# Technical Report: Darwin – Bynoe Harbours predictive mapping of benthic communities

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Cover Photo: Ronen Galaiduk

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## Executive Summary

This report describes the procedures undertaken to map the distribution of major benthic habitat classes in the Darwin-Bynoe Harbour region. This large-scale project (total mapped area of approximately 2000 $km^2$) was funded by INPEX-operated Ichthys LNG and executed through a collaborative effort by the Northern Territory Department of Environment and Natural Resources, the Australian Institute of Marine Science and Geoscience Australia.

Most of the benthos of both harbours was predicted to be highly suitable for a variety of filter-feeding biota such as sponges and octocorals with shallow areas along the arms found to be more suitable for the hard corals and macroalgae. Hard corals and macroalgae were also predicted in isolated pockets across outer areas of Darwin and Bynoe Harbours especially near Middle and Fish Reefs. In contrast, seagrass was mainly predicted to be associated with the shallow areas outside of the main channels. Water depth appeared to be the main driver of distribution of the modelled benthic classes. The shallow areas (< 10 m) were typically characterised by the presence of autotrophic communities such as macroalgae, seagrass and hard corals. The shallows were further divided based on the structural complexity with more complex areas were typically dominated by the hard corals and macroalgae whereas the seagrass areas were typically characterised by relatively lower complexity. The deeper slopes (> 10 m) with varying degrees of associated complexity were found to be highly suitable for the heterotrophic filter feeding communities. In contrast, deep, low complexity flat areas had typically no associated epibenthic biota.

The maps provide a solid baseline for benthic biodiversity and habitat distributions in this remote region and offer new insight into the marine environments of the Northern Territory coastline. Improvement can be made in the future to better predict the distributions of rare benthic classes in the shallow and intertidal environment. The benthic maps will support future management decisions including marine planning, long-term monitoring and environmental impact assessments as well as contribute to research and management of mobile biota such as dugongs, turtles and fish associated with these habitats.

# Introduction

This report provides the details of the benthic habitat mapping activities funded by INPEX-operated LNG and is a direct outcome of the previous collaborative work between the Northern Territory Department of Environment and Natural Resources (DENR), Geoscience Australia (GA) and the Australian Institute of Marine Science (AIMS). The overall goal of the program was developing comprehensive inventories and maps of the distribution and abundance of physical and biological seabed habitats, seagrasses and benthic assemblages to provide baseline environmental mapping and a description of ecological patterns.

## Background and survey aims

The Darwin Harbour Regional Plan of Management (Darwin Harbour Advisory Committee, 2003) identified that there is limited information on the local environmental values and attributes which could potentially be affected by coastal development. The plan identified a lack of data on broad-scale habitat and biodiversity distributions and of understanding of processes which maintain ecosystem health.

This report utilises the bathymetric, physical and biological data collected during this and historical field sampling campaigns to produce spatial predictive habitat models. It uses predictive models to build realistic representations of both the topography and composition of the seafloor and major biotic groups and to produce benthic habitat maps showing where benthic habitat types exist for the entire area of interest (Holmes et al. 2008, Brown et al. 2011).

## Study area

The Darwin – Bynoe Harbour region lies approximately 12.5° south of the equator on the north-western coast of the greater Joseph Bonaparte Gulf, Northern Australia (Figure 1). This region includes Port Darwin, outer Darwin Harbour (waters between Gunn Point and Charles Point and includes Shoal Bay) and Bynoe Harbour, which is bounded by Cox Peninsula in the east and five islands in the west. The total area of interest is about 2000 $km^2$ of which 1300 $km^2$ are subtidal environments.

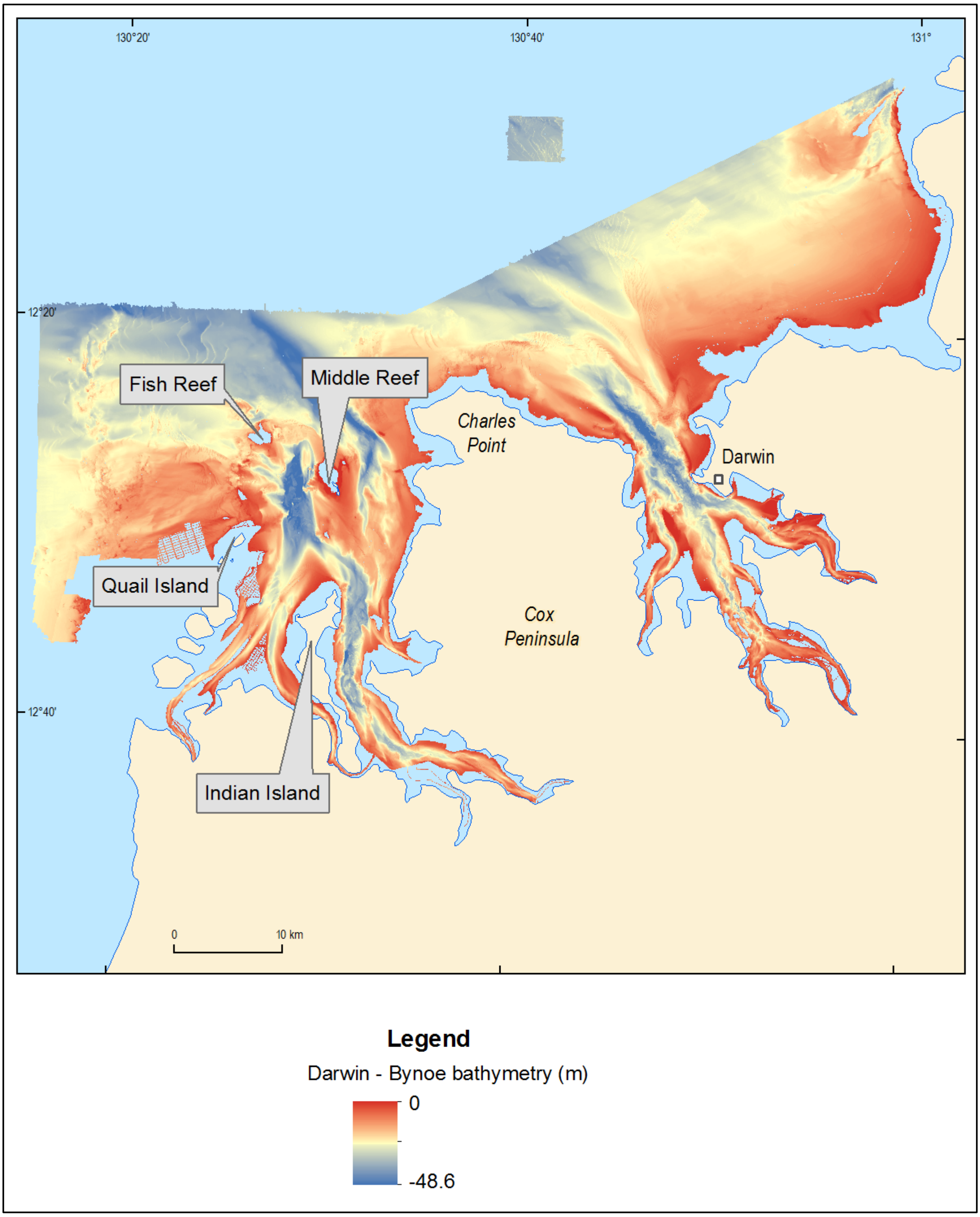


Figure 1. Darwin - Bynoe regional map.

Darwin Harbour is a drowned river valley which has been exposed to erosion and weathering for a large proportion of the past 650 000 years and has only been intermittently connected to the sea over that time (Lewis et al. 2013). As result, present day Darwin Harbour contains the main channel, and three elongate arms: West Arm, Middle Arm and East Arm, each with a distinct catchment. The Elizabeth River flows into East Arm, while the Darwin and Blackmore Rivers flow into Middle Arm. West Arm is without a prominent river. Each arm is comprised of deeper channels bordered by intertidal and subtidal mud flats, and these are in turn fringed by mangrove forest (Fortune 2006). Tides dominate sediment transport, while the effects of wind-driven currents, waves and river discharge appear negligible for sediment movement (Andutta et al. 2014). Turbid plumes can extend over wide areas of the harbour. While large parts of the river channel are free of sediment cover, most areas are dominated by unconsolidated sediment forming a wide variety of morphologies including mud flats, ripples, sediment sandwaves and even sub-aqueous dunes (Siwabessy et al. 2016).

Similarly, Bynoe Harbour is a drowned river valley (Lewis et al. 2013). Unlike Darwin Harbour, comparatively little information is available on the sediments and geomorphology of the seabed for Bynoe Harbour. Bynoe Harbour contains one main channel and near the entrance, this channel bifurcates around a single island, Indian Island. Darwin and Bynoe Harbours have a large tidal range (macrotidal) with a 7.9 m maximum tidal range (5.5 m mean spring range and 1.8 m mean neap range) (Woodroffe et al. 1988, Andutta et al. 2014). The tidal cycle is semidiurnal (two tidal cycles are experienced every 24 hours). Tidal currents can reach up to 2 m/s (7.2 km/h) during a maximum spring tide (Williams et al. 2006, Andutta et al. 2014).

## Scientific rationale

The nature and composition of the seafloor structure have a profound effect on the benthic communities that can develop (Kostylev et al. 2001). It is widely recognised that species are not randomly distributed among varying habitats; rather they show associations with the physical properties of the surrounding environment (Guisan & Zimmermann 2000). The complexity of the physical environment creates a diversity of habitats that marine organisms exploit causing species composition to often shifts gradually along the environmental gradients (e.g. Ellis & Schneider 2008, Stuart Gray & Elliott 2009).

Benthic habitat mapping is a complex multi-disciplinary task which combines the remote sensing technologies such as multibeam echosounder (MBES) Geographic Information Systems (GIS) and spatial modelling (Lund & Wilbur 2007, Hovey et al. 2012) to produce a full coverage predictive mapping of areas with similar environmental characteristics. For the marine environment, such modelling involves collecting spatial datasets on physical characteristics of the seafloor derived from MBES (e.g. depth, backscatter strength, slope, aspect, rugosity) and biological data on occurrence and distributions of benthic biota (e.g. Heap & Harris 2008, Ierodiaconou et al. 2011). Understanding the spatial complexity of existing distributions at an appropriate scale and mapping benthic communities across seascape can allow managers to identify areas of ecological significance, track changes, and gauge the success of management decisions by comparing data from future surveys.

## Benthic habitat mapping approach, purpose and desired outputs

Our approach utilizes detailed full coverage hydroacoustic datasets collected during previous steps of the program and field observations from towed video system on the spatial distribution and occurrence of biota to predict where major groups of benthic biota are likely located in areas not surveyed (Holmes et al. 2008, Brown et al. 2011). This approach is particularly useful for large, remote areas where practicality limits the number of samples that can be collected. Well established ecological theory (Pittman et al. 2009, Elith & Leathwick 2009, Ierodiaconou et al. 2011, Robinson et al. 2011) details how seafloor physical properties act as both direct and indirect drivers of landscape-scale ecological processes on the benthos. Implementing this knowledge within a GIS via robust statistical modelling techniques will allow for the development of benthic habitat maps predicting where ecologically significant habitats such as corals, seagrass, macroalgae, sponges and other invertebrates are likely to be found.

## Aims

The aim of the analysis is developing robust spatial models and comprehensive predicted distribution maps of benthic habitats for the Darwin and Bynoe Harbours. The specific objective was to map distributions of major benthic habitat classes, such as seagrasses, macroalgae, corals and sponges across the study area which can be achieved through three intermediate steps: 1) design and execute towed video survey to provide ground-truthing points for model generation and error assessment; 2) develop secondary datasets based on the MBES data to be used as environmental predictors for the spatial modelling; 3) develop predictive benthic habitat models to associate environmental predictors to probability of occurrence of different benthic habitat classes.

# Methods

## Developing secondary datasets

A variety of secondary (textural) datasets which may correlate with benthic biota were developed from the multibeam bathymetry raster using terrain analysis techniques (Holmes et al. 2008). These techniques quantify the relationships among depth values in small neighbourhoods to reveal textural differences. Calculations are run on a small number of cells surrounding each pixel. A 3-pixel radius analysis is illustrated in Figure 2. In this case, all neighbourhood calculations (such as the mean or slope) are run on the central cell plus the eight surrounding cells, and the value assigned to the central cell in the output, thus creating a derivative dataset. We used a custom-written Python code applied in ArcGIS 10.5 to derive environmental predictors of benthic habitat that describe the structure and complexity of the seafloor Table 1.

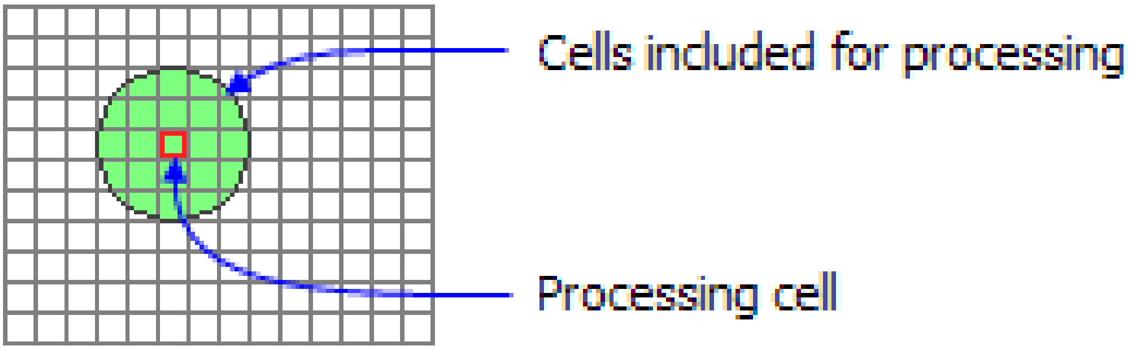


Figure 2. Example of defining local and neighbourhood cells for textual analysis. The red cell is the target cell and its neighbours for analysis are highlighted in green.

## Sampling design

### Geomorphic classes (Isoclasses)

Because no previous knowledge existed on habitat distributions across the entire study area to assist in the development of a robust sampling plan, we conducted a Principal Component Analysis (PCA) and a geomorphic gradient isoclassificaton (Isoclass) analyses on the developed secondary environmental datasets to categorise different regions of the study area and to significantly decrease order of variance across the numerous environmental predictors. This was performed separately on the grids from Darwin and Bynoe Harbours in order to preserve the relative environmental complexity of the individual study areas. By reducing the dimensionality of all available environmental predictors and combining them in geomorphic clusters based on increasing levels of complexity, it was possible to identify various types of benthic environments which could be potential drivers of occurrence of benthic biota and will provide guidance for the development of stratified towed video sampling plan.

PCA is a linear transformation, dimensionality reduction technique used extensively in remote sensing studies usually applied on highly correlated multidimensional data to reduce its dimensionality and transform it in a new coordinate system where the first three dimensions contain the greatest variance related with the environmental variables (Fung & LeDrew 1987, Rodarmel & Shan 2002).

**Table 1. Datasets derived from multibeam bathymetry that were used as environmental surrogate variables for spatial predictive modelling of mixed biota classes.**

| Benthic habitat predictor variable | Description | Predictor variable code |
|---|---|---|
| Bathymetry | Water depth in metres, interpolated from multi-beam data to a 10 m resolution | bathy |
| Aspect | Azimuthal direction of the steepest slope, calculated for a 3 x 3 pixel neighbourhood | aspect |
| Slope | First derivative of elevation. Average change in elevation, calculated on a 3 x 3 pixel neighbourhood (steepness of the terrain) | slp |
| Plan curvature | Second derivative of elevation: concavity/convexity perpendicular to the slope, calculated for a 3 x 3 pixel neighbourhood | plan |
| Profile curvature | Second derivative of elevation: concavity/convexity parallel to the slope, calculated for a 3 x 3 pixel neighbourhood | prof |
| Overall curvature | Combined index of profile and plan curvature | curv |
| Depth range across various spatial neighbourhoods | Maximum minus minimum depth within spatial neighbourhoods equivalent in width to: 5, 10, 20, 25, 30, 35, 40, 45 grid cells | rng5; rng10; … rng45 |
| Variability of depth across various spatial neighbourhoods | Standard deviation of depths within spatial neighbourhoods equivalent in width to: 5, 10, 20, 25, 30, 35, 40, 45 grid cells | std5; std10; … std45 |
| Average depth across spatial neighbourhoods | Average of depth within spatial neighbourhoods equivalent in width to: 5, 10, 15, 20, 25, 30, 35, 40, 45 grid cells | hyp5; hyp10; … hyp45 |

The three first axes resulted from the PCA analysis were then used as input bands in the Isoclass procedure. The Isoclass is an iterative optimization clustering procedure based on maximum likelihood. The algorithm separates all cells into a number of distinct unimodal clusters of complexity in the multidimensional space of the input bands (Ball & Hall 1965, Richards & Jia 2006). The resulted raster was then processed using the focal statistics toolbox in ArcGIS to identify localised 'pockets' of the study area that have a high variety of clusters within the radius of processing window of 10 raster cells. This process enabled us to categorise the two study areas into regions of varying complexity with regards to the environmental predictors. As a result of these analyses, there were 6 and 4 clusters of increasing complexity identified for Darwin and Bynoe Harbours respectively (Figure 3 and Figure 4 respectively).

### Towed video transects

The geomorphic clusters of habitat complexity derived from the environmental predictors were then used as a priori features for the sampling design for towed video transects structured to spread across the study area. Spatially balanced, unequal inclusion probabilities habitat survey design using GRTS (Generalized Random Tessellation; Stevens & Olsen 2004) was employed to allocate the starting points for towed video transects for Darwin Harbour and additional similar GRTS design was performed for the Bynoe Harbour. This type of survey planning allowed for targeting seafloor areas of high structural complexity which were expected to have higher abundance and diversity of benthic biota while still ensuring that the data collected was sufficient to build spatial predictive models over as large an extent of the region as possible and yield robust results.

The towed video survey transects were selected to provide ground-truth information on the occurrence of benthic biota for model generation and error assessment and were performed with a Seabotix LBV150s system. To effectively survey the extensive study area we allocated 150 and 120 transect for Darwin and Bynoe Harbours respectively with additional 30 transects for each of the study areas as oversample.

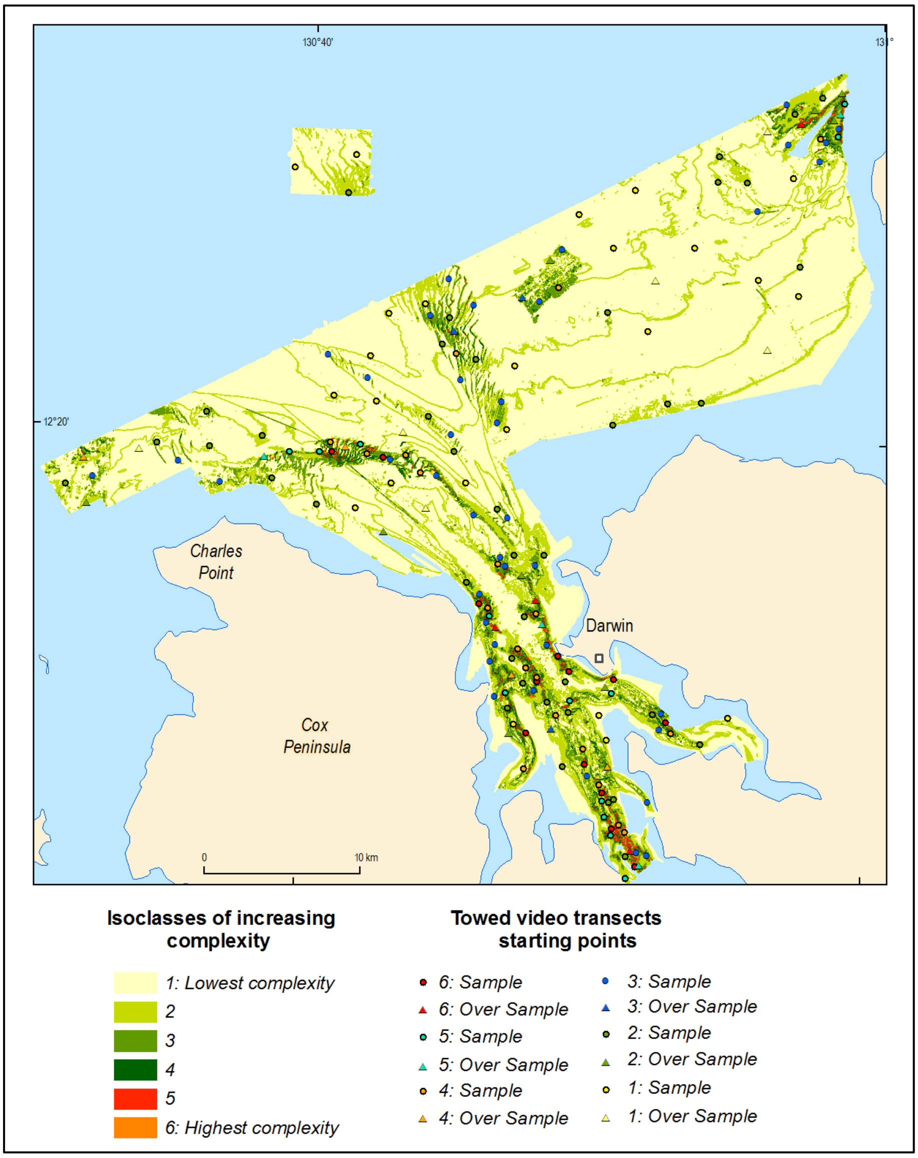


**Figure 3. GRTS allocated points for Darwin Harbour sampling indicating towed video transect heads stratified by the Isoclass polygons resulting from geomorphic classes analysis. Warmer colours in the polygon feature indicate higher levels of complexity (1-6). Numbers in the points legend correspond to the levels of complexity in the Isoclass layer.**

In addition, DENR staff were able to allocate additional transects based on the previous knowledge of the area in order to capture rare but ecological significant habitats, such as seagrass, as long as the additional transects followed the same guidelines as the GRTS transects. All the transects were typically 1.5 km long and laid from shallow to deep water to capture the gradient of biological communities. The video system was towed generally at speeds between 1 and 2 knots, approximately 1 m above the ground and tilted downward to cover the immediate benthos. The video signal was transferred to the surface via an umbilical cable where it was monitored and analysed in real-time, time-stamped and synchronised with the boat's GPS data that were recorded and 1 s intervals. In total there was 53 and 90 transects collected for Darwin and Bynoe Harbours respectively during the field sampling period between September and December 2017 (Figure 5).

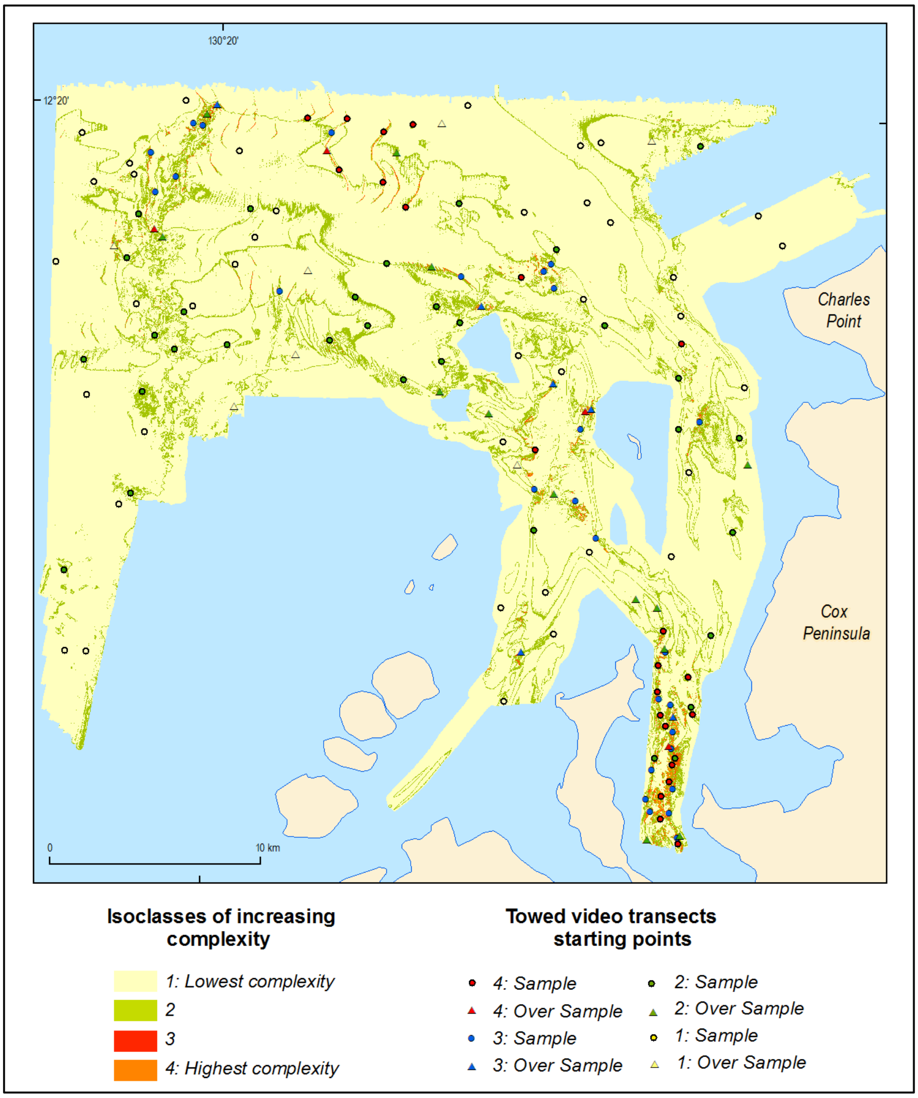


**Figure 4. GRTS allocated points for Bynoe Harbour sampling indicating towed video transect heads stratified by the Isoclass polygons resulting from geomorphic classes analysis. Warmer colours in the polygon feature indicate higher levels of complexity (1-6). Numbers in the points legend correspond to the levels of complexity in the Isoclass layer.**

Benthic categories of the observed biota were assigned using CATAMI classification scheme (http://catami.org/classification) and stored in a specialised relational database which was controlled for quality assurance purposes by an experienced benthic ecologist at a later stage.

## Defining mixed classes

As benthic communities often exist in intermixed assemblages we utilised a community-based analytical approach that allows for future mapping of the co-existing modelled mixed benthic communities. A community-based modelling approach is an ecologically more meaningful and robust process which is based on identified mixed benthic classes developed a priori via cluster analysis (on the 1- presence; 0 – absence transformed data) of the recorded towed video data based on levels of co-occurrence of benthic organisms across the two study regions.

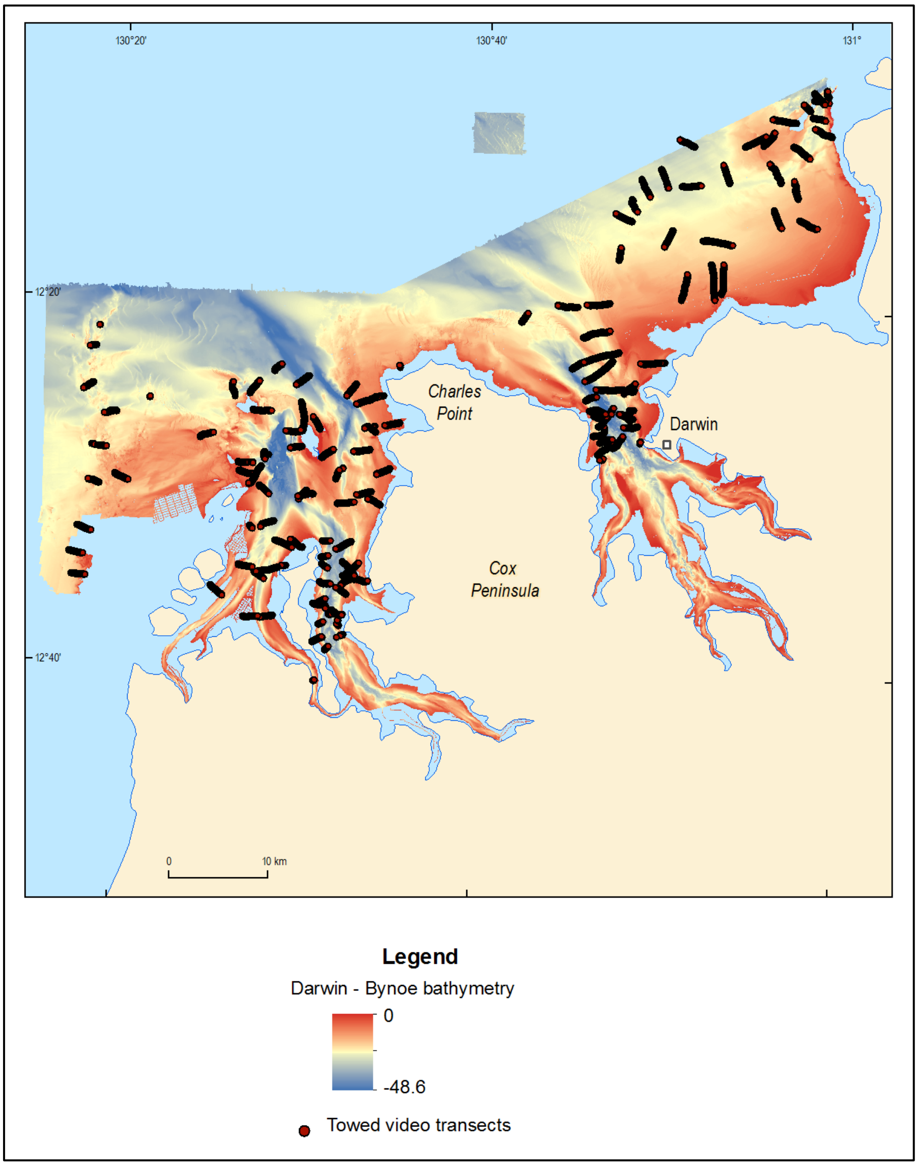


Figure 5. Towed video transects overlaid on multibeam bathymetry grid.

This determined which individual benthic classes tended to be located within a given distance of one another most frequently. The process was repeated across a range of spatial scales (10 m, 15 m, 20 m, 25 m, 30 m, 40 m, 50 m, 100 m) to ensure that the chosen mixed classes were not an artefact of scale. We deliberately selected dissimilarity cut-offs that preserved some of the less abundant benthic classes (such as macroalgae or hard corals) so they can be still mapped individually. The resulting five benthic classes are shown in Figure 6.

## Developing training and test data

A robust benthic habitat mapping requires validation of the developed models with test data (Barry & Elith 2006, Elith & Leathwick 2009). Thus, we withheld a random sample of 20 % of the towed video data to use for model performance estimates (testing set) and used 80 % of it (training set) for model development on how benthic classes of organisms respond to environmental predictors.

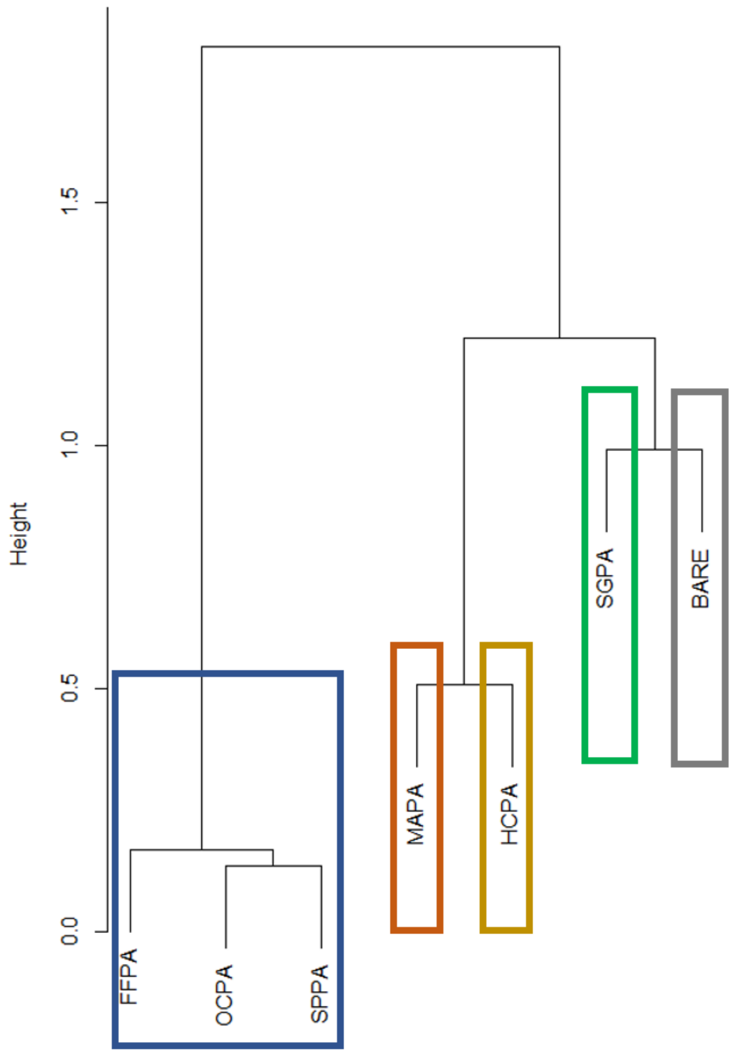


**Figure 6. Hierarchical cluster analysis at 10 m (Wards metric) of benthic habitats identifying five clusters defined by a dissimilarity cut-off of 1.2 which preserves the less abundant benthic classes. FFPA – filter feeders; OCPA – octocorals; SPPA – sponges; MAPA – macroalgae; HCPA- hard corals; SGPA – seagrass; BARE – sea bottom with no observed biota.**

## Model building and accuracy assessment

We modelled the relationship between the mixed biota classes and the bathymetry-related environmental variables using Random Forest modelling algorithm (Breiman 2001), which is a robust method commonly used for spatial modelling (Elith et al. 2006, Elith & Leathwick 2009). Random Forest models can fit both linear and complex non-linear models very efficiently without being prone to overfitting. It is particularly efficient with large datasets compared to other methods and can be run using computer parallel processing.

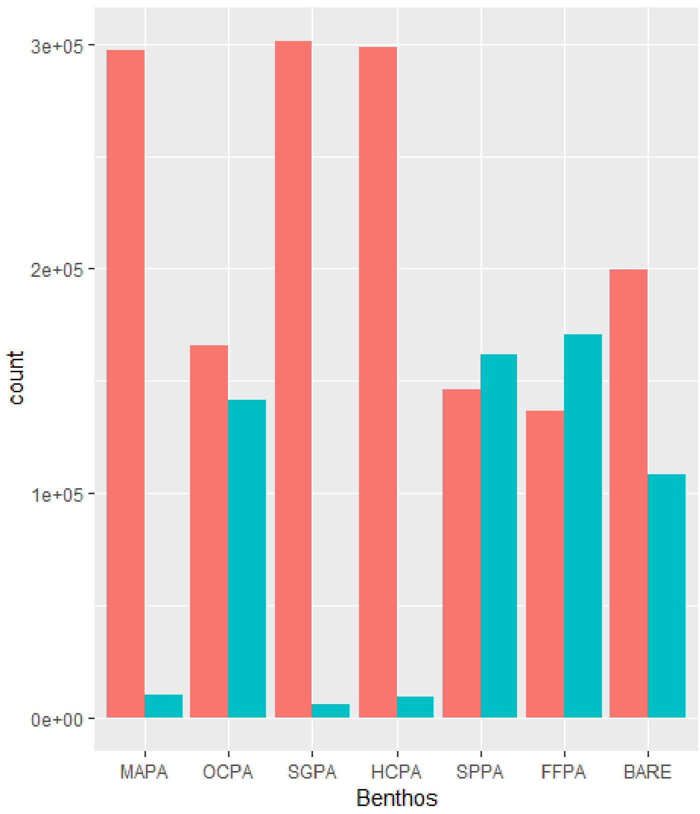


**Figure 7. Frequency distribution of presence (blue) and absence (red)of the seven major benthos classes in the towed video samples: FFPA – filter feeders; OCPA – octocorals; SPPA – sponges; MAPA – macroalgae; HCPA- hard corals; SGPA – seagrass; BARE – sea bottom with no observed biota.**

The models have high accuracy compared to other comparable methods and provide outcomes which are ecologically interpretable (Breiman 2001, Prasad et al. 2006). The model accuracy was assessed by predicting the values against the testing dataset using a confusion matrix in conjunction with total accuracy, Kappa statistics and measures of within-class model performance (sensitivity and specificity). Models with Kappa > 0.8 have high predictive power, values between 0.7 and 0.8 are acceptable, and models with Kappa of < 0.5 have no power of discrimination (Fielding & Bell 1997).

## Modelling rare benthic habitats

In addition, some of the benthic classes had a very low prevalence in the towed video data, which is known to affect modelling outcomes and performance of models (Franklin 2010). Prevalence of macroalgae, seagrass and hard corals was roughly 20 times lower than the prevalence of other benthic classes (Figure 7). Thus, we modelled these rare classes individually using Maximum Entropy (MaxEnt) modelling approach (Phillips et al. 2006, Phillips & Dudík 2008).

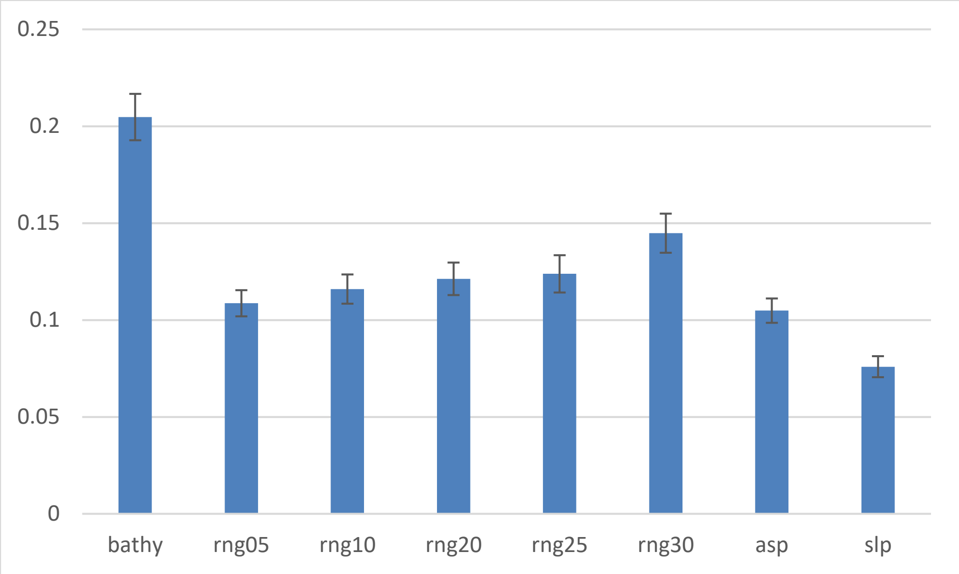


**Figure 8. Mean variable importance +/- standard deviation of top eight predictors from the random forest models. Predictor abbreviations as in Table 1.**

MaxEnt is the most common method for modelling species distributions (Guillera-Arroita et al. 2014) and its predictive performance is consistently comparable with the alternative highest performing methods (Elith et al. 2006). Unlike Random Forest, MaxEnt produces a relative likelihood surface of species occurrence from a set of presence-random background records. Despite its wide use, MaxEnt is sometimes criticized as the robust species distribution modelling method primarily because it is impossible to estimate species' prevalence from presence records only (see Guillera-Arroita et al. 2014 for some of the associated issues). Here, however, we parametrised MaxEnt models with empirical relative prevalence in the sample based on the observed prevalence in the towed video recordings. We also used 5-fold cross-validation to estimate errors around fitted functions and associated variance around the response curves of the fitted models (Elith et al. 2011).

In addition, we utilised the withheld presence-absence test data for independent testing of fitted models to assess their performance, discrimination and accuracy. A set of common evaluation metrics of predictive performance was calculated on the test datasets. We used Receiver Operating Characteristic (ROC) and the area under the curve (AUC) to test the sensitivity (true positive rate) and specificity (false positive rate) of model output (Fielding & Bell 1997). The AUC is prevalence and threshold-independent measure of the ability of a model to discriminate between a presence or absence observation and commonly varies between 0.5 (no predictive ability) and 1 (perfect fit; Allouche et al. 2006, Elith et al. 2006). In addition, we calculated a threshold dependent Kappa statistic which is commonly used in ecological studies with presence-absence data and provides an index between 0 and 1of how much a model predicted actual classes versus a guess (Cohen 1960).

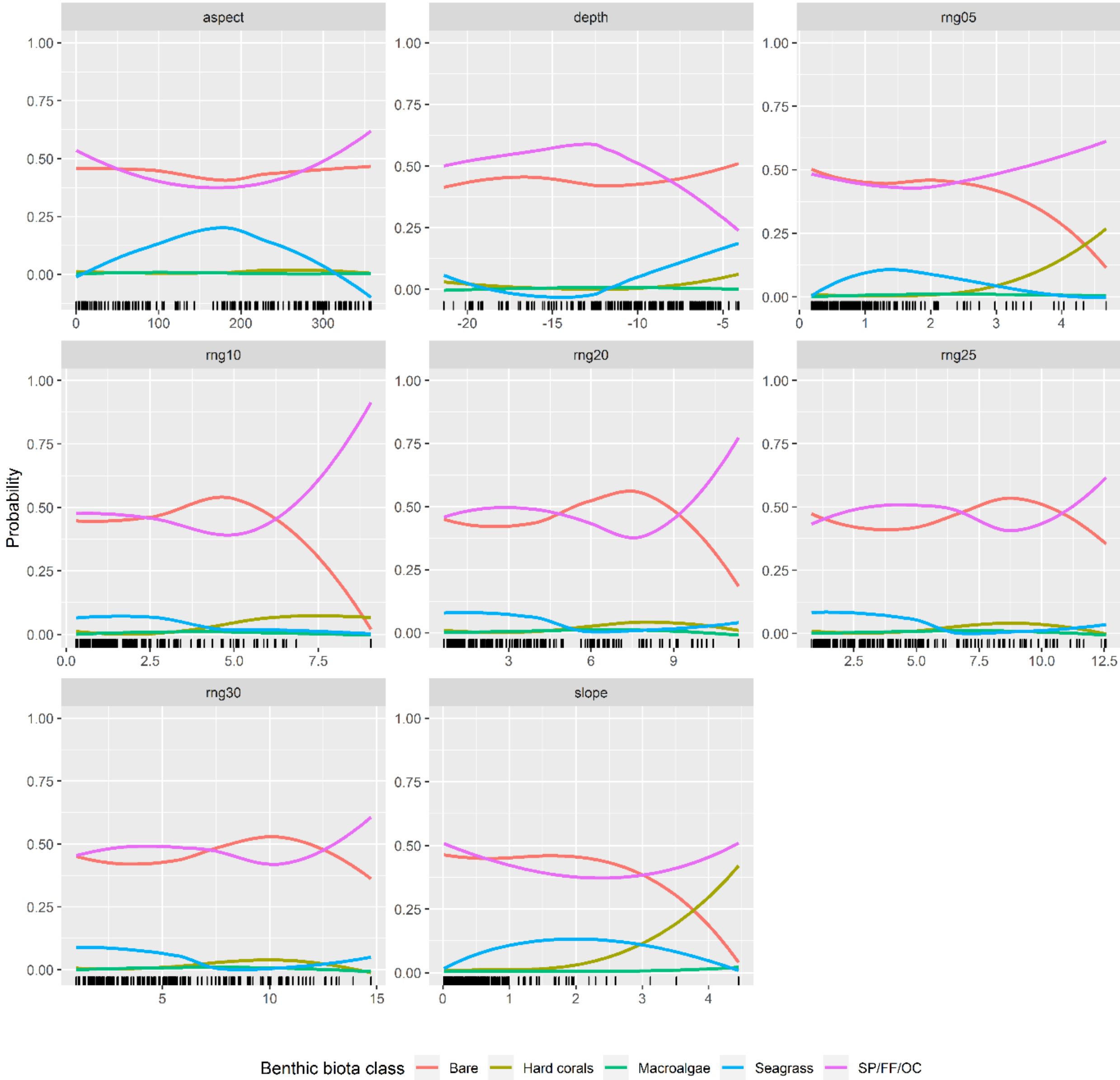


**Figure 9. Partial response plots showing the relationship between the variation of top eight predictor variables from the Random Forest model and the probability of occurrence of each benthic class (SP/FF/OC corresponds to the mixed filter feeders class made of sponges/filter feeders/octocorals). Rug plots on the bottom indicate the range of predictor values.**

There are multiple threshold optimisation routines available in the literature and some of them are suitable for customised use of the produced maps. Here we utilised two routines: MaxKappa, which makes full use of confusion matrix to assess the improvement over chance prediction and ReqSens at a sensitivity level of 90 %. This optimisation routine ensures that the misclassification level of the fitted model does not exceed a nominated sensitivity (90 % in this case) so the majority of the predicted environmental niche of the rare species is included (Freeman & Moisen 2008).

## Mapping model predictions

As the environmental covariates covered the entire study area, they were used to predict biota classes for areas where no towed camera data exists based on the statistical relationship developed through spatial modelling. After evaluation, the final models for each major biota class as well as mixed classes model were predicted over the 10 x 10 multibeam based raster grids covering the entire Darwin - Bynoe Harbours region.

# Results

## Random Forest results and accuracy

The Random Forest model had an overall accuracy of 95 % and Kappa = 0.85 indicating that the model had an outstanding fit and a high predictive power (Landis & Koch 1977). The most important eight predictors were associated with depth (bathy), small to intermediate-scale benthic rugosity (rng05, 10, 20, 25 and 30), orientation and steepness of the seabed (asp and slp respectively, Figure 8). The partial dependence plots for the top eight variables in the model are facilitating ecological interpretation of the relationships between the probability of occurrence of benthic habitat types and the most influential environmental predictors. The north orientation, deeper water and small scale structural complexity had a positive influence on the probability of occurrence of mixed filter feeder class (Figure 9). Shallow depths and low structural complexity were associated with higher probability of occurrence of seagrass species. Similarly, shallow depths but intermediate to high structural complexity and high slopes were predicted to be associated with a higher probability of occurrence of Hard Corals and Macroalgae (Figure 9). Not surprisingly, bare sea bottom was predicted to be associated with low complexity environments across the sampled depth range.

Class specific model sensitivities ranged from 0.66 for the Macroalgae to 0.96 for the Mixed filter feeders (SP/FF/OC) with specificity for all the classes well above 0.9 (Table 2). Despite the relatively high overall model performance metrics, some classes had a high level of misclassification. The observations from the Macroalgae, Seagrass and Hard Corals classes were misclassified primarily into the SP/FF/OC class (Table 3). To examine the difference in classification success between the individual classes, we used the Precision-Recall metrics and their harmonic mean (F1) which are useful measures of success of prediction when the classes are very imbalanced. For the Macroalgae and Hard Corals, model precision was roughly 10 % followed by the Seagrass with 42 % precision (Table 2).

The F1 score, a weighted average of the precision and recall, identified that the models for all rare benthic classes had very poor performance ratings based on this metric (Table 2). The underperformance of the rare benthic classes most probably can be attributed to the prevalence of observations in the individual classes (Figure 7) which can affect model performance (Franklin 2010).

**Table 2. Random Forest model accuracy scores for the mixed benthic classes based on the test data validation. SP/FF/OC corresponds to the mixed filter feeders class made of sponges/filter feeders/octocorals.**

| | Macroalgae | SP/FF/OC | Seagrass | Hard Corals | Bare |
|---|---|---|---|---|---|
| Sensitivity | 0.66 | 0.96 | 0.75 | 0.82 | 0.94 |
| Specificity | 0.99 | 0.94 | 0.99 | 0.99 | 0.99 |
| Precision | 0.09 | 0.99 | 0.42 | 0.10 | 0.94 |
| Recall | 0.66 | 0.96 | 0.75 | 0.82 | 0.94 |
| F1 | 0.16 | 0.97 | 0.54 | 0.18 | 0.94 |

**Table 3. Confusion matrix for the Random Forest model using the holdout validation data (predicted class on the x-axis observed class on the y-axis). Most of the observations in the Macroalgae, Seagrass and Hard Corals classes were misclassified into the mixed filter feeders class (SP/FF/OC).**

| | Macroalgae | SP/FF/OC | Seagrass | Hard Corals | Bare |
|---|---|---|---|---|---|
| Macroalgae | 212 | 2101 | 4 | 20 | 13 |
| SP/FF/OC | 69 | 148092 | 209 | 28 | 1787 |
| Seagrass | 0 | 945 | 723 | 0 | 35 |
| Hard Corals | 36 | 1873 | 0 | 216 | 0 |
| Bare | 3 | 1917 | 26 | 0 | 31259 |

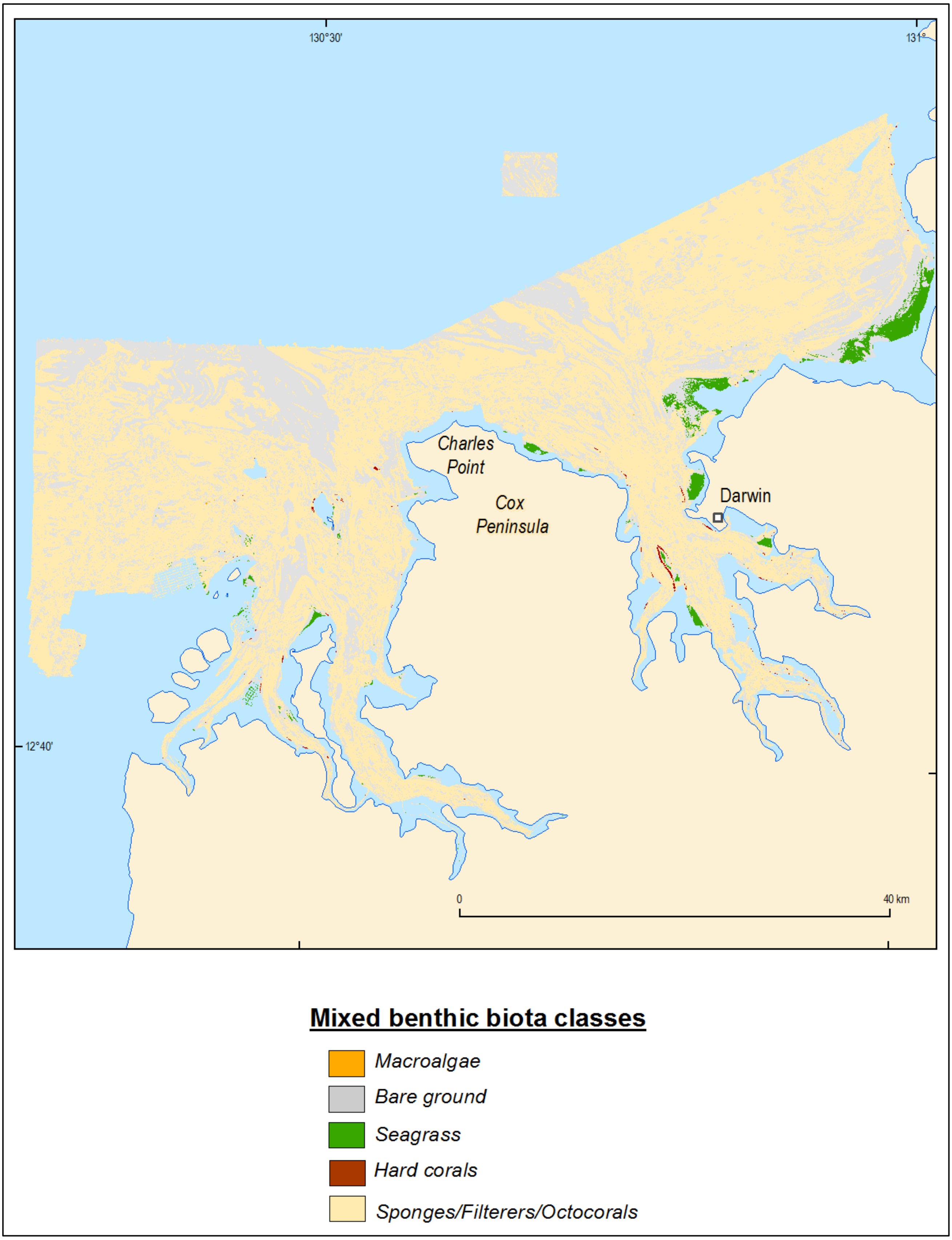


**Figure 10. Random Forest model prediction of the spatial distribution of the major benthic habitat classes across Darwin and Bynoe Harbours.**

## Spatial predictions of mixed classes Random Forest model

The predicted map of spatial distributions of the five mixed benthic classes for the entire Darwin-Bynoe region indicated most of this area (approximately 1356 km$^2$) to be suitable for various filter feeders such as sponges and octocorals followed by the bare seafloor class (approximately 585.5 km$^2$; Figure 10 and Table 4).

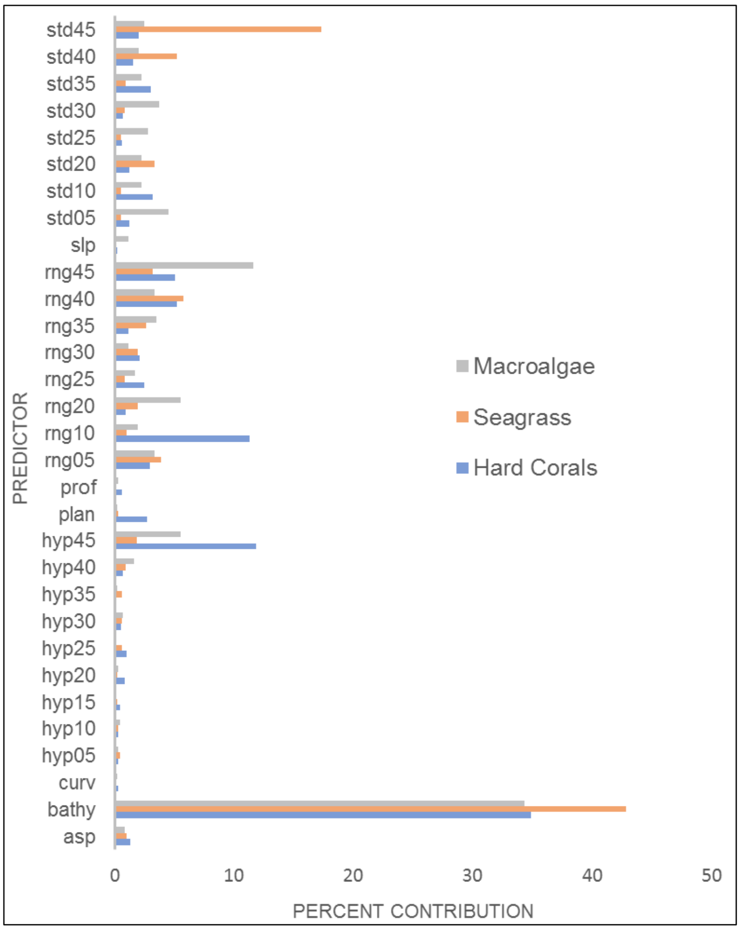


**Figure 11. The relative importance of top predictors as measured by percent contribution as indicated by the individual Maxent models for the three modelled classes. Predictor abbreviations as in Table 1.**

Seagrass was predicted in the near-coastal areas in the eastern part of the outer Darwin Harbour and in the north-west of Indian Island (approximately 33.5 km$^2$ of the total mapped area; Table 4 and Figure 10). Pockets of Hard Corals were predicted in the coastal areas of inner Darwin and Bynoe Harbours as well as in the surrounding of the Middle Reef (total predicted area of 2.48 km$^2$; Figure 10 and Table 4). Isolated pockets of Macroalgae were predicted primarily in the outer areas of Darwin and Bynoe Harbours which was by far the least abundant class of benthos (total predicted area of approximately 0.15 km$^2$). Predictions for individual benthic classes from the Random Forest model could be found in Appendix 1.

## Individuals models for rare benthic classes

Due to the high rate of misclassification (i.e. low precision, Table 3) of the rare benthic classes (Macroalgae, Seagrass, Hard Corals) in the Random Forest model, we produced individual models to predict the probability of occurrence of these classes in the Darwin-Bynoe area. The 5-fold cross-validated models identified bathymetry as the most important predictor of the probability of occurrence of the three modelled classes (Figure 11).

**Table 4. Predicted area suitable for the mapped benthic classes.**

| Benthos class | Area ($km^2$) | % Total Area |
|---|---|---|
| Macroalgae | 0.14 | 0.01 |
| SP/FF/OC | 1356.12 | 68.57 |
| Seagrass | 33.49 | 1.69 |
| Hard Corals | 2.48 | 0.13 |
| Bare seafloor | 585.43 | 29.60 |

Additional contributing predictors were associated with the large-scale standard deviation of depth (std45), structural complexity (rng45; rng10) and hypsometry (hyp45) for the Seagrass, Macroalgae and Hard Corals respectively (Figure 11). The partial response plots for the top six predictors demonstrate that the probability of occurrence of Macroalgae and Seagrass is higher in the shallow water with the high probability of occurrence of Hard Corals predicted for the shallow to intermediate depths (Figure 12). The large values of large scale hypsometry (hyp45) and structural complexity (rng45 and rng40) were predicted to have a positive influence on the probability of occurrence of all modelled classes. In contrast, small values of small structural complexity (rng5, rng10) were predicted to be positively associated with the probability of occurrence of Hard Corals and Seagrass (Figure 12). The standard deviation of depth at all scales was consistently predicted to be an important driver for the probability of occurrence of all modelled classes. After validation with the holdout data, the individual Maxent models were characterised by high AUC values ranging from 0.97 to 0.99 (Figure 13 and Table 4). The sensitivity and specificity of produced models varied with the choice of a threshold.

While the sensitivity of the predictions was maximised with the ReqSens threshold for all individual classes, this choice of threshold produced inferior Kappa values in comparison to the MaxKappa threshold (Figure 13 and Table 4). The selection of a threshold could be guided to produce final binary presence-absence maps based on future research interest. The confusion matrix for all the individual class models and the two thresholds can be found in Appendix 2.

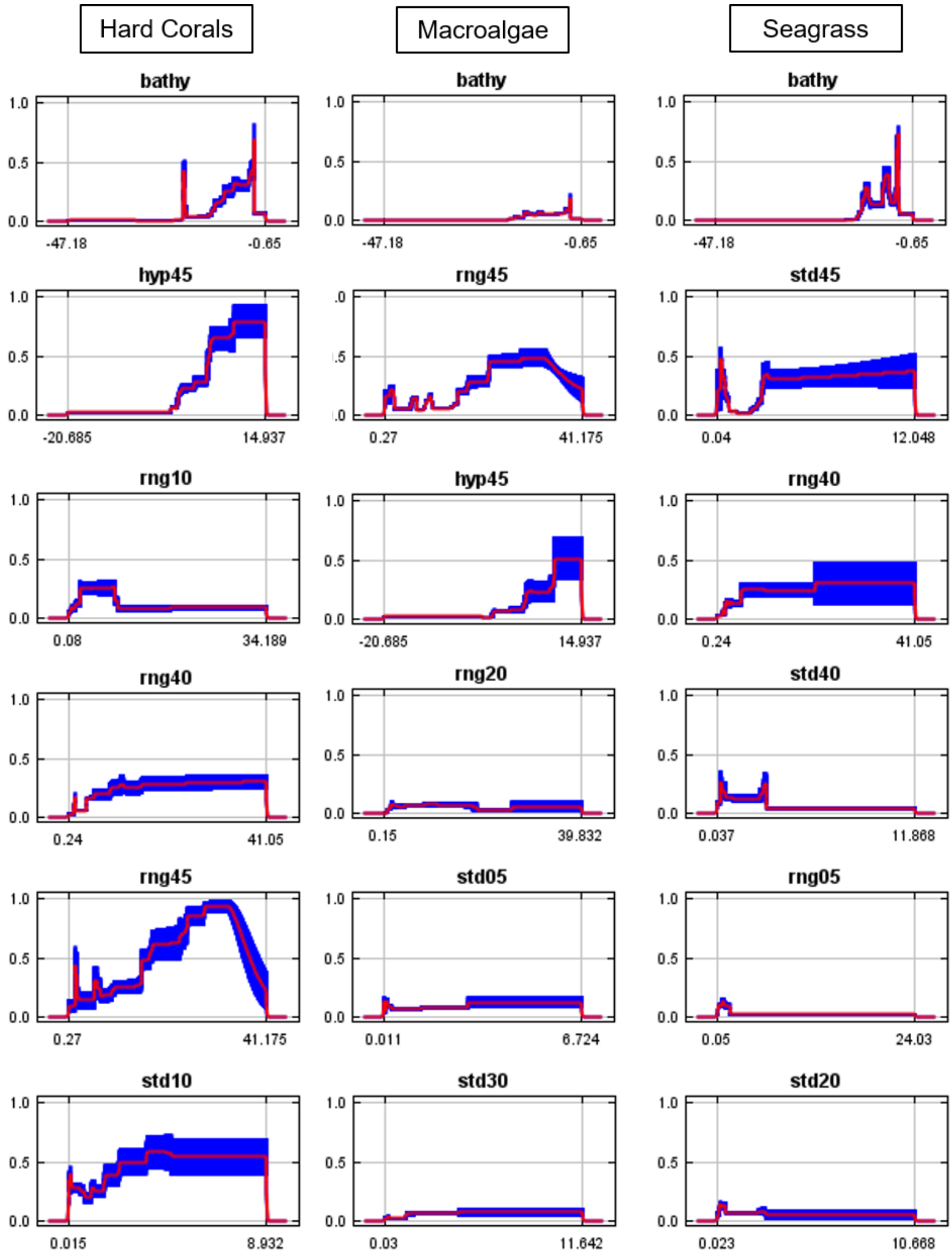


**Figure 12. Partial response plots showing the relationship between the variation of top six predictor variables ordered by percent contribution from top to bottom as result of the 5-fold cross-validated individual Maxent models and the probability of occurrence of each benthic class. Mean response in red +/- one standard deviation in blue. X-axis: range of values of the predictor; Y-axis: probability of occurrence of the benthic classes.**

## Spatial predictions of individual class Maxent models

The mean probability of occurrence maps identified the higher probability of occurrence of the Macroalgae along the channels of both harbours, north-west of the Quail Island as well as in the shallow areas of the outer Darwin and Bynoe Harbours (Figure 14). In contrast, a higher probability of occurrence of the Seagrass was predicted along coastal areas of the outer Darwin and Bynoe Harbours (Figure 15).

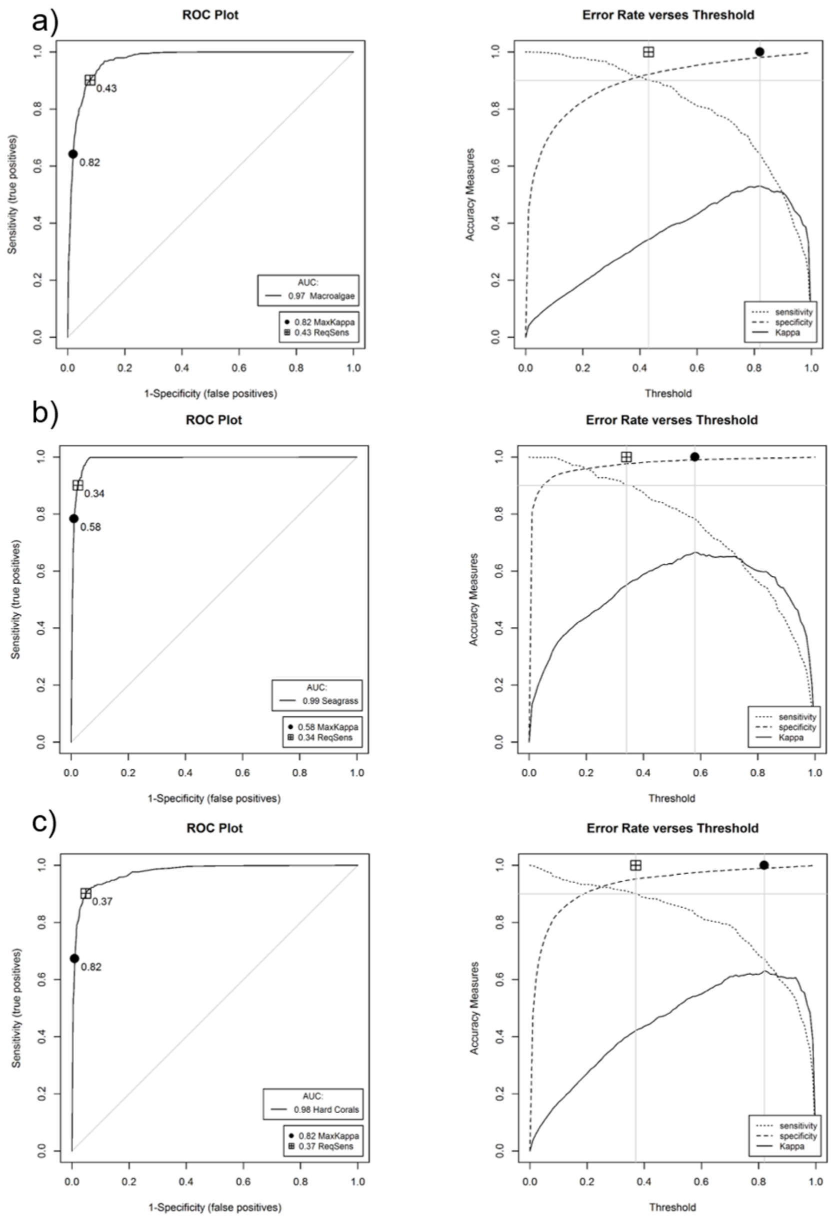


**Figure 13. Receiver operating plots (left side) and error measures (right) as a function of threshold for a) Macroalgae; b) Seagrass and c) Hard Corals as results of Maxent models. The optimised thresholds MaxKappa and ReqSens (at sensitivity level = 0.9) are marked along plots.**

Higher probability of occurrence of Hard Corals was predicted on the north side of Middle and Fish Reefs, west of the Charles Points and in the shallow parts of the channels of both Harbours (Figure 16). Lastly, we applied the identified ReqSens thresholds for the corresponding individual benthic classes to produce binary habitat maps for the rare benthic classes, which could be found in Appendix 3. We chose this threshold to produce the binary maps in order include most of the predicted environmental niche for these rare benthic classes.

**Table 5. Individual class Maxent model accuracy scores for the Macroalgae, Seagrass and Hard Corals based on the test data validation and across two selected thresholds.**

| Model | Threshold | Threshold value | PCC | Sensitivity | Specificity | Kappa | AUC |
|---|---|---|---|---|---|---|---|
| Macroalgae | MaxKappa | 0.82 | 0.97 | 0.64 | 0.98 | 0.53 | 0.97 |
| | ReqSens | 0.43 | 0.92 | 0.90 | 0.92 | 0.34 | 0.97 |
| Seagrass | MaxKappa | 0.58 | 0.99 | 0.78 | 0.99 | 0.67 | 0.99 |
| | ReqSens | 0.34 | 0.98 | 0.90 | 0.98 | 0.55 | 0.99 |
| Hard Corals | MaxKappa | 0.82 | 0.98 | 0.67 | 0.99 | 0.63 | 0.98 |
| | ReqSens | 0.37 | 0.95 | 0.90 | 0.95 | 0.42 | 0.98 |

## Discussion

In this report, we successfully developed robust spatial models and comprehensive predicted distribution maps of major benthic habitats for the Darwin and Bynoe Harbours. These maps provide an initial inventory of subtidal habitats in this extensive and remote region with a total mapped area of approximately 2000 $km^2$. Previous research in this region identified a knowledge gap in the baseline information on large-scale biodiversity and environmental values of this region which could be affected by coastal development. In addition to the produced maps, we also identified the most influential environmental predictors that drive distributions of the major benthic biota in the region. Together, the predicted distribution maps and the identified environmental predictors of major benthic classes which are integral to ecosystem health, management and conservation will improve understanding and management efforts of the marine habitats in the Northern Territory.

Most of the benthos of both harbours was predicted to be highly suitable for a variety of filter-feeding biota (approx. 68.6 % of the total mapped area) such as sponges and octocorals with shallow areas along the arms found to be more suitable for the Hard Corals and Macroalgae. Hard Corals and Macroalgae were also predicted in isolated pockets across outer areas of Darwin and Bynoe Harbours especially near Middle and Fish Reefs (0.01 and 0.13 % respectively, of the total mapped area). In contrast, seagrass was mainly predicted to be associated with the shallow areas outside of the main channels (approx. 1.7 % of the total mapped area). Water depth appeared to be the main driver of distribution of the modelled benthic classes.

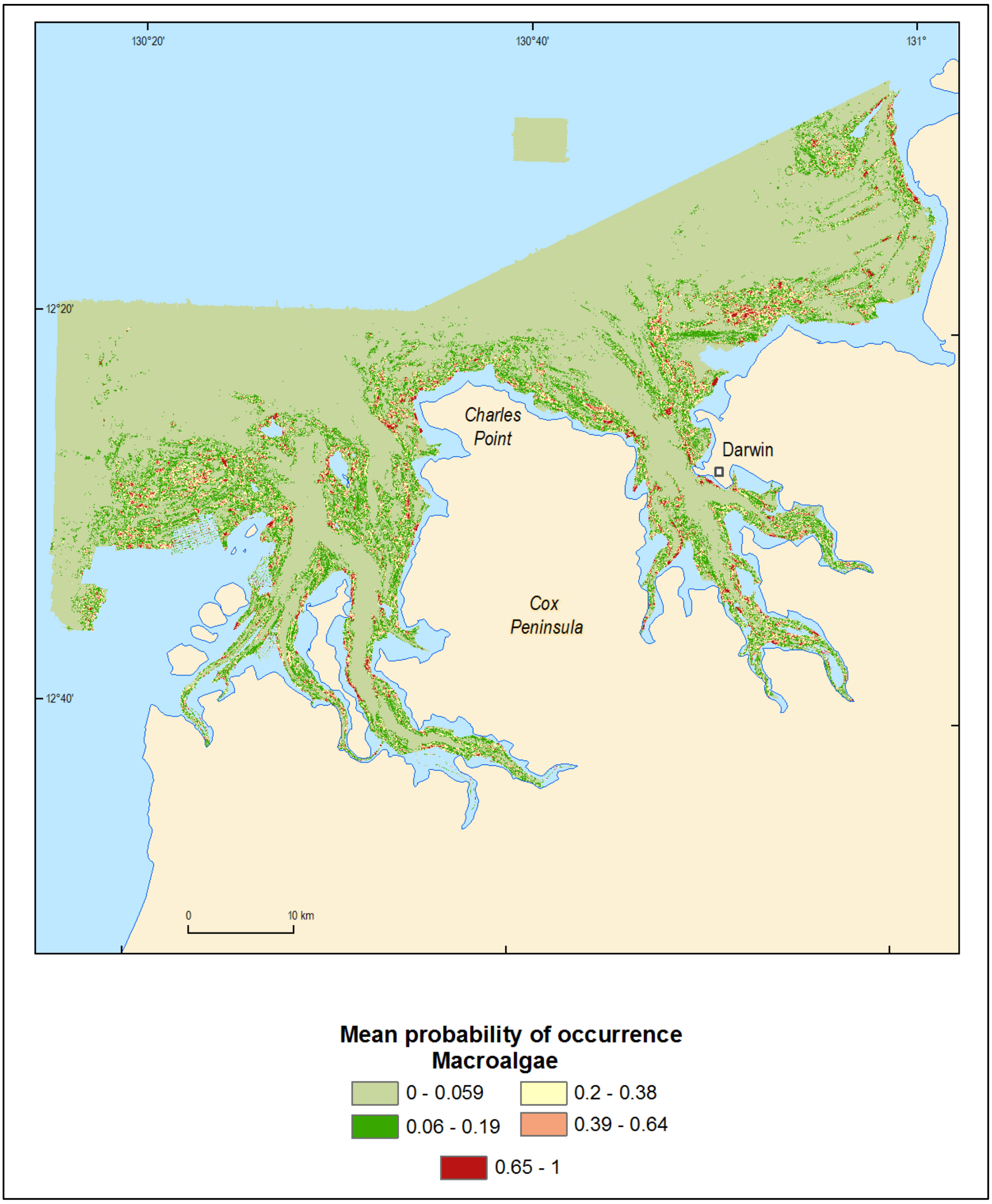


**Figure 14. Mean predicted probability of occurrence of macroalgae. Warmer colours indicate higher probability.**

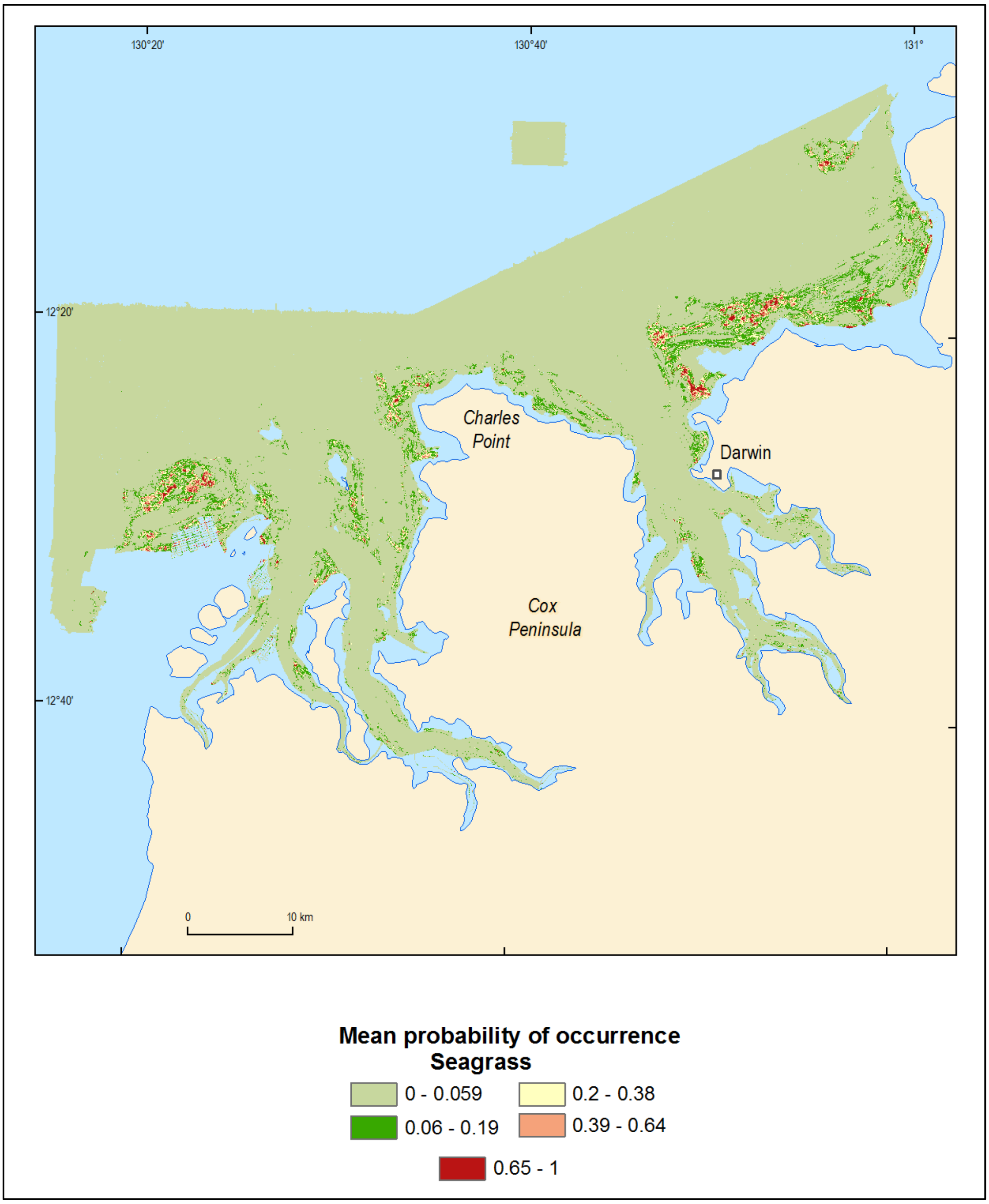


**Figure 15. Mean predicted probability of occurrence of seagrass. Warmer colours indicate higher probability.**

The shallow areas (< 10 m) were typically characterised by the presence of autotrophic communities such as Macroalgae, Seagrass and Hard Corals. The shallows were further divided based on the structural complexity with more complex areas were typically dominated by the Hard Corals and Macroalgae whereas the Seagrass areas were typically characterised by relatively lower complexity. The deeper slopes (> 10 m) with varying degrees of associated complexity were found to be highly suitable for the heterotrophic filter feeding communities. In contrast, deep, low complexity flat areas had typically no associated epibenthic biota. There were, however, bioturbation marks often observed on the bare sediment (R. Galaiduk pers. obs.) can be evidence of infauna activity.

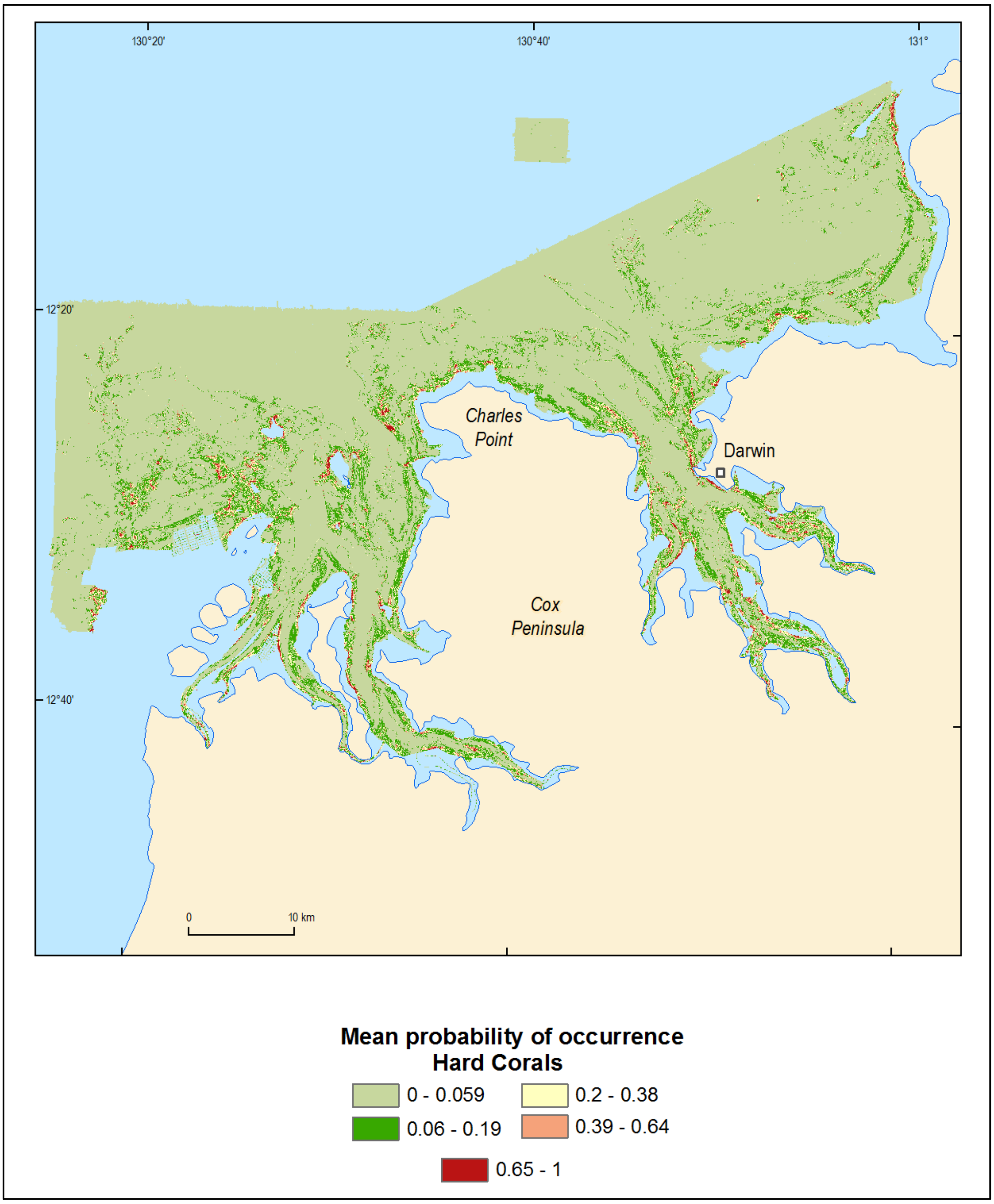


**Figure 16. Mean predicted probability of occurrence of hard corals. Warmer colours indicate higher probability.**

The depth and various derivatives of structural complexity are common drivers of distributions of benthic biota (Holmes et al. 2008). Here depth most probably acts as a surrogate for turbidity which could reach more than 400 NTU during the wet season storms (Siwabessy et al. 2016) acting as a natural barrier for benthic organisms relying on photosynthesis as a food source.

The produced models were characterised by high accuracy and high predictive power for both Random Forest and Maxent models after validation with held out datasets. Despite the high accuracy of the Random Forest model, however, it was characterised by a high proportion of misclassified rare benthic classes. While overall model accuracy is a very common measure of model performance, it was previously criticised for allocating high accuracies for rare species (Fielding & Bell 1997, Allouche et al. 2006). In addition, the prevalence of observations in a sample is known to affect model performance (Franklin 2010). While the Random Forest model can still be used with a high confidence for predicting the distribution of the most abundant classes (SP/FF/OC and Bare sea bottom), in this case the Maxent models are more suitable for predicting the probability of occurrence of the rare benthic classes (Macroalgae, Seagrass and Hard Corals).

The most direct approach to improve the model performance for the rare classes would be collecting more data in the shallow and intertidal areas which were shown to have a high proportion of the rare benthic classes. Current models were limited to the extent of the multibeam bathymetry in the shallow water which in some cases required removing the towed video observations that did not overlap with the shallow multibeam layer. However, access to the intertidal areas is often restricted due to safety concerns for the small boat operations and may require alternative approaches for collecting data on benthic assemblages in these areas such as satellite, drone or LiDAR imagery. These approaches will be most certainly limited by depth due to high water column turbidity in this region. In addition, while all the effort was made to execute all the pre-planned transects, weather conditions and other logistics limited actual towed video data collected to 53 and 90 transects in Darwin and Bynoe Harbours respectively instead of the initially planned 150 and 120 transects. This contributed to the reduced prevalence of the rare benthic classes.

To produce binary presence-absence maps of the distribution of benthic habitat classes and to calculate additional model performance metrics, we applied two different threshold optimisation routines. These metrics demonstrate two different approaches for producing binary predictive maps with respect to a relevant ecological or environmental management question. If the management purpose is to define a niche for rare classes without omitting parts of the area, ReqSens could be used with the desired sensitivity threshold. This threshold will produce a binary map which may overestimate the actual environmental niche but will include most of the probable areas for finding the species. Another alternative is the MaxKappa threshold which ensures that predicted environmental niche is closely related to the fitted model and is an improvement over chance prediction (Freeman & Moisen 2008). This is a suitable threshold to use for estimating the environmental niche based on the observed distributions in the model. There are other alternatives available for threshold selection based on the requirements for the produced binary maps (Liu et al. 2005, Freeman & Moisen 2008 for a review and examples).

In conclusion, this report summarises the development of predictive benthic habitat maps for the Darwin-Bynoe Harbours. It is clear that there needs to be further effort to improve mapping the distribution of rare benthic classes in the shallow and intertidal environments. Nonetheless, the maps produced here provide a robust baseline for benthic biodiversity and habitat distributions in this remote region and offer new insight into the marine environments of the Northern Territory coastline. They will support future management decisions including marine planning, long-term monitoring and environmental impact assessments as well as contribute to research and management of mobile biota such as dugongs, turtles and fish associated with these habitats.

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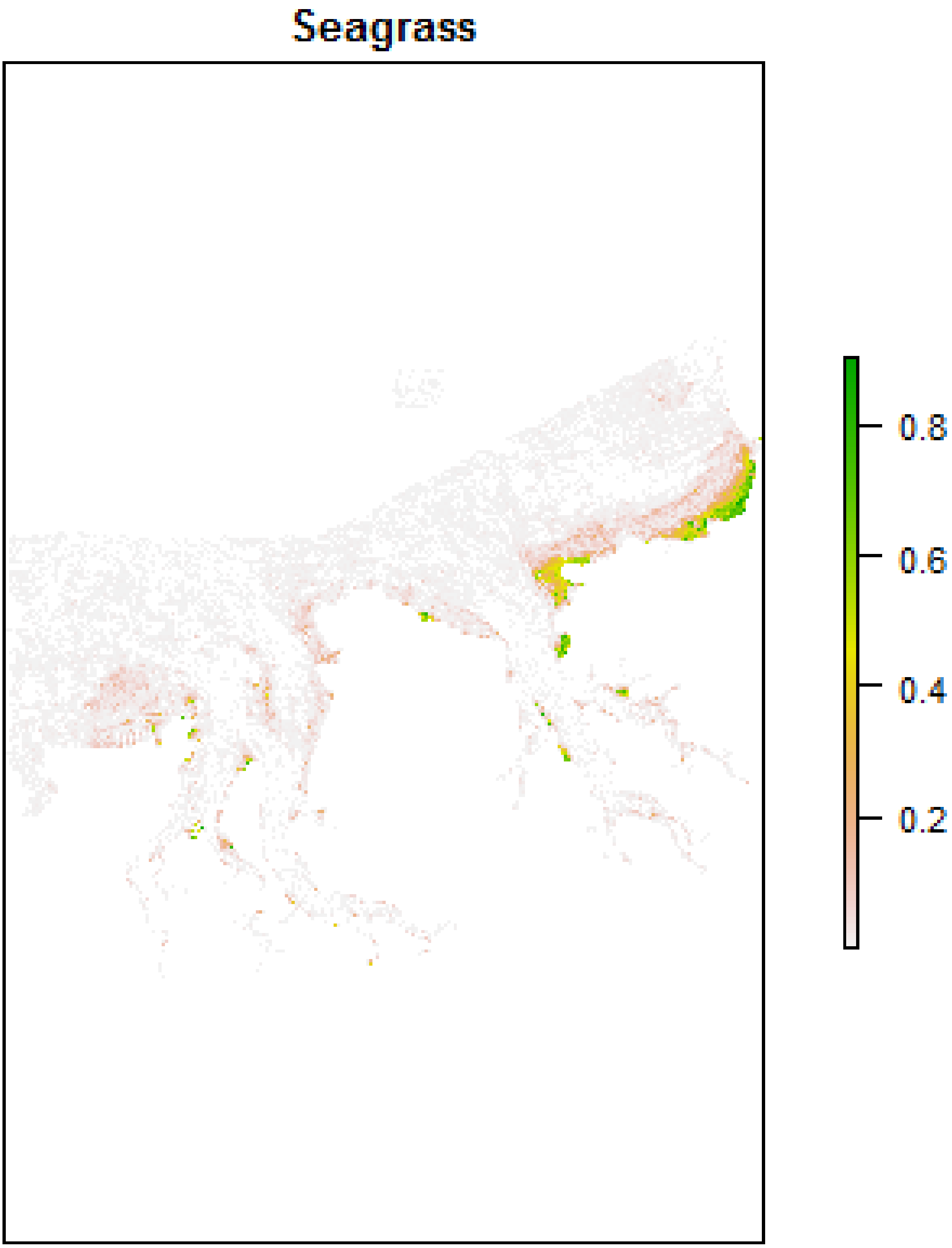
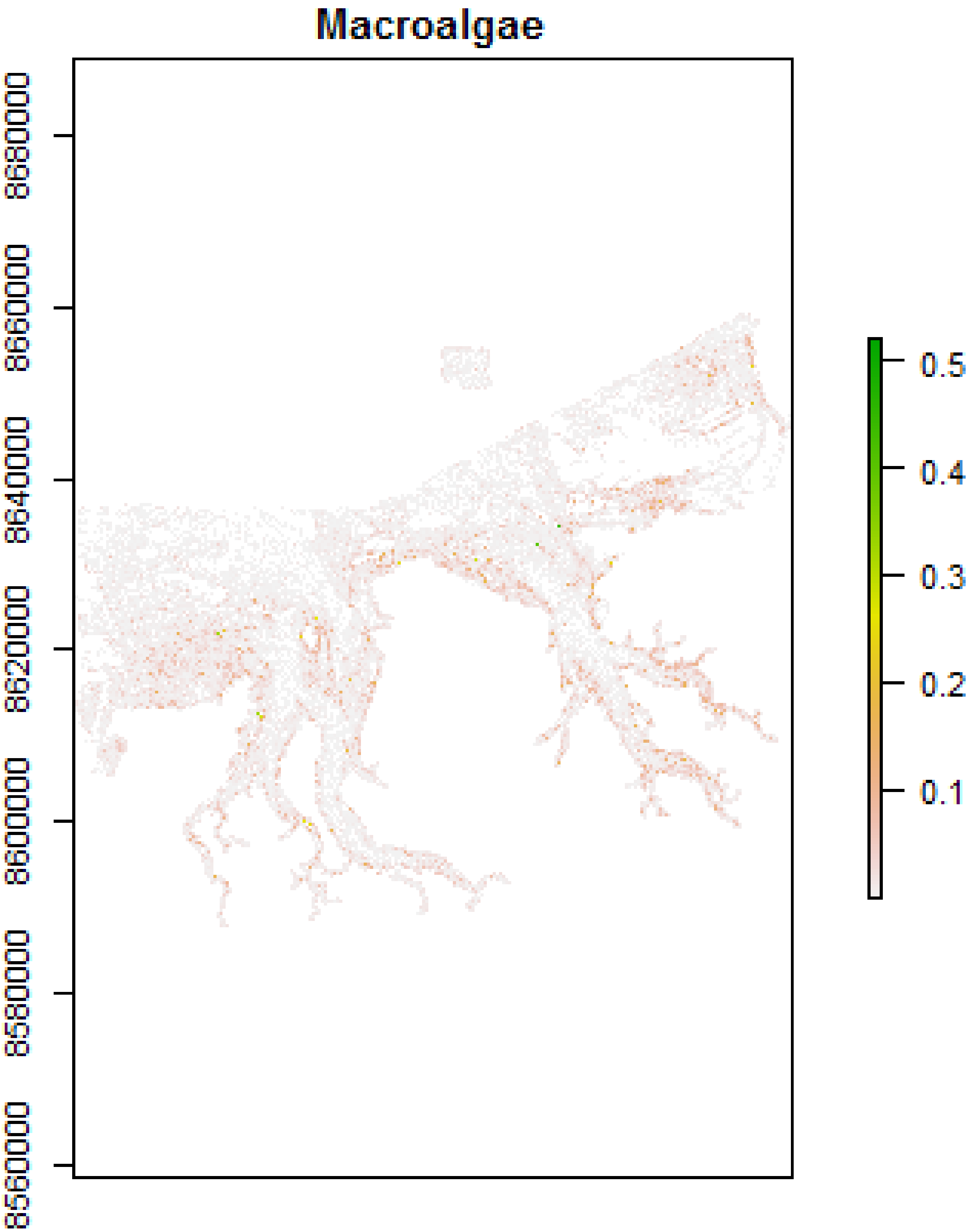
# Appendices

## Appendix 1




Appendix 1. Individual maps of predicted probability of occurrence of five mixed benthos classes from the Random Forest model.

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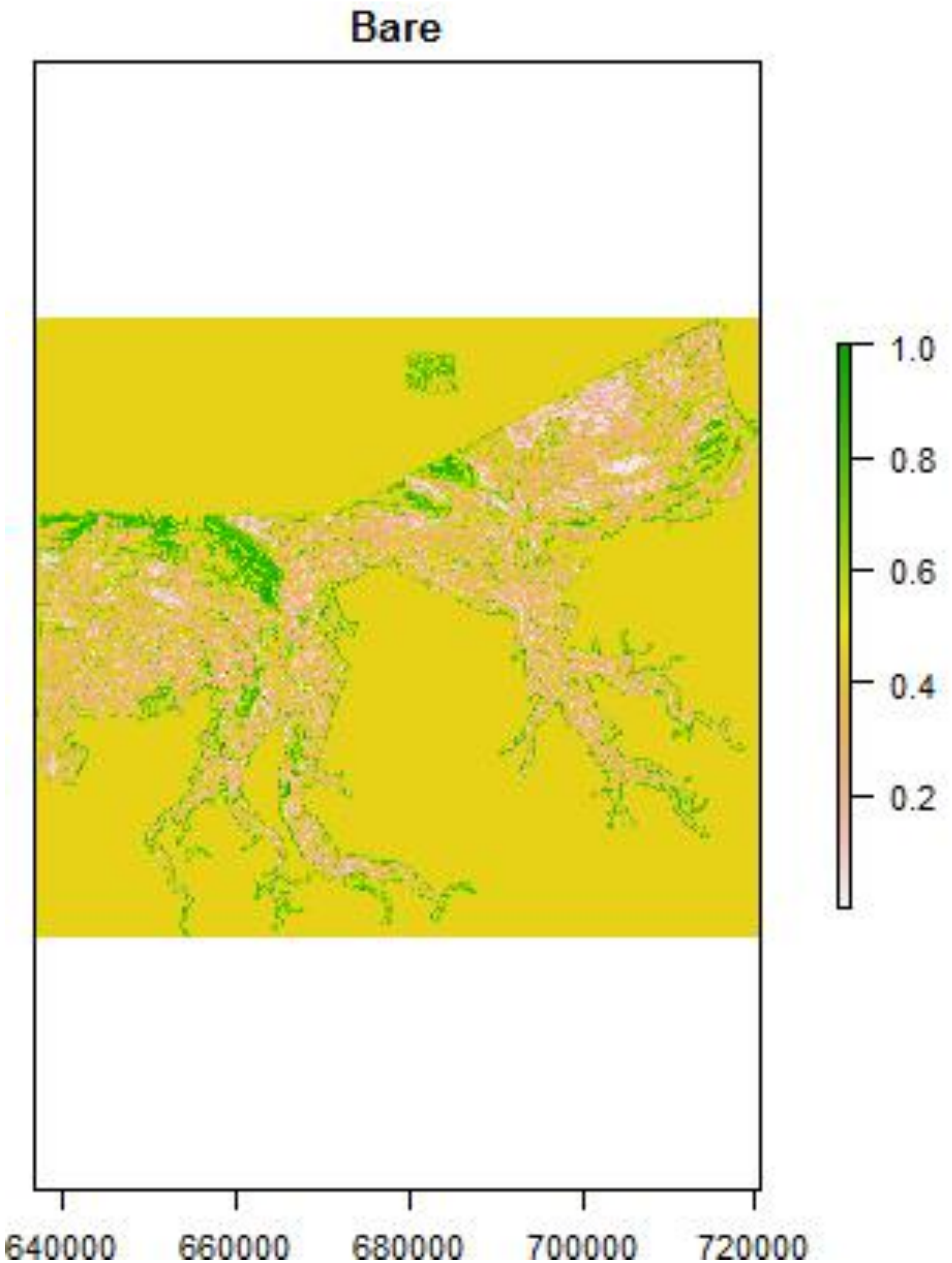


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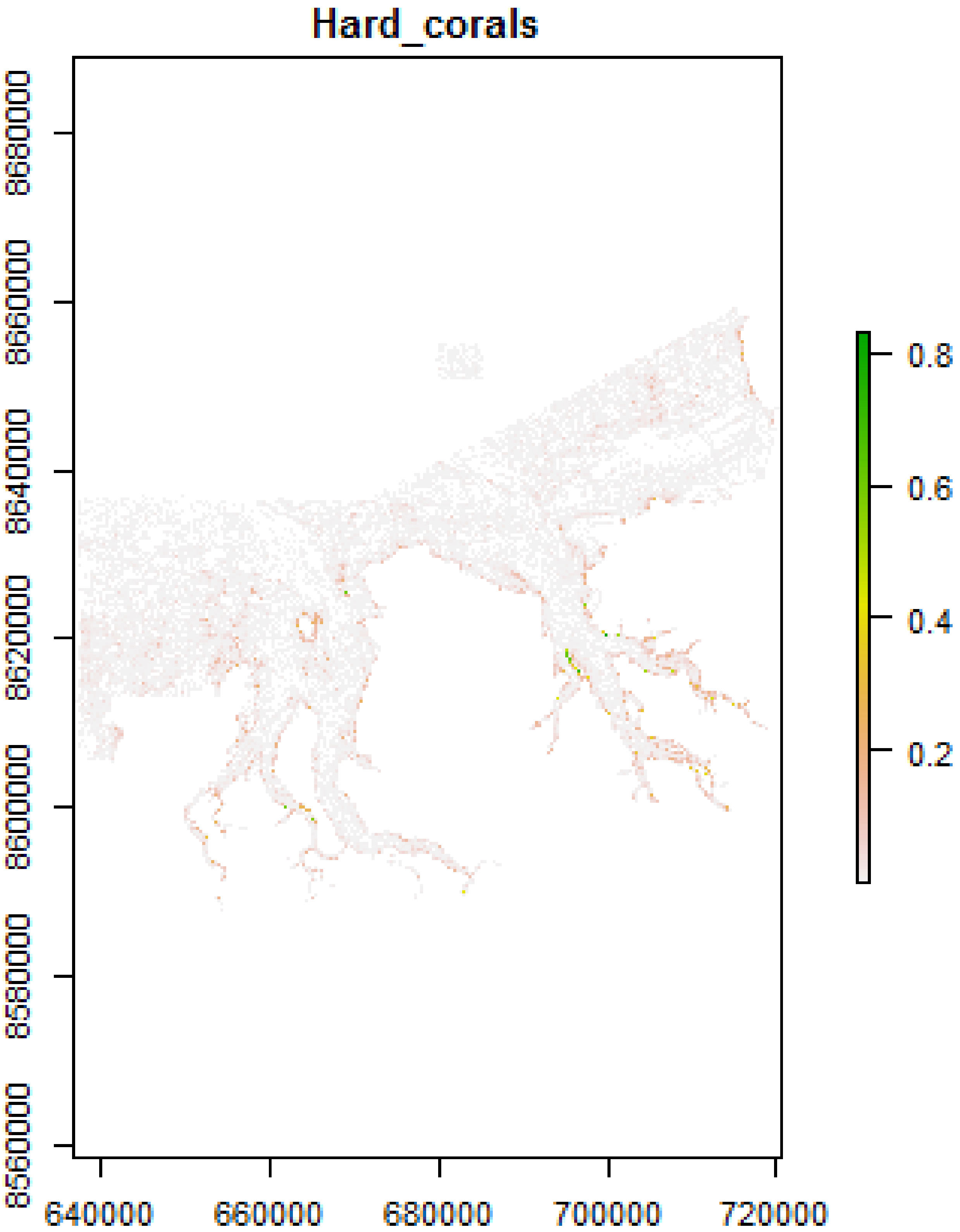


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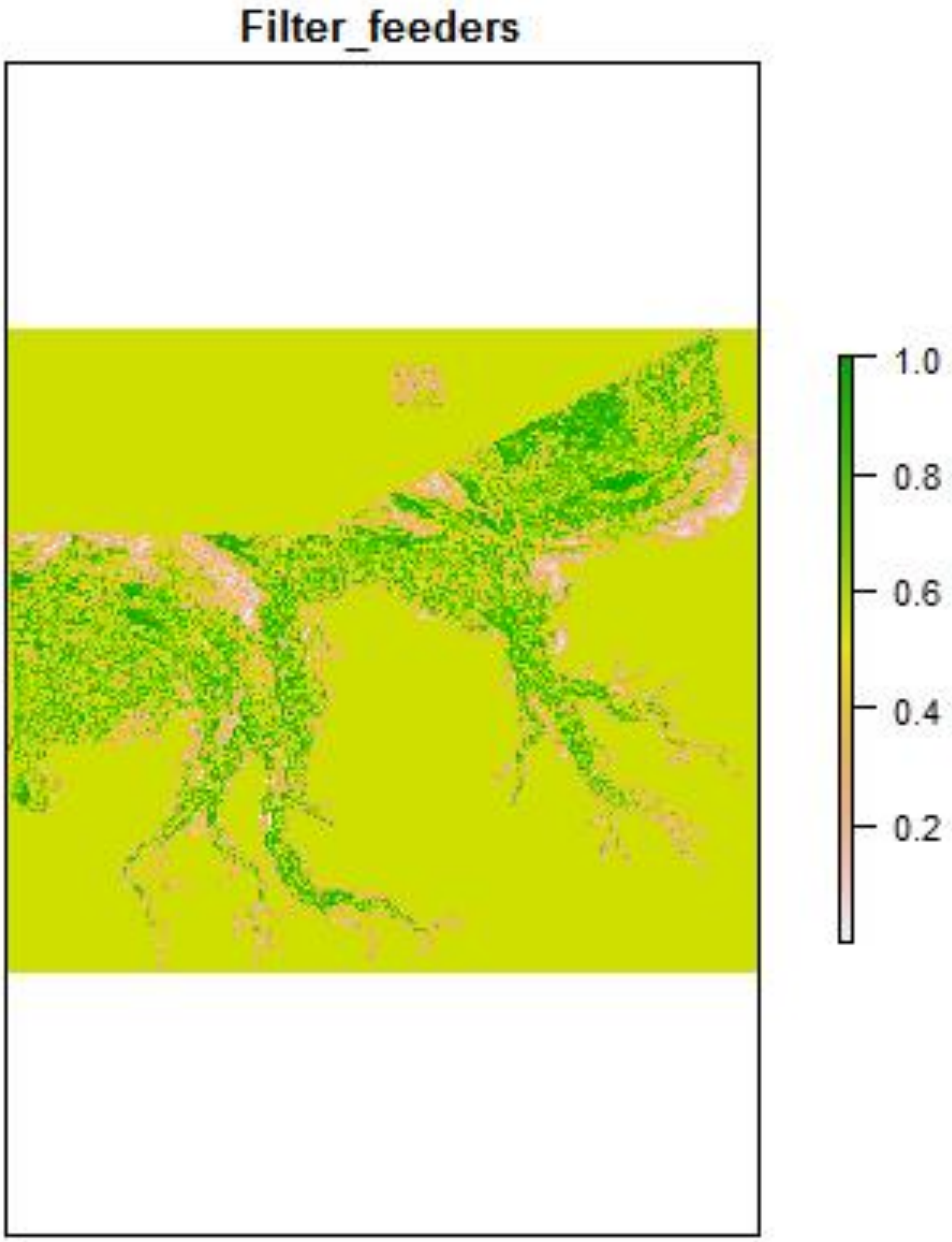


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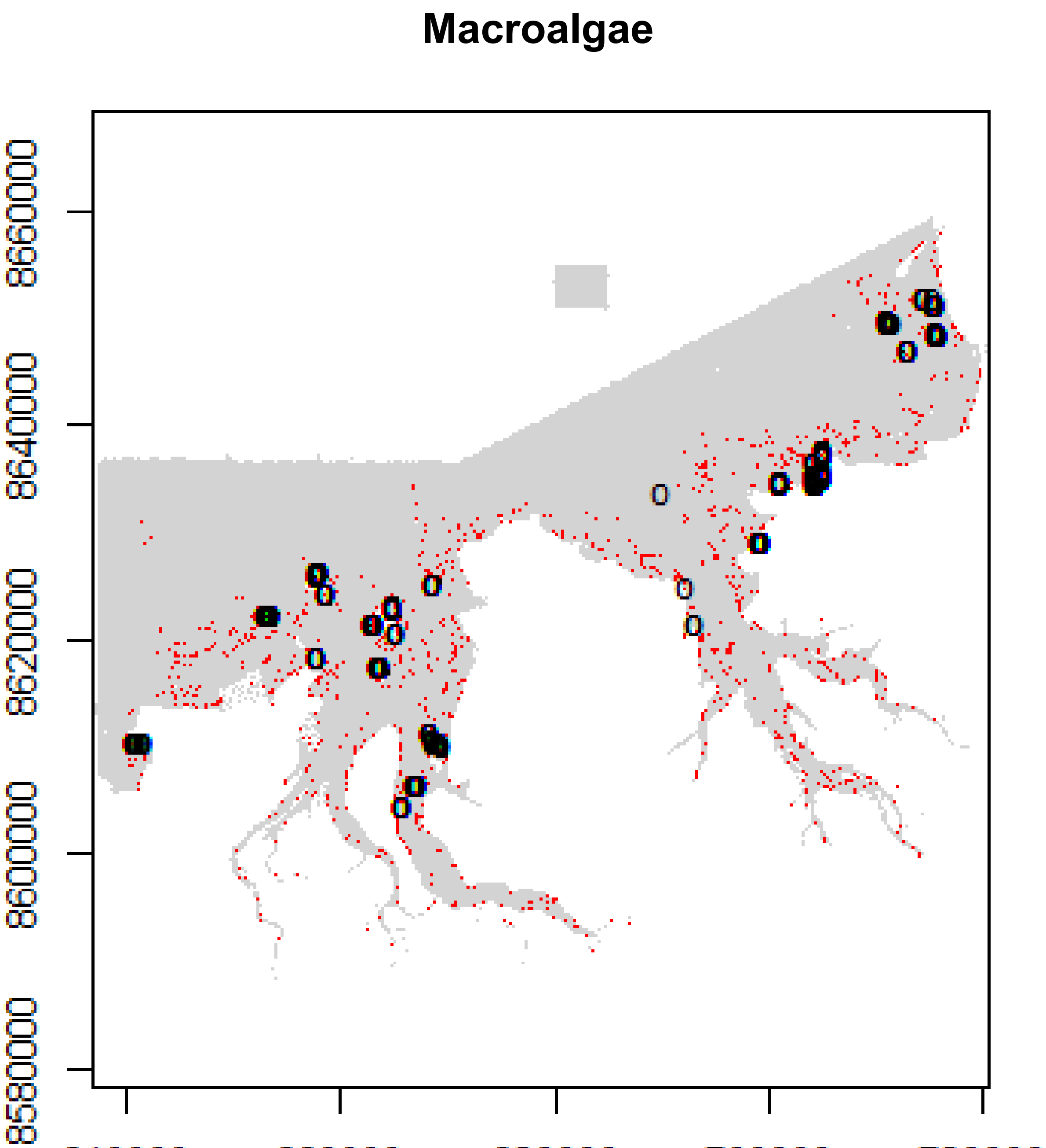
## Appendix 2

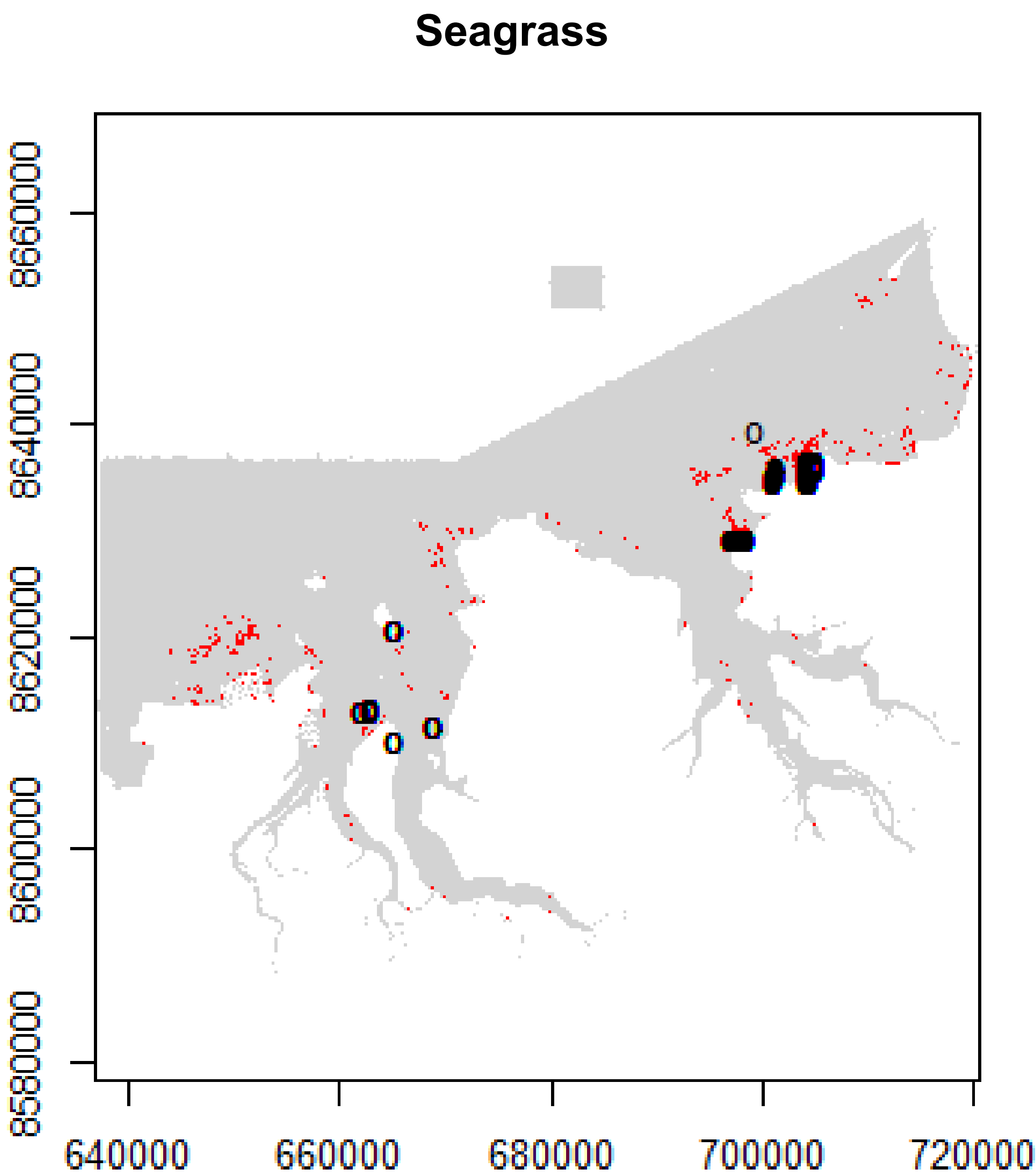
Appendix 2. Confusion matrix for the individual class Maxent models using the holdout validation data across two selected thresholds (predicted class on the x-axis observed class on the y-axis).

| | | MaxKappa | | ReqSens | |
|---|---|---|---|---|---|
| | | 1 | 0 | 1 | 0 |
| Macroalgae | 1 | 958 | 1073 | 1346 | 4448 |
| | 0 | 535 | 55793 | 147 | 52418 |
| Seagrass | 1 | 814 | 564 | 936 | 1358 |
| | 0 | 225 | 56860 | 103 | 56066 |
| Hard Corals | 1 | 842 | 543 | 1128 | 2753 |
| | 0 | 409 | 56522 | 123 | 54312 |

## Appendix 3




Appendix 3. Individual binary maps of predicted occurrence (red cells) of the three rare benthic classes from the 5-fold cross-validated Maxent model. The thresholds used for map production are ReqSens at 90 % of sensitivity. Observed presences from the withheld testing dataset are marked with 'o'.

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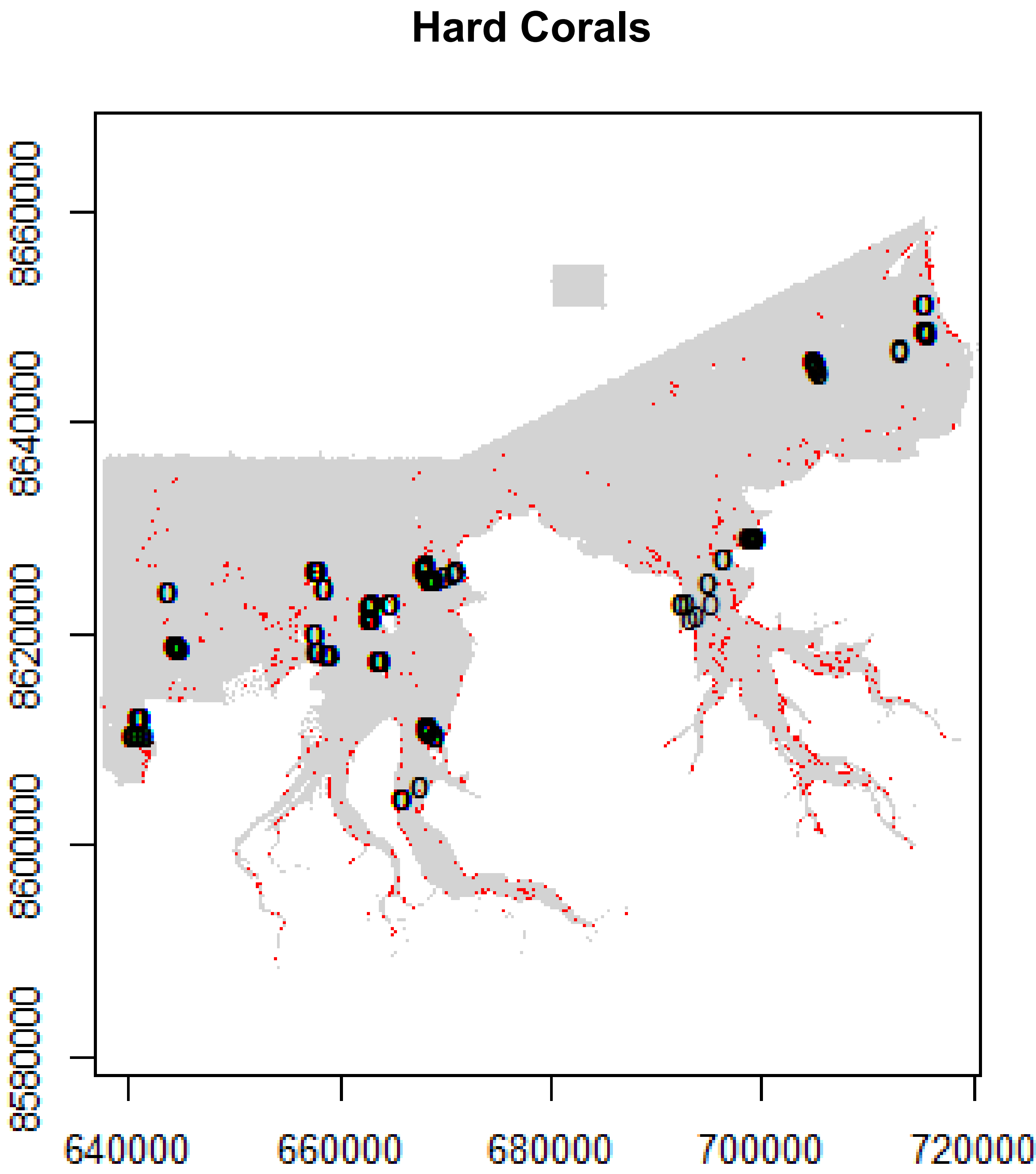


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