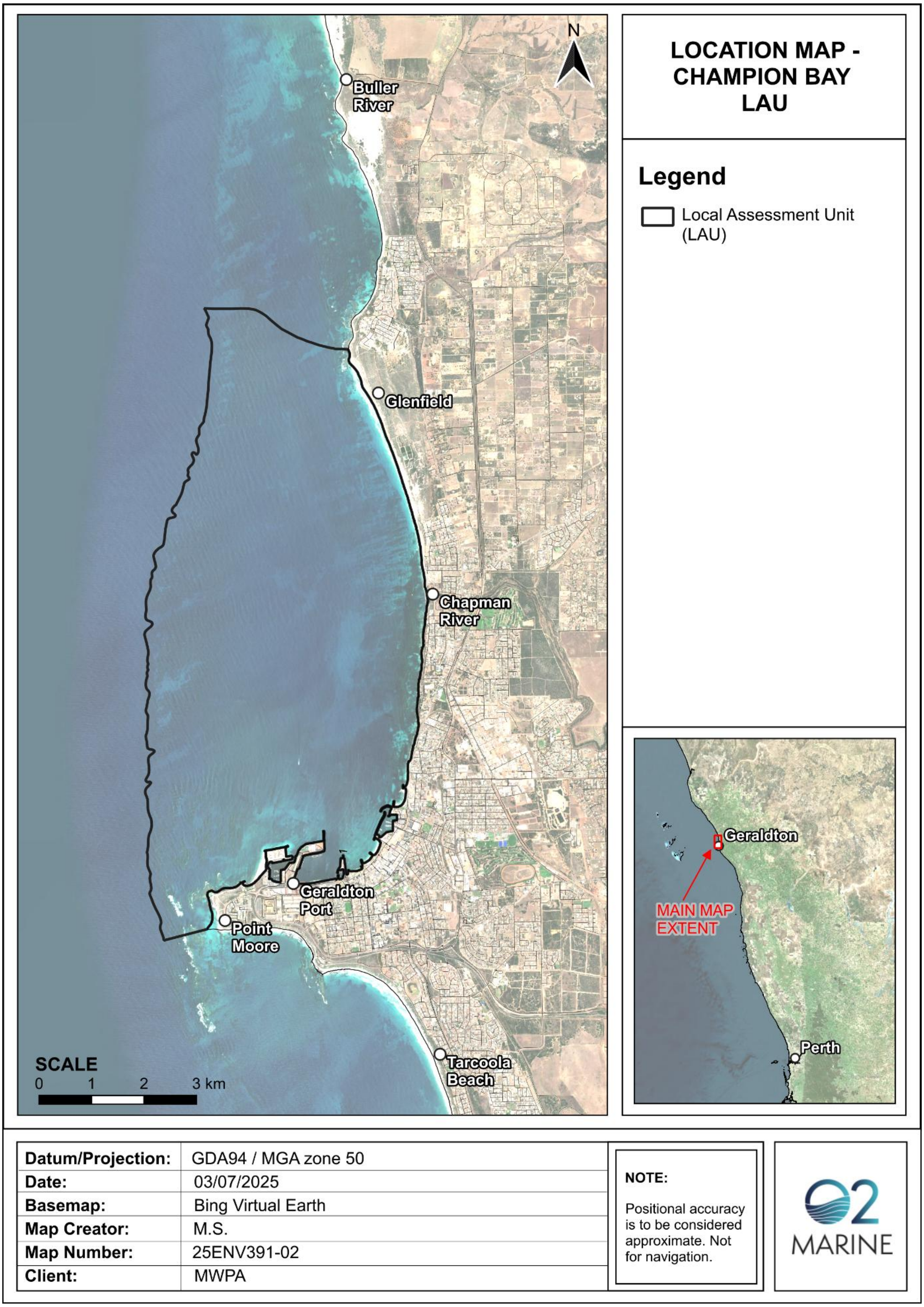
# 1. Introduction

The Port of Geraldton is located approximately 430 km north of Perth in the Mid-West region of Western Australia. The Port is administered by Mid West Port Authority (MWPA) and presently consists of a shipping channel, a seven berth inner harbour (the 'harbour'), a large fishing boat harbour, a tug boat harbour and associated land-based infrastructure. The town of Geraldton has grown around the Port and the shelter of Point Moore, other major industries of the region include farming and fishing.

In August 2024, MWPA referred the Geraldton Port Maximisation Project (PMaxP) to the Environmental Protection Authority (EPA) for assessment under Part IV of the *Environmental Protection Act 1986 (WA)*. As part of the Environmental Impact Assessment (EIA) process, MWPA committed to undertaking Benthic Communities and Habitats (BCH) mapping of the Local Assessment Unit (LAU; covers Point Moore to Glenfield region), including ground truthing surveys, every five years.

In light of the above, MWPA engaged O2 Marine (O2M) to produce an updated subtidal benthic habitat map of the Champion Bay LAU (Figure 1), to be informed by a ground-truthing dataset set to be acquired in autumn 2025. This area has been mapped previously in 2020 by AECOM (2020) (Figure 2).



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| **Map Number:** | 25ENV391-02 |
| **Client:** | MWPA |

Figure 1: Location map showing the Point Moore to Glenfield Local Assessment Unit (LAU) representing the targeted mapping area

# 2. Champion Bay

Located adjacent to the coastal city of Geraldton, Western Australia, Champion Bay is a highly dynamic marine environment shaped by strong winds and swell-driven currents. This high-energy setting significantly influences the composition of substrates and benthic habitats throughout the bay.

A defining morphological feature of Champion Bay is its limestone substrate, which extends across much of the bay and its surrounding areas. The presence and profile of limestone reefs, along with the depth of sand covering these reefs, are key factors determining the distribution and composition of benthic communities in the region. Exposure to prevailing south-westerly swells plays a crucial role in sand movement and redistribution within the bay (Tecchiato et al. 2015). Processes such as deposition, erosion, and frequent resuspension of sand driven by wind, wave activity, and tidal currents all have a significant effect on which epibenthic communities establish in different areas. Throughout the bay, the influence of varying degrees of wave and swell exposure is evident as habitats with similar depth, topography, and substrate can display noticeable differences in community structure.

A 2020 habitat mapping study conducted by AECOM classified the benthic environments of Champion Bay into several distinct habitat types, based on factors such as substrate composition, water depth, and biological assemblages (Figure 2). Mosaic habitats of macroalgae, seagrass, and bare sand are common across the bay, mainly associated with transitional zones where limestone pavement meets sandy substrate. As such, the constant movement of sediment throughout the bay means that these mosaic habitats can frequently vary in composition and cover (BMT, 2021). There are also areas where certain species are dominant, including seagrass species like *Amphibolis* spp. and *Posidonia* sp., or high-relief reef areas support dense macroalgal communities of *Sargassum* sp. or *Ecklonia* sp.

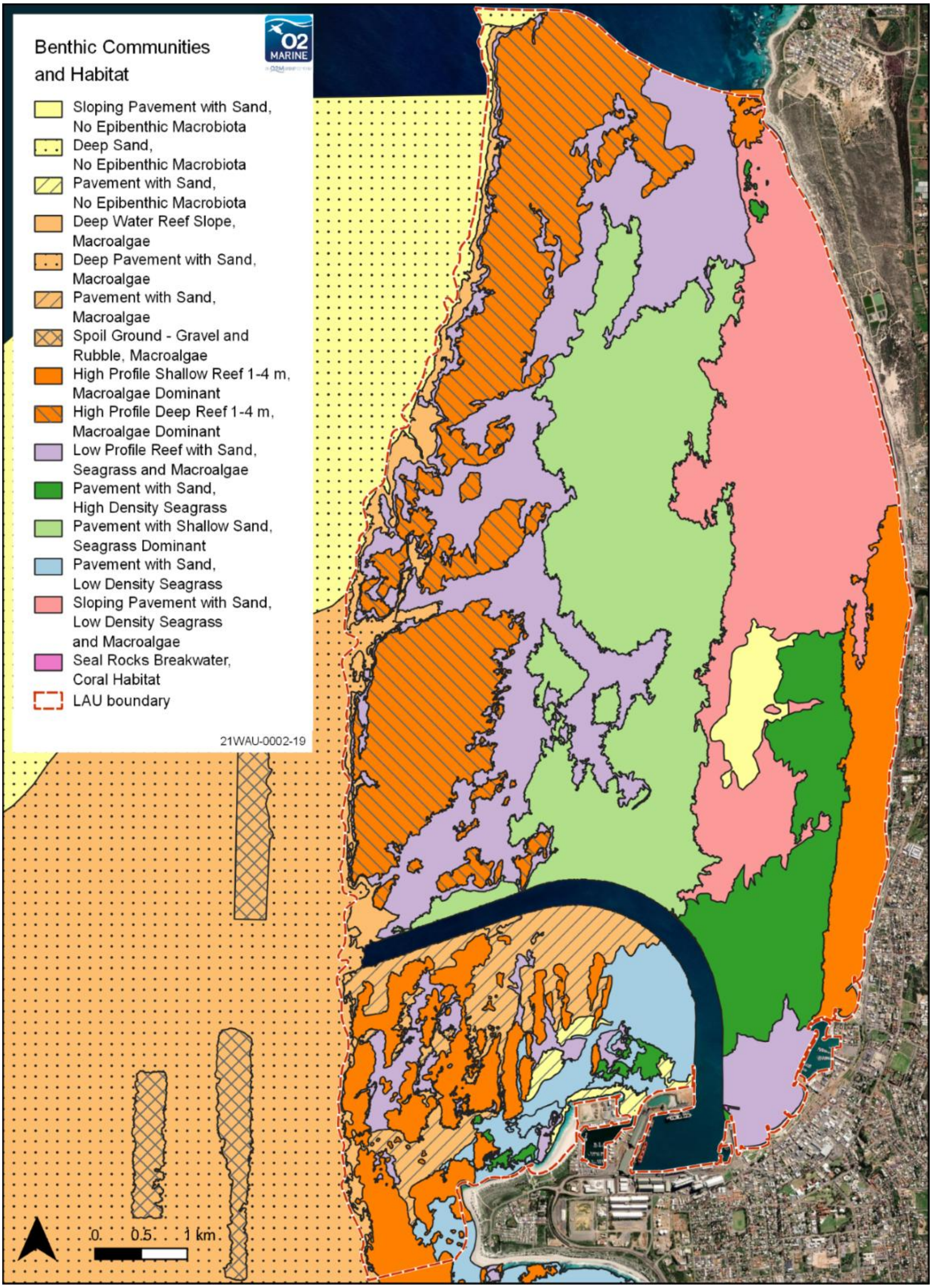


Figure 2: Champion Bay benthic habitat map produced by AECOM (2020) and BMT (2021)

# 3. Approach and Methods

## 3.1. Overarching Approach / Survey Design

Benthic habitat mapping was conducted using a predictive modelling approach that applies machine learning to analyse satellite imagery, environmental predictor layers, and an extensive ground-truth dataset. The environmental layers serve as proxies for habitat distribution, allowing the algorithm to identify relationships between habitat types and environmental conditions. By leveraging known habitat locations from ground-truth data, the model can infer and predict habitat distribution across the targeted mapping area.

An overview of the approach and methods used to develop the 2025 Champion Bay benthic habitat map, including the key stages from pre-field, the field survey campaign for collection of ground truth data, the post-field processes and reporting, is presented in Figure 3.

The pre-field methodologies associated with the acquisition and preparation of these datasets are described in Section 3.1 to 3.2, with the approach used to complete the ground-truthing survey described in Section 3.3, while post-field classification of ground truth data and the processes used to develop the final habitat map are described in Section 3.4 to 3.6.

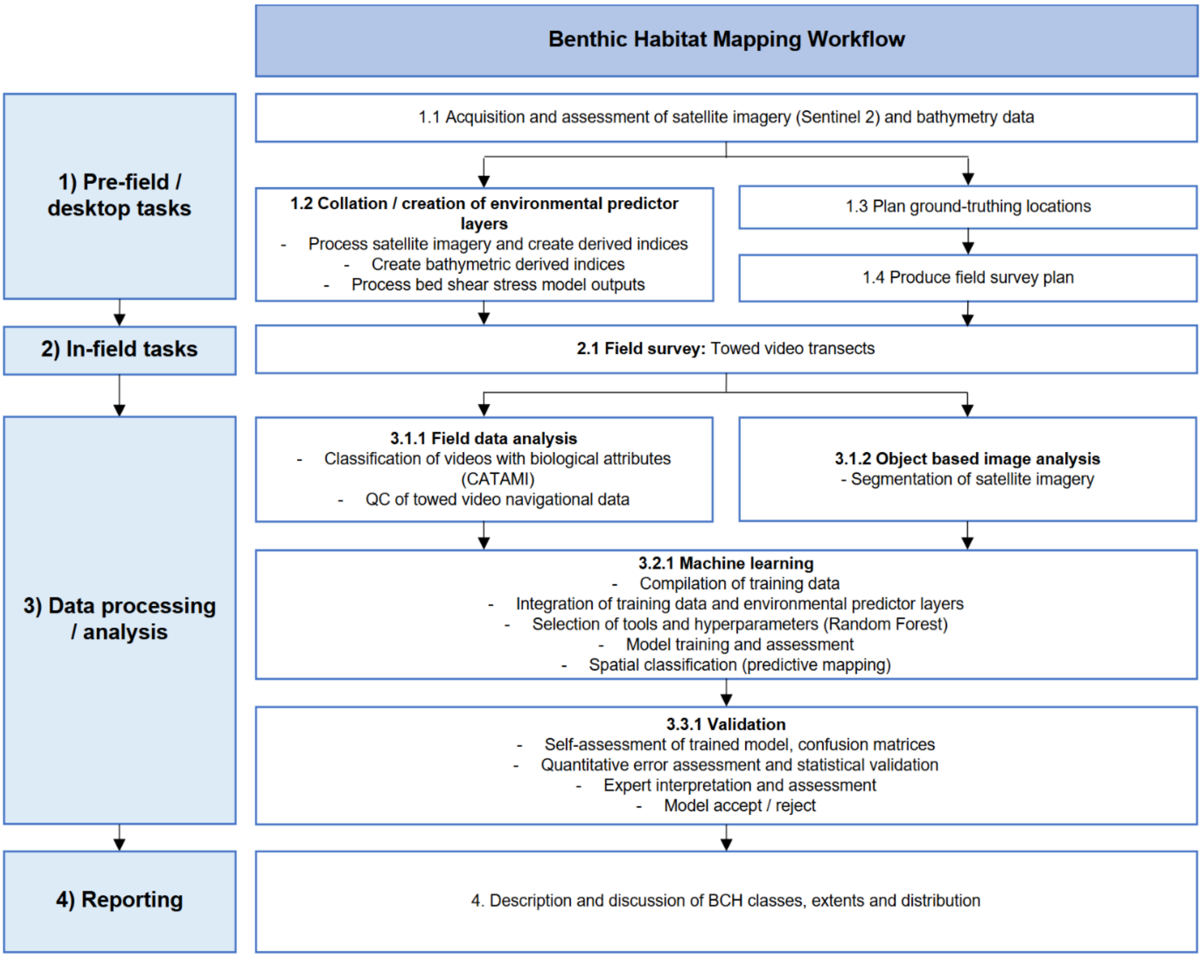


Figure 3: Workflow diagram of the habitat mapping process

## 3.2. Environmental Predictor Layers

Environmental predictor layers are datasets that act as proxies for habitat distribution. By sampling the values of these layers at the known locations of habitats (ground-truthing data), profiles of physical characteristics of each habitat type can be assembled and as such used to predict the distribution of these habitats across the area of interest.

Environmental predictor layers are derived from three main sources:

- Satellite imagery
- Bathymetric data
- Oceanographic modelling (bed shear stress).

### 3.2.1. Satellite-derived Layers

Images from the Sentinel-2 satellite system (10 x 10 m grid cell resolution) have been reliably used for benthic habitat mapping and have been shown to produce high accuracy in mapping seagrass habitats (Wicaksono et al., 2021).

An excellent quality Sentinel-2 image was identified, dating from 10/5/2025, selected from a large number of Sentinel 2A scenes of the Geraldton region. Image selection primarily focussed on identifying periods of low ocean turbidity and minimal sea state as close as possible to the period of 2025 ground truth data acquisition.

The selected image was deglinted, and depth invariant indices were calculated (Table 1), creating water column corrected imagery of the substrate useful to a depth of at least 16 m. The effects of sun glint were removed using the methods described by Hedley et al. (2005).

Table 1: Satellite bands and derived indices used as environmental predictor layers

| Environmental Predictor Layer | Derivation | Comment | Reference |
|---|---|---|---|
| B02 | Sentinel 2 band (490 nm) | Blue band | N/A |
| B03 | Sentinel 2 band (560 nm) | Green band | N/A |
| B04 | Sentinel 2 band (665 nm) | Red band | N/A |
| DII23 | Sentinel 2 | $\frac{\text{Blue}}{\text{Green}}$ | Lyzenga (1978) |
| DII24 | Depth Invariant Ratio | $\frac{\text{Blue}}{\text{Red}}$ | Lyzenga (1978) |
| DII34 | Sentinel 2 | $\frac{\text{Green}}{\text{Red}}$ | Lyzenga (1978) |
| Turbidity | Depth Invariant Ratio | $\frac{\text{Green} \times \text{Red}}{\text{Blue}}$ | Pisanti et al. (2022) |

### Depth Invariant Index (DII)

The effect of water depth on benthic reflectance values was compensated for using a simple linear regression, following the methodology of Lyzenga (1978) and Green et al. (2000), using:

$X_i = -ln(R_i - R_i^{deep})$, where:

- $R_i$ is the pixel reflectance in band i, and

- $R_i^{deep}$, is the deep-water reflectance in that band.

A ratio of Bands 2 and 3 was used to maximise water penetration, computed from sample pixels over the same bottom type at different depths, and a reference deep-water sample.

### Turbidity

Satellite remote sensing instruments can obtain an optical measurement of water turbidity as it increases the backscattering of light (Pisanti et al. 2022). Multiple studies have found correlation between the in-situ measurements and the individual bands known to be most sensitive to water turbidity, namely Sentinel bands blue (B2), green (B3), red (B4). The index ratio showing the best correlation was:

$$\frac{(B3 \times B4)}{B2}$$

While a site-specific regression against field samples was not possible, this band ratio was applied to the 2025 Champion Bay data processing procedures, as it provides a suitable approximation of relative turbidity.

## 3.2.2. Bathymetric-derived layers

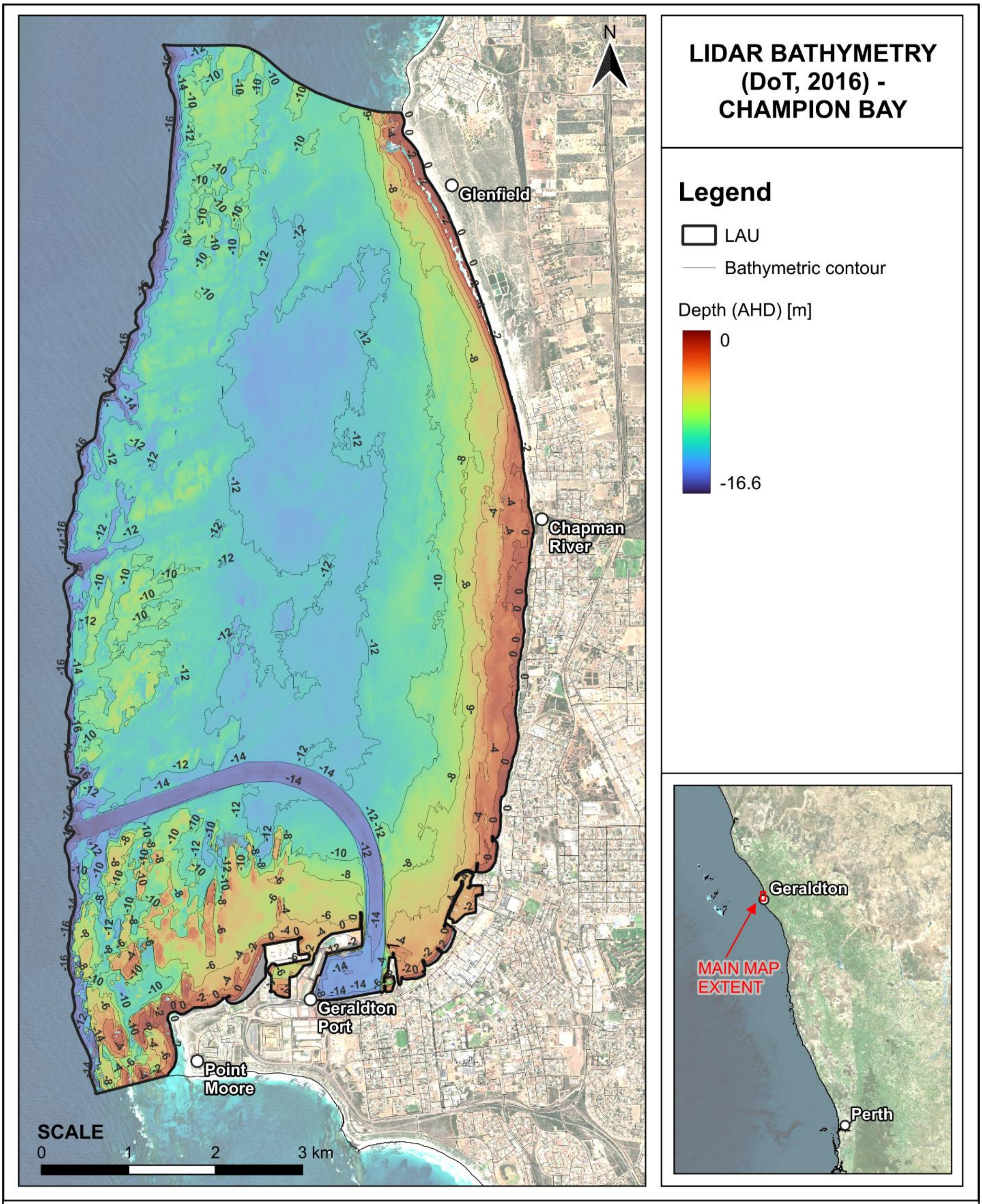
Bathymetric information for this study was derived from a LiDAR bathymetry data collected of the Geraldton and Oakajee marine areas (Figure 4) by the Western Australian Department of Transport (DoT) in 2016 (Archive 17620702 and 17620703). The product has a grid cell resolution of 2 x 2 m, making it ideal for mapping large regions such as the study area. In addition to depth, a LiDAR intensity grid was also available for analysis. The dataset was cropped to cover the full extents of the study area.

Preliminary data analysis was undertaken using a topographic gridding and sun-shading tool, highlighting terrain features. The dataset was assessed for quality within the proposed mapping area. Significant artefacts in the bathymetry data can have an impact on benthic classification results, potentially causing misclassification and unreliable results.

The LiDAR was used to create a large number of potential predictor layers, which were first compared to each other using a Pearsons correlation to eliminate redundancy. Seven layers were carried through for subsequent classification (Table 2). Derivatives are obtained by calculating, for each pixel in a primary data layer, a summary statistic from the values of all surrounding pixels within a defined neighbourhood (Olaya & Conrad 2009; Fisher et al.2017; Wilson & Gallant, 2000).

Table 2: Bathymetric-derived indices used as environmental predictor layers

| Environmental Predictor Layer | Comment | Reference |
|---|---|---|
| Depth | Depth in mean sea level (MSL) | |
| Slope | Terrain slope (Horns method) | Florinsky (2016) |
| Aspect | Orientation of slope | Florinsky (2016) |
| Multiscale Roughness | Local topographic relief | Riley et al., (1999) |
| Topographic Position Index | Elevation of a cell relative to its neighbouring cells (e.g. peak or pit) | Lindsay et al. (2014, 2015); Newman et al., (2018) |
| Profile Curvature | Rate of change in slope along a flow line / downslope | Florinsky (2017) |
| Plan Curvature | Curvature of a contour line at a given point on the topographic surface | Florinsky (2016) |



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| **Map Number:** | 25ENV391-03 |
| **Client:** | MWPA |

**NOTE:**

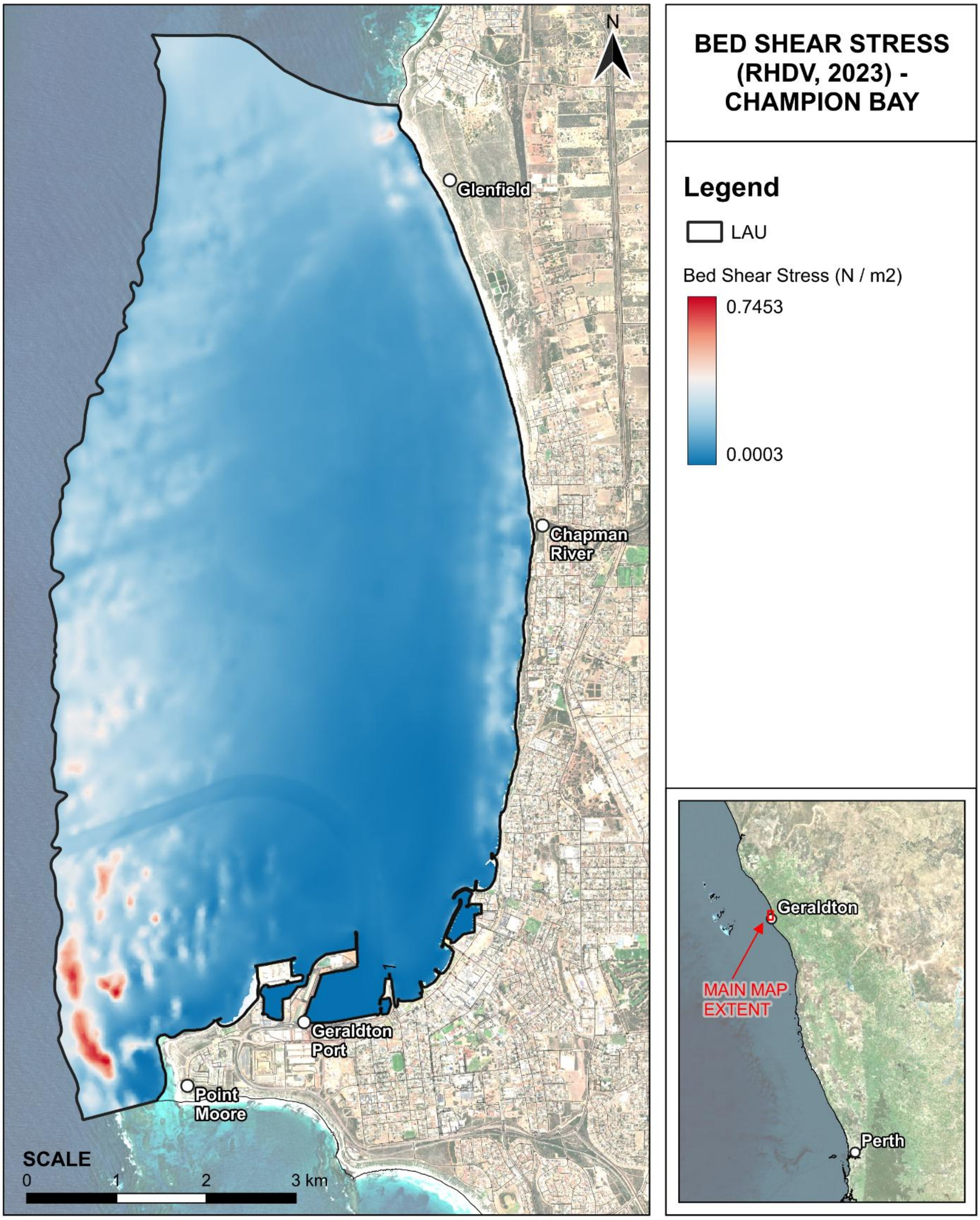
Positional accuracy is to be considered approximate. Not for navigation.

Figure 4: LiDAR bathymetry dataset from DoT (2016)

### 3.2.3. Modelled Layers – Bed Shear Stress

Bed shear stress is the force per unit area exerted by a flowing fluid on the bed of a seafloor surface, acting parallel to the bed. It's a measure of the frictional force between the fluid and the bed, and it's a crucial factor in sediment transport, erosion, and other hydraulic processes. It is considered a critical element to predictive mapping as hydrodynamic conditions, including exposure to waves and currents, have been shown to influence benthic community habitat distribution though their influence on sediment grain size and mobility, and seabed disturbance (Post et al. 2006).

A bed shear stress model was available for the Champion Bay area (Figure 5) (RoyalHaskoningDHV, 2023). The maximum bed shear stress value was calculated as a raster for two separate scenarios (SC1 and SC2). A single maximum bed shear stress raster was generated by utilising the maximum for each cell from SC1 and SC2. The resultant raster was integrated with the other predictor layers.



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**NOTE:**

Positional accuracy is to be considered approximate. Not for navigation.

Figure 5: Modelled maximum bed shear stress Champion Bay (RoyalHaskoningDHV, 2023)

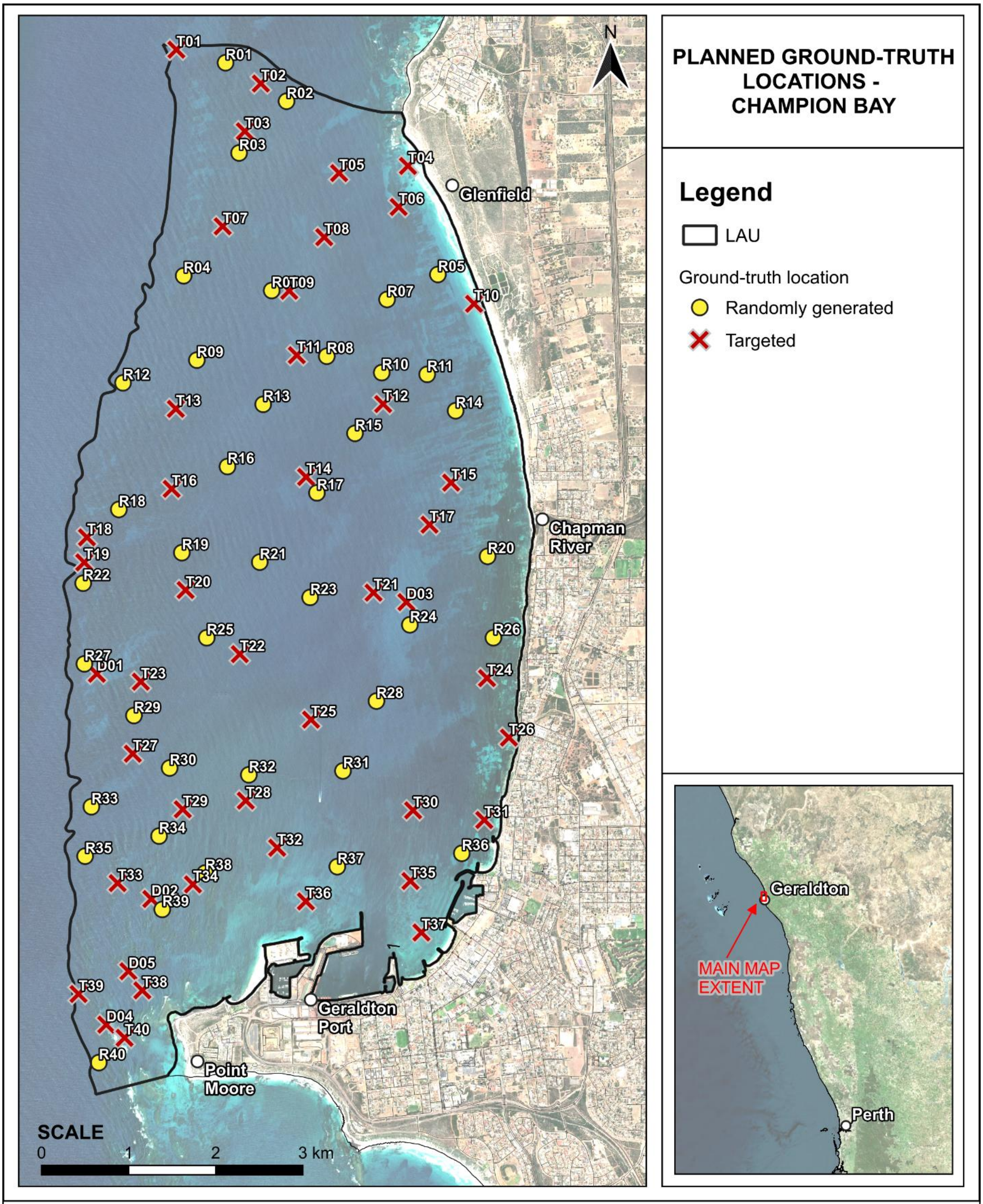
## 3.3. Ground-Truth Survey

### 3.3.1. Survey Design

To obtain the primary ground-truth dataset for this study, the location of pre-determined transects were identified by a GIS analyst prior to the field survey (Figure 6), where the transects comprised both targeted and randomly generated locations (~50% of each):

- targeted transects: were positioned to verify the nature of benthic features of visible in satellite imagery and bathymetric data
- randomly generated transects: were haphazardly positioned to ensure that diverse habitat types are well represented, reducing potential bias from under- or over-sampling certain classes.

Each ground-truth transect was planned to be approximately 50 m in length.



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| **Client:** | MWPA |

**NOTE:**

Positional accuracy is to be considered approximate. Not for navigation.

MARINE

Figure 6: Planned ground-truth locations across Champion Bay

### 3.3.2. Equipment

Ground-truth survey acquisition was carried out across two days (29/04 - 30/04/2025). The survey took place onboard a locally operated 6.6 m charter vessel, *'Sarafore'*. Two towed video camera systems were used for the ground truth survey, including a Technautics tow camera (Figure 7a), and a Spot X SQUID 3 (Figure 7b). Both systems are operated using a topside video app, where a live video feed can be viewed, and settings can be adjusted. GPS positioning was recorded on a GlobalSat BU 353S4 receiver, and backup tracks were recorded on a handheld Garmin GPS. A DJI Action Camera was attached to both systems to provide a backup recording for each transect.

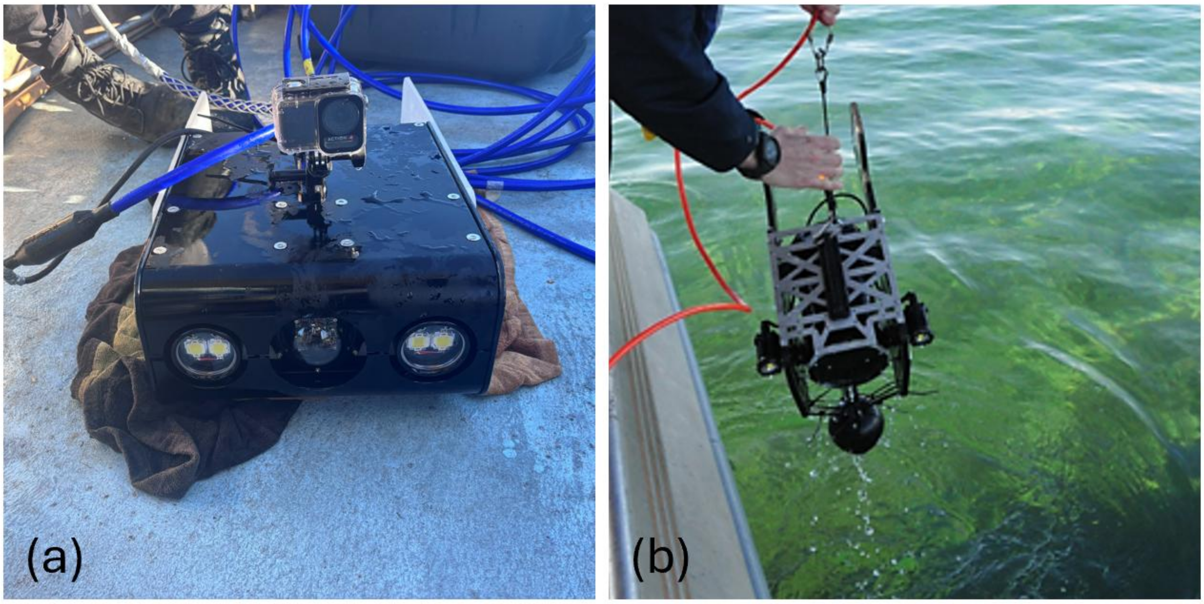


Figure 7: Towed video systems used in the ground-truth survey: a) Technautics towed video system, b) Spot X Pro Squid 3

During the survey, the camera was flown at a depth of approximately 0.5 m above the seabed, with the operator recording between 3 to 4 minutes (60 - 80 m) of benthic video footage at each transect. Vessel speed ranged between 1-2 knots to allow for the acquisition of good-quality imagery.

Key information was recorded on field sheets at each targeted location including date and time, GPS coordinates, water depth, dominant BCH type, and comments to aid post-processing.

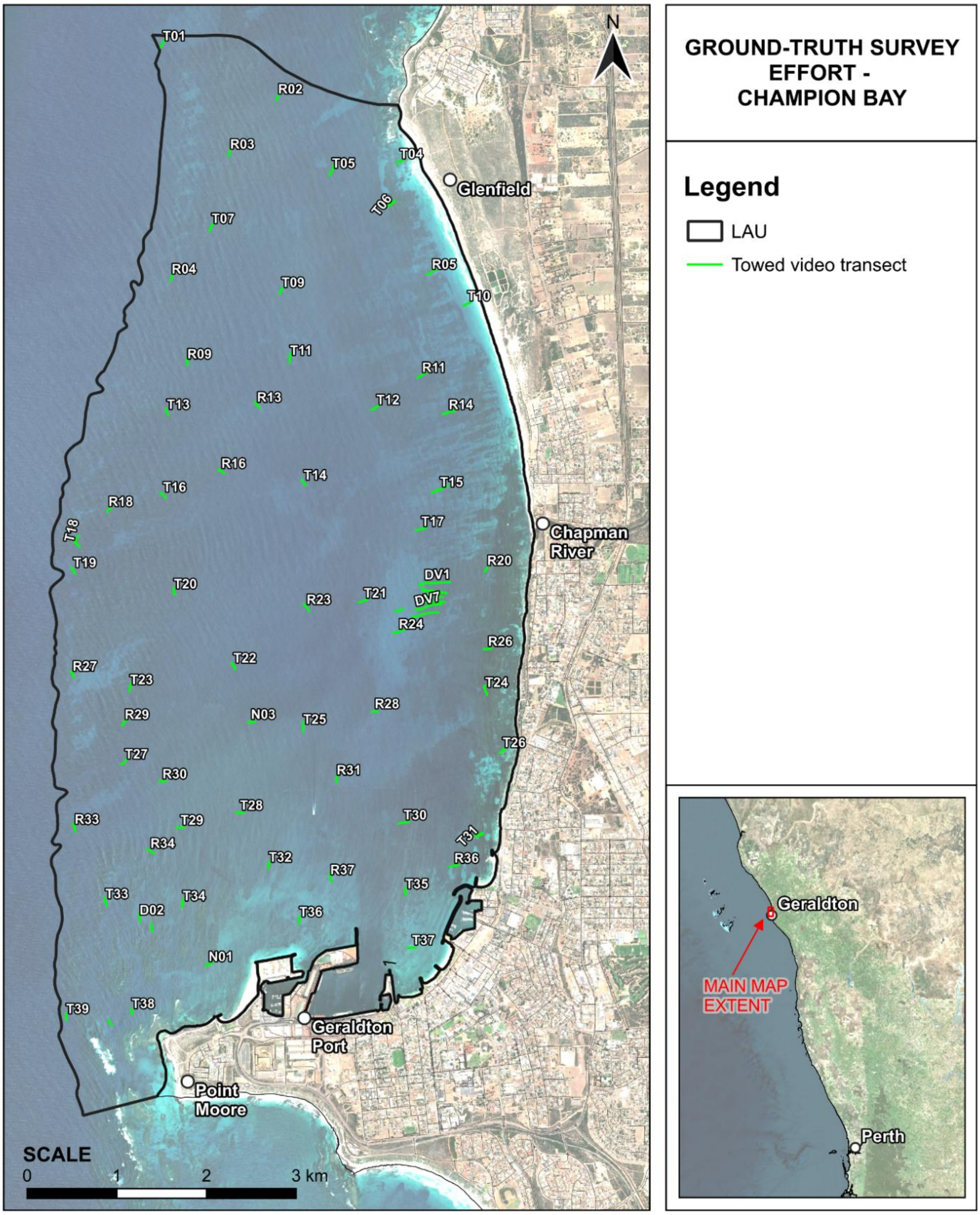
### 3.3.3. Survey Effort

Daily survey effort is outlined in Table 3. Additionally, seven transects (DV1 to DV7) were surveyed as part of a separate scope of work. Although these transects were longer (approximately 250 m) and more closely spaced (around 80 m) than the others, they still provided valuable data and were included in the final ground-truth dataset.

Overall survey effort is illustrated in Figure 8. Not all planned sites were surveyed, as the survey design intentionally included a surplus of locations to ensure ample options were available during fieldwork. Additionally, seven transects (DV1 to DV7) were surveyed as part of a separate scope of work. Although these transects were longer (approximately 250 m) and more closely spaced (around 80 m) than the others, they still provided valuable data and were included in the final ground-truth dataset.

Table 3: Daily survey effort for towed video

| Survey Date | Towed Video Transects | Transect Distance (km) |
|---|---|---|
| 29/04/2025 | 34 | 3.8 |
| 30/04/2025 | 39 | 5.9 |



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| **Map Number:** | 25ENV391-09 |
| **Client:** | MWPA |

**NOTE:**

Positional accuracy is to be considered approximate. Not for navigation.

Figure 8: Ground-truthing survey effort

## 3.4. Classification of Towed Video Footage

Ground-truth videos were assessed for quality, and any videos with poor visibility (e.g. high turbidity obscuring the identification of biota) were discarded. Recordings were visually analysed by a suitably qualified marine scientist using TransectMeasure software and classified into habitat classes (Table 4) following the Collaborative and Automated Tools for Analysis of Marine Imagery (CATAMI) standard classification scheme for scoring marine biota and physical characteristics (Althaus et al., 2015) from underwater imagery.

A quality assurance and control check of the classifications was conducted by an experienced marine scientist specialising in benthic taxonomy and habitat classifications, including verification of percent cover estimates and species identification.

The TransectMeasure data output was synced with the GPS track log, as well as the corresponding auxiliary information (time, depth), to attribute the appropriate BCH characteristics at each point location. GPS offsets and cable lengths, which were recorded during the field survey, were applied to the transects to obtain the most accurate positioning of data. Navigation from each transect was checked for quality control in QGIS.

Table 4: Towed video classification

| Substrate | Major Biota Class | Biota (minor subcategory) | Percent cover |
|---|---|---|---|
| Sand / mud<br>Pebbles / gravel<br>Cobbles<br>Boulders<br>Rock with flat relief<br>Rock with low relief (<1 m)<br>Rock with moderate relief (1 – 3 m) | Bare | N / A | Bare (< 1%)<br>Sparse (1 - 10%)<br>Low (10 - 20%)<br>Moderate (20 – 50%)<br>High (50 - 75%)<br>Dense (>75%) |
| | Macroalgae | *Ecklonia* sp. | |
| | | *Sargassum* sp. | |
| | | Brown macroalgae | |
| | | Green macroalgae | |
| | | Red macroalgae | |
| | | Filamentous macroalgae | |
| | | Mixed macroalgae | |
| | Seagrass | *Amphibolis* spp. | |
| | | *Halophila* spp. | |
| | | *Posidonia australis* | |
| | | *Posidonia coriacea* | |
| | | *Posidonia sinuosa* | |
| | | *Syringodium* spp. | |
| | Filter Feeders | Ascidians | |
| | | Mixed | |
| | | Octocorals | |
| | | Sponges | |

| Substrate | Major Biota Class | Biota (minor subcategory) | Percent cover |
|---|---|---|---|
|  |  | Soft Corals |  |
|  | Mixed Assemblage | Seagrass and macroalgae |  |
|  |  | Filter feeders and macroalgae |  |
|  |  | Filter feeders and seagrass |  |

## 3.5. Mapping Procedure

### 3.5.1. Combined-Area Classification Approach

To improve model performance, the classification was conducted over a combined spatial extent that included both Champion Bay and the adjacent Oakajee area to the north. This approach provided access to a larger and more ecologically diverse training dataset, allowing the model to learn a broader range of habitat–spectral relationships, incorporate a higher representation of rare habitat types and reduce the risk of overfitting to local conditions within Champion Bay.

Although the model was trained and run across the combined extent, this report focuses exclusively on mapping outputs for the Champion Bay LAU. Input datasets and results for the Oakajee area are documented separately in O2 Marine (2025).

### 3.5.2. OBIA

In order to integrate different scale ground truthing point observations, 2 m Lidar bathymetry data and 10 m Sentinel 2 data products, an object-based image analysis (OBIA) technique was employed. OBIA is a method of image analysis that groups pixels into meaningful objects (polygons) based on spectral, shape and neighbourhood properties (Hossain & Chen, 2019). This allows integration of data of different scales, reduction of speckle noise, and faster processing times. Segmentation was undertaken on a high-resolution image of the study area using a meanshift algorithm, resulting in the creation of polygons, ranging in surface area between approximately 20 - 80 m$^2$, adhering to the 'shapes' of visible seabed features. The polygons are attributed with ground-truthing and environmental predictor layer statistics and subsequently subjected to classification techniques.

## 3.6. Training Data for Machine Learning

Training data refers to the input dataset used to train a machine learning model. For this study, the primary dataset comprised classified towed video observations collected during the 2025 Champion Bay ground-truthing campaign. To improve class balance and model robustness, supplementary data were incorporated from the Oakajee area, immediately north of Champion Bay (O2 Marine, 2025) (Table 5). These additional data provided greater spectral and environmental variability, helping the model distinguish between classes with overlapping signatures. The Oakajee dataset was well suited for integration with the primary dataset, as it was collected and classified using the same methodology.

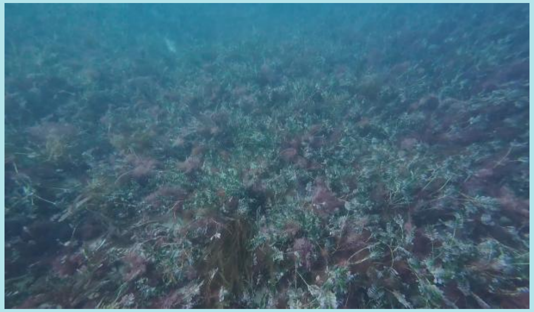
Further targeted training points for *Posidonia sinuosa* dominated habitat were added from within Champion Bay itself, using historic survey data from known locations of this less common but ecologically important habitat (Table 5). These additions ensured that *Posidonia sinuosa* was adequately represented in the training set and could be predicted reliably.

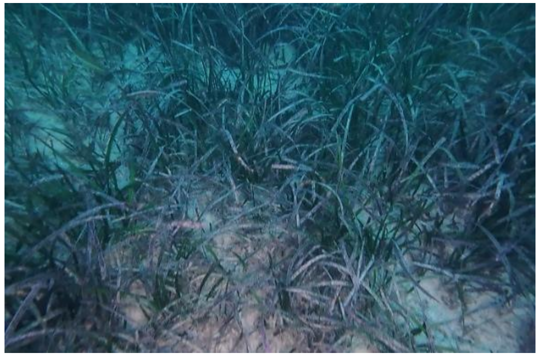
The ground-truthing data were linked to the OBIA polygons which intersect spatially. Dominant and subdominant biota classes, and substrate classes were assigned to each polygon. The classes were assessed for significance, with many hundreds of classes possible through substrate and biota combinations. Only the most commonly occurring classes were retained, and rare classes merged with similar more common classes. Following assessment, nine mapping categories (Table 6) were decided and assigned to the training data points (Figure 9).

Table 5: Ground-truthing datasets used to supplement the primary dataset

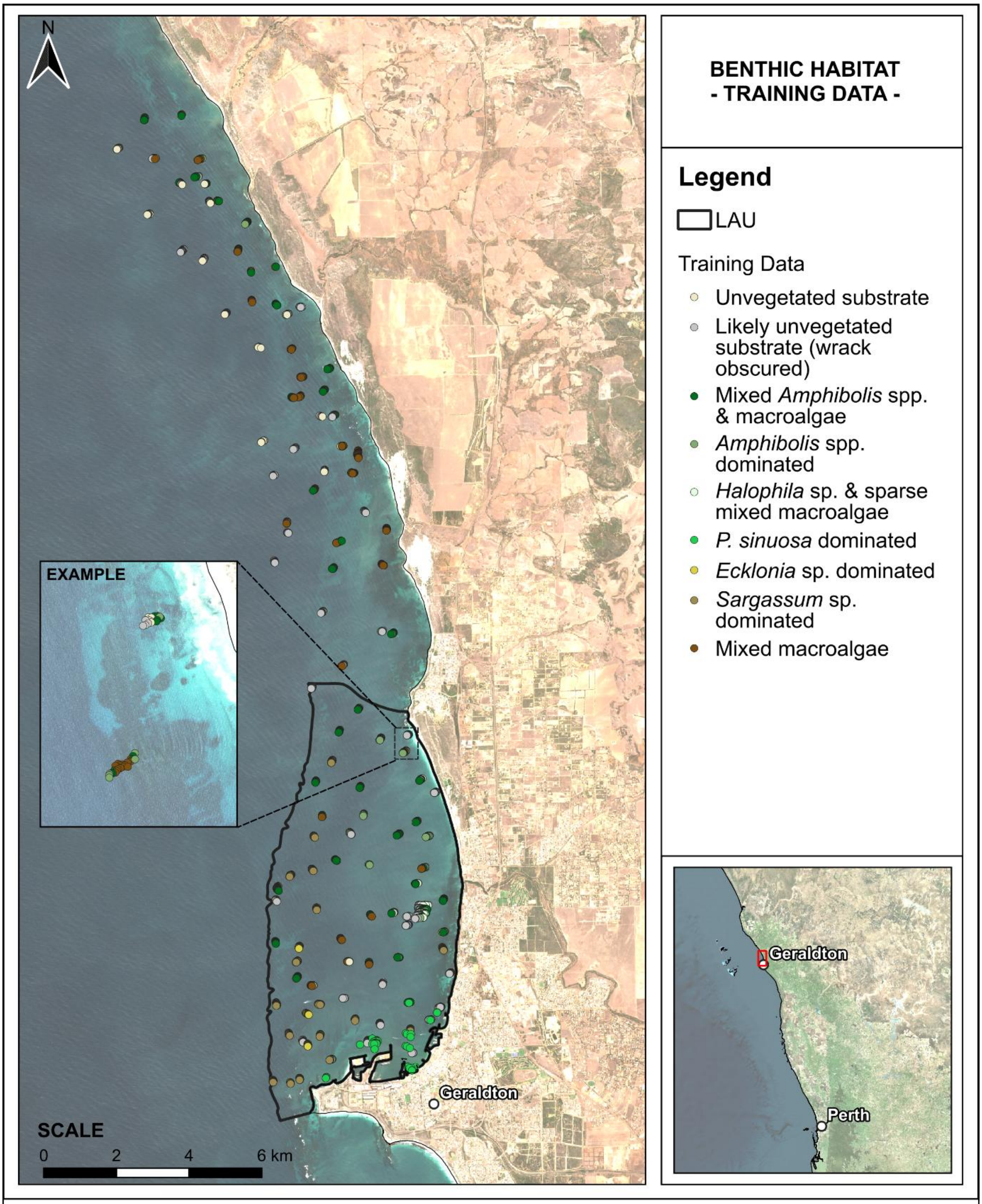
| Dataset Collector | Year | Purpose | Comments | Reference |
|---|---|---|---|---|
| O2 Marine | 2025 | Provide additional training data to improve model ability to distinguish between classes with overlapping characteristics. | Ground-truthing obtained for Oakajee benthic habitat mapping campaign. Methodology and classification scheme is consistent with the Champion Bay dataset. | O2 Marine (2025) |
| O2 Marine | 2025 | Enhance representation of *Posidonia sinuosa* to reduce model bias towards more common seagrass types. | Classified drop camera points near Geraldton Port and Fishing Boat Harbour. | O2 Marine internal dataset |
| SLR | 2024 | Enhance representation of *Posidonia sinuosa* to reduce model bias towards more common seagrass types. | Classified drop camera points near Geraldton Port and Fishing Boat Harbour. | Dataset provided by MWPA<br>SLR (2024) |
| BMT | 2022 | Enhance representation of *Posidonia sinuosa* to reduce model bias towards more common seagrass types. | Post dredge / long-term seagrass health study locations. Locations with persisting *Posidonia sinuosa* throughout study period (2007 - 2021). | BMT (2022) |

Table 6: Mapping classifications with examples from ground-truth video

| BCH Classification | Description | Example Images From Ground-truth Video |
|---|---|---|
| Unvegetated substrate | Bare sediment with flat relief or exhibiting 2D/3D ripple patterns, supporting sparse (<3%) or no visible biota. |   |
| Mixed *Amphibolis* spp. & macroalgae | Heterogeneous cover of *Amphibolis* species and macroalgae, including but not limited to *Sargassum* sp., various red and brown macroalgae, and epiphytes. Typically found over pavement reef and stable sand veneer. |   |
| *Amphibolis* spp. dominated | Area of seagrass dominated by *Amphibolis* species. Typically found over pavement reef and stable sand veneer. |   |

| BCH Classification | Description | Example Images From Ground-truth Video |
|---|---|---|
| *Halophila* sp. & sparse mixed macroalgae | Area of seagrass dominated by *Halophila* species. Typically found on unconsolidated sediment or patches of sediment within areas of pavement reef. |   |
| *Posidonia sinuosa* dominated | Area of seagrass dominated by *Posidonia sinuosa*. Typically growing on areas of unconsolidated sediment. Limited macroalgal cover, may feature some epiphytes and leaf detritus. |   |
| *Ecklonia* sp. dominated | *Ecklonia* sp. dominated macroalgal assemblage on low to moderate relief reef. Typically high to dense levels of cover with limited visibility of the substrate beneath. May co-occur encrusting red algae, or turfing species, but *Ecklonia* clearly dominates the vertical structure and biomass. |   |

| BCH Classification | Description | Example Images From Ground-truth Video |
|---|---|---|
| *Sargassum* sp. dominated | Area of macroalgae dominated by *Sargassum* species on limestone pavement or low to moderate relief reef. Some co-occurring biota may include filamentous or encrusting algae. |  |
| Mixed macroalgae | Macroalgal assemblage with no single dominant species or genus. May include *Sargassum* sp., *Ecklonia* sp., various red, brown and green filamentous macroalgae. Occurs over limestone pavement, rubble, or low-relief reef. |  |
| Likely unvegetated substrate (wrack obscured) | Benthic areas that are likely to be bare or sparsely vegetated, but true substrate or biotic cover cannot be clearly identified due to the presence of drift algae, seagrass wrack. It is a provisional classification, used to account for spectral ambiguity in imagery caused by accumulated organic material on the seafloor. |  |



| | |
|---|---|
| **Datum/Projection:** | GDA94 / MGA zone 50 |
| **Date:** | 04/09/2025 |
| **Basemap:** | Bing Virtual Earth |
| **Map Creator:** | M.S. |
| **Map Number:** | 25ENV391-20 |
| **Client:** | MWPA |

**NOTE:**

Positional accuracy is to be considered approximate. Not for navigation.

Figure 9: Benthic habitat mapping training data with zoomed example

### 3.6.1. Supervised Classification

The supervised classification method used utilises Random Forest; an ensemble learning method for supervised classification that operates by constructing a large number (500) of decision trees during training. Random Forest classification uses a combination of 'tree' predictors, where each tree depends on the values of a random vector sampled independently for all trees in the 'forest'. Multiple trees are generated at each node, with classes being assigned through a majority vote (Breiman, 2001). The random forest classification technique has been successfully applied in numerous benthic habitat mapping studies involving the use of bathymetry and its derivatives, and other related work (Brown et al., 2011; Hasan et al., 2012).

Using the training data (Figure 9), the known locations of identified habitats are used to query the environmental predictor layers (Figure 10). Once a signature set has been developed for each confirmed habitat location, the machine learning algorithm then interrogates the entire dataset and attempts to identify other 'suitable' background signature combinations which might also indicate the existence of the habitat.

Supervised data classification was undertaken in a Python-based software implementation based on WhiteBoxTools (Lindsay, 2014). Classes are outlined in Table 6. The classification was then applied to the entire dataset, allowing the algorithm to assess the band spectral values for each pixel cell. The classification was undertaken on every Sentinel 2 image (time slice) in order to capture variation in habitat distribution over time. Classified images were further integrated for analysis using a fusion of classes (majority vote) procedure to produce a single robust classification map. This procedure integrates all classification maps to obtain a majority vote to determine the final class assigned to each cell, providing the most rigorous assessment of habitat distribution. A 'Mixed Biota' class is assigned when no majority can be found (indicating high variability in that cell).

Following classification, a quality control check of the output raster was carried out by an ecologist. Minor areas which were considered affected by noise or artefacts in predictor layers were manually corrected to the appropriate classifications.

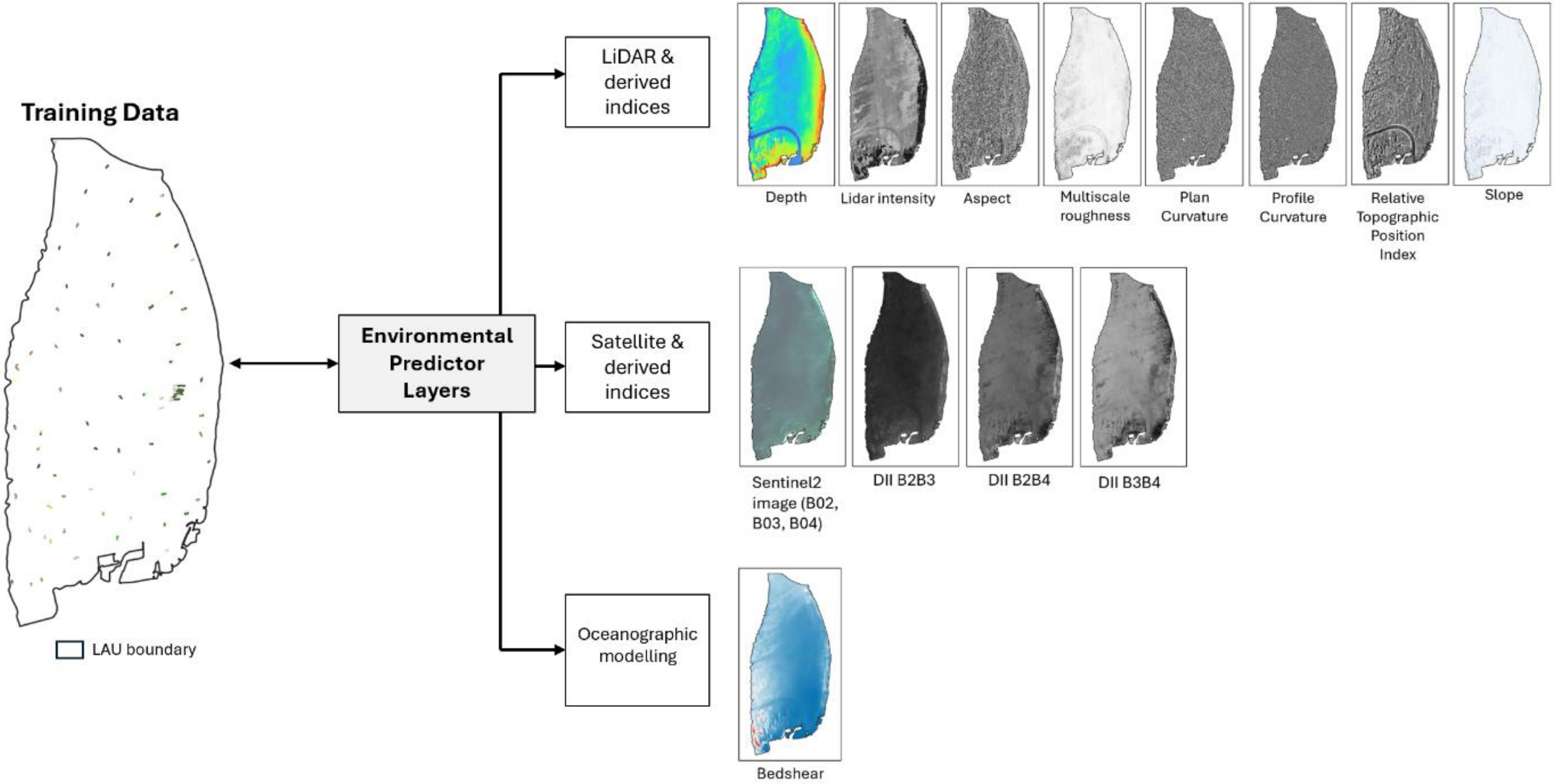


Figure 10: Schematic diagram illustrating the process of sampling the values of the environmental predictor layers at the locations of the training data

# 4. Results

## 4.1. Ground-truthing

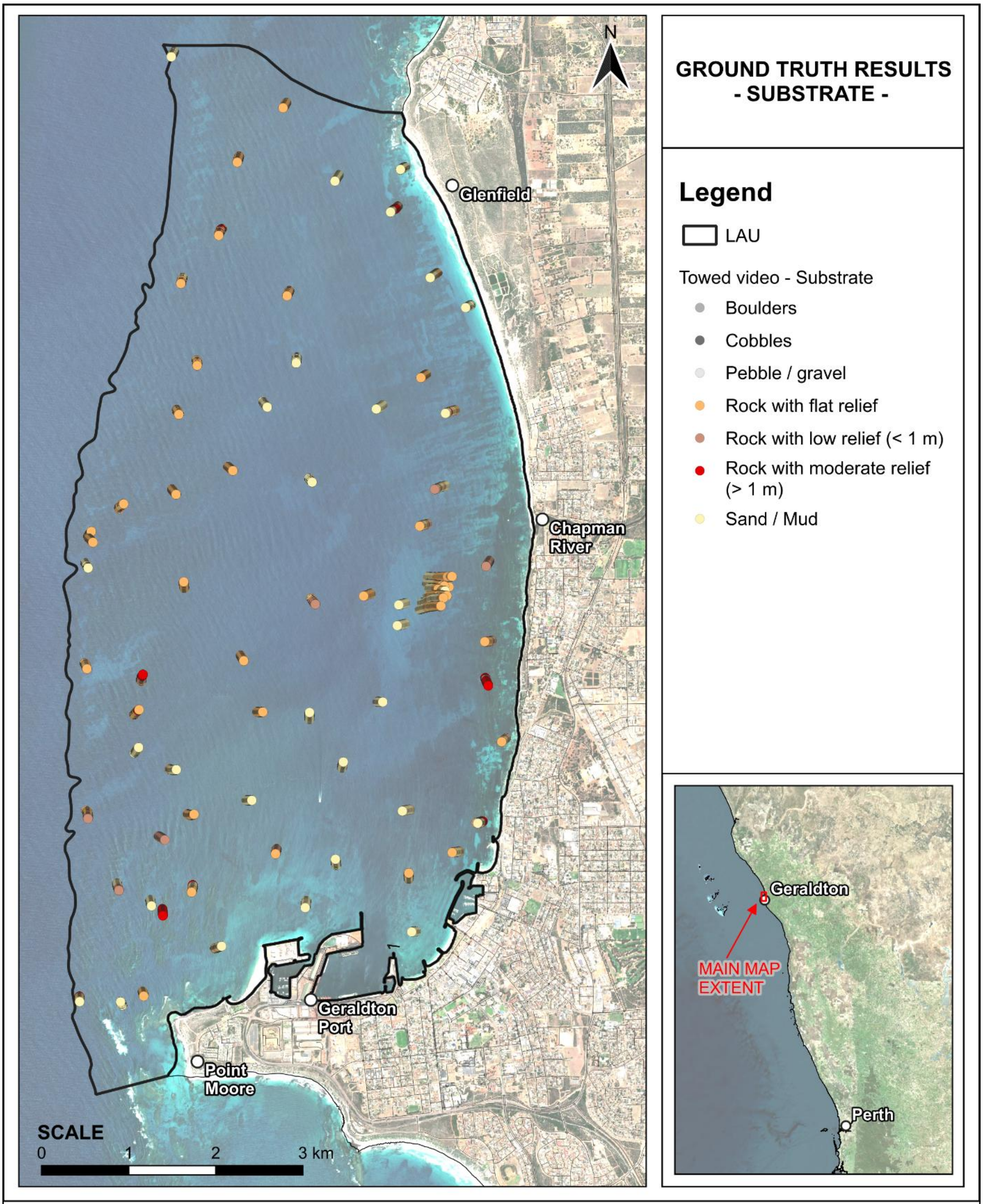
### 4.1.1. Substrates

Using the 2025 towed video data, a total of 22904 points across Champion Bay were classified with biological attributes and habitat classifications (Table 7, Figure 11). Note that due to the scale of the maps relative to the length of the transects, Figure 11, Figure 13, Figure 14 and Figure 15 do not reveal habitat and substrate changes across transects. The purpose of these figures is to provide an overview of the dataset, and classifications observed at each transect on these maps should not be considered completely representative of the broader BCH type at each location. For a focused example of classified transects see Figure 16.

An overview of the substrate information classified along ground-truthing transects is presented in Figure 11, with the proportion of each substrate class presented in Table 7. Sand / Mud, and Rock - Flat were the dominant substrate classes observed throughout the dataset, comprising 44.0% and 41.1%, respectively, of all classified points with substrate information. Both substrate types appear distributed throughout the LAU (Figure 11), however Sand / Mud is most commonly found across the eastern and southern regions, adjacent to the coastline. Rock – Flat was observed throughout the LAU, however there are a notable lack of observations of this substrate type throughout the central area of Champion Bay. Rock - Low (<1 m) (8.7%) was the next most common substrate class, followed by Rock – Moderate (1-3 m) (1.2%). Pebble / Gravel, Boulders and Cobbles collectively accounted for <1% of classified substrate points. These three substrate types were all identified across just three transects in the southeast of Champion Bay.

Table 7: Observed substrate types identified in ground-truthing data

| Substrate | Number of points classified | Proportion of classified points |
|---|---|---|
| Sand / Mud | 10076 | 44.0% |
| Rock with flat relief | 9413 | 41.1% |
| Rock with low relief (< 1 m) | 1993 | 8.7% |
| Rock with moderate relief (> 1 m) | 1266 | 5.5% |
| Pebble / Gravel | 108 | 0.5% |
| Boulders | 36 | 0.2% |
| Cobbles | 12 | 0.1% |
| Total | **22904** | **100** |



| | |
|---|---|
| **Datum/Projection:** | GDA94 / MGA zone 50 |
| **Date:** | 24/06/2025 |
| **Basemap:** | Bing Virtual Earth |
| **Map Creator:** | M.S. |
| **Map Number:** | 25ENV391-11 |
| **Client:** | MWPA |

**NOTE:**

Positional accuracy is to be considered approximate. Not for navigation.

Figure 11: Ground-truthing results overview - Substrate class

### 4.1.2. Biota

Figure 13 provides an overview of the major biota classes recorded along the ground-truthing transects, with a proportional representation of each class detailed in Table 8. Macroalgae was the most frequently observed biota type, comprising approximately 40% of all classified points. While macroalgae was recorded throughout the LAU, the highest concentration of observations occurred in deeper offshore areas to the west, particularly in association with pavement reef and low to moderate relief reef. Macroalgal cover is predominantly moderate to dense (Moderate: 9.2%, High: 16.9%, Dense: 12.5%), while sparse to low coverage is relatively uncommon. The most dominant single biota type is *Sargassum* spp. (Figure 12), found mainly over offshore pavement reef. Mixed macroalgal assemblages are also widely distributed. *Ecklonia* sp. is consistently identified in offshore regions surrounding Point Moore, where it is closely associated with low to moderate relief reef.

Seagrass accounts for 24.4% of all classified points. Like macroalgae, it is primarily observed in high to dense coverage classes (High: 12.3%, Dense: 6.2%), with sparse and low cover being rare (<1%). The dominant seagrass is *Amphibolis* spp. (Figure 12), typically associated with pavement reef and stable sand veneer in mid-depth areas of the LAU. *Halophila* sp. is moderately represented, while *Posidonia* spp. is uncommon, comprising less than 2.5% of the total.

Mixed assemblages of seagrass and macroalgae - where no single biota type dominates - represent a smaller portion of the dataset (12.4%), with most observations falling into the moderate cover category.

Drift algae / wrack is also relatively common, comprising 19.7% of all points. Approximately 70% of these observations were classified as having sparse cover. Wrack is primarily observed in the southern and nearshore regions of the LAU.

Table 8: Number of ground-truth points classified per major biota and cover class

| Biota Class | Cover | Number of points classified | Class total | Proportion of points classified (%) | Proportion of classified points with biota (%) |
|---|---|---|---|---|---|
| Macroalgae (MA) | MA - Sparse | 70 | 9104 | 0.3 | 0.4 |
| | MA - Low | 198 | | 0.9 | 1.1 |
| | MA - Moderate | 2107 | | 9.2 | 12.0 |
| | MA - High | 3871 | | 16.9 | 22.1 |
| | MA - Dense | 2858 | | 12.5 | 16.3 |
| Seagrass (SG) | SG - Sparse | 60 | 5595 | 0.3 | 0.3 |
| | SG - Low | 192 | | 0.8 | 1.1 |
| | SG - Moderate | 1125 | | 4.9 | 6.4 |
| | SG - High | 2806 | | 12.3 | 16.0 |
| | SG - Dense | 1412 | | 6.2 | 8.1 |
| Mixed Assemblage – Seagrass & Macroalgae (MX) | MX - Sparse | 0 | 2835 | 0.0 | 0.0 |
| | MX - Low | 19 | | 0.1 | 0.1 |
| | MX - Moderate | 2153 | | 9.4 | 12.3 |
| | MX - High | 663 | | 2.9 | 3.8 |
| | MX - Dense | 0 | | 0.0 | 0.0 |
| Bare Sediment (BS) | Bare | 861 | 861 | 3.8 | |
| | | | | 0.0 | |

| Biota Class | Cover | Number of points classified | Class total | Proportion of points classified (%) | Proportion of classified points with biota (%) |
|---|---|---|---|---|---|
| | | | | 0.0 | |
| | | | | 0.0 | |
| | | | | 0.0 | |
| Drift Algae / Wrack (OT) | OT - Sparse | 3286 | 4509 | 14.4 | |
| | OT - Low | 904 | | 3.9 | |
| | OT - Moderate | 116 | | 0.5 | |
| | OT - High | 203 | | 0.9 | |
| | OT - Dense | 0 | | 0.0 | |
| **Total** | | 22904 | 22904 | 100.0 | 100.0 |

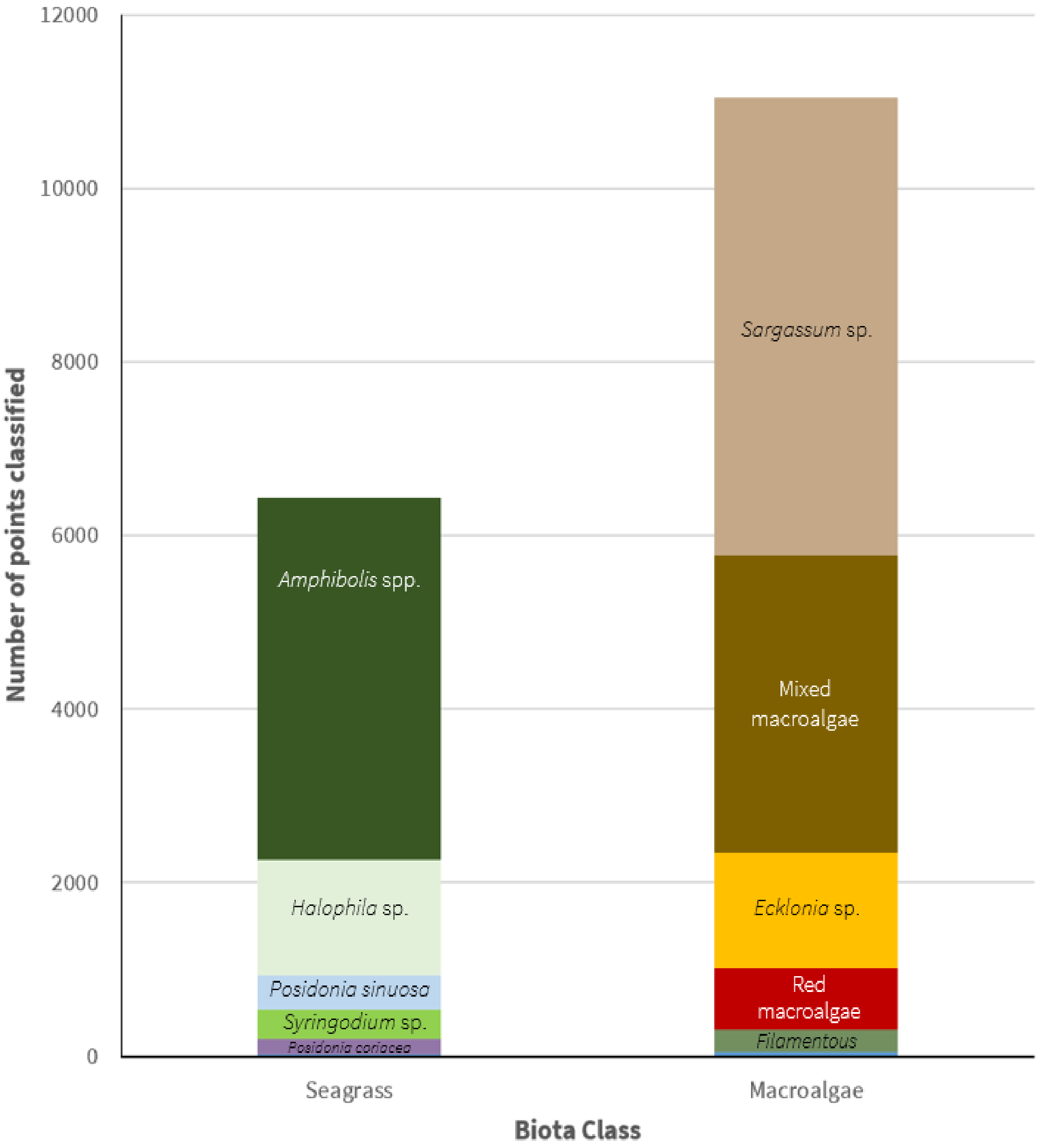
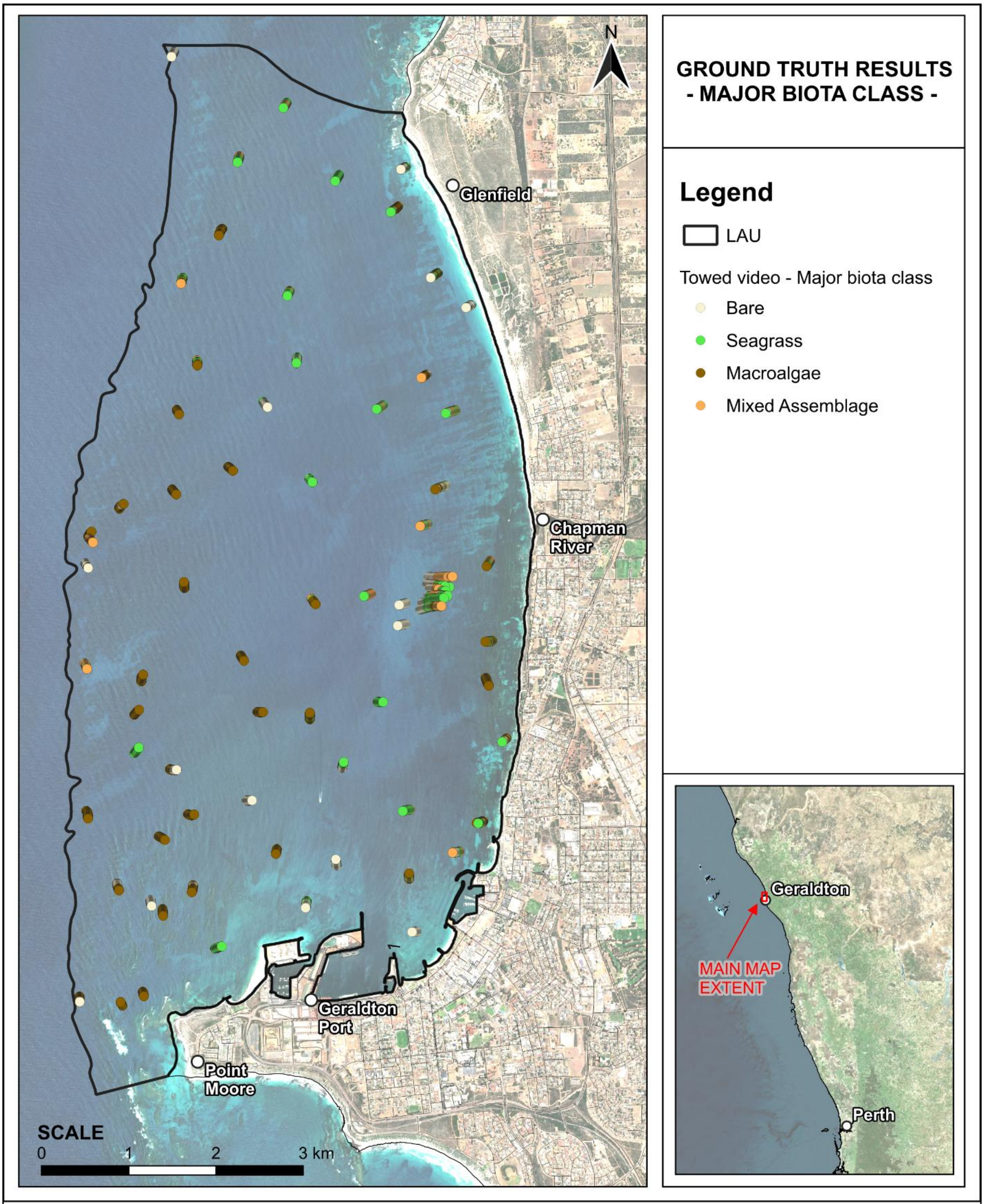


Figure 12: Number of ground-truth points classified as each dominant biota class for seagrass and macroalgae

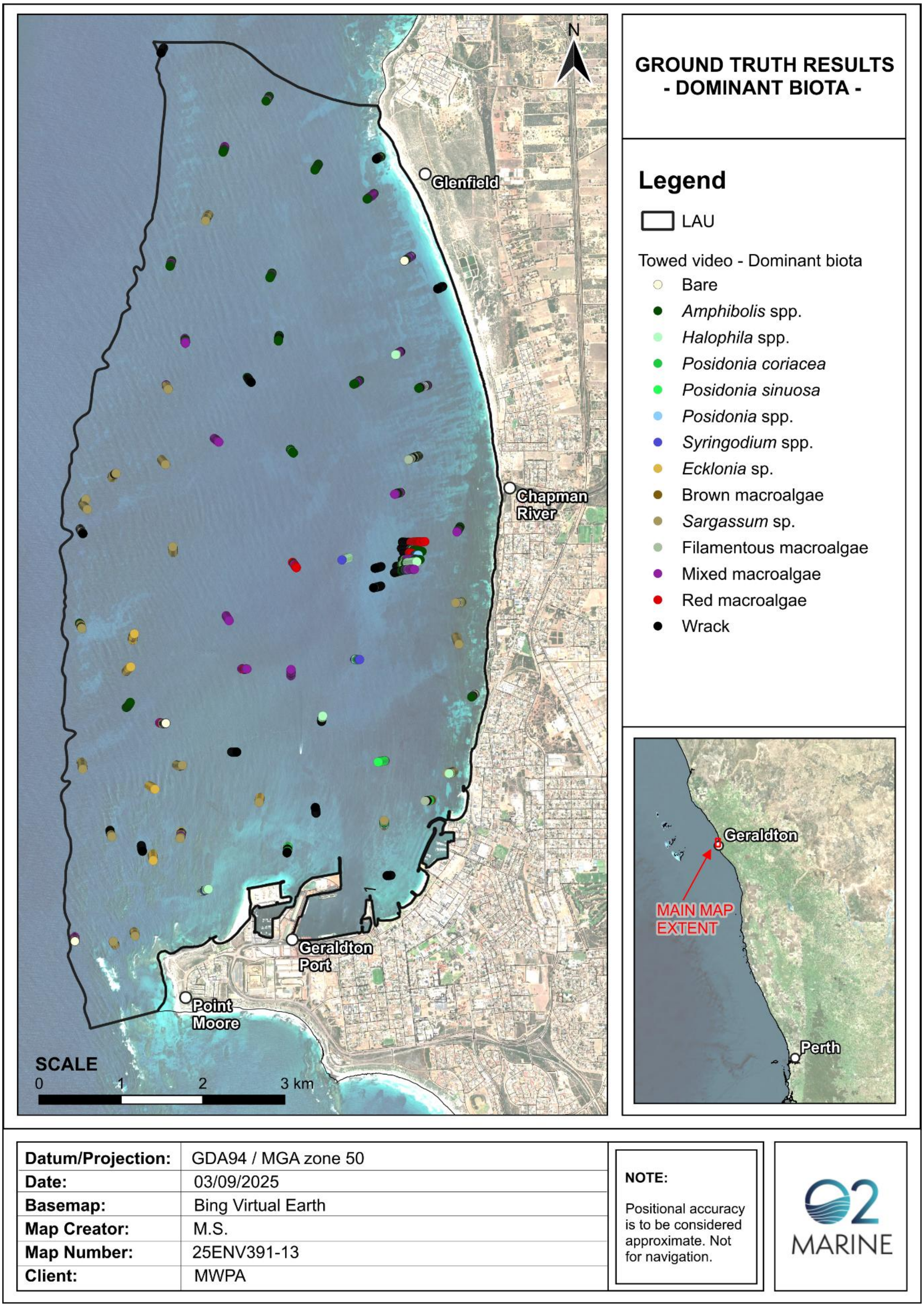


| | |
|---|---|
| **Datum/Projection:** | GDA94 / MGA zone 50 |
| **Date:** | 24/06/2025 |
| **Basemap:** | Bing Virtual Earth |
| **Map Creator:** | M.S. |
| **Map Number:** | 25ENV391-10 |
| **Client:** | MWPA |

**NOTE:**

Positional accuracy is to be considered approximate. Not for navigation.

Figure 13: Ground-truthing results overview - major biota class



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|---|---|
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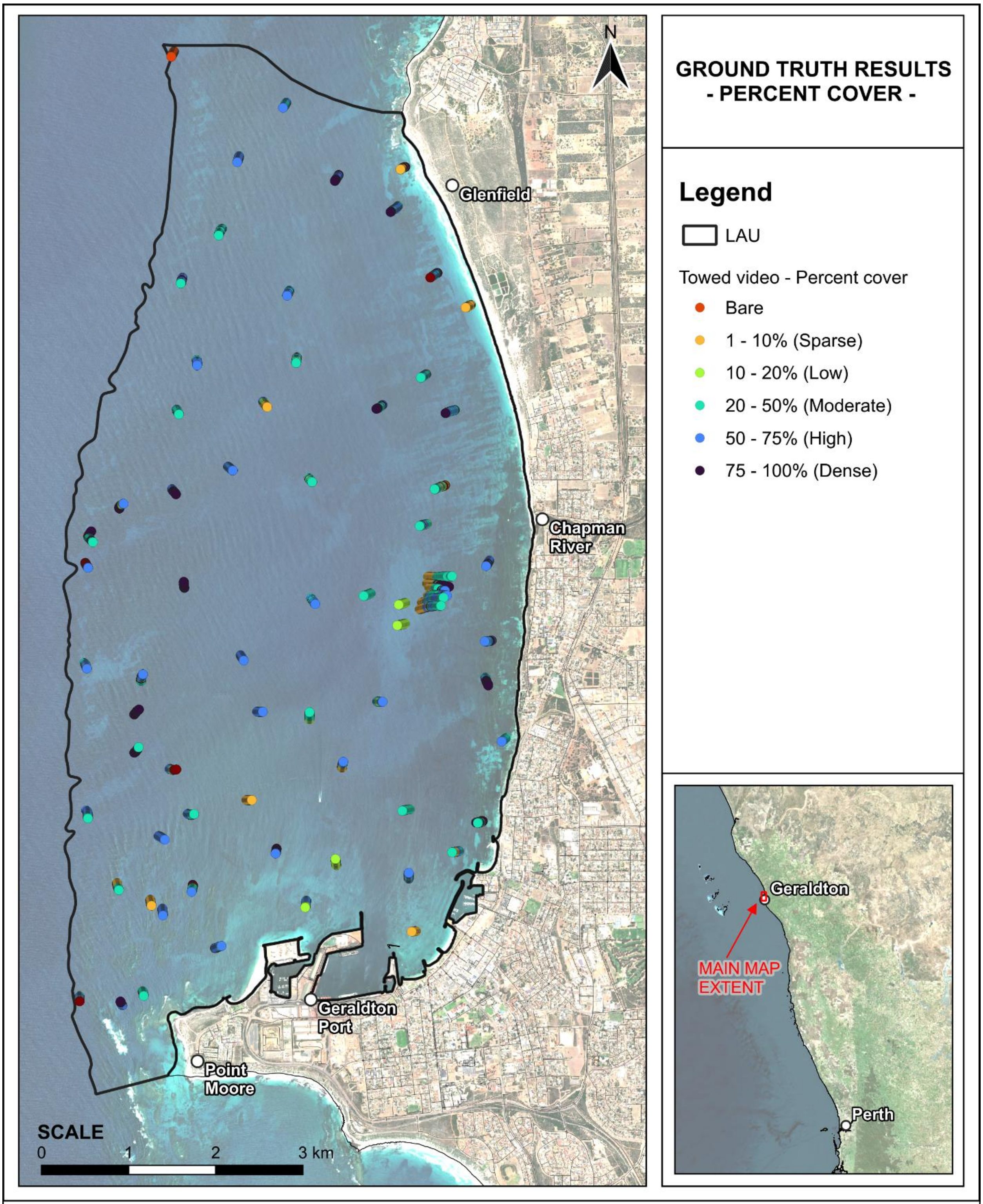
| **Basemap:** | Bing Virtual Earth |
| **Map Creator:** | M.S. |
| **Map Number:** | 25ENV391-13 |
| **Client:** | MWPA |

**NOTE:**

Positional accuracy is to be considered approximate. Not for navigation.

Figure 14: Ground-truthing results overview – dominant biota

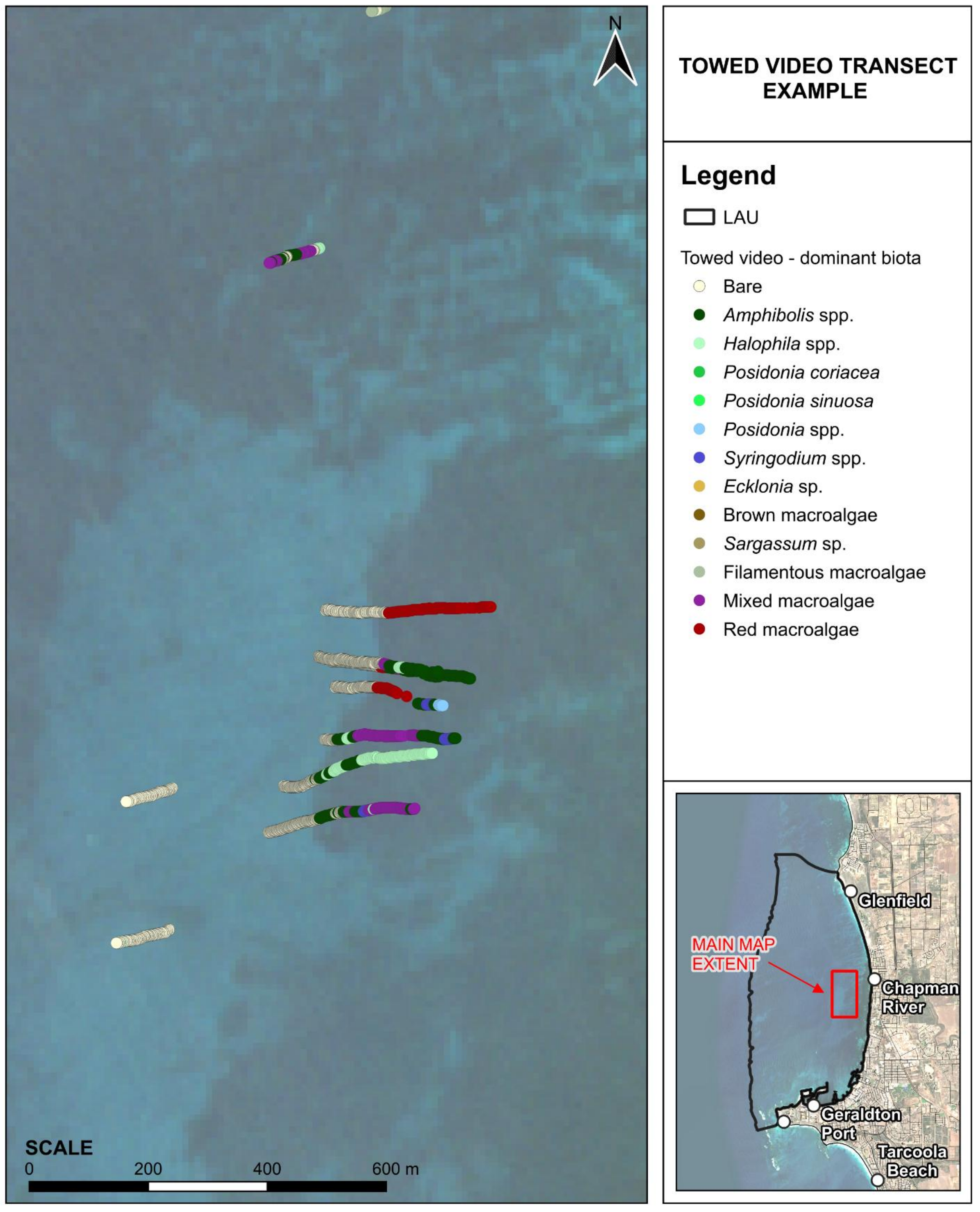


| | |
|---|---|
| **Datum/Projection:** | GDA94 / MGA zone 50 |
| **Date:** | 24/06/2025 |
| **Basemap:** | Bing Virtual Earth |
| **Map Creator:** | M.S. |
| **Map Number:** | 25ENV391-12 |
| **Client:** | MWPA |

**NOTE:**

Positional accuracy is to be considered approximate. Not for navigation.

Figure 15: Ground-truthing results overview - percent cover



| | |
|---|---|
| **Datum/Projection:** | GDA94 / MGA zone 50 |
| **Date:** | 03/09/2025 |
| **Basemap:** | Sentinel 2 (10/05/25), Bing Virtual Earth |
| **Map Creator:** | M.S. |
| **Map Number:** | 25ENV391-22 |
| **Client:** | MWPA |

**NOTE:**

Positional accuracy is to be considered approximate. Not for navigation.

Figure 16: Zoomed example of classified towed video transects

## 4.2. Mapping

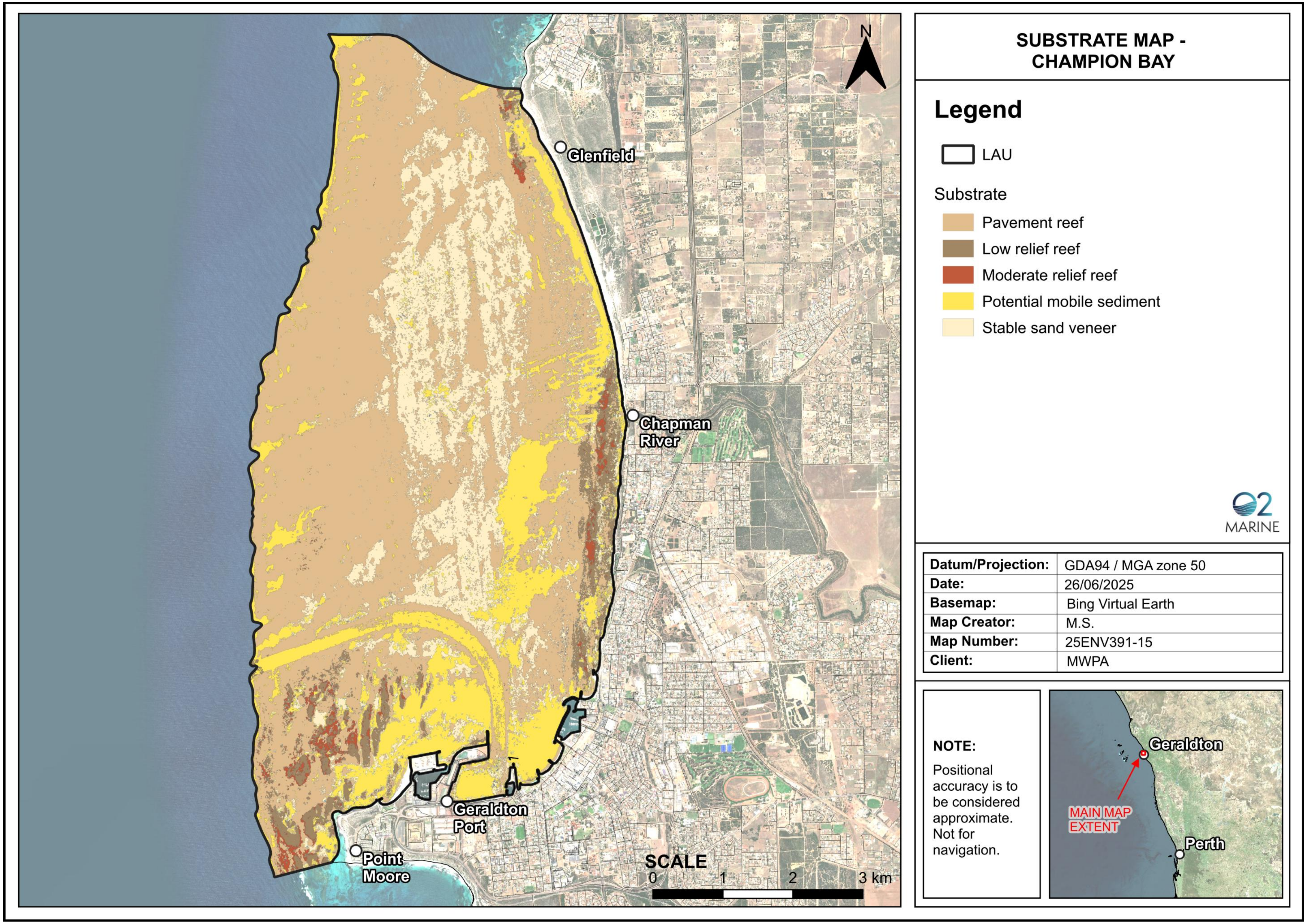
### 4.2.1. Substrates

The random forest classification procedure undertaken on the composite stack and training dataset provided a coherent substrate map, which comprised five final classes mapped across a total area of 4696.3 ha (Table 9, Figure 17).

Pavement reef was the most prevalent substrate type, covering 56.4% of the mapped area. It is especially widespread across the offshore region of the LAU, dominating much of the seafloor between depths of 12 and 16 meters. Pavement reef is also present in inshore areas. The next most common substrate types are stable sand veneer (20.4%) and potential mobile sediment (17.4%). Stable sand veneer is primarily concentrated in the central part of the LAU, interspersed between patches of exposed pavement reef. Potential mobile sediments are mainly found around the outer edges of the LAU and in the southeastern region, including the nearshore Dredge Material Placement Area (DMPA). Low relief reef and moderate relief reef make up the remaining substrate types, accounting for 4.5% and 1.3% of the area, respectively. These reef types are located exclusively at two key areas, including along the west-facing shoreline of the LAU, extending from Sunset Beach southward to Batavia Coast Marine, as well as an area offshore of Point Moore. Moderate relief reef is limited to localised areas within the broader zones of low relief reef.

Table 9: Substrate classes by mapped area in Champion Bay

| Substrate | Area (ha) | Percentage of mapped area (%) |
|---|---|---|
| Pavement reef | 2647.68 | 56.4 |
| Stable sand veneer | 959.18 | 20.4 |
| Potential mobile sediment | 818.76 | 17.4 |
| Low relief reef | 210.66 | 4.5 |
| Moderate relief reef | 59.97 | 1.3 |
| Total | **4696.25** | **100** |



| | |
|---|---|
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| **Basemap:** | Bing Virtual Earth |
| **Map Creator:** | M.S. |
| **Map Number:** | 25ENV391-15 |
| **Client:** | MWPA |

**NOTE:**

Positional accuracy is to be considered approximate. Not for navigation.

Figure 17: Substrate map of Champion Bay

### 4.2.2. Benthic Habitats

The random forest classification procedure undertaken on the composite stack and training dataset provided a coherent 'dominant class' habitat map, which comprised nine final classes mapped across a total area of 4728.4 ha (Table 10,

Figure 18).

The most widespread habitat class within the LAU was Mixed *Amphibolis* spp. and macroalgae, covering 1909.3 hectares (40.2% of the total area). Although this habitat type occurs throughout the LAU, it is most commonly found between depths of 6 and 12 meters. Analysis of associated substrate types ( Figure 17) indicates that this habitat is primarily linked to pavement reef and stable sand veneer.

Three additional seagrass-dominated habitat classes were identified within the LAU, including *Halophila* sp. & sparse mixed macroalgae (187.9 ha, 4.0%), *Amphibolis* spp. dominated habitat (168.6 ha, 3.6%) and *Posidonia sinuosa* dominated habitat (75.4 ha, 1.6%). The *Halophila* sp. habitat is primarily distributed in nearshore areas south of Chapman River, as well as an offshore area immediately north of the shipping channel. The offshore area features a mosaic of benthic habitats, including *Sargassum* sp. dominated habitat, mixed macroalgae, and mixed *Amphibolis* spp. and macroalgae. *Amphibolis* spp. dominated habitat has a patchy distribution, primarily across the mid depths of the LAU amongst the broader area of mixed *Amphibolis* spp. and macroalgae. *Posidonia sinuosa* dominated habitat occupies nearshore areas across the south and east of the LAU, with the most significant distributions found adjacent to the fishing boat harbour entrance, Pages Beach, and an area between the shipping channel and Batavia Coast Marina.

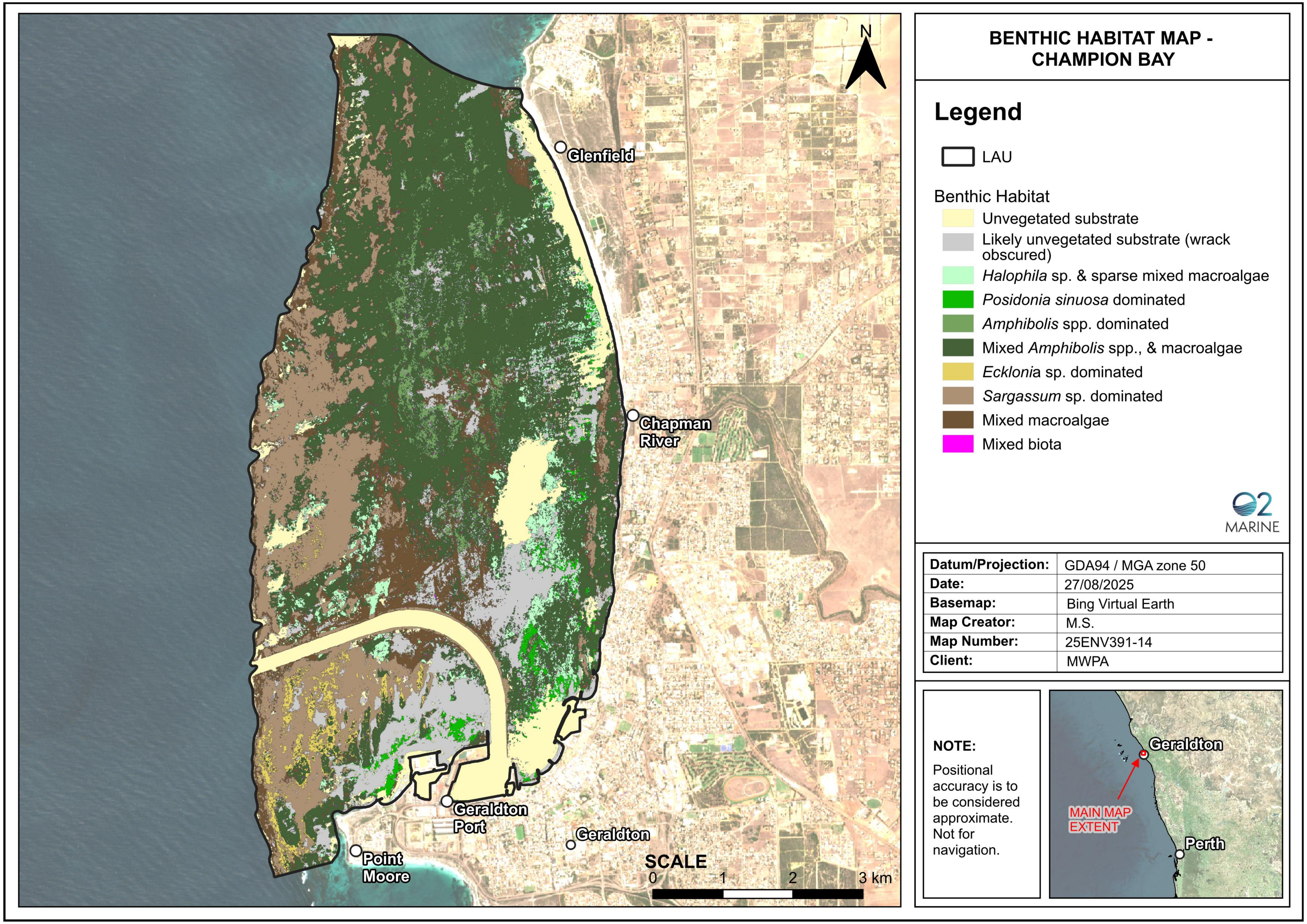
Three macroalgae-dominant habitat classes were mapped across the LAU. *Sargassum* sp. dominated habitat is the most extensive, covering 793.1 hectares (16.7%). It is widely distributed across offshore areas, particularly in association with pavement reef along the western side of the LAU and with low to moderate relief reef near the west-facing shoreline and offshore of Point Moore. Mixed macroalgae habitat (519 ha, 10.9%) is mostly associated with pavement reef and occurs in a few distinct locations, including areas adjacent to the shipping channel, north and south of the DMPA, and along the Glenfield shoreline. *Ecklonia* sp. dominated habitat (84.6 ha, 1.78%) is primarily associated with low to moderate relief reef offshore of Point Moore, though some isolated patches also occur further north across areas of pavement reef.

Unvegetated substrate accounts for 532.3 hectares (11.2%) and appears in scattered patches throughout the LAU, including areas between pavement reefs, the dredged shipping channel, nearshore beach zones, and around the nearshore dredge material placement area. Some additional areas are likely to feature unvegetated substrate, but confirmation is limited due to wrack obscuring satellite and ground-truth observations. These potentially unvegetated zones include the region near the fishing boat harbour and two offshore patches near Beresford and Sunset Beach.

The mixed biota class, representing areas without a single dominant habitat type, covers a very small area of 11.6 hectares (0.2%). It typically appears as small patches (10 - 20 m in size) scattered throughout the LAU.

Table 10: Benthic habitat classes by mapped area in Champion Bay

| **Benthic Habitat Class** | **Area (ha)** | **Percentage of mapped area (%)** |
|---|---|---|
| Mixed *Amphibolis* spp. & macroalgae | 1909.33 | 40.2 |
| *Sargassum* sp. dominated | 793.12 | 16.7 |
| Unvegetated substrate | 532.29 | 11.2 |
| Mixed macroalgae | 519.00 | 10.9 |
| Likely unvegetated substrate (wrack obscured) | 471.85 | 9.9 |
| *Halophila* sp. & sparse mixed macroalgae | 187.91 | 4.0 |
| *Amphibolis* spp. dominated | 168.57 | 3.6 |
| *Ecklonia* sp. dominated | 84.61 | 1.8 |
| *Posidonia sinuosa* dominated | 75.4 | 1.6 |
| Mixed biota | 11.6 | 0.2 |
| **Total** | **4728.43** | **100** |



| | |
|---|---|
| **Datum/Projection:** | GDA94 / MGA zone 50 |
| **Date:** | 27/08/2025 |
| **Basemap:** | Bing Virtual Earth |
| **Map Creator:** | M.S. |
| **Map Number:** | 25ENV391-14 |
| **Client:** | MWPA |

**NOTE:**

Positional accuracy is to be considered approximate. Not for navigation.

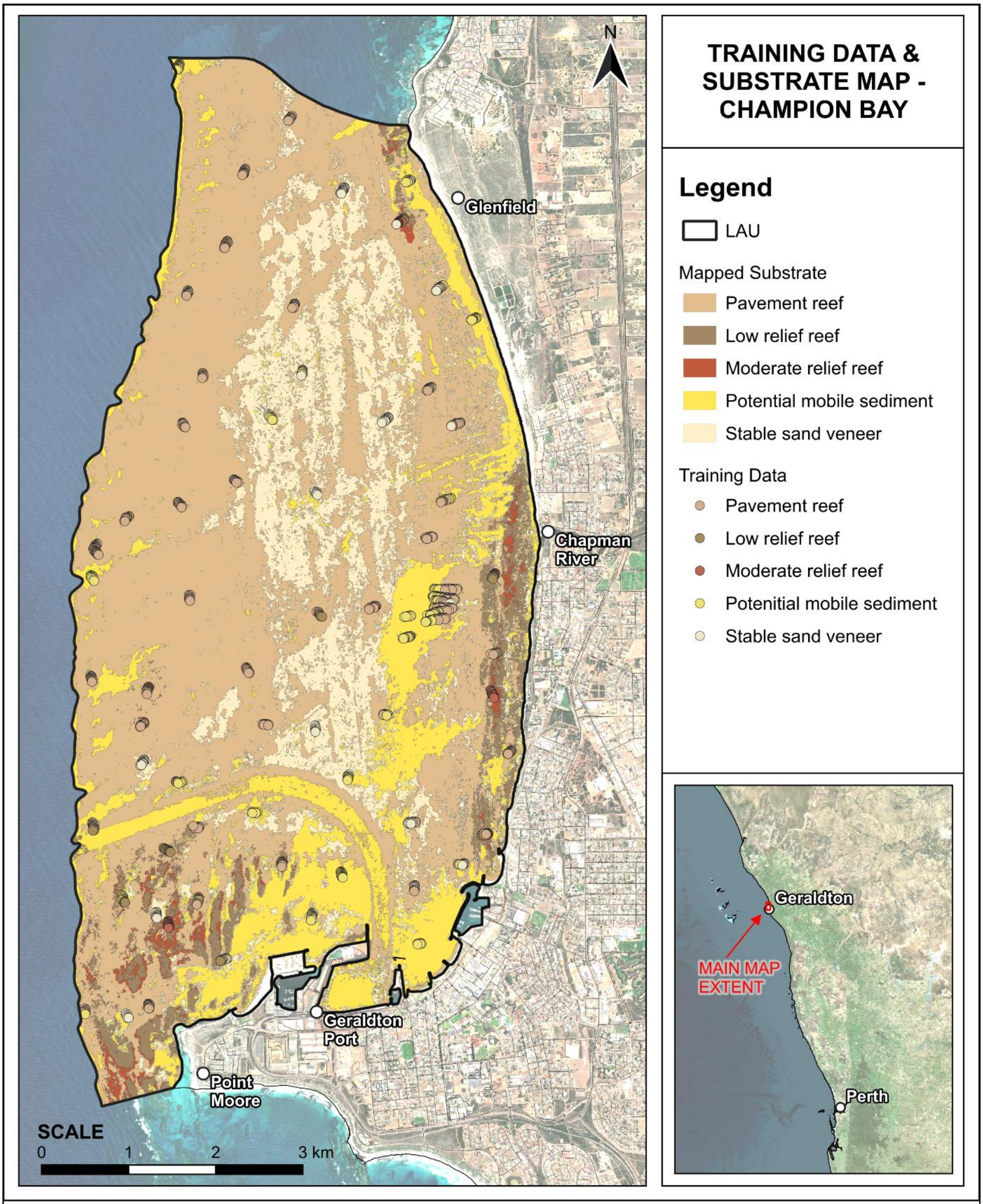
Figure 18: Benthic habitat map of Champion Bay

## 4.3. Mapping Validation

On completion of the model training, validation metrics were generated to assess the performance of the classifier across different substrate and habitat types. The confusion matrices (Table 11, Table 12) and class statistics (Table 13, Table 14) present a detailed account of the model's predictive accuracy, with the rows indicating reference (true) labels and the columns depicting the labels predicted by the model. This premise is also visually depicted in Figure 19 and Figure 20.

The calculation of accuracy is derived from the confusion matrix, which compares actual vs. predicted classifications. Indicators of accuracy include key performance metrics used in classification tasks to evaluate the accuracy of a model:

- True Positives: correctly predicted as positive for each class.
- True Negatives: correctly predicted as negative i.e. not belonging to a particular class.
- False Positives: incorrectly predicted as positive.
- False Negatives: incorrectly predicted as negative.
- Precision: measures the proportion of true positive predictions out of all positive predictions made (True positives/(True Positives + False Positives)), indicating how many of the predicted positive instances are actually correct.
- Recall (also known as sensitivity): measures the proportion of true positive predictions out of all actual positive instances (True positives/(True Positives + False Negatives)), reflecting the model's ability to identify all relevant cases.
- F-score: the harmonic mean of precision and recall, providing a single metric that balances both aspects. It is particularly useful in scenarios where both false positives and false negatives are critical.



| | |
|---|---|
| **Datum/Projection:** | GDA94 / MGA zone 50 |
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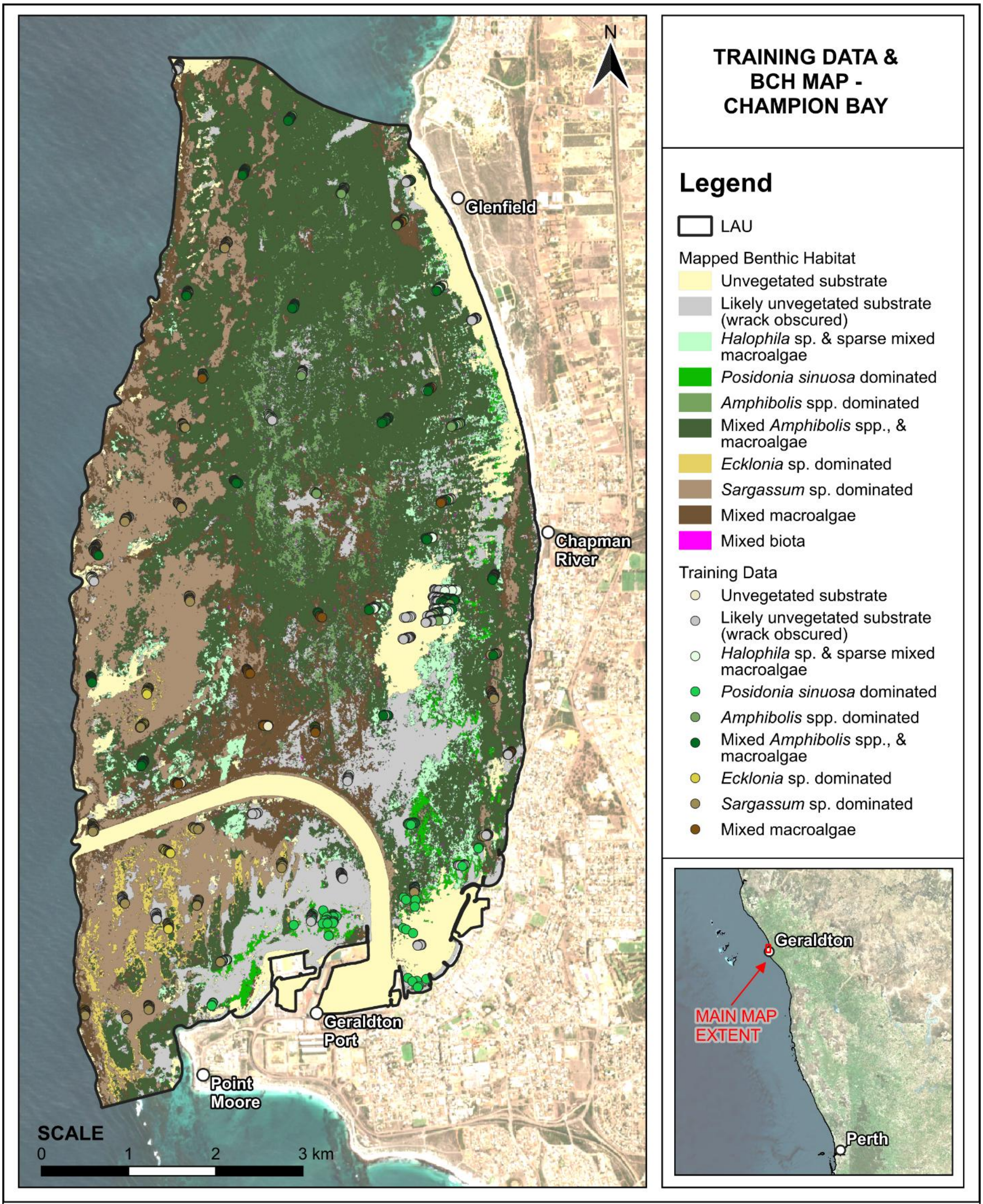
| **Basemap:** | Bing Virtual Earth |
| **Map Creator:** | M.S. |
| **Map Number:** | 25ENV391-19 |
| **Client:** | MWPA |

**NOTE:**

Positional accuracy is to be considered approximate. Not for navigation.

Figure 19: Model training data overlaid on the Champion Bay benthic habitat map



| | |
|---|---|
| **Datum/Projection:** | GDA94 / MGA zone 50 |
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| **Basemap:** | Bing Virtual Earth |
| **Map Creator:** | M.S. |
| **Map Number:** | 25ENV391-18 |
| **Client:** | MWPA |

**NOTE:**

Positional accuracy is to be considered approximate. Not for navigation.

Figure 20: Model training data overlaid on the Champion Bay benthic habitat map

Table 11: Confusion matrix for substrate classifications (misclassification assessment)

| | | MODEL PREDICTION | | | | |
|---|---|---|---|---|---|---|
| TRAINING DATA | CLASS | Pavement reef | Low relief reef | Moderate relief reef | Potential mobile sediment | Stable sand veneer |
| | Pavement reef | **19.0** | 0.5 | 0.0 | 0.0 | 0.5 |
| | Low relief reef | 9.0 | **9.0** | 1.5 | 0.5 | 0.0 |
| | Moderate relief reef | 5.0 | 0.5 | **14.0** | 0.5 | 0.0 |
| | Potential mobile sediment | 1.5 | 0.0 | 0.0 | **17.5** | 1.0 |
| | Stable sand veneer | 5.3 | 0.0 | 0.0 | 1.3 | **13.5** |

Table 12: Confusion matrix for benthic habitat classifications (misclassification assessment)

| | | MODEL PREDICTION | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| TRAINING DATA | CLASS | Unvegetated substrate | Likely unvegetated substrate (wrack obscured) | *Halophila* sp. & sparse mixed macroalgae | *Ecklonia* sp. dominated | *Amphibolis* spp. dominated | Mixed *Amphibolis* spp. & macroalgae | Mixed macroalgae | *Sargassum* sp. dominated | *Posidonia sinuosa dominated* |
| | Unvegetated substrate | 15.3 | 3.0 | 0.0 | 0.0 | 0.3 | 0.7 | 0.3 | 0.0 | 0.4 |
| | Likely unvegetated substrate (wrack obscured) | 0.1 | 19.3 | 0.0 | 0.0 | 0.0 | 0.6 | 0.0 | 0.0 | 0.0 |
| | *Halophila* sp. & sparse mixed macroalgae | 0.0 | 1.7 | 12.9 | 0.0 | 0.7 | 2.7 | 1.6 | 0.0 | 0.4 |
| | *Ecklonia* sp. dominated | 0.6 | 0.1 | 0.0 | 11.0 | 0.0 | 0.6 | 0.4 | 7.3 | 0.0 |
| | *Amphibolis* spp. dominated | 0.3 | 3.7 | 2.9 | 0.0 | 5.1 | 6.4 | 0.9 | 0.7 | 0.0 |
| | Mixed *Amphibolis* spp. & macroalgae | 0.4 | 0.7 | 0.6 | 0.1 | 0.1 | 16.6 | 1.3 | 0.0 | 0.1 |
| | Mixed macroalgae | 0.0 | 1.4 | 0.1 | 0.0 | 0.0 | 2.0 | 15.1 | 1.3 | 0.0 |
| | *Sargassum* sp. dominated | 0.0 | 0.1 | 0.0 | 0.7 | 0.0 | 0.6 | 1.1 | 17.0 | 0.0 |
| | *Posidonia sinuosa* dominated | 0.3 | 1.1 | 0.1 | 0.0 | 0.0 | 3.0 | 0.1 | 0.0 | 15.3 |

Table 13: Class statistics for substrate types

| Class | Precision | Recall | F-Score | Comment |
|---|---|---|---|---|
| Pavement reef | 0.48 | 0.95 | 0.64 | Moderate precision and very high recall, indicating that the model is able to capture most instances of this substrate type. |
| Low relief reef | 0.90 | 0.45 | 0.59 | High precision but relatively low recall, indicating that the model confuses some true instances of this habitat. |
| Moderate relief reef | 0.92 | 0.70 | 0.79 | High precision and moderate recall. Suggests that the model is generally accurate when it does predict this class, however there is a large degree of overlapping spectral signatures which likely reflects a combination of imperfect predictor layers as well as actual habitat overlap. |
| Potential mobile sediment | 0.89 | 0.88 | 0.88 | Strong overall performance with very high precision and recall, indicating that there are almost no false positives and the model effectively identifies most cases. |
| Stable sand veneer | 0.90 | 0.68 | 0.77 | High precision but moderate recall, reflecting some difficulty in capturing all true instances. |

Table 14: Class statistics for benthic habitats

| Class | Precision | Recall | F-Score | Comment |
|---|---|---|---|---|
| Unvegetated substrate | 0.82 | 0.83 | 0.83 | Strong overall performance with very high precision and recall, indicating that there are almost no false positives and the model effectively identifies most cases. |
| Mixed *Amphibolis* spp. & macroalgae | 0.53 | 0.84 | 0.65 | Moderate precision with high recall. This indicates the model detects most actual habitats but at the cost of some false predictions. |
| *Amphibolis* spp. dominated | 0.81 | 0.34 | 0.48 | High precision with low recall. This means the model produces few false positives but missing many actual instances of this habitat. |

| Class | Precision | Recall | F-Score | Comment |
|---|---|---|---|---|
| *Halophila* sp. & sparse mixed macroalgae | 0.80 | 0.64 | 0.71 | High precision meaning most predicted instances are correct. Moderate recall, indicating that the model confuses some true instances of this habitat. |
| *Posidonia sinuosa* dominated | 0.91 | 0.83 | 0.87 | Strong overall performance with very high precision and recall, indicating that there are almost no false positives and the model effectively identifies most cases. |
| *Ecklonia* sp. dominated | 0.90 | 0.63 | 0.74 | High precision meaning most predicted instances are correct. However, recall is moderate, indicating that the model confuses some true instances of this habitat. |
| *Sargassum* sp. dominated | 0.63 | 0.92 | 0.75 | Strong overall performance with moderate precision and a high recall, indicating that the model is able to capture most instances of this habitat. |
| Mixed macroalgae | 0.61 | 0.84 | 0.71 | Strong overall performance with moderate precision and a high recall, indicating that the model is able to capture most instances of this habitat. |
| Likely unvegetated substrate (wrack obscured) | 0.63 | 1.0 | 0.77 | Moderate precision but perfect recall, meaning the model detects all actual instances of this habitat but generates some false positives. |
| Mixed biota | N/A | N/A | N/A | There are no statistics for this class as it is not predicted. This class serves to represents uncertain model predictions (no dominant class). |

# 5. Discussion

The distribution of ten benthic habitat types were predicted across 4728.3 ha in Champion Bay using random forest supervised classification. Mapping results and associated validation statistics provide opportunity to assess the value of this mapping in contributing to an improved understanding of benthic habitat distribution within Champion Bay.

The dominance of Mixed *Amphibolis* spp. and macroalgae (40.1%) aligns well with what is known about the mid-depth benthic zones in Champion Bay. These areas commonly support dense *Amphibolis* seagrass interspersed with macroalgae on pavement reef and stable sand veneers (BMT, 2021). Additionally, the model is effective in distinguishing between *Sargassum*, *Ecklonia*, and mixed macroalgae classes - each tied to different reef types and energy regimes. *Sargassum* sp. is correctly mapped over pavement reef and moderate relief areas west of the bay and around Point Moore, matching the exposed, high-energy reef zones (DEP, 2006). *Ecklonia* sp., typically found in slightly deeper or more turbid waters (Wernberg et al., 2011), is accurately mapped offshore of Point Moore, confirming the model's sensitivity to this more niche habitat. The model performance for these macroalgal classes (F1 = 0.71–0.75) is likely aided by the predictive strength of the underlying substrate map, which accurately distinguishes between flat pavement and relief features, based on spectral and terrain data (moderate precision and recall for both reef types).

The detection of *Halophila* and *P. sinuosa* habitats is strong, largely due to the inclusion of supplementary training data and refined class definitions. Validation statistics indicate that these rarer habitats are predicted with high recall (*P. sinuosa*: 0.83; *Halophila* sp. & sparse mixed macroalgae: 0.64), demonstrating reliable identification across the study area. While the mixed *Amphibolis* spp. and macroalgae class is dominant, its moderate precision (0.53) reflects occasional misclassification of less common habitats. The inclusion of a separate *Amphibolis* spp. dominated seagrass class improves ecological specificity by distinguishing areas where *Amphibolis* spp. is the primary biota from those with mixed macroalgal cover, allowing for more accurate representation of seagrass dominance patterns. The high performance of *P. sinuosa* and *Halophila* sp. suggests that spectral similarities with dominant classes, which can be compounded by wrack cover, have been mitigated through targeted training. Some rarer classes, such as *Amphibolis* spp. dominated seagrass, still show lower recall (0.34), indicating that underprediction can occur where sample representation is limited. These findings highlight the importance of representative ground-truth data and carefully defined classes for reliably detecting ecologically important but less abundant benthic communities.

Champion Bay experiences regular wrack deposition, particularly near the fishing boat harbour and inshore beaches (O2 Marine, 2023). By including a separate class for "Likely unvegetated substrate (wrack obscured)", the model handles the spectral confusion caused by wrack, improving classification realism and interpretability. The separation of "true" unvegetated areas from potentially obscured zones reflects a nuanced understanding of local temporal variability and sediment dynamics (e.g. seasonal wrack accumulation, dredge spoil influence near the DMPA). Delineation of wrack from permanent benthic features could be improved through multi-temporal analysis, as demonstrated in previous studies (Ahmed et al., 2021; Vahtmäe et al., 2011). While incorporating ground-truthing data collected across multiple seasons would likely enhance the accuracy of wrack identification, this was beyond the scope of the current project. Similarly, the use of satellite imagery from multiple acquisition dates may offer additional benefits; however, the availability of clear Sentinel-2 imagery during the survey period was limited.

# 6. Conclusion

The Random Forest classification model effectively mapped ten benthic habitat types across Champion Bay, providing a robust representation of habitat distribution within an ecologically diverse coastal region. The model demonstrated strong performance across both common and rare habitats, accurately detecting dominant communities such as *Sargassum* and *Ecklonia* associated with reef structures and energy regimes, as well as ecologically important seagrasses like *Halophila* and *Posidonia sinuosa*. Classes exhibited a generally good balance between precision and recall, reflecting the model's ability to manage complex, non-linear relationships in optically and structurally heterogeneous benthic environments.

By incorporating ecologically meaningful class definitions and addressing sources of spectral ambiguity, such as wrack-obscured substrate, the model provided realistic and ecologically sensitive habitat predictions. Overall, the results demonstrate that Random Forest classification is well-suited to the optically and structurally complex benthic environments of Champion Bay. To further refine habitat mapping in this area, future surveys should consider incorporating additional targeted sampling for rare habitat types and expanding validation in wrack-prone zones to improve model generalisability and class balance.

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