Broad-scale distribution and habitat modelling of Indo-Pacific bottlenose dolphins (*Tursiops aduncus*) in Owen Anchorage and Cockburn Sound using boat-based survey data from 2011-2015

Theme: Apex Predators and Iconic Species

WAMSI Westport Marine Science Program

WESTERN AUSTRALIAN MARINE SCIENCE INSTITUTION

WESTPORT

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WAMSI WESTPORT MARINE SCIENCE PROGRAM

ABOUT THE MARINE SCIENCE PROGRAM

The WAMSI Westport Marine Science Program (WWMSP) is a $13.5 million body of marine research funded by the WA Government. The aims of the WWMSP are to increase knowledge of Cockburn Sound in areas that will inform the environmental impact assessment of the proposed Westport development and help to manage this important and heavily used marine area into the future. Westport is the State Government's program to move container trade from Fremantle to Kwinana, and includes a new container port and associated freight, road and rail, and logistics. The WWMSP comprises more than 30 research projects in the biological, physical and social sciences that are focused on the Cockburn Sound area. They are being delivered by more than 100 scientists from the WAMSI partnership and other organisations.

FUNDING SOURCES
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DATA
Finalised datasets will be released as open data, and data and/or metadata will be discoverable through Data WA and the Shared Land Information Platform (SLIP).

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Theme: Apex predators and iconic species
Front cover image: A pod of dolphins in Cockburn Sound.
Photo courtesy of: Delphine Chabanne (Murdoch University).

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Project

Spatio-temporal distribution of key habitat uses and key prey species for Indo-Pacific bottlenose dolphins in Owen Anchorage and Cockburn Sound, including a fine-scale understanding of the use of the habitats in the Kwinana Shelf

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Executive Summary

This study aims to address gaps in our understanding of the ecology of Indo-Pacific bottlenose dolphins (*Tursiops aduncus*) in Owen Anchorage and Cockburn Sound in order to improve the scientific basis for environmental impact assessment (EIA) of the proposed Westport port development. This report presents the results from analysing data collected between 2011 and 2015, focusing on the broad-scale spatial and temporal distribution of the two communities of Indo-Pacific bottlenose dolphins' resident in Owen Anchorage and Cockburn Sound.

A total of 72 surveys were conducted in Owen Anchorage, and 73 surveys were conducted in Cockburn Sound. These surveys followed three systematic zigzag survey routes that were pre-designed in each region, spanning from June 2011 and May 2015. During these surveys, we performed photo-identification and recorded environmental variables such as water depth, sea surface temperature, and water visibility for dolphin sightings within the study area. We observed a total of 94 dolphin groups (incl. 36 foraging and 13 resting) in Owen Anchorage and 119 dolphin groups (Incl. 49 foraging and 19 resting) in Cockburn Sound, with the majority being mixed-sex groups. Additionally, calves, which are individual dolphins still dependent on their mothers, were present in most of the groups with adult dolphins.

To model the distribution of dolphin occurrence (presence/absence) in the study area, Ensemble Modelling using Species Distribution Modelling methods was employed. Separate modelling was conducted for Owen Anchorage and Cockburn Sound due to the distinct social and spatial characteristics of the two resident dolphin communities.

The study design employed for collecting longitudinal data during 2011-2015 was optimised to estimate abundance and measure individual-specific association and ranging patterns within the designated study area. In this study, the data collected from the 2011-2015 research was utilised to examine the overarching distribution patterns and habitat associations of dolphins at a broad scale.

As dolphins spend a significant amount of time underwater and may not always be visible at the water's surface, pseudo-absence data were incorporated into the SDMs. The pseudo-absence data corresponded to areas (250 m x 250 m cells) where no dolphins were observed despite high survey effort.

Dolphins in Owen Anchorage

The results of the ensemble models revealed the distribution of dolphins in Owen Anchorage was primarily influenced by the distance to the coastline and recreational boat ramps/harbour. Important dolphin habitats were identified within 1,000 m from the coastline, extending to 2,500 m in winter and autumn. The distribution patterns of dolphins varied across seasons, showing shifts in response to sea surface temperature and water visibility.

Other factors not available for testing in this study may influence dolphin distribution in Owen Anchorage. The complex system of estuarine flows, including tidal but mostly from climatic events like heavy rainfall, affect temperature, salinity and water visibility fluctuations, potentially influencing dolphin prey composition and distribution. Future research should also focus in understanding how additional underwater noise and induced-wave movement in the homogenous shallow environment and ecosystem diversity of Owen Anchorage may influence the dolphin distribution. This highlights the importance of comprehending the local effects of underwater noise caused by vessel activities and operations on dolphin behaviour and health.

Dolphins in Cockburn Sound

The results of the ensemble models revealed that the distribution of dolphins in Cockburn Sound was primarily influenced by depth, with important areas occurring in shallow waters (< 10 m). Specific locations with high and very high probabilities of dolphin occurrence were identified along the northern tip of Garden Island, the southern part of Garden Island, the south-eastern coastline, and across the Kwinana Shelf. The central basin exhibited the lowest probability of dolphin occurrence, indicating a more consistent distribution compared to Owen Anchorage.

Although substrate type was not identified as a significant variable, areas characterized by reef, cobble, and seagrass overlapped with high probability of dolphin occurrence. These habitats are believed to be important for dolphins due to the diverse prey types supported by these ecosystems. Seagrass meadows in particular serve as crucial breeding and nursery areas for various fish species, which are likely prey targets for dolphins. The Kwinana Shelf was identified as a long-term key area for dolphins, with consistent distribution patterns observed over several decades. The importance of these habitats for feeding aggregations, which include mother-calf pairs, highlight its significance. The lack of similar habitat in nearby regions presents challenges for dolphins to adapt or relocate, with further activities that can have adverse effects at the individual level resulting in long-term implications for population dynamics.

Conclusions

The results of this study offer valuable insights into the distribution patterns of dolphins in Owen Anchorage and Cockburn Sound, emphasising the importance of considering ecological complexities and potential risks associated with activities related to the proposed Westport port development. While determining the specific environmental variables that explain the dolphin distribution has proven challenging, the information provided in this study can contribute to environmental impact assessments and guide management and conservation efforts aimed at ensuring the sustainable coexistence of dolphins in future development in these regions. It is recommended that further research and dedicated studies be conducted in both Owen Anchorage and Cockburn Sound closer to, during, and after the development phase to fully understand the potential effects of construction-related activities, vessel traffic, and environmental changes on the behaviour, health, and population dynamics of dolphins that use the areas.

1 Introduction

1.1 Background

Activities associated with the establishment and operation of a port in the Kwinana Shelf, Cockburn Sound, have the potential to adversely affect the local marine biodiversity, including the Indo-Pacific bottlenose dolphins (*Tursiops aduncus*), which are recognised as apex predators and iconic species in the region. The Indo-Pacific bottlenose dolphin is protected in Australia under the Environment Protection and Biodiversity Conservation Act 1999 and in Western Australia by the corresponding Biodiversity Conservation Act 2016 (WA). Recently, this dolphin has also been listed as 'near threatened' globally in the IUCN Red List of Threatened Species due to several factors: '1) the formation of small resident populations in restricted near-shore areas; 2) inhabiting habitats subject to increasing anthropogenic threats leading to habitat loss and degradation; 3) being highly vulnerable to entanglement in fishing gear; and, 4) experiencing mortality rates that put populations at risk of decline (Braulik et al. 2019).

In the Perth metropolitan waters, the Indo-Pacific bottlenose dolphins (hereafter referred to as 'dolphins') exhibit a population structure characterised by long-term residency, strong site fidelity, and limited ranging patterns within Cockburn Sound (<65 individuals), Owen Anchorage[1] (<45 individuals) and the Swan Canning Riverpark (~16 individuals) (Finn 2005, Chabanne et al. 2012, Chabanne et al. 2017a, Chabanne et al. 2017b). In Cockburn Sound, resident dolphins use the entire region, with their core area located across the Kwinana Shelf, the designated area for port development. The Kwinana Shelf is recognised as an important foraging habitat for dolphins, where large feeding aggregations involving dolphins and seabirds occur (see Figure 1, Finn 2005, Finn & Calver 2008, Chabanne et al. 2017a). C (Figure 1, Chabanne et al. 2017a). While the broad-scale distribution patterns of the communities of dolphins remained consistent over decades, the fine-scale distribution patterns within their respective residency regions may shift rapidly, within a few years (Hartel et al. 2015). Therefore, a comprehensive understanding of the dolphins' distribution at both individual and ecosystem levels, considering spatial and temporal scales, requires detailed investigation.

[1]Owen Anchorage is defined as the whole area from Fremantle to woodman Point and extending to Carnac Island (western margin)

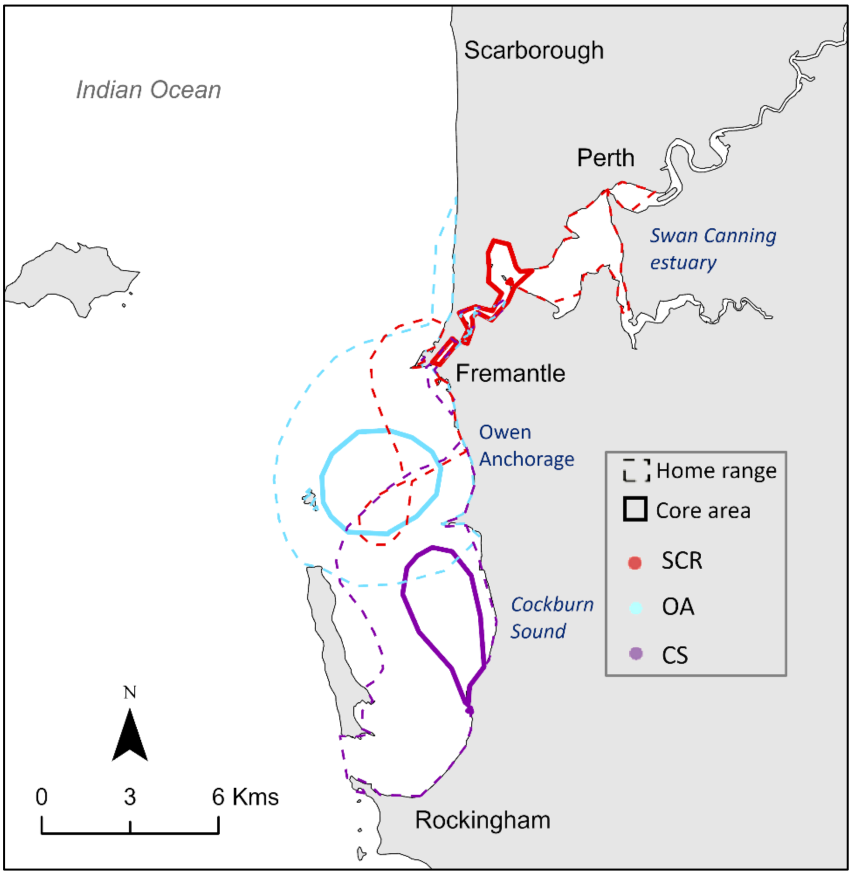

Figure 1. Core areas (derived from 50% kernel density) and home ranges (derived from 95% kernel density) of each resident community of Indo-Pacific bottlenose dolphins identified in Perth metropolitan waters: SCR – Swan Canning Estuary; OA – Owen Anchorage; CS – Cockburn Sound (Figure edited from Chabanne et al. 2017a).

In response to the proposed port development in the Kwinana Shelf, Cockburn Sound, further analysis was conducted using data from photo-identification boat-based surveys for dolphins collected between 2011 and 2015. The surveys were part of the Coastal and Estuarine Dolphin Project (CEDP), a collaborative research program focused on the health, ecology, and conservation of dolphins in the Perth region. The new findings presented in this report should be considered in environmental impact assessments related to the proposed port development. They can help guide the application of the EIA 'mitigation hierarchy,' such as identifying key areas to avoid (the preferred option in the EIA mitigation hierarchy for biodiversity factors) or exploring other mitigation options to minimise potential effects on the resident dolphin communities.

1.2 Species distribution modelling and ensemble modelling

Information regarding the influence of various environmental and anthropogenic factors on the distribution of dolphins is fundamental for understanding their ecology and guiding spatial conservation efforts. Species distribution modelling (SDM), also known as habitat modelling or predictive habitat distribution modelling, has become increasingly valuable in identifying and predicting habitat associations (Tyne et al. 2015, Azzolin et al. 2020, Hunt et al. 2020). SDM relies on computer algorithms to predict species distribution in a specific study area based on environmental factors (e.g. seas surface temperature, water depth) and/or anthropogenic parameters (e.g. distance to human activities, boat density). However, selecting the most suitable modelling algorithm for a given dataset can be challenging due to significant disparities in performance and spatial predictions among different techniques (Thuiller et al. 2009, Grenouillet et al. 2011, Hunt et al. 2020). To address these challenges, an ensemble modelling (EM) approach has emerged as a solution, providing more robust estimates of species distribution by combining multiple models and accounting for biases inherent in individual models (Araújo & New 2007, Franklin 2010, Grenouillet et al. 2011).

The ensemble model approach has been successfully employed in numerous studies focusing on coastal dolphins, informing future spatial planning and conservation decisions, such as the review of marine parks management plans (e.g., Passadore et al. 2018, Hunt et al. 2020) and the implementation of additional management strategies accordingly (e.g., Zanardo et al. 2017).

1.3 Aims and objectives

By establishing links between habitat characteristics and the presence of dolphins, it becomes possible to identify important areas for population viability and assess the potential adverse effects of human disturbance on the dolphin population. This study aimed to achieve an overall understanding of the preferred habitat and areas with a high probability of dolphin occurrence for both dolphin communities in Owen Anchorage and Cockburn Sound, utilising data collected between 2011 and 2015.

The specific objectives of the study were as follows:

- To identify the most relevant environmental and/or anthropogenic variables that influenced the distribution of dolphins in Owen Anchorage and Cockburn Sound on a broad scale, employing an ensemble of SDMs;
- To assess whether there were any temporal variations in the broad-scale distribution of dolphins and the variables influencing it;
- To generate a map depicting the predicted distribution of dolphins in Owen Anchorage and Cockburn Sound using the ensemble of SDMs and identify preferred habitat areas (i.e. areas with a high probability of dolphin occurrence based on the EM).

The identification of spatial, temporal, and significant areas within Owen Anchorage and Cockburn Sound can provide valuable information for conducting more detailed evaluations, facilitating effective zoning design, and implementing appropriate mitigation strategies to minimise the potential effects of port development scenarios.

2 Materials and Methods

2.1 Data available

2.1.1 Scientific permits and animal ethics

The 2011-2015 dolphin surveys were conducted under Scientific Permits SF008067, SF008682, SF009286 and SF009874 issued by the Department of Biodiversity, Conservation and Attractions and Animal Ethics approval W2342/10 and R2649/14 from the Animal Ethics Committee of Murdoch University.

2.1.2 *Study site and data collection*

The study area encompassed approximately 180 km^2 of coastal waters, spanning from Rockingham to Fremantle, and extending along the eastern side of Garden Island (**Figure 2**). Within this area, two distinct geographic regions were identified based on the topography and bathymetry of the waters:

- Cockburn Sound: This is a semi-enclosed embayment characterising by varying depths ranging from less than 2 m to over 20 m.
- Owen Anchorage: This embayment features depths of less than 10 m, except in the channel where the maximum depth reaches 14.7 m. The northern boundary of Owen Anchorage is situated at the channel that passes through the Fremantle Inner Harbour.

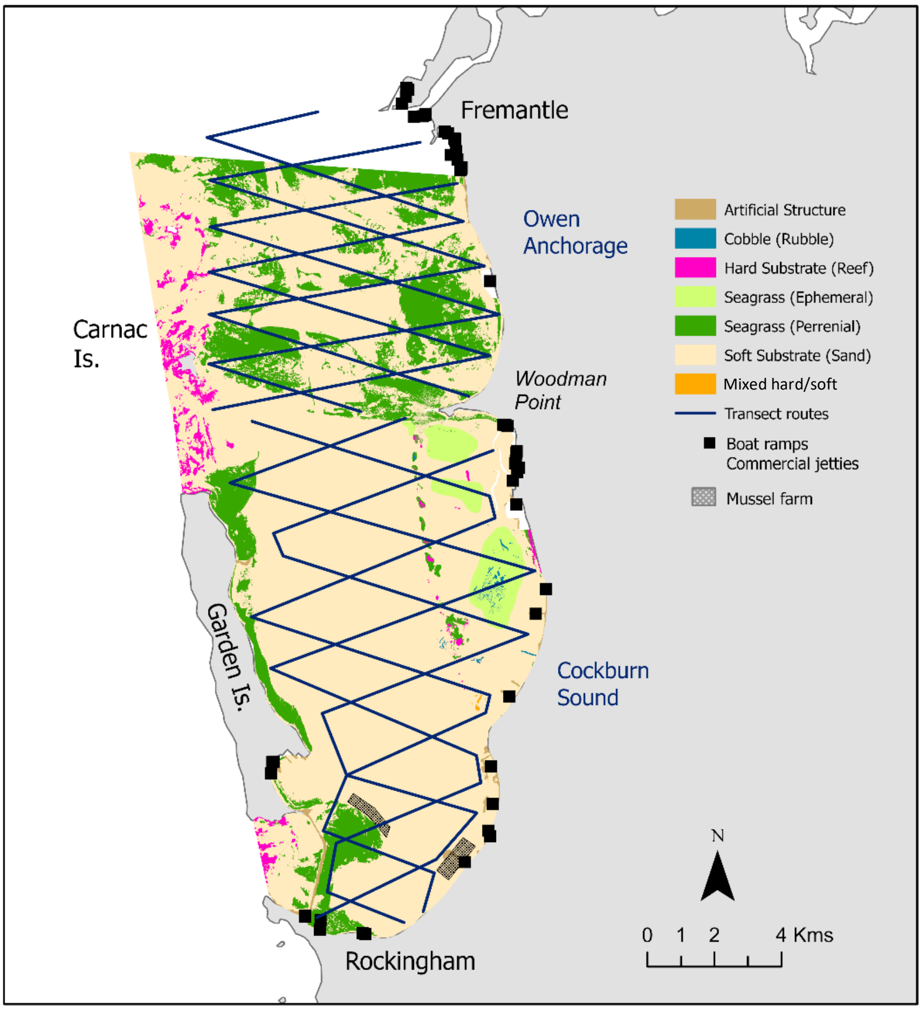

Figure 2. Map of the study area showing Owen Anchorage (OA) and Cockburn Sound (CS), and the three zig-zag transect routes conducted seasonally between June 2011 and May 2015. For logistic purposes, the transect routes were designed separately for OA and CS. Substrate data were retrieved from the WAMSI Westport ArcGIS portal in March 2023.

Sightings of dolphins were collected between June 2011 and May 2015 through systematic boat-based photo-identification surveys. The surveys followed predetermined transect routes as described in Chabanne et al. (2017b). To maximise sampling coverage (Figure 2) while minimising the risk of incomplete surveys due to changing weather conditions, we employed three zigzag transect routes that were designed using Distance 6.0 (Thomas et al. 2010) and offset by 2 km (**Figure 2**). Surveys were conducted at a constant speed of 8-12 knots and aligned with the Australasian calendar (Winter: June to August; Spring: September to November; Summer: December to February; Autumn: March to May).

The surveys were carried out under favourable conditions, namely wind speeds below 10 knots, Beaufort Sea State ≤ 3 and no rain. Each survey involved a crew of two to five observers on board (mode = 3) with only 2.6% of the surveys that were conducted with two observers. The observers scanned the area forward of the vessel's beam, searching for dolphins with the naked eye. When a dolphin group was encountered along our transect routes, search efforts were paused, and the dolphins were approached.

During these encounters, we recorded the location coordinates using a handheld GPS device (Garmin *GPS 72H*). We also documented the predominant behaviour observed within the first 5 minutes of observation and photographed the dorsal fin of each individual on both sides, whenever possible, regardless of the distinctiveness of the fins. Additionally, we collected *in situ* environmental data, including water depth, sea surface temperature (SST) and water visibility. The research vessel's depth sounder was used to measure water depth (in m) and SST (in °C). Water visibility was determined by measuring visibility with a Secchi disk and calculating it as a proportion of the total depth.

Furthermore, for the purpose of this project, additional environmental data for the summer months from multiple locations in Cockburn Sound were obtained. These data included Chlorophyll-a (Chl-a) concentration (in µg/L), light attenuation in water (Log_{10}/m), and surface and bottom salinity (in ppt). These data were provided by the Cockburn Sound Management Council.

2.2 Data analysis

2.2.1 Modelling framework

The objective of this study was to identify dolphin distribution patterns and key areas in Owen Anchorage and Cockburn Sound waters. The following steps were undertaken:

- Mapping the presence of dolphin sightings onto a 250 by 250 m grid resolution;
- Creating raster files of predictor variables at the same resolution;
- Assessing collinearity between predictor variables;
- Randomly selecting pseudo-absence cells and repeated the process ten times, resulting in ten datasets;
- Selecting model algorithms based on single model algorithm assessments conducted ten times for each dataset. The models were tested using 80% of the data for training and 20% of for evaluation;
- Predicting the distribution of the dolphins using an ensemble model prediction.

2.2.2 Ecogeographic explanatory variables

Ecogeographic explanatory variables used to model the dolphin distribution in Owen Anchorage and Cockburn Sound waters consisted of biotic, abiotic, and anthropogenic factors. Abiotic variables encompassed SST, water visibility, water depth, slope, distance to the coastline (mainland and islands), as well as salinities, Chl-a, and light attenuation, specifically for Cockburn Sound during the summer period. Anthropogenic variables included distance to boat ramps, commercial jetties, and entrance of the Fremantle Inner Harbour. Some of these variables are known to influence dolphin presence or prey distribution, while others act as proxies for predation risk or anthropogenic disturbance.

Raster files for each ecogeographic variable were created in ArcGIS Pro (ESRI, Redlands, California) using a 250 x 250 m grid resolution. The mapping projection was GDA2020 datum, and MGA2020 Zone 50 (Central Meridian 117˚East). Abiotic predictor variable layers were generated using *in situ* data and the *Ordinary Kriging Interpolation* tool, with a spherical semi-variogram model, a 250 m cell size, and 12-point variable search radius. Water depth data across the study area were obtained from the Department of Transport (previously used in Chabanne et al. 2017a) and adjusted to a 250 x 250 m resolution using the *Sample* tool. Slope was calculated using the *slope* tool, derived from water depth. Distance to the coastline was calculated using the *Euclidean distance* tool, providing the shortest straight-line distance. Distance to recreational boat ramps or commercial jetties, and entrance to the Fremantle Inner Harbour was determined using the *Cost distance* tool, considering land in the calculation. These tools were available in the Spatial Analyst extension for ArcGIS Pro.

Substrate type data for the entire area were obtained from the ArcGIS platform (Westport). Within Cockburn Sound, substrate types included seagrass (ephemeral and perennial), soft substrate (sand), hard substrate (reef and cobble), and a small patch of mixed substrate (hard/soft) released as a shapefile in March 2023. However, in Owen Anchorage, the substrate shapefile did not cover the northern section surveyed during the 2011-2015 research. Although it is highly likely that sand and seagrass dominate this unmapped section, the northern section of the study was excluded to minimise bias associated with an 'unknown' substrate category.

All ecogeographic variables and presence-absence layers were scaled separately for Owen Anchorage or Cockburn Sound regions, considering the socially and spatially distinct dolphin communities previously defined in those regions and accounting for variation in substrate distribution.

2.2.3 Presence-absence of dolphins

The study area was divided into 250 x 250 m grid cells, resulting in a total of 2,915 cells (1,052 cells for Owen Anchorage and 1,863 cells for Cockburn Sound) that were covered by the survey efforts and used for further analysis. Each grid cell was assigned a code of "1" to indicate the presence of dolphins if at least one sighting was recorded, and "0" to indicate absence otherwise. Sightings of dolphins observed while travelling were excluded from the analysis (although see Appendices 5 and 9).

The survey effort within each 250 x 250 m grid cell was quantified using only the 'on effort' survey tracks. A 250 m buffer area was added on either side of each transect line to account for the distance from the boat where dolphins can reliably be observed under various sea conditions.

False absences, which occur when dolphins are present but not detected, can arise from factors such as sampling design, observer effort, group size (smaller groups are more likely to go undetected), and species detection probability (Barbet-Massin et al. 2010). Biased models can result from failure to detect a species, leading to inaccurate estimates of species distributions (Lahoz-Monfort et al. 2013). In a study by Sprogis et al. (2018) or Haughey et al. (2021), false absences were mitigated by selecting absence cells with the highest effort (Phillips et al. 2009). Pseudo-absence cells were then chosen as cells with the highest effort but no recorded dolphin presence, with the total number of selected cells matching the number of presence cells. However, for this study, this method resulted in clustered groups of absence cells in the same area. To address this issue, Barbet-Massin et al. (2012)and Colin MacLeod (*personal communication*) recommended using a random selection method, with equal weight given to models averaging several runs of selection. Specifically, the following steps were taken: 1) pseudo-absence cells were selected from cells without dolphin presence but with higher survey effort than the mean effort of all cells (including those with presence), with a distance restriction of 250 m from presence cells (minimising overlap); 2) the total number of selected cells was three times the number of presence cells (Barbet-Massin et al. 2012) and thus for each temporal scale (overall, seasonal, yearly); 3) ten repeats of the selection process were performed, resulting in ten datasets of pseudo-absence cells (Barbet-Massin et al. 2012). Since the surveys were independently designed for

Owen Anchorage and Cockburn Sound, with two distinct dolphin communities identified (Chabanne et al. 2017a), the cell selection was done independently, and all SDMs were run separately for each region.

The distribution of dolphins was analysed for each region (Owen Anchorage and Cockburn Sound) for the entire study period (years 2011-2015 pooled) and by season (years pooled). All SDMs were run using only non-travelling dolphin sightings. Due to the limited sample size for SDMs, detailed information on the distribution of dolphins at smaller scales, such as by season for each year could not be provided.

2.2.4 Data exploration

Prior to running SDMs, stepwise procedures were employed, namely vifcor and vifstep, which were implemented in the *usdm* package (Naimi et al. 2014) using R version 4.1.3 (R Core Team 2022) in RStudio (RStudio Team 2021) to examine collinearity among the continuous numerical biotic, abiotic and anthropogenic variables. Variance inflation factors (VIFs) were calculated for each ecogeographic variable, along with the correlation coefficient (r) for all variable combinations. The vifcor procedure identified variable pairs with a maximum linear correlation greater than the threshold ($r = 0.7$), while the vifstep procedure excluded variables with the highest VIF exceeding the threshold (VIF = 3). These procedures were repeated iteratively until no variable had a correlation higher than 0.7 or a VIF greater than 3 (Naimi et al. 2014).

2.2.5 Ensemble modelling approach

To ensure accurate and unbiased modelling of dolphin presence-absence in relation to explanatory variables within the study area, an ensemble modelling approach was adopted and combines results from multiple single modelling algorithms. Using the *Biomod2* package (Thuiller et al. 2009) in RStudio, eight different modelling algorithms within three modelling methods were tested: regression methods (4) including generalised additive model (GAM), generalised boosted model (GBM), generalised linear model (GLM), and multivariate adaptive regression splines (MARS); classification methods (2) including classification tree analysis (CTA) and flexible discriminant analysis (FDA); and machine learning methods (2) including maximum entropy (MAXENT) and random forest (RF).

The parameters for each model algorithm were left at the default settings of *Biomod2,* with a binomial error distribution and logit link function. Detailed information on the default settings for each algorithm can be found in the users' guide of the *Biomod2* package (Thuiller et al. 2021).

For each SDM, a 10-fold cross-validation process was performed with a randomly split the data, with 80% used for model calibration and 20% for testing. SDMs were run using a subset of presence datasets for each season (years pooled) or each year (season pooled).

2.2.6 Model evaluation and statistical tests

To eliminate the avoidance of false positives (i.e. predicting species occurrence in areas where the species is absent) and false negatives (i.e. failing to predict species occurrence in areas where the species is present), the predictive performance of the SDMs were evaluated using the area under curve (AUC) of the receiver operating characteristic (ROC) metric (Fielding & Bell 2002). The ROC represents the ratio between observed presence-absence values and model predictions. ROC values range from 0 to 1, with values above 0.5 indicating that the models perform better than expected by chance

(Fielding & Bell 2002, Peterson et al. 2011). ROC values between 0.5 and 0.7 were considered indicative of poor model performance, while values between 0.7 and 0.9 are deemed reasonable predictions, and values above 0.9 represent excellent model performance. Additionally, the True Skill Statistic (TSS), which is independent of prevalence date (Allouche et al. 2006) was used and provided an alternative to ROC for models based on smaller sample sizes, as in the case of SDMs run interannually or seasonally. TSS values range from -1 to 1, with values above 0 indicating that the models perform better than random. Values around 0.4 are considered good predictions, while values closer to 1 indicate excellent model performance (Allouche et al. 2006). The combination of ROC and TSS served as complementary performance statistics since the former is threshold-independent, while the latter is unaffected by the size of the validation set (Allouche et al. 2006).

In addition to the model evaluation, a randomisation procedure consisting of 10 permutation runs was implemented to assess the importance of predictor variables (Thuiller et al. 2009). This procedure calculates the Pearson correlation between standard predictions (i.e. fitted values) and predictions obtained by randomly permutating one variable. A high correlation indicates little difference in the predictions of variable importance, suggesting that the variable is not influential in the model. Conversely, a low correlation indicates that the variable plays a significant role. Each variable was then ranked on a scale of 0 (no influence) to 1 (most influential) based on the mean correlation coefficient (Thuiller et al. 2009).

This report presents the results of the ensemble modelling for the overall study period and each season. Results of the ensemble models by years or behaviour (years and season pooled) can be found in Appendices 6 to 9.

3 Results

3.1 Survey effort and dolphin encounters.

A total of 73 boat-based systematic surveys were conducted in Owen Anchorage between June 2011 and May 2015, resulting in the encounter of 94 dolphin groups. Similarly, in Cockburn Sound, 72 boat-based systematic surveys were completed during the same period, with a total of 119 dolphin groups encountered (refer to Appendix 1 for the survey effort map). The group size varied from one to 29 dolphins, and there was no difference in group size between the two communities (Owen Anchorage mean = 8, SE 0.6; Cockburn Sound mean = 8, SE 0.6, including calves).

Out of all the groups observed, only seven groups (four in Owen Anchorage and three in Cockburn Sound) consisted exclusively of juveniles. The remaining groups were a combination of different age classes or consisted of subadults/adults only. Calves were present in 67% of the groups in Owen Anchorage and 65% of the groups in Cockburn Sound. Calves were defined as individuals dependent on their mothers, observed in close proximity (< 0.3 m), and ranging in ages from 0 to 3 years, depending on the individual.

While not all subadults and adults were sexed, a minimum of 46.3% of the groups in Owen Anchorage and 51.3% of the groups in Cockburn Sound were composed of individuals from both sexes. The proportion of groups consisting solely of males was low (ranging from 3.2% and 7.5% in Owen Anchorage and from 12.4% and 21.2% in Cockburn Sound), and there were no discernible patterns in the distribution of sightings based on sex categories (**Figure 3**). Therefore, investigating the distribution of dolphins by sex category was not pursued.

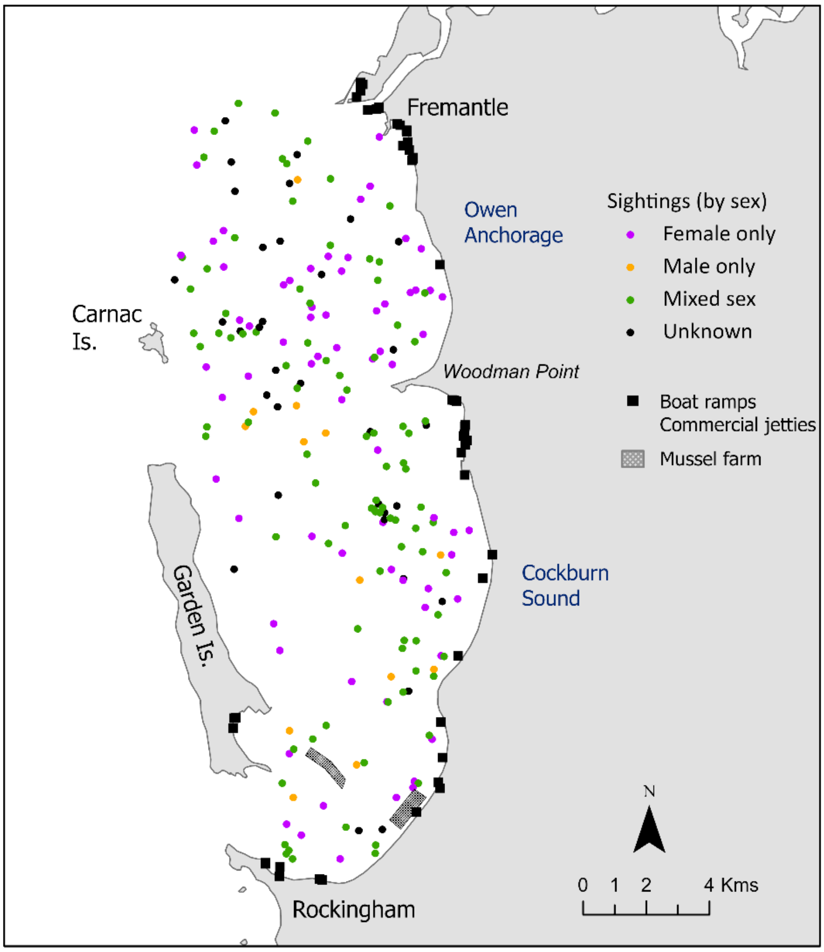

Figure 3. *Group sightings of Indo-Pacific bottlenose dolphins in Owen Anchorage and Cockburn Sound. Information on the adult/subadult sex composition for each group is provided below: purple dots for females only; orange dots for males only; green dots for mixed sexes; and black dots for groups where all subadults/adults were not sexed.*

The majority of the encountered dolphin groups in both Owen Anchorage and Cockburn Sound were mainly engaged in either foraging or travelling behaviours. In Owen Anchorage, approximately 37% of the groups were foraging, while 38% were travelling. Similarly, in Cockburn Sound, 46% of the groups were foraging, and 33% were travelling. Only a small portion of the observed groups were found to be resting or socializing within the first 5 minutes of our approach.

Since travelling behaviour does not necessarily indicate that dolphins are in a suitable habitat (as they may use corridors with unsuitable habitat to move between two suitable habitats), the analysis was conducted using all sightings except those associated with travelling behaviour.

3.2 Owen Anchorage

3.2.1 Dolphin distribution for the overall study period (2011-2015) in Owen Anchorage using all sightings except travelling behaviour

Using data collected over the entire study period of four years across Owen Anchorage, the overall distribution and areas with high probability of dolphin occurrence was analysed. Preliminary results from the yearly SDMs indicated some spatial shifts across Owen Anchorage over the years. However, when the years were pooled together, all areas with high likelihood of dolphin occurrence were consistently identified (refer to Appendix 4 for details).

Preliminary collinearity test between the seven explanatory variables available to model the distribution of dolphins across Owen Anchorage revealed no significant correlations among them all. These variables included substrate type, water visibility, SST, water depth, slope, distance to the coastline and distance to recreational boat ramps/commercial jetties.

The evaluation of single SDM algorithms using ROC and TSS indicated that most models performed better than random (ROC range = 0.57-1, median = 0.82; TSS range = 0.14-1, median = 0.54, **Figure *4***). However, GAM runs were not successful. After excluding the poorly performing algorithm and single runs for others, the ensemble model demonstrated the highest performance, with a ROC value of 0.97 and TSS of 0.90, indicating excellent model performance.

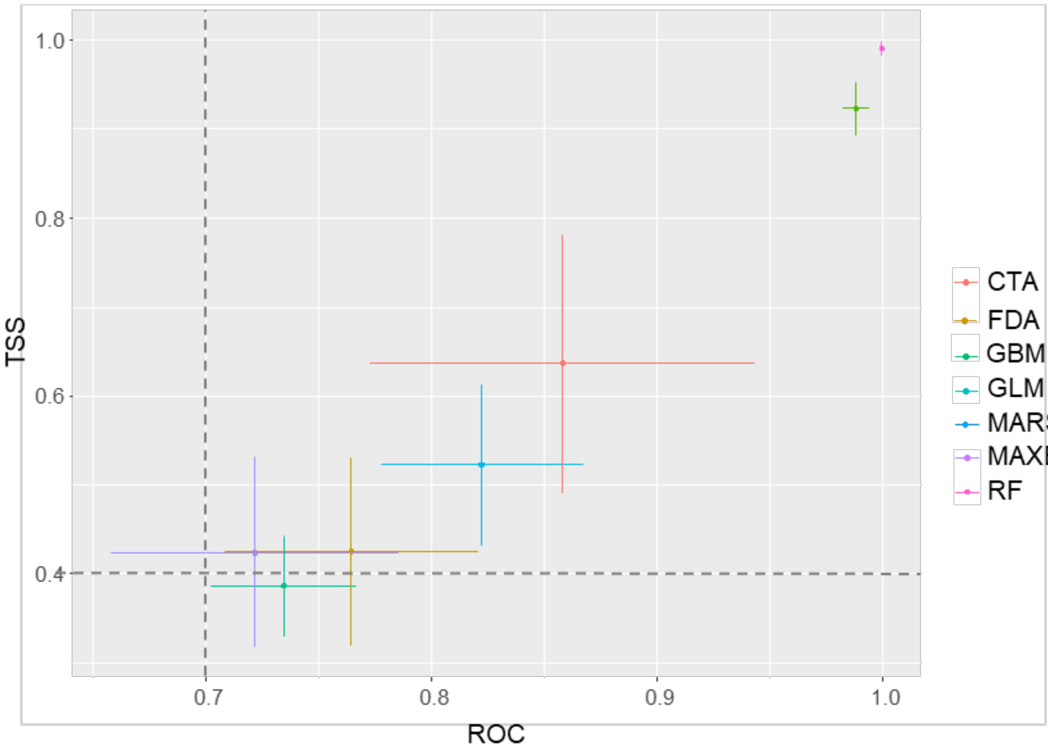

Figure 4. Model performance comparison of the models run per algorithm for Indo-Pacific bottlenose dolphins in Owen Anchorage (2011-2015 data pooled and excluded travelling behaviour) using the area under the receiver operating characteristic curve (ROC) and the true skill statistic (TSS). The solid lines represent the 95% confidence intervals, and the centre points represent the mean estimates for each algorithm. CTA: classification tree analysis; FDA = flexible discriminant analysis; GBM = gradient boosting machine; GLM = generalized linear model; MARS = multivariate adaptive regression splines; MAXENT = maximum entropy model; RF = random forest. Grey dash lines show the threshold values used for model's selection (ROC = 0.7; TSS = 0.4).

Based on the ranking method, the ensemble model revealed that the most influential variable driving dolphin distribution in Owen Anchorage, was the distance to the coastline, from both the mainland and island (**Figure 5** and refer to Appendix 2 for details). The response curves generated by the ensemble model indicated that the probability of dolphin occurrence was higher within the first 1,500 m from the coastline, with a slight increase in occurrence likelihood as water depth increased. Notably, there was a peak occurrence observed at around 7 m depth (see **Figure 6**).

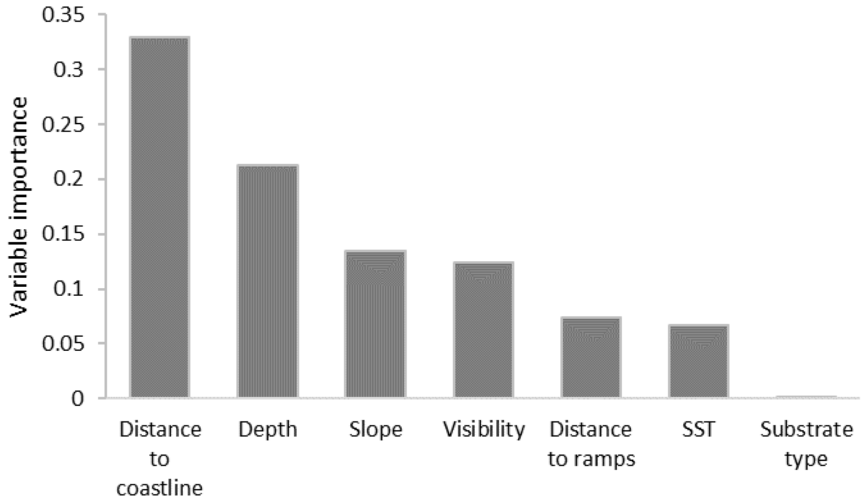

Figure 5. Importance of the explanatory variables used in the ensemble SDMs of Indo-Pacific bottlenose dolphins in Owen Anchorage for the overall study period (2011-2015 data pooled and excluded travelling behaviour).

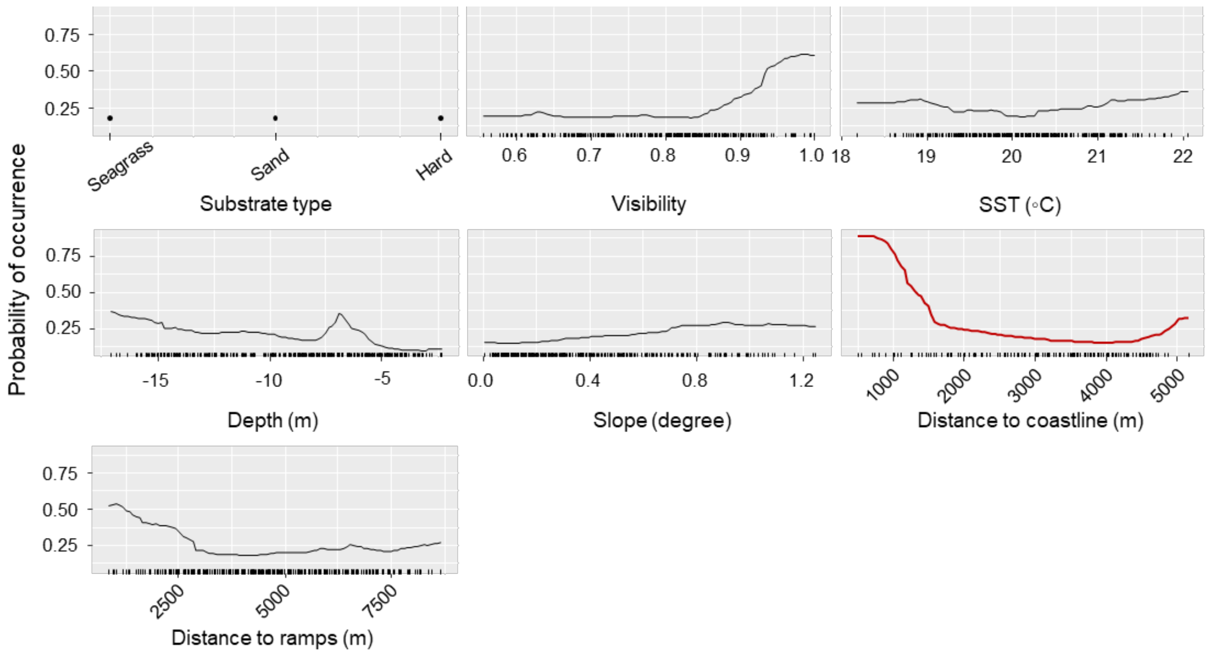

Figure 6. Response curves of the probability of occurrence of dolphins in relation to the explanatory variables obtained for the ensemble SDMs run for distribution mapping of Indo-Pacific bottlenose dolphins in Owen Anchorage over the entire study period (2011-2015 data pooled and excluded travelling behaviour). Curves highlighted in red identified the most influential variables.

The ensemble model revealed that dolphins had very high probabilities of occurrence (> 0.80) along the coastline spanning from Fremantle to Woodman Point, as well as around Carnac Island. Conversely, locations with the lowest probability of occurrence were observed in scattered small patches throughout the study area (**Figure 7**).

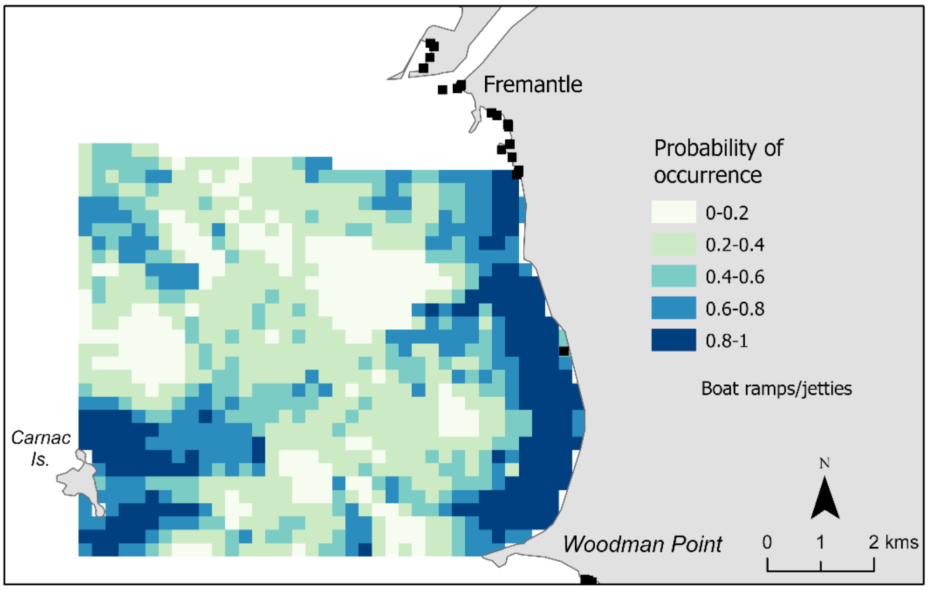

Figure 7. Overall ensemble models of Indo-Pacific bottlenose dolphin probability of occurrence in Owen Anchorage (2011-2015 data pooled and excluded travelling behaviour). Colours as shown in the legend indicate the probability of occurrence of dolphins: very low (0-0.2); low (0.2-0.4); moderate (0.4-0.6); high (0.6-0.8); very high (0.8-1).

3.2.2 Seasonal distribution of dolphins in Owen Anchorage

No collinearity was detected among the variables for most seasons. However, for Autumn, the variable distance to recreational boat ramps/commercial jetties exhibited a VIF > 3 and was consequently excluded for that season. The remaining explanatory variables tested were substrate type, water visibility, SST, water depth, slope, distances to the coastline and distance to recreational boat ramps/commercial jetties, with the exception of the latter for Autumn only.

Only a limited number of GAM models were successfully executed, with none for the Autumn season. The ROC values for the single seasonal SDMs indicated that the majority of the models performed better than random: Winter (ROC range = 0.60-1, median = 0.87), Spring (ROC range = 0.58-1, median = 0.89), Summer (ROC range = 0.585-1, median = 0.91), and Autumn (ROC range = 0.52-1, median = 0.83 (see **Figure 8**). TSS evaluation also demonstrated good performance for most models: Winter (TSS range = 0.21-1, median = 0.67), Spring (TSS range = 0.15-1, median = 0.71), Summer (TSS range = 0.15-1, median = 0.73), and Autumn (TSS range = 0.17-1, median = 0.61) (see **Figure 8**). After excluding the poorly performing algorithm runs, the ensemble models for each season outperformed all respective single SDMs with ROC values ranging from 0.89 to 0.98 and TSS values from 0.68 to 0.92, indicating good to excellent model performance.

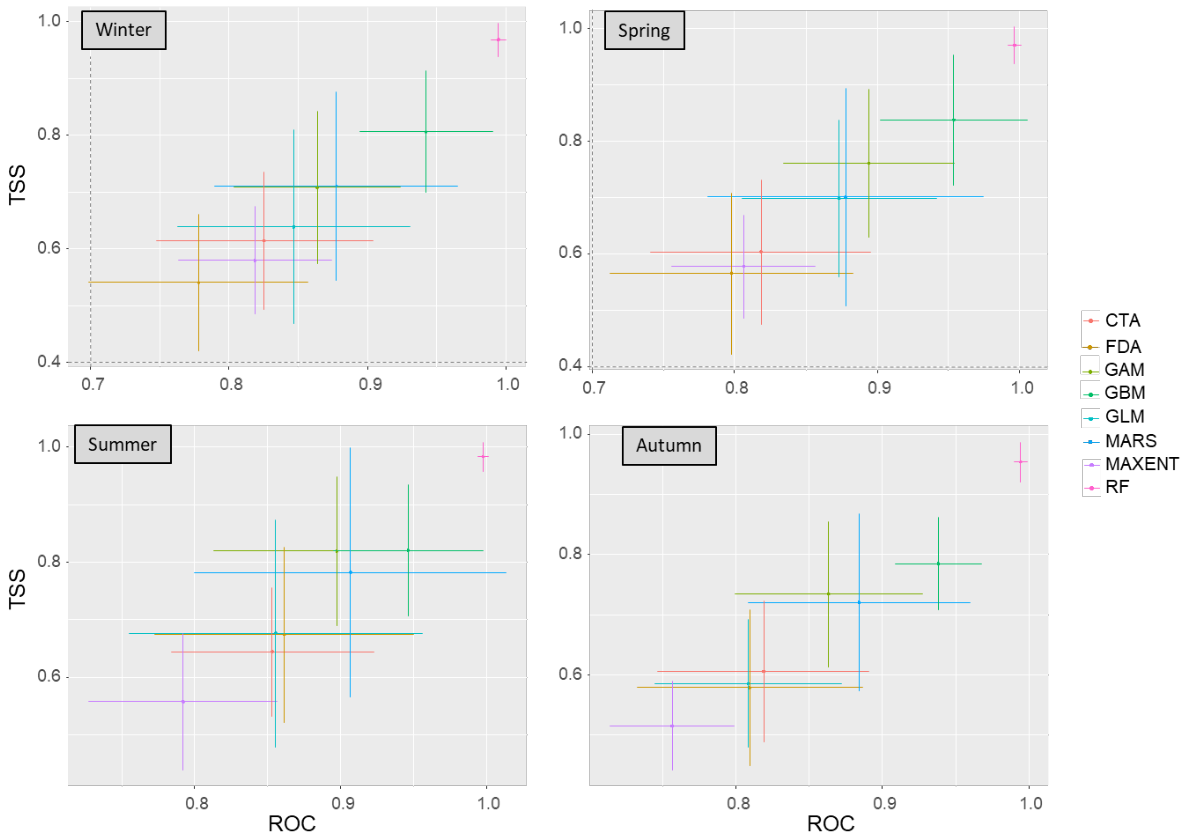

Figure 8. Model performance comparison of the seasonal models run per algorithm for Indo-Pacific bottlenose dolphins in Owen Anchorage using the area under the receiver operating characteristic curve (ROC) and the true skill statistic (TSS). Datasets were pooled by season (Winter, Spring, Summer, Autumn; excluded travelling behaviour). The solid lines represent the 95% confidence intervals, and the centre points represent the mean estimates for each algorithm. CTA: classification tree analysis; FDA = flexible discriminant analysis; GAM = generalized additive model; GBM = gradient boosting machine; GLM = generalized linear model; MARS = multivariate adaptive regression splines; MAXENT = maximum entropy model; RF = random forest. X and Y-axes scales vary for each season. Grey dash lines show the threshold values used for model's selection (ROC = 0.7; TSS = 0.4).

The ensemble models for each season revealed the significance of certain variables in influencing dolphin distribution in Owen Anchorage. In Winter, Spring, and Summer, distance to the coastline emerged as one of the most influential variables (**Figure 9**). However, in Autumn, the occurrence of dolphins was primarily associated with the distance to recreational boat ramps/commercial jetties. Additionally, water visibility and SST were identified as important explanatory variables in Spring and Autumn, respectively. Conversely, the distribution of dolphins in Summer was found to be more influenced by the slope of the area (**Figure 9**, and see Appendix 3 for details of the single models).

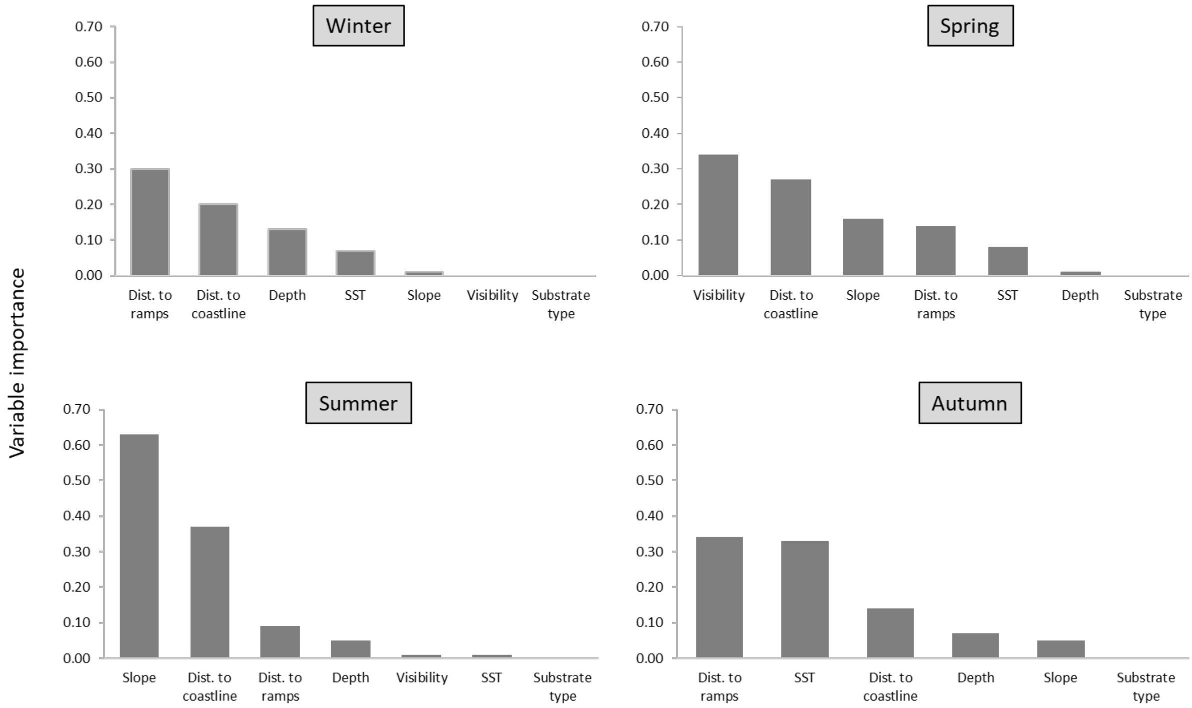

Figure 9. Importance of the explanatory variables used in the ensemble SDMs of Indo-Pacific bottlenose dolphins in Owen Anchorage for Winter, Spring, Summer and Autumn (years pooled by season and excluded travelling behaviour).

The response curves generated by the ensemble models (**Figure 10**) revealed valuable insights into the probability of dolphin occurrence in Owen Anchorage across different seasons. Generally, the likelihood of dolphin presence was higher in areas located closer to the coastline from the mainland or islands, particularly within a distance of less than 1,000 meters. Additionally, in Autumn and Winter, the distribution of dolphins was significantly influenced by areas within 2,500 meters from recreational boat ramps/commercial jetties. In Spring, high visibility played a crucial role in shaping their distribution, while in Summer, the presence of dolphins was associated with areas characterized by high slope. Lastly, cooler temperatures in Autumn were found to be a determining factor in the distribution of dolphins (**Figure 10**).

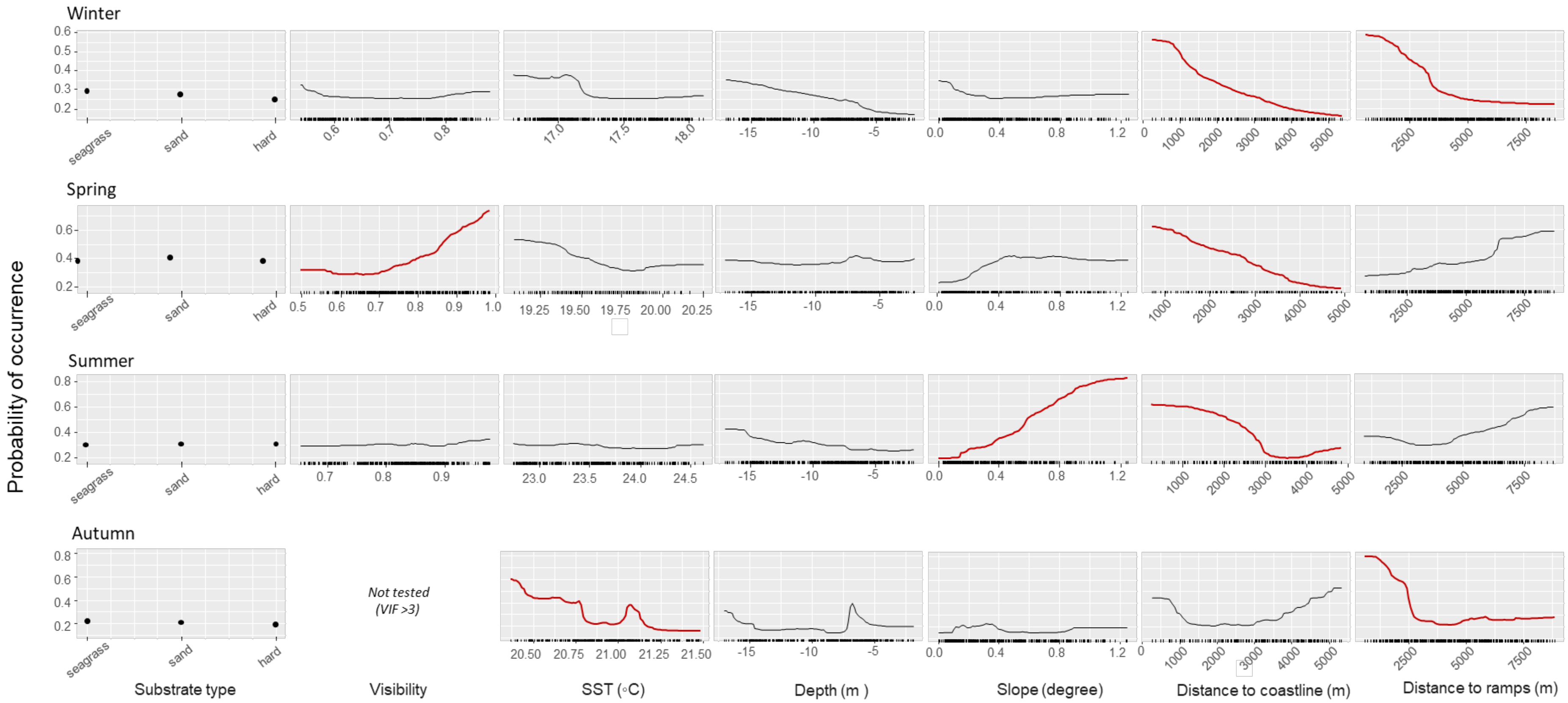

Figure 10. Response curves of the seasonal ensemble models of Indo-Pacific bottlenose dolphin probability of occurrence in Owen Anchorage (years pooled by season and excluded travelling behaviour). The variables visibility was removed from the SDM run for Autumn due to high VIF. Curves highlighted in red identified the biggest influential variable for each season.

The combined ensemble models revealed seasonal shifts of the distribution probabilities of dolphin occurrence in Owen Anchorage. Across seasons, dolphins exhibited a higher occurrence along the coastline from the mainland, specifically from Fremantle to Woodman Point. This pattern gradually shifted towards Carnac Island during Spring and Summer. In Autumn, there was a notable return of high dolphin occurrence along the mainland coastline, with moderate occurrence observed in the southern part of the shipping area (**Figure 11**).

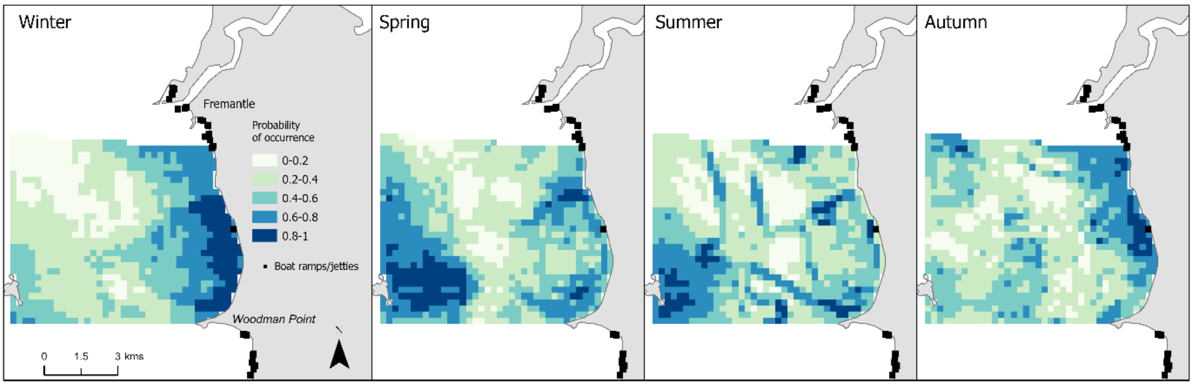

Figure 11. Seasonal ensemble models of Indo-Pacific bottlenose dolphin probability of occurrence in Owen Anchorage (years pooled by season and excluded travelling behaviour). Colours as shown in the legend indicate the probability of occurrence of dolphins: very low (0-0.2); low (0.2-0.4); moderate (0.4-0.6); high (0.6-0.8); very high (0.8-1).

3.3 Cockburn Sound

In Cockburn Sound, the benthic habitat was classified into six types, but for the purpose of this analysis, were grouped into four similar types: seagrass (ephemeral and perennial), sand, hard substrate (rubble and reef), and mixed substrate (soft and hard).

3.3.1 Dolphin distribution for the overall study period (2011-2015) in Cockburn Sound using all but travelling behaviour

Preliminary results from the yearly SDMs indicated that the spatial distribution and areas of high likelihood of dolphin occurrence in Cockburn Sound remained similar across years (refer to Appendix 8 for details).

The collinearity between water visibility and water depth was observed (r = 0.74). Considering the ecological significance of water depth in determining habitat suitability in previous studies of coastal dolphin habitats (e.g. Sprogis et al. 2018, Hunt et al. 2020, Haughey et al. 2021), water visibility was excluded as an explanatory variable in the models. There was no further collinearity detected after removing water visibility. If water depth had been removed instead, distance to recreational ramps/commercial jetties would have been discarded as well. Consequently, the SDMs were conducted using six variables: substrate type, SST, water depth, slope, distance to the coastline and distance to recreation boat ramps/commercial jetties.

Evaluation of the ROC and TSS metrics for single SDM algorithms in Cockburn Sound indicated that most models performed better than random (AUC range = 0.64-1, median = 0.77; TSS range = 0.28-1, median = 0.47, **Figure 12**). After excluding the poorly performing algorithm runs, the ensemble model demonstrated superior performance compared to all single SDMs, yielding an ROC value of 0.91 and a TSS value of 0.66, indicating good to excellent model performance.

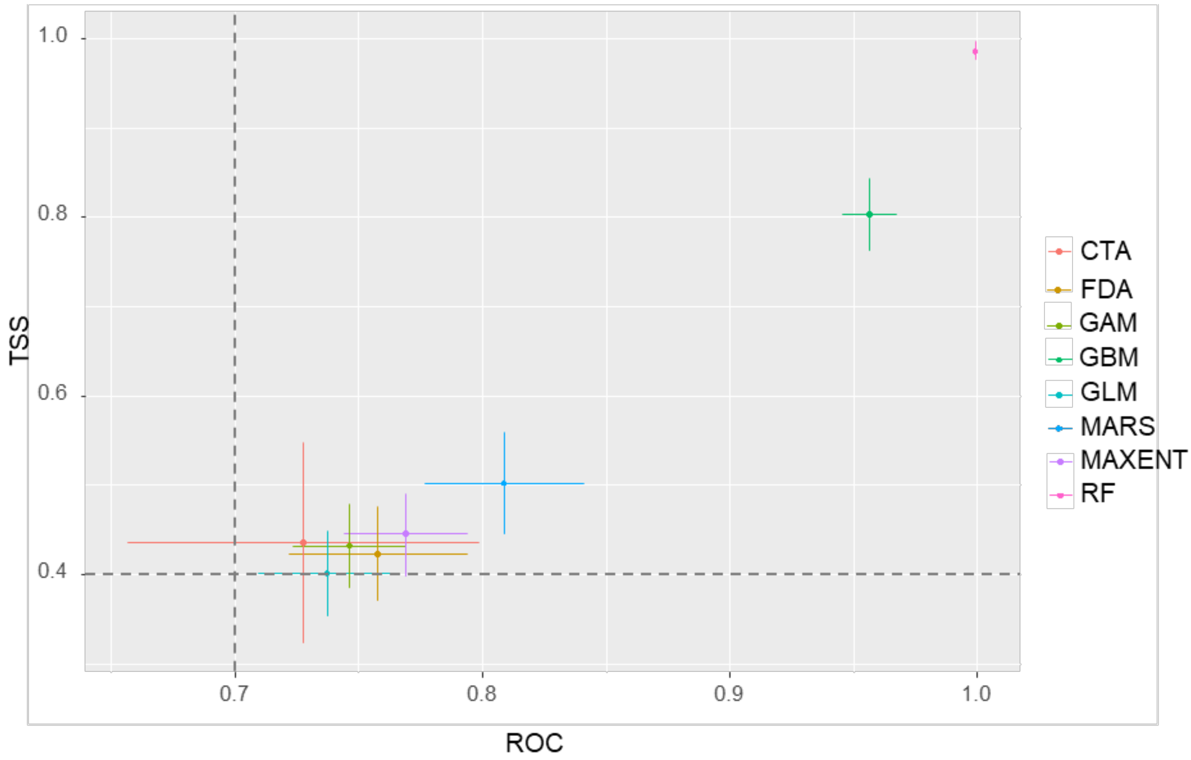

Figure 12. Model performance comparison of the models run per algorithm for Indo-Pacific bottlenose dolphins in Cockburn Sound (2011-2015 data pooled and excluded travelling behaviour) using the area under the receiver operating characteristic curve (ROC) and the true skill statistic (TSS). The solid lines represent the 95% confidence intervals, and the centre points represent the mean estimates for each algorithm. CTA: classification tree analysis; FDA = flexible discriminant analysis; GAM = generalized additive model; GBM = gradient boosting machine; GLM = generalized linear model; MARS = multivariate adaptive regression splines; MAXENT = maximum entropy model; RF = random forest. Grey dash lines show the threshold values used for model's selection (ROC = 0.7; TSS = 0.4).

The ensemble model for the entire study period in Cockburn Sound revealed that water depth was the most influential variable driving dolphin distribution, followed by distance to recreation boat ramps/commercial jetties (**Figure 13**, refer to Appendix 6 for details of the single models). The response curve demonstrated that the probability of dolphin occurrence was highest in depths ranging from 5 to 13 m. Additionally, dolphins were more likely to occur at locations either in close proximity (<2,500 m) or farther away (>7,500 m) from the recreation boat ramps/commercial jetties (**Figure 14**).

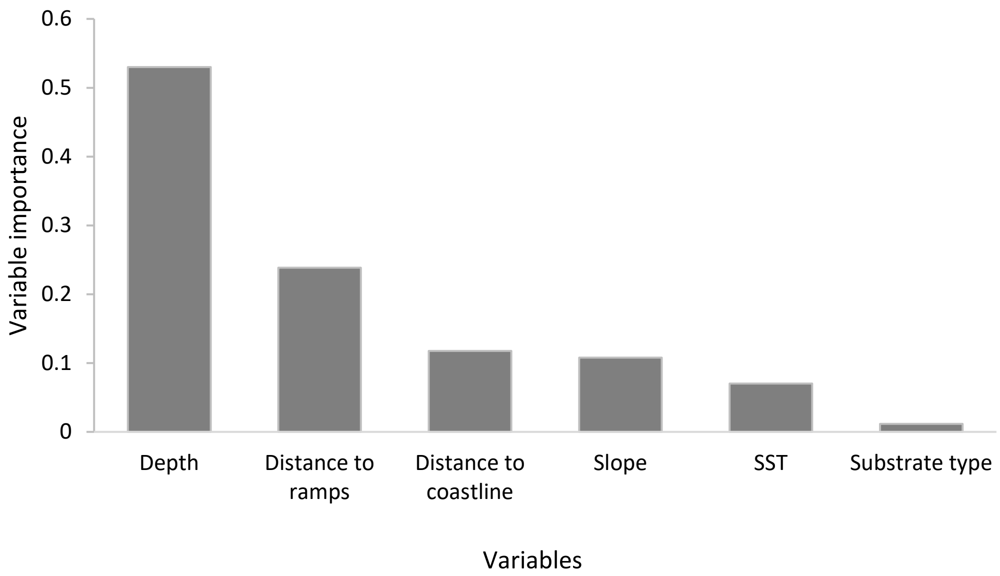

Figure 13. Importance of the predictor variables used in the ensemble SDMs of Indo-Pacific bottlenose dolphins in Cockburn Sound for the overall study period (2011-2015 data pooled and excluded travelling behaviour).

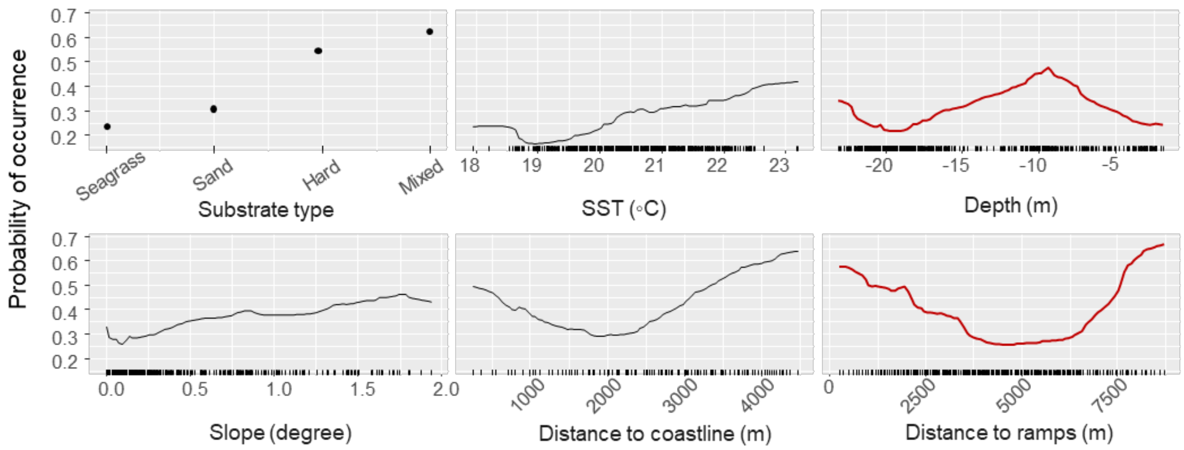

Figure 14. Response curves of the presence of dolphins in relation to the explanatory variables obtained for the ensemble SDMs run for distribution mapping of Indo-Pacific bottlenose dolphins in Cockburn Sound over the entire study period (2011-2015 data pooled and excluded travelling behaviour). Curve highlighted in red identified the biggest influential variable.

The ensemble model for the 4-year study period in Cockburn Sound indicated a high probability of dolphin occurrence (> 0.60) along the eastern and western edges of the sound, with a broader coverage extending to the Kwinana Shelf (until the drop in water depth that outlines the central basin). Conversely, dolphins had the lowest probability of occurrence (≤ 0.40) in the central basin area which is also identified as the deeper part of the sound (**Figure 15**).

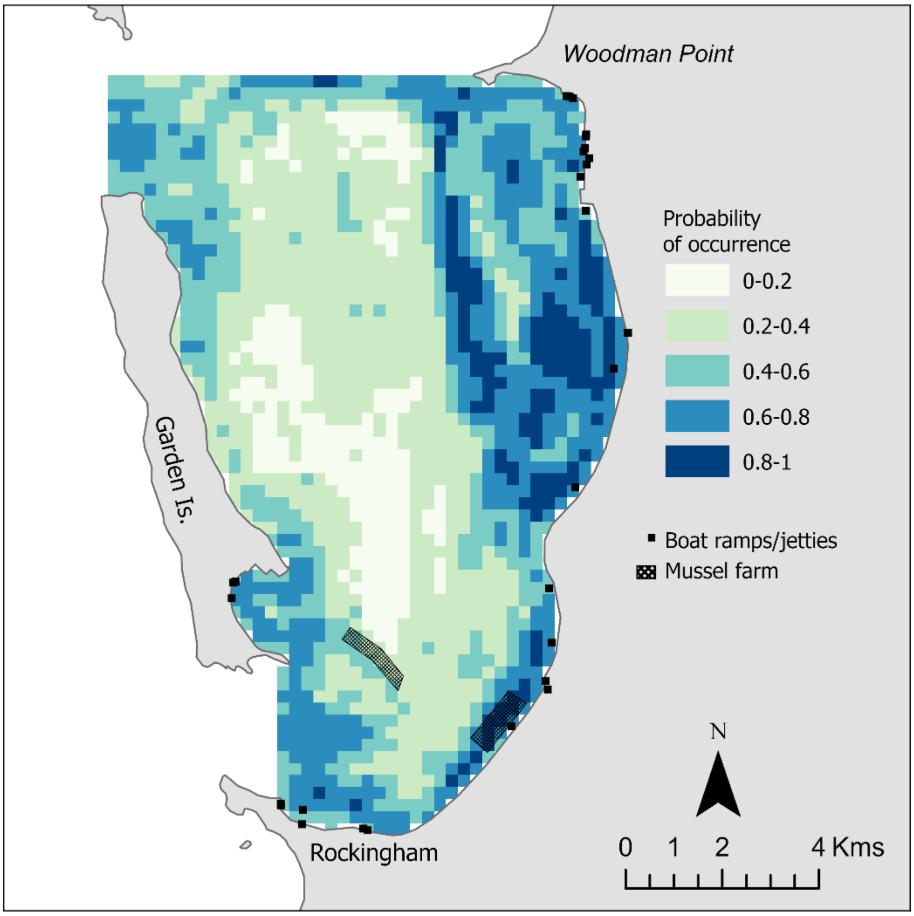

Figure 15. Overall ensemble models of Indo-Pacific bottlenose dolphin probability of occurrence in Cockburn Sound (2011-2015 data pooled and excluded travelling behaviour). Colours as shown in the legend indicate the probability of occurrence of dolphins. Colours as shown in the legend indicate the probability of the occurrence of dolphins: very low (0-0.2); low (0.2-0.4); moderate (0.4-0.6); high (0.6-0.8); very high (0.8-1).

3.3.2 Seasonal dolphin distribution in Cockburn Sound

Correlation testing revealed collinearity among the biotic and abiotic variables, which varied across seasons. For Autumn and Spring, all seven variables were retained: substrate type, SST, water visibility, water depth, slope, distance to the coastline, and distance to recreation boat ramps/commercial jetties. However, in Winter, the variable distance to recreation boat ramps/commercial jetties was excluded due to a VIF > 3 and high correlation with SST (r = 0.79). In Summer, five additional biotic parameters were tested, including salinity (surface and bottom), water temperature at the bottom, light attenuation, and Chl-a. Preliminary correlation tests indicated a high correlation between salinity at the surface and bottom (r = 0.81), as well as between Chl-a and light attenuation (r = 0.79). Additionally, the variable distance to recreation boat ramps/commercial jetties had a VIF > 3. Consequently, the remaining variables used in the Summer SDM were substrate type, SST, water temperature at the bottom, visibility, salinity (surface only), Chl-a, water depth, slope, and distance to the coastline.

The ROC analysis of all single seasonal SDMs indicated moderate to good performance for most models (Winter: ROC range = 0.54-1, median = 0.87; Spring: ROC range = 0.59-1, median = 0.87; Summer: 0.65-

1, median = 0.91; Autumn: ROC range = 0.58-1, median = 0.86; **Figure 16**). However, the evaluation of the TSS showed more variability in the performance of the single models, though still moderately overall (Winter: TSS range = 0.19-1, median = 0.67; Spring: TSS range = 0.23-1, median = 0.67; Summer: TSS range = 0.30-1, median = 0.76; Autumn: TSS range = 0.15-1, median = 0.66; **Figure 16**). After excluding the poorly performing algorithm runs, the ensemble models for each season outperformed all their respective single SDMs, with ROC values above 0.91 and TSS values above 0.68, all indicating good to excellent model performance.

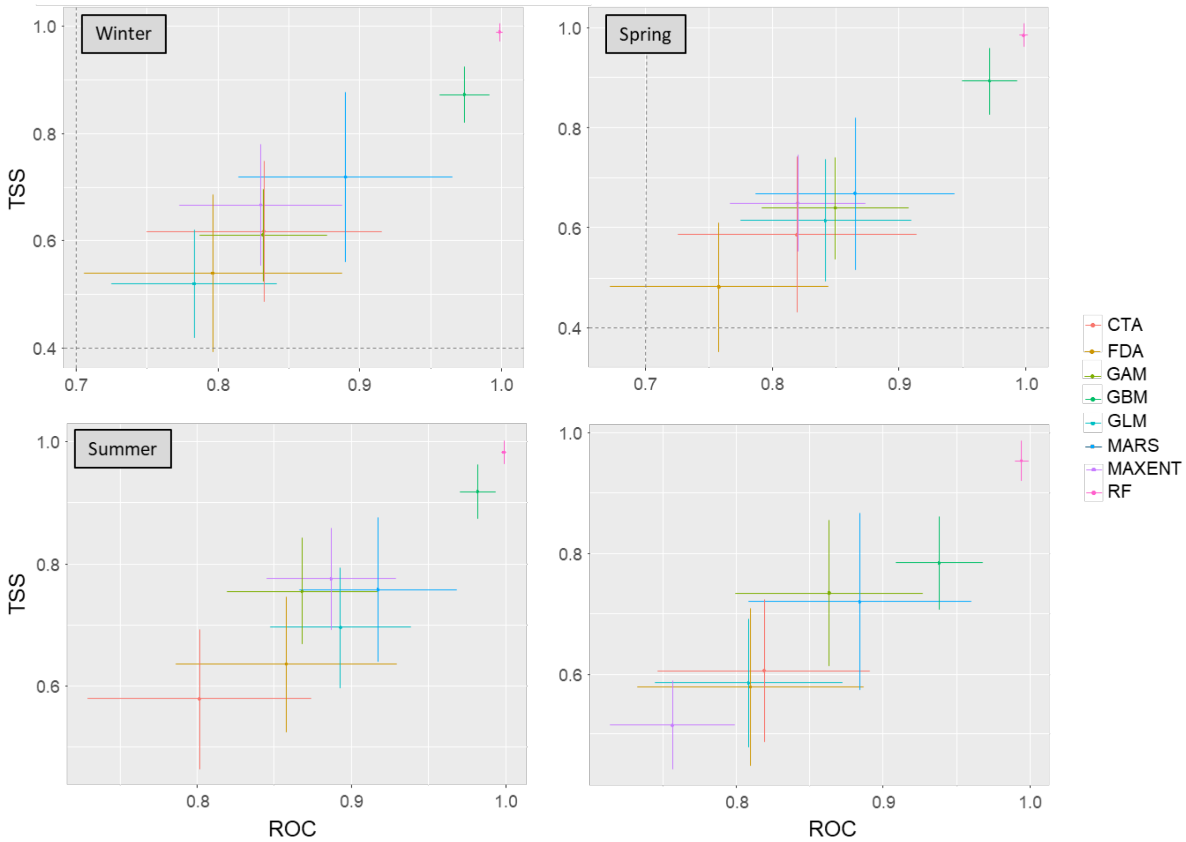

Figure 16. Model performance comparison of the seasonal models run per algorithm for Indo-Pacific bottlenose dolphins in Cockburn Sound using the area under the receiver operating characteristic curve (ROC) and the true skill statistic (TSS). Datasets were pooled by season (Winter, Spring, Summer, Autumn; excluded travelling behaviour). The solid lines represent the 95% confidence intervals, and the centre points represent the mean estimates for each algorithm. CTA: classification tree analysis; FDA = flexible discriminant analysis; GAM = generalized additive model; GBM = gradient boosting machine; GLM = generalized linear model; MARS = multivariate adaptive regression splines; MAXENT = maximum entropy model; RF = random forest. X and Y-axes scales vary for each season. Grey dash lines show the threshold values used for model's selection (ROC = 0.7; TSS = 0.4).

All ensemble models exhibited consistency with the single models. In particular, the seasonal ensemble models, with the exception of Spring, consistently identified water depth as the most important variable followed by either slope for Winter, Chl-a for Summer or water visibility for Autumn (**Figure 17**, and refer to Appendix 7 for details). In Spring, the two most important variable were slope and water visibility (**Figure 17**).

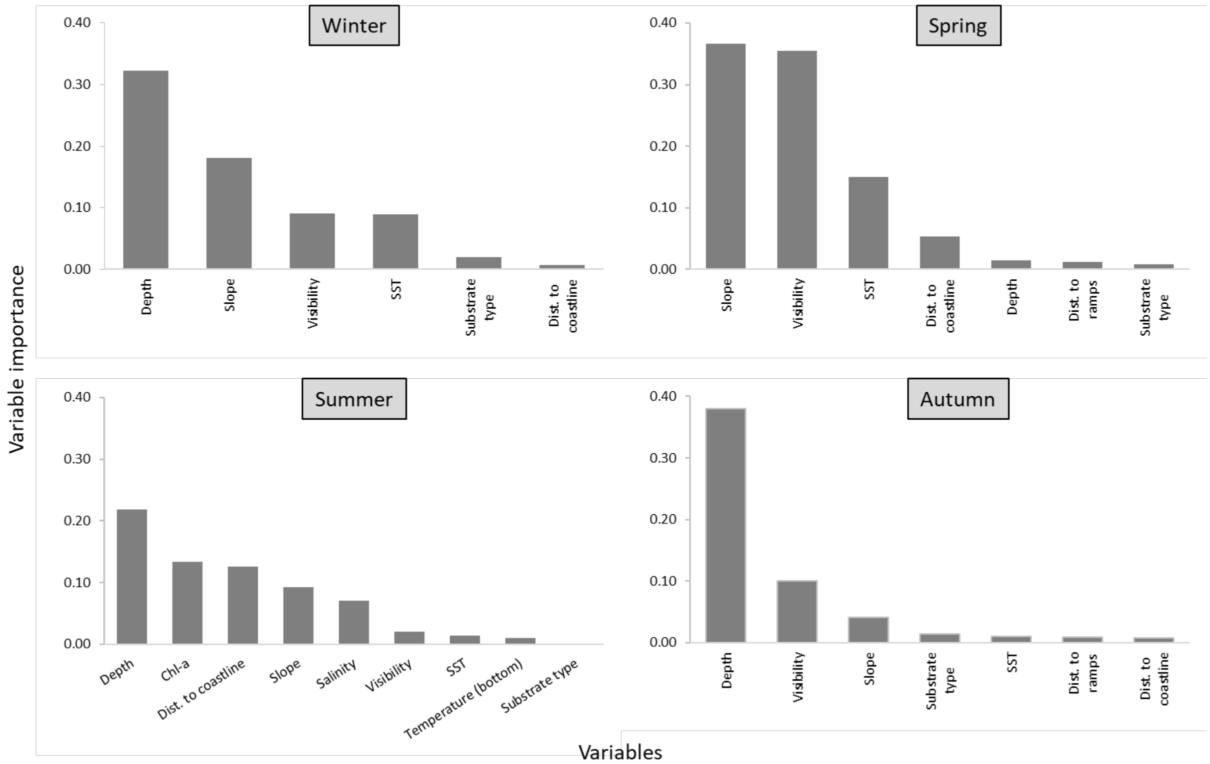

Figure 17. Importance of the predictor variables used in the ensemble SDMs of Indo-Pacific bottlenose dolphins in Cockburn Sound for the overall study period (years 2011-2015 pooled and excluded travelling behaviour).

In Winter, Summer and Autumn, the response curves revealed that the probability of dolphin occurrence was greater in areas with a depth less than 17 m, with a distinct peak around 9 m in Autumn (**Figure 18**). Additionally, in Autumn and Spring, dolphin occurrence was also higher in areas with high water visibility. In Summer, the occurrence of dolphins was further influenced by higher concentration of Chl-a. The response curve for slope indicated a higher occurrence of dolphins in areas with a moderate slope (0.5 degrees) in Spring, extending to areas with more pronounced slopes in Winter.

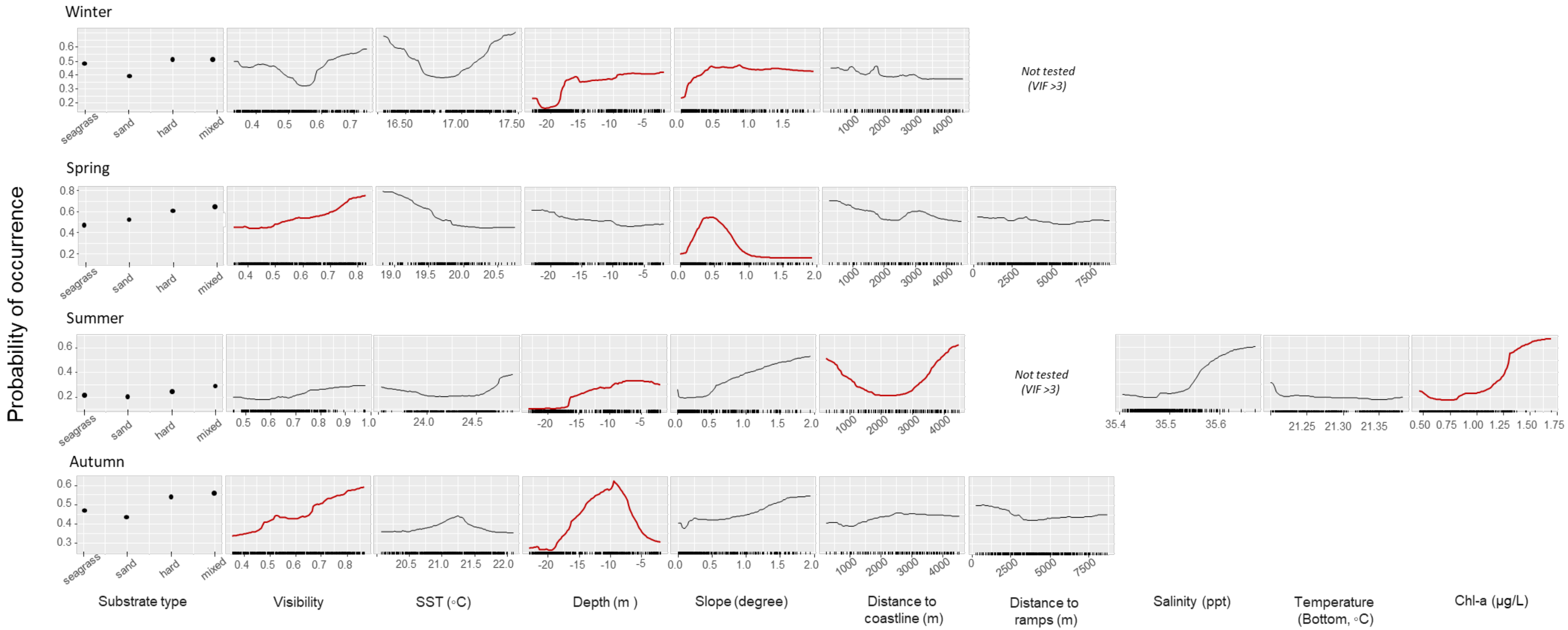

Figure 18. Response curves of the seasonal ensemble models averaging for the two most influencing variables for distribution mapping of Indo-Pacific bottlenose dolphins in Cockburn Sound. The seasons are Winter, Spring, Summer, and Autumn. Curves highlighted in red identified the biggest influential variable(s) for each season.

Consistent with the findings from the ensemble model for the entire study period, the lowest probabilities of dolphin occurrence were observed across the central basin of the sound, irrespective of the season (**Figure 19**). While there were seasonal variations along the central western edge of the sound, particularly along the shore of Garden Island, the probability of encountering dolphins remained consistently high (>0.6) on the Kwinana Shelf throughout all seasons (**Figure 19**).

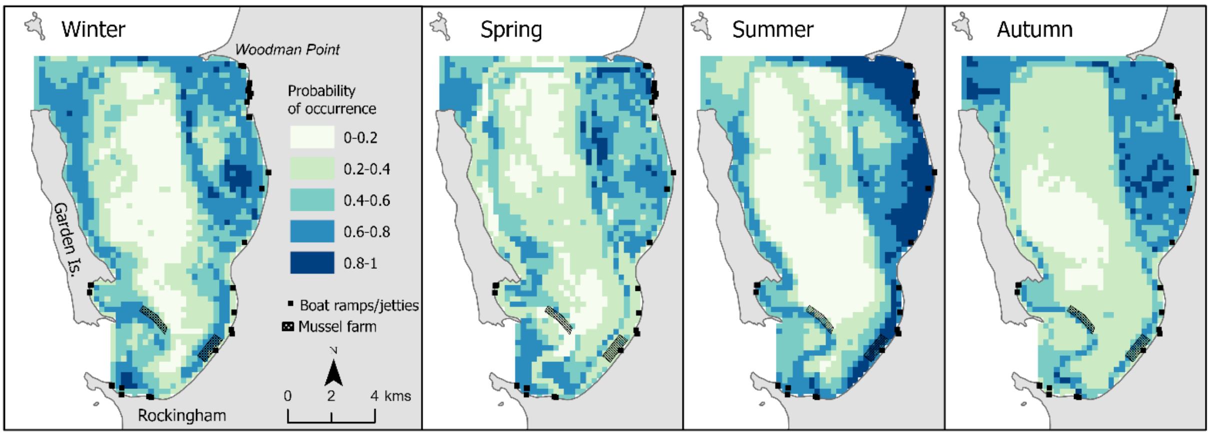

Figure 19. Seasonal ensemble models of Indo-Pacific bottlenose dolphin probability of occurrence in Cockburn Sound (years pooled by season and excluded travelling behaviour). Colours as shown in the legend indicate the probability of the occurrence of dolphins. Colours as shown in the legend indicate the probability of occurrence of dolphins: very low (0-0.2); low (0.2-0.4); moderate (0.4-0.6); high (0.6-0.8); very high (0.8-1).

4 Discussion

In this report, the results of the spatio-temporal distribution patterns of dolphins in Owen Anchorage and Cockburn Sound, two regions located in Perth metropolitan waters and subject to potential port development were presented. The ensemble model was used to determine important areas of dolphin occurrence by evaluating various ecogeographical and anthropogenic variables. Since both regions consist of socially and spatially distinct dolphin communities, ensemble models were run separately to account for variations in habitat usage (e.g. Passadore et al. 2018). However, there were indications that dolphins in both regions were generally associated with areas within 1,000-2,000m from the coastline or recreational boat ramps/harbour, a characteristic commonly observed in other coastal dolphin populations (e.g. Sprogis et al. 2018, Haughey et al. 2021). Water depth was also found to be an important factor for the CS community and generally preferring depths between 7 and 13m. Resting behaviours were mainly observed in shallower areas (less than 5m), while foraging activities extended to slightly deeper areas (up to 15m). The identified key habitats, characterised by the highest occurrence of resident dolphins in Owen Anchorage and Cockburn Sound were consistent with previously identified core areas (Chabanne et al. 2017a). Specifically, Owen Anchorage exhibited a moderate to very high probability of dolphin occurrence throughout the entire region, with seasonal and interannual shifts, while the Kwinana Shelf in Cockburn Sound showed a long-term moderate to very high probability of dolphin occurrence.

4.1 Distribution of dolphins residing in Owen Anchorage

In Owen Anchorage, the results of ensemble models revealed that dolphin distribution was primarily influenced by the distance to the coastline or recreational boat ramps/harbour, with important habitats identified within 1,000 m from the coastline (mainland and Carnac Island) and extended to 2,500m from the mainland in Winter and Autumn (omitting potential interannual variations that could not be tested). Areas with high probabilities of dolphin occurrence within this distance range seemed to also be influenced by the seasonal patterns of SST and visibility with shift of the distribution being observed across seasons. Areas of high (>0.60) and very high (>0.80) probabilities of occurrence were generally found along the mainland during Autumn and Winter and shifted toward the west margin of Owen Anchorage and around Carnac Island in Spring and Summer. Unfortunately, the interannual variation in the distribution patterns of the probability of occurrence highlights some uncertainties on those seasonal shifts. The relatively uniform physiography and homogeneous area (patches of sand/seagrass) suggest that seasonal and 'forced' (e.g., climatic events) hydrological and biological variables would have a larger influence on the distribution of fish species and consequently on the distribution of dolphins. This complexity is reinforced by the estuarine flows during tidal and climatic events such as heavy rainfall during Winter (Pearson et al. 2006, Bureau of Meteorology 2023) as well as the long-term shellsand dredging operations (Environmental Protection Authority 2001, BMT Oceania 2014), all creating a complex system with seasonal and interannual shifts of the distribution of dolphins that are challenging to predict .

4.1.1 Adjacent to tidal and rain flow from the Swan Canning estuary

The range of *in situ* SST values indicated colder temperatures during the first year compared to the subsequent three years, most likely occurring in the winter season. Rainfall across the Perth metropolitan area during Winter 2011 was near average, with consistent rainfall throughout much of the season. This was in contract to the following winters of 2012, 2013 and 2014, which experienced below-average rainfall and recorded dry months (Bureau of Meteorology 2023). As Owen Anchorage is located at the mouth of the Swan Canning estuary, sea surface temperature, salinity and water visibility fluctuations may occur due to tidal flows. During extreme weather conditions, larger discharges can displace the oceanic water, potentially leading to changes in dolphin prey composition, abundance, and distribution in Owen Anchorage in response to environmental variations and 'forced' migration of fish species. It is important to note that the study area, along with the entire western Australian coastline, was affected by a marine heatwave in 2011 (prior to data collection for this study), resulting in the decline of several fish species and impacting the spawning and migration patterns of many fish species in subsequent years (Fletcher et al. 2017) until neutral or El Niño conditions allow for recruitment (Molony et al. 2021). For populations residing in open coastal regions, the distribution of dolphins was found to extend to deeper offshore waters during the colder months, most likely associated with the stronger Leeuwin current enhancing nutrient availability for primary producers (e.g. Sprogis et al. 2016). However, in the case of Owen Anchorage (and Cockburn Sound), the lack of seasonal fluctuations in dolphin abundance (Chabanne et al. 2017b) suggests that such movement patterns are less likely to occur here or for short-time period (i.e. a few days). While the diet of dolphins is currently being investigated (*Project 8.3.3*), temporal changes in their distribution, from shallow to deeper waters and *vis versa,* may indicate their adaptation in foraging techniques and diet based on the abundance and energy content of prey species (McCluskey et al. 2016).

4.1.2 Long-term dredging operation and increase of shipping vessels

Owen Anchorage has been subjected to long-term shellsand dredging operations since 1972 (Environmental Protection Authority 2001, BMT Oceania 2014). The extensive coverage of shallow (< 10 m) sand areas and seagrass meadows (BMT Oceania 2014) that is sheltered from the oceanic swell in Owen Anchorage makes it likely to support a diverse range of prey species for dolphins (Kendrick et al. 2000, Heithaus & Dill 2002, Hyndes et al. 2003, Finn 2005, Sampey et al. 2011). Since dredging operations focus on areas without seagrass, the impacts on prey availability for dolphins are expected to be localised, with possible short-term responses from dolphins. For instance, a study in Aberdeen harbour, Scotland, found that common bottlenose dolphins (*Tursiops truncatus*) spent less time in the area as the intensity of dredging activities increased over a three-year period (Pirotta et al. 2013). While interactions with dredging are unlikely to pose a significant risk due to slow vessel speeds, the main impact on dolphins is likely related to underwater noise that depends on the material and type of dredging, operational stage, and environmental conditions. Suction hopper dredges, such as those used in Owen Anchorage, are known to produce higher noise levels (up to 190dB with a bandwidth of 31-40hz) compared to other types, like backhoe dredges (Robinson et al. 2011, Todd et al. 2015). The long-term dredging and high usage of Owen Anchorage, including recreational and shipping activities, suggest that dolphins in this region may be accustomed to high levels of noise from vessel traffic and industrial operations, as previously indicated by Marley et al. (2016) for dolphins using the Fremantle Inner harbour and other highly urbanised estuaries (e.g., Bossley et al. 2022). However, the accumulation of multiple activities and increased shipping, resulting in either acute noise levels or prolonged exposure to consistent noise beyond the range dolphins are habituated to, combined with the shallow characteristics of Owen Anchorage, could trigger behavioural responses (e.g., increase or suppression of activity), and affect their health (Dey et al. 2019, Sørensen et al. 2023). The extensive range of responses to underwater noise found worldwide (Erbe et al. 2019) makes it challenging to fully understand the response of dolphins in Owen Anchorage to potential increased of noise. In addition to gaining an understanding of the background noise within the regions (*Theme 7: Noise*), dedicated research that combines acoustic and visual observations should be conducted. This research will help to understand the type of responses dolphins inhabiting Owen Anchorage and adjacent regions may have to both short-term and long-term. Furthermore, it will provide valuable data to evaluate the potential long-term consequences on the health of individual dolphins and the overall population viability.

4.1.3 Shipping channel

The maintained shipping channels provide a habitat characterised by deeper water and a high slope strength. While the steeply sloping benthic topography may offer high concentrations of prey fish or assist dolphins in their foraging activities, the absence of high probabilities of dolphin occurrence in most of the channel area and close surroundings and their inconsistency across temporal periods suggest that seabed slope alone is unlikely to be a primary factor for suitable foraging habitat. Other parameters, such as shipping noise or water movement associated with the speed of the ships influencing fish behaviour and distribution (Gabel et al. 2017, Jezequel et al. 2021), could restrict the presence of dolphins in this area. In adjacent waters, dolphin occupancy in the Fremantle Inner Harbour remains consistently high (Chabanne et al. 2017a) despite the high levels of vessel traffic (Marley et al. 2016). It has been suggested that dolphins have a cost-effective response, considering the value of the habitat, structure, prey abundance *versus* high-traffic vessel presence (Marley et al. 2016). In the Inner harbour, the slow speed of the ships would suppress any ship-induced waves compared to ships using the channel between Parmelia and Success banks, where speeds can reach up to 12 knots (or more with approval; Fremantle Ports 2018). Other than exposure to more regular noise, which could have greater impacts on dolphin health, ship-induced waves have previously been shown to influence invertebrates and fish (Gabel et al. 2017). Further research should be conducted to fully understand the consequences of additional induced-wave movement in the homogenous shallow environment and ecosystem diversity of Owen Anchorage, as potential impacts may extend beyond the channel, including areas that were described as key-habitat in this study.

4.2 Distribution of dolphins residing in Cockburn Sound

In Cockburn Sound, the results of the ensemble models revealed that dolphin distribution was primarily influenced by depth, with important areas occurring in shallow waters (less than 15 m depth), an apparent variable for many coastal cetaceans species (e.g., Hunt et al. 2020, Jackson-Ricketts et al. 2020, Haughey et al. 2021). Additionally, areas with high probabilities of dolphin occurrence were influenced by the strength of the slope (greater than 0.5 degrees), high visibility, and high concentration of Chl-a (only tested in Summer). Specifically, areas with high (>0.60) and very high (>0.80) probability of occurrence were identified along the northern tip of Garden Island, the southern part of Garden Island, including west of Mangle Bay and along the south-eastern coastline, and across the Kwinana Shelf. Conversely, the central basin extending from north to south was characterised by the lowest probability of dolphin occurrence throughout the seasons and years, indicating a more consistent distribution compared to Owen Anchorage.

4.2.1 Importance of substrate type

While SDMs did not identify substrate type variable as an important variable influencing the distribution of dolphins, areas characterised by reef, cobble and seagrass overlapped with high probability of occurrence, therefore highlighting a risk for the viability of the dolphins associated with a permanent loss of habitat. Other studies on bottlenose dolphins have also emphasised the significance of reef habitats for coastal dolphin populations (e.g. Zanardo et al. 2017, Sprogis et al. 2018). It is likely that dolphins attribute high importance to reef environments due to the diverse prey types supported by these ecosystems (Wakefield et al. 2013). Similarly, seagrass meadows in Cockburn Sound serve as crucial breeding and nursery areas for various fish species, including pink snapper, calamari, whiting and blue swimmer crabs (Wakefield et al. 2013), which are likely prey targets for dolphins. Although the data initially suggested that the seagrass meadows in the western part of Mangles Bay and along the Causeway, were more important for resting than foraging, further observations of dolphins following rays in similar habitats in Owen Anchorage (unpublished data) and in Shoalwater Bay (*personal comment by Krista Nicholson*) indicated otherwise or at least indicated an equal importance for both behaviours. While dolphins may appear to be resting on the surface, they may actually be engaging in a ‘passive foraging’ behaviour by following rays that disturb the seagrass. To my current knowledge, this behaviour may be limited to a few individuals, and further research is needed to fully understand the interaction between dolphins and rays in this context.

4.2.2 Kwinana Shelf – a long-term key area

Despite variations in survey design between the periods of 2001-2003 (i.e., using belt transect routes across Kwinana Shelf; Finn 2005) and 2011-2015 (i.e., using zig-zag transect routes across the entire sound; Chabanne et al. 2017b), the results consistently indicated no change in dolphin distribution over a long period, spanning decades. The study conducted in 2001-2002 also emphasised the strong connection between feeding aggregations and the habitat of the Kwinana Shelf, which is utilised by seabirds such as Pied cormorants for breeding during the cooler season (Finn & Calver 2008). The persistent spatial association with the Kwinana Shelf, including a high occurrence of mother-calf pairs and the absence of similar habitat in nearby areas, presents challenges for dolphins to adapt or relocate. Adjacent regions with suitable habitat available across Owen Anchorage, the Swan Canning Riverpark (Chabanne et al. 2017a), and Shoalwater Bay (Nicholson et al. 2021), are already occupied by resident communities, potentially lacking sufficient resources to support an additional larger community (Chabanne et al. 2017a). Furthermore, dolphins observed further north in Gage Roads region exhibited more transient behaviour and did not demonstrate similar site fidelity but more transient behaviour, which suggest, suggesting a lack of suitable habitat (Chabanne et al. 2017a, Chabanne et al. 2017b).

In the scenario where dolphin displacement is unlikely, construction-related activities such as dredging, piling work, underwater blasting, and large increases in vessel traffic associated with the port development could have adverse effects at the individual-level. These activities have the potential to cause acoustic masking, hearing loss, behavioural changes, and increased stress levels in dolphins (Marley et al. 2017, Dey et al. 2019, Sørensen et al. 2023). The impact of these activities is further influenced by environmental factors and animal behaviour (La Manna et al. 2019). Since the Kwinana Shelf habitat is crucial for nursing (Finn 2005), female dolphins and their calves may be at a higher risk, resulting in significant fitness costs and reduced reproductive success for individual dolphins. Given the small size of the dolphin community, short-term changes in individual behavior and physiology could have long-term implications for population dynamics (e.g., Manlik et al. 2016, Nicholson et al. 2022).

The latest observation of dolphins across the Kwinana Shelf also revealed the presence of visiting individual dolphins known to be part of the resident communities of Owen Anchorage and the Swan Canning Riverpark (unpublished data collected for *Project 8.3.2*). These findings suggest that the connections between these communities are more significant than previously described, or there has been a change in dynamics over the last decade (Chabanne et al. 2017a). In this context, the Kwinana Shelf may serve as a suitable habitat where interactions, including reproduction between different dolphin communities, could take place (Chabanne et al. 2021). These recent observations and the potential short-term health issues that may arise with the port development highlight the importance of conducting long-term evaluations to assess the status and health of the dolphin communities and their utilisation of the Perth metropolitan waters. Best practices would recommend conducting focal follows to evaluate the activity budget of dolphins, allowing for the assessment of temporal and spatial variations. These observations can include evaluations of *in situ* anthropogenic factors (i.e., based on small scale acoustic and visual observations of human activities). Additionally, obtaining remote samples, such as tissue samples or photos, can provide valuable information for evaluating individual health.

4.3 Limitations

4.3.1 Temporal variability

Due to the small sample sizes, it was not possible to test for seasonal variability in dolphin distribution by year. However, the identification of some variations in the probability of occurrence between years suggests that other non-seasonal parameters may influence the distribution of dolphins on a yearly basis, in addition to any seasonal patterns. In early 2011, prior to the data collection period, a marine heatwave associated with the strongest La Niña events recorded at that time affected over 2,000 km of the southwestern Australian (Wernberg et al. 2012). This resulted in Cockburn Sound experiencing bottom water temperatures 3-4◦C warmer than the years 2002-2010, accompanied by depressed dissolved oxygen levels (Rose et al. 2012). The effects of La Niña on dolphins have been observed in other regions, with a decrease in reproduction success attributed to females having to spend more time foraging due to changes or reductions in prey distribution (Wild et al. 2019). Unfortunately, as data collection began after the La Niña event (start of collection in June 2011), our ability to understand the effect of this event on the dolphin distribution in Owen Anchorage and Cockburn Sound is limited.

4.3.2 Explanatory variables

The SDMs in this study were developed using a set of explanatory variables that do not encompass all potential factors influencing the spatial distribution of dolphins. Indeed, the majority of the influential factors had weak overall effects, contributing minimally to the explanation of majority of the SDM findings. Additionally, biotic variables such as salinity, Chl-a, and light attenuation were made provided by the Cockburn Sound Management Council, but their measurements were limited to the summer months and only at 18 stationary stations across Cockburn Sound. For dolphins inhabiting coastal and enclosed areas like Owen Anchorage and Cockburn Sound, developing biologically meaningful SDMs can be challenging due to their specific foraging habits, which are difficult to quantify and often limited to a subset of available habitats (*personal comment by Colin MacLeod* [GIS in Ecology]). Predictive abilities of SDMs for coastal bottlenose dolphins may be low when using typical variables such as depth and slope and as demonstrated by several SDMs conducted in the study. These variables do not directly define their niche but serve as proxies for other biologically meaningful components (Bryn et al. 2021). To test hypotheses related to prey distribution, it is recommended to include factors such as prey presence and abundance *(Theme 4: Fisheries*) in dolphin distribution models (Bennington et al. 2020). Additionally, interactions among prey items at various temporal and spatial scales should be considered (Torres et al. 2008). The natural stochastic processes of fish species, events associated with the El Niño-Southern Oscillation (ENSO), and climate change contribute to interannual variation in prey availability (Fletcher et al. 2017). Given these considerations and the limited size of presence data for seasonal, interannual, or behaviour-specific modelling (Pearson et al. 2006), caution should still be exercised when using the findings of the response variables explaining the distribution of dolphins in Owen Anchorage and Cockburn Sound.

5 Conclusions

The SMD exercise outlined here provides some valuable insights into the broad-scale distribution of dolphins in Owen Anchorage and Cockburn Sound. The results indicate of key areas, particularly in close proximity to the shore and the Kwinana Shelf in Cockburn Sound, although the temporal patterns in Owen Anchorage are more complex. Determining the specific environmental variables that explain the dolphin distribution was challenging, with weak overall effects of the most influential variables and with depth being the commonly identified variable for coastal dolphins in general. It is important to note that Owen Anchorage and Cockburn Sound have unique hydrological and biological characteristics due to their enclosed embayment and connection to large catchment area, i.e. the Swan Canning estuary.

In contrast to other coastal dolphin populations that tend to move further offshore and in deeper waters during the coldest months (Zanardo et al. 2017, Sprogis et al. 2018, Haughey et al. 2021), dolphins in Owen Anchorage and Cockburn Sound exhibit strong year-round site fidelity with limited emigration (Finn 2005, Chabanne et al. 2017b). However, this study reveals variation in habitat distribution patterns between Owen Anchorage and Cockburn Sound. The interpretation is that Owen Anchorage offers a more uniform topography and substrate, with hydrological and biological factors potentially influencing dolphin distribution within the region. In Cockburn Sound, suitable habitats are more limited due to the presence of a deep central basin, and hydrological and biological variables may play a more localised (e.g., within the Kwinana Shelf) role in dolphin distribution. Future operational activities and the ongoing increase in shipping activities may elicit different responses from the dolphin communities, with those in Owen Anchorage having a low impact response on the population compared to those in Cockburn Sound. However, this interpretation does not take into account the potential influence of more frequent and stronger climatic events (Cai et al. 2015).

A study looking at the current distribution of dolphins across the Kwinana Shelf is being conducted in order to better understand their use of the area at a finer-scale (*sub-project 8.3.2*). Additional variables, such as presence of vessels (recreational, shipping) will also be tested in this study. In addition to the finer-scale distribution, a study looking at the stable isotopes of dolphins in comparison to those from a random selection of fish species using Cockburn Sound and Owen Anchorage will enhance to further understand their diet and any variations that may exist between the regions and between seasons (*sub-project 8.3.3*).

Continued monitoring of dolphin density and behaviour before, during, and after the period of the potential disturbances is necessary to assess the species distribution and quality of habitat that should be noted for avoidance in the development of future port infrastructure and associated operations. Ongoing surveys for long-lived animals will help determine the effectiveness of mitigation measures aimed at minimising noise, ship-induced waves, injuries, and other impacts associated with human activities in order to protect the resident communities of dolphins and maintain their quality of their habitat.

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8 Appendices

8.1 Appendix 1. Spatial distribution of survey effort in Owen Anchorage and Cockburn Sound

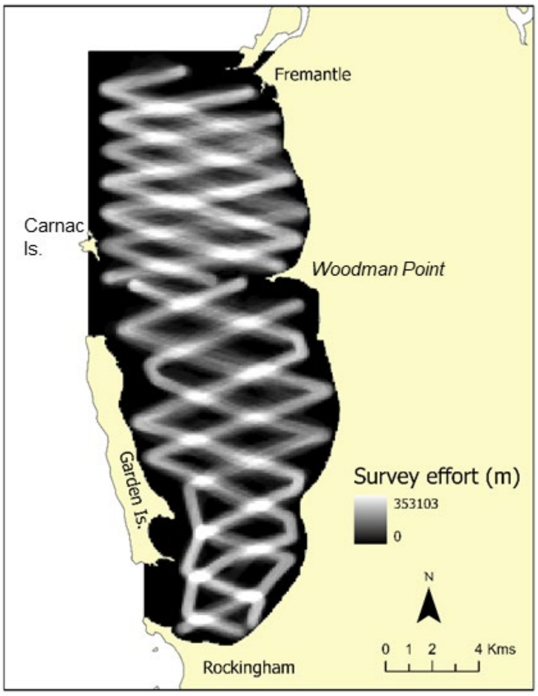

Figure 20. Map of the survey efforts carried out in Owen Anchorage and Cockburn Sound from 2011 to 2015.

8.2 Appendix 2. Statistical summary of SDMs of dolphins in Owen Anchorage over the entire study period.

Among all the single algorithms, distance to the coastline was identified as one of the most influential variables, followed by depth in five algorithms (**Table 1**). Both GLM and RF models also recognised slope as an important variable (**Table 1**).

Table 1. Importance of the predictor variables used in the SDMs of Indo-Pacific bottlenose dolphins in Owen Anchorage for the overall study period (years pooled and excluded travelling behaviour). SDMs algorithms were classification tree analysis (CTA); flexible discriminant analysis (FDA); generalised additive model (GAM); generalised boosted model (GBM); generalised linear model (GLM), multivariate adaptive regression splines (MARS); maximum entropy (MAXENT) and random forest (RF). Variable importance is presented as the mean value over 10 runs performed for each algorithm and for 10 datasets of randomly selected pseudo-absence cells. The number of runs of each algorithm that was included in the ensemble is indicated in subscript (i.e. runs meeting the ROC ≥0.7 and TSS ≥0.4 thresholds). Variables of greatest influence are highlighted in bold.

Algorithms	Explanatory variables						
	Substrate type	SST	Depth	Visibility	Slope	Distance to coastline	Distance to ramps/jetties
CTA^{93}	0.00	0.25	**0.31**	0.16	0.19	**0.42**	0.20
FDA^{56}	0.00	0.03	**0.21**	0.20	0.03	**0.68**	0.03
GAM^{0}	-	-	-	-	-	-	-
GBM^{100}	0.00	0.10	**0.23**	0.08	0.16	**0.31**	0.09
GLM^{39}	0.03	0.08	0.19	0.12	**0.21**	**0.62**	0.03
$MARS^{90}$	0.01	0.06	**0.50**	0.26	0.06	**0.41**	0.13
$MAXENT^{53}$	0.09	0.29	**0.35**	0.30	0.33	**0.45**	0.30
RF^{100}	0.00	0.09	0.11	0.11	**0.14**	**0.19**	**0.14**
Ensemble	0.00	0.07	**0.21**	0.12	0.13	**0.33**	0.07

8.3 Appendix 3. Statistical summary of the seasonal SDMs of dolphins in Owen Anchorage

In Winter, all models identified distance to recreation boat ramps/commercial jetties as one of the most influential variables. Additionally, the majority of algorithms (n = 5) recognised distance to the coastline as another important variable, while CTA and GBM models identified SST and MARS identified depth (**Table 2**).

In Spring, water visibility was identified as an important variable by all models, with the majority of the algorithms also highlighting distance to the coastline (n = 4) or distance to recreation boat ramps/commercial jetties (n = 3) as significant factors (**Table 2**). However, GBM models indicated that slope played a crucial role in the distribution of dolphins during Spring.

For Summer, both slope and distance to the coastline were identified as the most influential variables by the majority of algorithms, while GAM models revealed a stronger influence of water visibility and the distance to recreation boat ramps/commercial jetties (**Table 2**).

In Autumn, the majority of algorithms identified distance to recreation boat ramps/commercial jetties and SST as the most influencing variables, with CTA and GBM also highlighting the significance of slope (**Table 2**).

Table 2**.** Importance of the predictor variables used in the seasonal SDMs of Indo-Pacific bottlenose dolphins in Owen Anchorage (years pooled by season and excluded travelling behaviour). SDMs algorithms were classification tree analysis (CTA); flexible discriminant analysis (FDA); generalised additive model (GAM); generalised boosted model (GBM); generalised linear model (GLM), multivariate adaptive regression splines (MARS); maximum entropy (MAXENT) and random forest (RF). Variable importance is presented as the mean value over 10 runs performed for each algorithm and for 10 datasets of randomly selected pseudo-absence cells. The number of runs of each algorithm that was included in the ensemble is indicated in subscript (i.e. runs meeting the ROC ≥0.7 and TSS ≥0.4 thresholds). Variables of greatest influence are highlighted in bold.

Season	Algorithms	Explanatory variables						
		Substrate type	SST	Water depth	Visibility	Slope	Distance to coastline	Distance to ramps/jetties
Winter	CTA^{96}	0.00	**0.30**	0.16	0.05	0.05	0.21	**0.32**
	FDA^{73}	0.00	0.12	0.09	0.05	0.01	**0.37**	**0.37**
	GAM^{17}	0.16	0.30	0.29	0.36	0.20	**0.60**	**0.59**
	GBM^{99}	0.00	**0.21**	0.14	0.02	0.07	0.08	**0.20**
	GLM^{95}	0.08	0.13	0.25	0.09	0.11	**0.52**	**0.26**
	$MARS^{93}$	0.03	0.21	**0.29**	0.09	0.07	0.26	**0.33**
	$MAXENT^{97}$	0.02	0.10	0.16	0.01	0.06	**0.51**	**0.20**
	RF^{100}	0.00	0.05	0.06	0.07	0.05	**0.17**	**0.15**
	Ensemble	0.00	0.07	0.13	0.00	0.01	**0.20**	**0.30**
Spring	CTA^{99}	0.01	0.04	0.09	**0.28**	0.21	0.18	**0.30**
	FDA^{69}	0.00	0.05	0.05	**0.49**	0.12	0.21	**0.23**
	GAM^{35}	0.14	0.23	0.18	**0.54**	0.49	**0.48**	0.29
	GBM^{98}	0.00	0.06	0.12	**0.28**	**0.23**	0.17	0.07
	GLM^{99}	0.05	0.13	0.12	**0.41**	0.27	**0.45**	0.25
	$MARS^{89}$	0.01	0.09	0.14	**0.43**	0.21	**0.30**	0.28
	$MAXENT^{97}$	0.03	0.03	0.10	**0.34**	0.12	**0.38**	0.17
	RF^{100}	0.00	0.03	0.08	**0.15**	0.10	0.11	**0.14**
	Ensemble	0.00	0.08	0.01	**0.34**	0.16	**0.27**	0.14

Table2. *Ongoing*

Season	Algorithms	Explanatory variables						
		Substrate type	SST	Water depth	Visibility	Slope	Distance to coastline	Distance to ramps/jetties
Summer	CTA[99]	0.01	0.08	0.11	0.11	**0.54**	**0.33**	0.07
	FDA[64]	0.00	0.04	0.10	0.11	**0.56**	**0.42**	0.21
	GAM[18]	0.26	0.45	0.37	**0.63**	0.45	0.49	**0.51**
	GBM[98]	0.00	0.06	0.06	0.04	**0.47**	**0.43**	0.10
	GLM[91]	0.07	0.15	0.24	0.23	**0.64**	**0.29**	0.22
	MARS[84]	0.01	0.15	0.18	0.19	**0.43**	**0.56**	0.31
	MAXENT[84]	0.05	0.01	0.04	0.01	**0.66**	**0.32**	0.08
	RF[100]	0.00	0.04	0.06	0.05	**0.28**	**0.14**	0.09
	Ensemble	0.00	0.01	0.05	0.01	**0.63**	**0.37**	0.09
Autumn	CTA[76]	0.01	**0.37**	0.14	-	**0.30**	0.11	0.25
	FDA[17]	0.01	**0.22**	0.18	-	0.02	0.09	**0.49**
	GAM[0]	-	-	-	-	-	-	**-**
	GBM[37]	0.02	0.17	0.16	-	**0.28**	0.09	**0.22**
	GLM[79]	0.12	**0.43**	0.12	-	0.14	0.18	**0.27**
	MARS[16]	0.02	**0.45**	0.24	-	0.14	0.16	**0.27**
	MAXENT[99]	0.10	**0.42**	0.11	-	0.15	0.06	**0.19**
	RF[100]	0.01	**0.13**	0.10	-	0.09	0.13	**0.17**
	Ensemble	0.00	**0.33**	0.07	-	0.05	0.14	**0.34**

8.4 Appendix 4. Yearly ensemble SDMs for dolphins in Owen Anchorage

8.4.1 Statistical summary of the models

Preliminary check showed no correlation found between the environmental and anthropogenic variables used to model the annual distribution of dolphins in Owen Anchorage. Therefore, the selected explanatory variables for all years were substrate type, SST, water depth, water visibility, slope, distance to the coastline and distance to recreational ramps/commercial jetties. The number of presence cells was small but within the same range for Years 1, 2 and 3 (**Table 3**), while it was higher in Year 4. Consequently, caution should be exercised with the interpretation of the distribution of dolphins across years.

Evaluation of ROC and TSS indicated that the majority of models performed better than random (**Table 3**). However, a minority of the GAM models performed poorly regardless of the Year tested, and the majority of MAXENT models performed poorly for Year 3. After excluding the poorly performing algorithm runs, the ensemble model outperformed all single SDMs with a minimum ROC value of 0.90 and a minimum TSS value of 0.76, indicating excellent model performance for all years.

*Table 3***.** Statistic summary of the predictive performance for yearly SDMs run for dolphins in Owen Anchorage. The two metrics used for evaluation were the area under curve of the receiver operating characteristic (ROC) metric and the True Skill Statistic (TSS). Selection of the pseudo-absence cells was repeated 10 times (i.e. total of 10 datasets tested).

Period	Nb presence cells	Nb pseudo-absence cells per dataset	AUC/ROC		TSS	
			Range	Median	Range	Median
Year 1	11	33	0.58-1	0.88	0.16-1	0.70
Year 2	13	39	0.62-1	0.88	0.30-1	0.71
Year 3	12	36	0.46-1	0.85	0-1	0.66
Year 4	17	51	0.56-1	0.86	0.19-1	0.66

8.4.2 Variable importance and response curves

Most of the yearly SDMs identified distance to the coastline as one of the most important variables influencing the dolphin distribution in Owen Anchorage (**Table 4**). However, for Year 3, the majority of the algorithms provided better support for water depth. The response curves of the ensemble models throughout the year indicated that the probability of dolphin occurrence was highest in waters located within 2,500-3,000 m from the coastline (mainland and island, < 1,000 m in Year 4) and in deeper areas (> 10 m) (**Figure 21**). In Year 1, visibility was identified as another important variable, with a higher probability of dolphin occurrence in lower water visibility conditions (less than 70% of the water depth). However, in Year 3, an opposite response to water depth was detected, with a higher occurrence of dolphins in shallower areas (between 5 and 10 m) (**Figure 21**).

***Table 4*. Importance of the predictor variables used in the SDMs of Indo-Pacific bottlenose dolphins in Owen Anchorage by Year (Year 1: June 2011-May 2015; Year 2: June 2012-May 2013; Year 3: June 2013-May 2014; Year 4: May 2014-June 2015). SDMs algorithms were classification tree analysis (CTA); flexible discriminant analysis (FDA); generalised additive model (GAM); generalised boosted model (GBM); generalised linear model (GLM), multivariate adaptive regression splines (MARS); maximum entropy (MAXENT) and random forest (RF). Variable importance is presented as the mean value over 10 runs performed for each algorithm and for 10 datasets of randomly selected pseudo-absence cells. The number of runs of each algorithm that was included in the ensemble is indicated in subscript (i.e. runs meeting the ROC ≥0.7 and TSS ≥0.4 thresholds). Variables of greatest influence are highlighted in bold.

Year	Algorithms	Explanatory variables						
		Substrate type	SST	Water depth	Visibility	Slope	Distance to coastline	Distance to ramps/jetties
Year 1	CTA^{88}	0.04	0.08	**0.30**	**0.28**	0.21	0.20	0.07
	FDA^{29}	0.06	0.04	0.11	**0.52**	0.15	**0.21**	0.11
	GAM^{24}	0.35	0.39	0.43	**0.53**	0.25	0.41	**0.51**
	GBM^{99}	0.02	0.09	0.11	**0.33**	**0.19**	0.14	0.11
	GLM^{89}	0.29	0.14	0.31	**0.38**	0.17	**0.35**	0.20
	MARS^{70}	0.06	0.07	**0.29**	0.28	0.15	**0.33**	0.09
	MAXENT^{75}	**0.28**	0.09	0.20	**0.32**	0.08	0.06	0.07
	RF^{100}	0.01	0.07	**0.13**	**0.19**	0.10	0.07	0.07
	Ensemble	0.06	0.06	**0.27**	**0.37**	0.11	**0.23**	0.06
Year 2	CTA^{99}	0.00	0.17	**0.18**	0.13	0.06	**0.44**	0.15
	FDA^{62}	0.01	0.11	**0.16**	0.09	0.07	**0.54**	0.13
	GAM^{33}	0.17	0.37	**0.40**	0.33	0.39	**0.49**	0.39
	GBM^{99}	0.00	**0.14**	**0.14**	0.09	0.09	**0.29**	0.08
	GLM^{98}	0.05	0.15	0.16	**0.29**	0.11	**0.55**	0.12
	MARS^{92}	0.03	0.09	**0.23**	0.11	0.10	**0.62**	0.17
	MAXENT^{98}	0.03	0.08	**0.20**	0.04	0.05	**0.56**	0.15
	RF^{100}	0.00	0.07	0.08	0.06	0.07	**0.20**	**0.11**
	Ensemble	0.00	0.05	**0.13**	0.05	0.02	**0.57**	0.09

Table 4. Ongoing

Year	Algorithms	Explanatory variables						
		Substrate type	SST	Water depth	Visibility	Slope	Distance to coastline	Distance to ramps/jetties
Year 3	CTA[95]	0.00	**0.31**	**0.50**	0.07	0.08	0.05	0.13
	FDA[28]	0.01	0.23	**0.36**	0.04	0.03	0.09	**0.35**
	GAM[15]	0.21	0.27	0.51	0.51	0.30	**0.71**	**0.54**
	GBM[91]	0.00	**0.34**	**0.23**	0.04	0.14	0.05	0.15
	GLM[68]	0.08	0.11	**0.56**	0.09	0.10	0.22	**0.28**
	MARS[68]	0.02	**0.22**	**0.55**	0.10	0.04	0.07	0.18
	MAXENT[56]	0.04	0.09	**0.53**	0.06	0.08	0.06	**0.21**
	RF[100]	0.00	0.12	**0.13**	0.04	0.09	0.07	**0.13**
	Ensemble	0.00	0.12	**0.66**	0.01	0.07	0.02	0.12
Year 4	CTA[89]	0.00	0.05	0.10	**0.16**	0.13	**0.60**	0.06
	FDA[64]	0.00	0.02	0.14	**0.32**	0.05	**0.51**	0.10
	GAM[29]	0.10	0.19	0.31	0.20	0.32	**0.53**	**0.66**
	GBM[97]	0.00	0.05	0.11	0.08	**0.13**	**0.47**	0.06
	GLM[87]	0.05	0.08	0.25	**0.38**	0.25	**0.44**	0.12
	MARS[89]	0.00	0.06	**0.24**	0.16	0.17	**0.53**	0.19
	MAXENT[77]	0.02	0.02	0.12	**0.26**	0.14	**0.60**	0.03
	RF[100]	0.00	0.04	0.07	0.10	**0.11**	**0.20**	0.09
	Ensemble	0.00	0.02	0.13	0.10	0.14	**0.61**	0.06

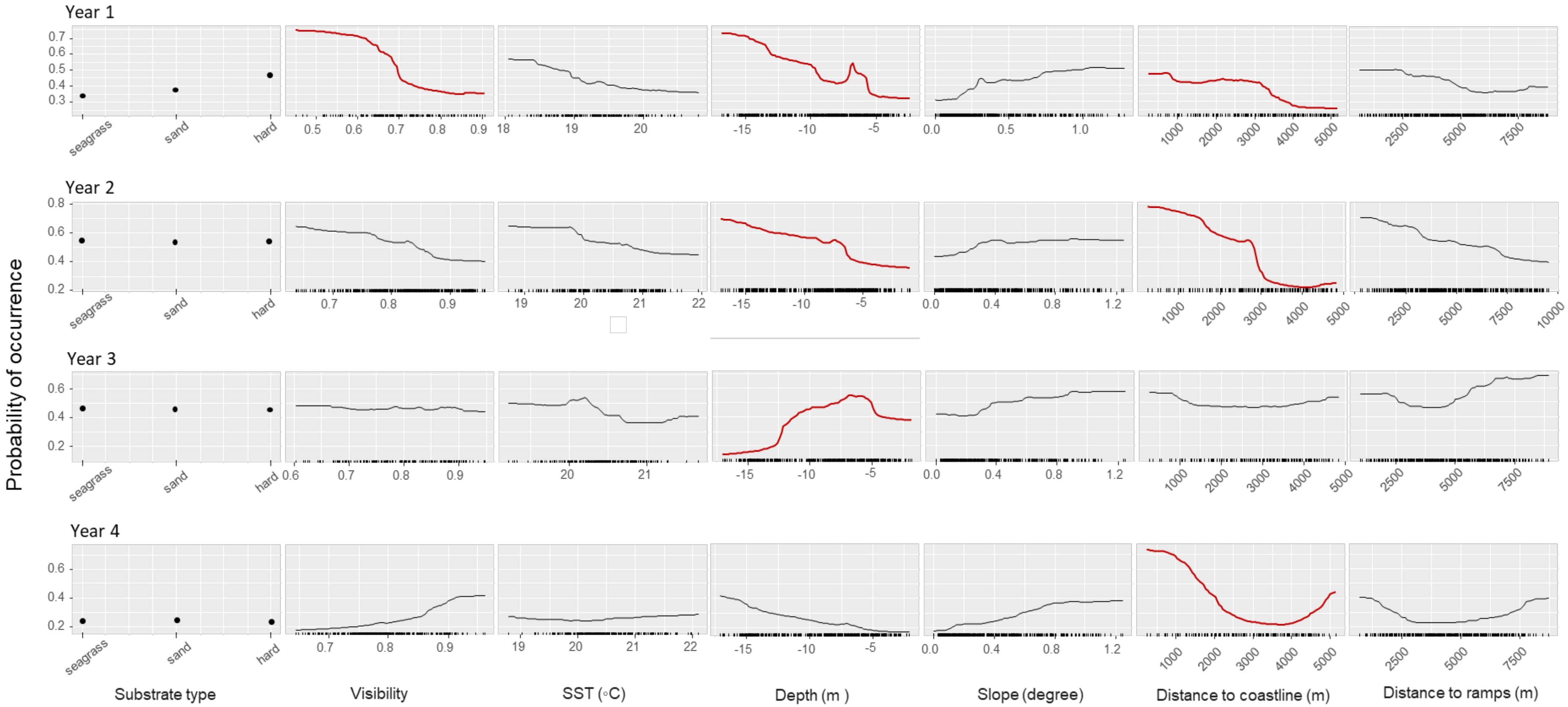

Figure 21. Response curves of the yearly presence of dolphins in relation to the explanatory variables obtained for the ensemble SDMs run for distribution mapping of Indo-Pacific bottlenose dolphins in Owen Anchorage. Year 1: June 2011-May 2015; Year 2: June 2012-May 2013; Year 3: June 2013-May 2014; Year 4: May 2014-June 2015. Curves highlighted in red identified the biggest influential variable for each year.

8.4.3 Distribution and maps

There was no consistency pattern in the distribution of the probability of dolphin occurrence in Owen Anchorage across all four years. However, Years 2 and 4 exhibited a higher probability of occurrence along the coastline of the mainland, while Year 3 showed a concentrated high probability of occurrence on the west side of the shipping channel, including around Carnac Island. In Year 1, the shipping area was also identified as an area with a high occurrence of dolphins (**Figure 22**).

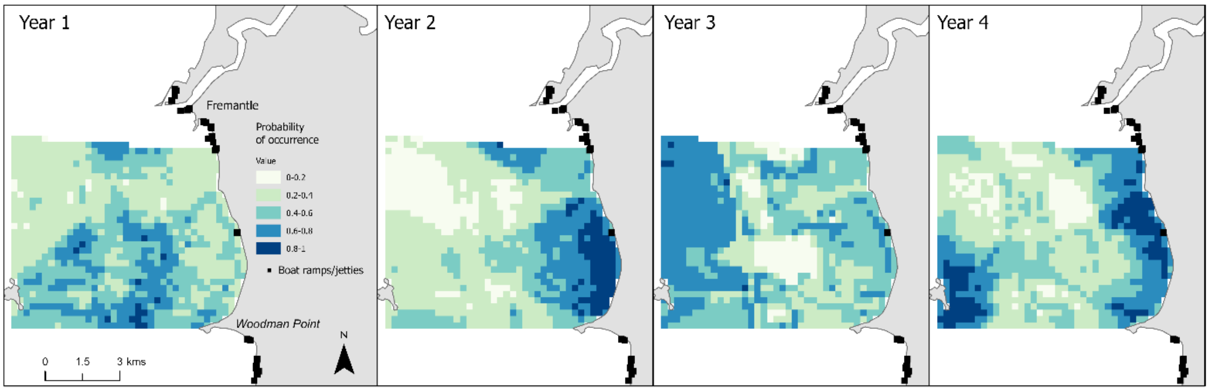

Figure 22. Yearly ensemble models of Indo-Pacific bottlenose dolphin probability of occurrence in Owen Anchorage. Colours as shown in the legend indicate the probability of occurrence of dolphins: very low (0-0.2); low (0.2-0.4); moderate (0.4-0.6); high (0.6-0.8); very high (0.8-1).

8.5 Appendix 5. Results of behaviour ensemble SDMs for dolphins in Owen Anchorage

8.5.1 Statistical summary of the models

All seven available variables (SST, water visibility, water depth, slope, distance to the coastline and distance to recreational boat ramps/commercial jetties) were retained in the SDMs for the entire study. The SDMs were conducted separately for foraging and resting behaviours, while the sample size for socialising behaviour was too small to be evaluated. Additionally, the distribution of dolphins using travelling sightings was examined, although any differences from the results obtained in the SDMs for foraging or resting could be considered as potential corridors between suitable habitats rather than required habitat.

The evaluation of ROC and TSS revealed that most models performed better than random (**Table 5**), although there were limitations with certain algorithms. Specifically, only a few or no GAM models worked well with the foraging and resting datasets, and models run using FDA and GLM algorithms were also limited with the travelling dataset. After excluding the poorly performing algorithm runs, the ensemble models demonstrated superior performance compared to all single SDMs, with ROC values ranging from 0.90 to 0.97 and TSS values ranging from 0.64 – 0.89. These results indicated good to excellent model performance for all three behaviours.

Table 5**.** Statistic summary of the predictive performance for SDMs run using sightings of dolphins foraging, resting, and travelling in Owen Anchorage. The two metrics used for evaluation were the area under curve of the receiver operating characteristic (ROC) metric and the True Skill Statistic (TSS). Selection of the pseudo-absence cells was repeated 10 times (i.e. total of 10 datasets tested).

Behaviour	Nb presence cells	Nb pseudo-absence cells per dataset	ROC		TSS	
			Range	Median	Range	Median
Foraging	36	108	0.56-1	0.84	0.15-1	0.58
Resting	13	39	0.63-1	0.91	0.34-1	0.77
Travelling	32	96	0.55-1	0.76	0.15-1	0.46

8.5.2 Variable importance and response curves

Both the foraging and resting SDMs highlighted the distance to the coastline as one of the most influential variables in shaping the distribution of dolphins in Owen Anchorage. Additionally, water depth was identified as an important variable specifically for foraging (**Table 6**). The response curves for both behaviours indicated that the probability of dolphin occurrence was highest near the coastline, within a 1,000 m range from the mainland or island. Further suitable habitat extended beyond 5,000 m from the coastline. Foraging behaviour was more prevalent in deeper waters compared to resting behaviour, which exhibited a preference for shallower water (approximately 7 m, **Figure 23**).

On the other hand, the SDMs for travelling behaviour identified the distance to recreational boat ramps/harbour and slope as the two most influential variables. According to the response curves, dolphins were more likely to be observed travelling when they were farther away from recreational boat ramps. However, there were moderate observations of this behaviour at closer distances. In contrast to foraging and resting behaviours, travelling behaviour generally occurred in areas with no significant slope (**Figure 23**).

***Table 6*. Importance of the predictor variables used in the SDMs of Indo-Pacific bottlenose dolphins in Owen Anchorage by behaviour (foraging; resting; travelling). SDMs algorithms were classification tree analysis (CTA); flexible discriminant analysis (FDA); generalised additive model (GAM); generalised boosted model (GBM); generalised linear model (GLM), multivariate adaptive regression splines (MARS); maximum entropy (MAXENT) and random forest (RF). Variable importance is presented as the mean value over 10 runs performed for each algorithm and for 10 datasets of randomly selected pseudo-absence cells. The number of runs of each algorithm that was included in the ensemble is indicated in subscript (i.e. runs meeting the ROC ≥0.7 and TSS ≥0.4 thresholds). Variables of greatest influence are highlighted in bold.

Behaviour	Algorithms	Explanatory variables						
		Substrate type	SST	Water depth	Visibility	Slope	Distance to coastline	Distance to ramps/jetties
Foraging	CTA^{90}	0.01	0.18	**0.42**	0.24	0.18	**0.31**	0.20
	FDA^{54}	0.01	0.02	0.21	**0.23**	0.04	**0.69**	0.03
	GAM^{0}	-	-	**-**	-	-	-	**-**
	GBM^{100}	0.01	0.10	**0.30**	0.11	0.17	**0.25**	0.12
	GLM^{71}	0.08	0.02	**0.40**	0.17	0.19	**0.46**	0.17
	$MARS^{91}$	0.03	0.02	**0.48**	0.31	0.11	**0.41**	0.08
	$MAXENT^{90}$	0.14	0.21	**0.38**	0.33	0.32	**0.47**	0.32
	RF^{100}	0.01	0.05	**0.15**	0.13	0.12	**0.18**	0.13
	Ensemble	0.02	0.04	**0.33**	0.19	0.16	**0.29**	0.09
Resting	CTA^{97}	0.01	0.06	0.17	**0.20**	0.08	**0.53**	0.03
	FDA^{87}	0.00	0.15	0.17	0.07	0.03	**0.41**	**0.33**
	GAM^{15}	0.13	0.31	0.31	**0.40**	0.34	**0.40**	**0.41**
	GBM^{100}	0.00	0.09	**0.12**	0.10	0.08	**0.37**	0.05
	GLM^{99}	0.13	0.19	**0.25**	0.09	0.13	**0.46**	0.14
	$MARS^{100}$	0.02	0.21	**0.38**	0.08	0.06	**0.39**	0.28
	$MAXENT^{98}$	**0.13**	0.08	0.07	0.05	0.07	**0.63**	0.02
	RF^{100}	0.00	0.09	0.04	0.05	0.06	**0.16**	**0.10**
	Ensemble	0.01	0.09	0.07	0.02	0.03	**0.45**	0.03

Table 6. *Ongoing*

Behaviour	Algorithms	Explanatory variables						
		Substrate type	SST	Water depth	Visibility	Slope	Distance to coastline	Distance to ramps/jetties
Travelling	CTA[93]	0.01	0.07	0.10	0.08	**0.32**	0.14	**0.55**
	FDA[10]	0.00	0.01	0.02	0.02	0.09	0.04	**0.84**
	GAM[30]	0.18	0.12	0.20	0.11	0.22	**0.48**	**0.61**
	GBM[98]	0.00	0.08	0.10	0.09	**0.23**	0.08	**0.30**
	GLM[17]	0.08	0.02	0.08	0.04	0.17	**0.20**	**0.67**
	MARS[66]	0.02	0.03	0.05	0.07	0.29	**0.32**	**0.55**
	MAXENT[89]	0.12	0.21	0.24	0.25	**0.40**	0.30	**0.52**
	RF[100]	0.00	0.07	0.08	0.07	**0.19**	0.07	**0.20**
	Ensemble	0.02	0.03	0.09	0.03	**0.26**	0.18	**0.45**

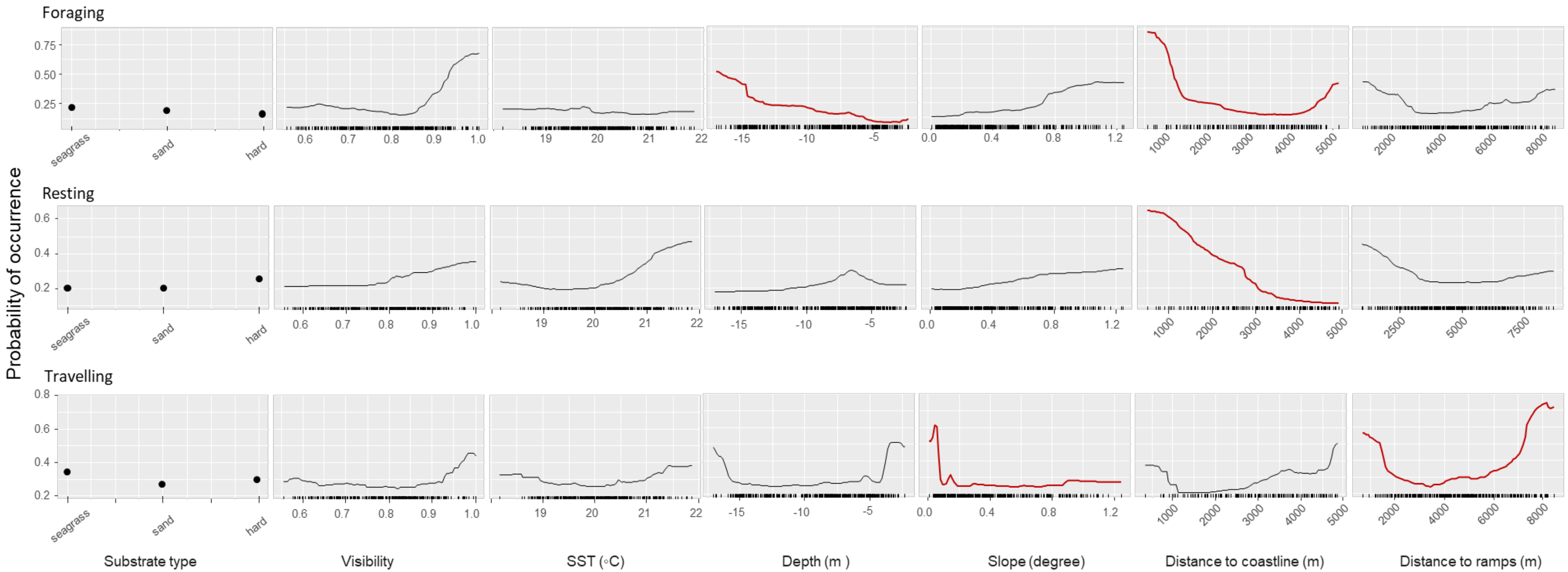

Figure 23. Response curves of the presence of dolphins in relation to the explanatory variables obtained for the ensemble SDMs run for each behaviour distribution mapping of Indo-Pacific bottlenose dolphins in Owen Anchorage. Behaviour tested were foraging, resting, and travelling. Curves highlighted in red identified the biggest influential variable in each behaviour.

8.5.3 Distribution and maps

While there were some overlaps in the areas with the highest concentration of cells displaying high to very high probabilities of occurrence (> 0.60) across different behaviours, there were also notable variations. The most favourable habitat for both foraging and resting behaviours was predominantly observed along the coastline from Fremantle to Woodman Point, including around Carnac Island (**Figure 24**). However, the central and northwest areas of Owen Anchorage also provided suitable habitat specifically for foraging. Conversely, areas that were less suitable for foraging and resting were used for travelling, as indicated by moderate to very high probabilities of occurrence in areas where foraging and resting had lower probabilities (**Figure 24**). This pattern aligns with travelling being a behaviour primarily associated with moving between suitable habitats, which may or may not overlap with the distribution of foraging and resting behaviours, depending on the specific circumstances (unknown here). Therefore, the presence of high probabilities for travelling in areas with low probabilities for foraging and resting may or may not have biological significance for the dolphins in Owen Anchorage.

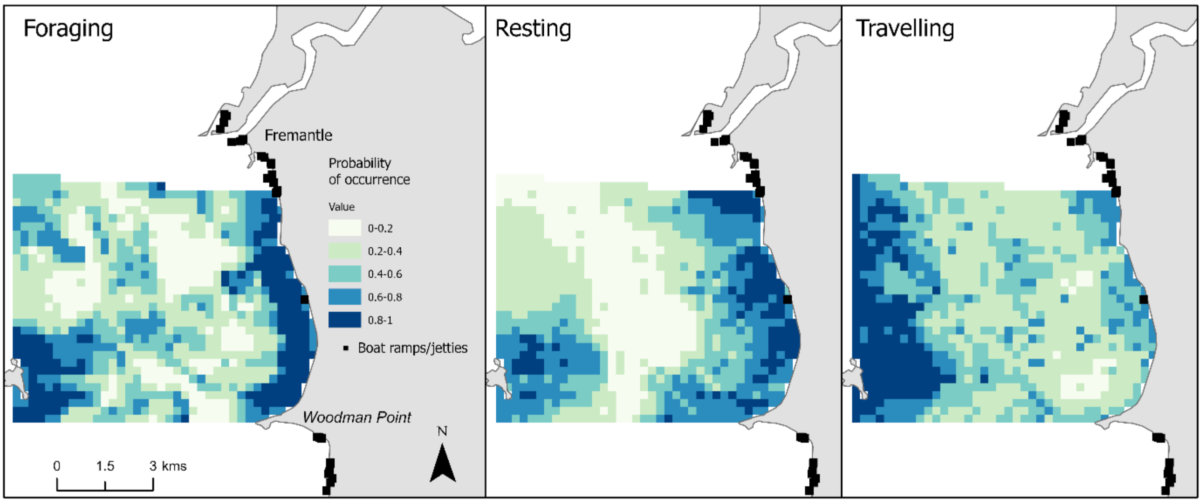

Figure 24. Behaviour specific (foraging, resting, travelling) of the ensemble models of Indo-Pacific bottlenose dolphin probability of occurrence in Owen Anchorage. Colours as shown in the legend indicate the probability of occurrence of dolphins: very low (0-0.2); low (0.2-0.4); moderate (0.4-0.6); high (0.6-0.8); very high (0.8-1).

8.6 Appendix 6. Statistical summary of SDMs of dolphins in Cockburn Sound over the entire study period

Water depth and distance to recreation boat ramps/commercial jetties were identified as the most influential variables across the majority of single algorithms (**Table 7**).

Table 7. Importance of the predictor variables used in the SDMs of Indo-Pacific bottlenose dolphins in Cockburn Sound for the overall study period using all sightings but travelling. SDMs algorithms were classification tree analysis (CTA); flexible discriminant analysis (FDA); generalised additive model (GAM); generalised boosted model (GBM); generalised linear model (GLM), multivariate adaptive regression splines (MARS); maximum entropy (MAXENT) and random forest (RF). Variable importance is presented as the mean value over 10 runs performed for each algorithm and for 10 datasets of randomly selected pseudo-absence cells. The number of runs of each algorithm that was included in the ensemble is indicated in subscript (i.e. runs meeting the ROC ≥0.7 and TSS ≥0.4 thresholds). Variables of greatest influence are highlighted in bold.

Algorithms	Explanatory variables					
	Substrate type	SST	Water depth	Slope	Distance to coastline	Distance to ramps/jetties
CTA^{47}	0.00	0.05	**0.84**	0.03	0.07	**0.19**
FDA^{66}	0.06	0.04	**0.57**	**0.18**	0.09	0.16
GAM^{72}	0.02	0.08	**0.43**	0.06	0.11	**0.57**
GBM^{100}	0.00	0.10	**0.46**	0.13	0.11	**0.23**
GLM^{48}	0.10	0.07	**0.57**	0.09	0.04	**0.13**
$MARS^{95}$	0.01	0.08	0.31	0.15	**0.33**	**0.48**
$MAXENT^{83}$	0.07	0.14	**0.53**	0.17	0.18	**0.20**
RF^{100}	0.05	0.10	**0.33**	0.13	0.19	**0.21**
Ensemble	0.01	0.07	**0.53**	0.11	0.12	**0.24**

8.7 Appendix 7. Statistical summary of the seasonal SDMs of dolphins in Cockburn Sound

In Winter, the majority of the algorithms identified water depth as the most influential variables, while FDA, GAM, MAXENT, and RF models also identified SST and/or water visibility (**Table 8**).

For Spring, water visibility and slope were determined to be the most important variables in describing the occurrence of dolphins in Cockburn Sound, with FDA and RF models also highlighting SST (**Table 8**).

In Summer, Chl-a and water depth were identified as the most influential variables by all algorithms, except for GAM models where water visibility and temperature at the bottom had a stronger influence (**Table 8**).

Lastly, in Autumn, water depth was identified by all algorithms as the most important variable influencing the distribution of dolphins in Cockburn Sound (**Table 8**).

Table 8. Importance of the predictor variables used in the seasonal SDMs of Indo-Pacific bottlenose dolphins in Cockburn Sound (all years pooled by season and excluded travelling behaviour). SDMs algorithms were classification tree analysis (CTA); flexible discriminant analysis (FDA); generalised additive model (GAM); generalised boosted model (GBM); generalised linear model (GLM), multivariate adaptive regression splines (MARS); maximum entropy (MAXENT) and random forest (RF). Variable importance is presented as the mean value over 10 runs performed for each algorithm and for 10 datasets of randomly selected pseudo-absence cells. The number of runs of each algorithm that was included in the ensemble is indicated in subscript (i.e. runs meeting the ROC ≥0.7 and TSS ≥0.4 thresholds). Variables of greatest influence are highlighted in bold.

Season	Algorithms	Explanatory variables									
		Substrate type	SST	Water depth	Visibility	Slope	Distance to coast	Distance to ramps/jetties	Salinity	Temperature (bottom)	Chl-a
Winter	CTA^{94}	0.00	0.11	**0.54**	0.23	**0.30**	0.05	-	-	-	-
	FDA^{79}	0.03	**0.24**	0.19	**0.41**	**0.24**	0.02	-	-	-	-
	GAM^{100}	0.31	**0.41**	**0.43**	0.20	0.16	0.15	-	-	-	-
	GBM^{100}	0.00	0.07	**0.38**	0.15	**0.25**	0.05	-	-	-	-
	GLM^{87}	0.16	0.06	**0.40**	0.11	**0.24**	0.13	-	-	-	-
	MARS^{97}	0.18	0.27	**0.32**	0.28	**0.29**	0.08	-	-	-	-
	MAXENT^{99}	0.22	**0.44**	**0.43**	**0.43**	0.42	0.30	-	-	-	-
	RF^{100}	0.04	0.08	**0.15**	**0.12**	**0.12**	0.05	-	-	-	-
	Ensemble	0.02	0.09	**0.32**	0.09	0.18	0.01	-	-	-	-
Spring	CTA^{83}	0.01	0.30	0.08	**0.35**	**0.25**	0.12	0.11	-	-	-
	FDA^{63}	0.06	**0.43**	0.06	**0.27**	0.14	0.05	0.05	-	-	-
	GAM^{97}	0.15	0.32	0.25	**0.46**	**0.36**	0.19	0.25	-	-	-
	GBM^{100}	0.00	0.13	0.08	**0.27**	**0.18**	0.08	0.09	-	-	-
	GLM^{94}	0.12	0.26	0.13	**0.36**	**0.40**	0.07	0.10	-	-	-
	MARS^{94}	0.02	0.23	0.06	**0.27**	**0.43**	0.15	0.13	-	-	-
	MAXENT^{99}	0.19	0.40	0.34	**0.49**	**0.42**	0.39	0.35	-	-	-
	RF^{100}	0.02	**0.14**	0.05	**0.16**	0.10	0.07	0.06	-	-	-
	Ensemble	0.01	0.15	0.02	**0.36**	**0.37**	0.05	0.01	-	-	-

Table 8. *Ongoing*

Season	Algorithms	Explanatory variables									
		Substrate type	SST	Water depth	Visibility	Slope	Distance to coast	Distance to ramps/jetties	Salinity	Temperature (bottom)	Chl-a
Summer	CTA[95]	0.00	0.01	**0.65**	0.04	0.08	0.09	-	0.04	0.03	**0.13**
	FDA[92]	0.02	0.03	**0.24**	0.03	0.22	0.17	-	0.21	0.03	**0.27**
	GAM[96]	0.12	0.32	0.26	**0.56**	0.18	0.35	-	0.26	**0.42**	0.38
	GBM[100]	0.00	0.02	**0.19**	0.05	0.07	0.07	-	0.06	0.04	**0.11**
	GLM[100]	0.05	0.05	**0.30**	0.09	0.16	0.22	-	0.23	0.06	**0.34**
	MARS[100]	0.02	0.07	**0.32**	0.10	0.17	0.30	-	0.17	0.05	**0.35**
	MAXENT[100]	0.10	0.19	**0.39**	0.20	0.32	0.39	-	0.27	0.26	**0.35**
	RF[100]	0.00	0.02	**0.08**	0.02	0.08	0.07	-	0.08	0.03	**0.12**
	Ensemble	0.00	0.01	**0.22**	0.02	0.09	**0.13**	-	0.07	0.01	**0.13**
Autumn	CTA[98]	0.00	0.06	**0.54**	**0.26**	0.17	0.01	0.03	-	-	-
	FDA[87]	0.07	0.09	**0.79**	0.05	0.04	0.01	0.02	-	-	-
	GAM[100]	0.32	0.28	**0.56**	0.38	0.29	0.39	**0.43**	-	-	-
	GBM[99]	0.00	0.05	**0.22**	0.12	**0.19**	0.02	0.08	-	-	-
	GLM[92]	0.20	0.06	**0.37**	**0.35**	0.11	0.07	0.04	-	-	-
	MARS[96]	0.09	0.20	**0.74**	0.11	0.06	0.04	0.06	-	-	-
	MAXENT[87]	0.03	0.02	**0.29**	**0.40**	0.07	0.02	0.04	-	-	-
	RF[100]	0.03	0.03	**0.09**	0.08	**0.11**	0.03	0.04	-	-	-
	Ensemble	0.01	0.01	**0.38**	0.10	0.04	0.01	0.01	-	-	-

8.8 Appendix 8. Yearly ensemble SDMs for dolphins in Cockburn Sound

8.8.1 Statistical summary of the models

The selected explanatory variables for all years were substrate type, visibility, SST, water depth, slope, distance to the coastline and distance to recreational boat ramps/commercial jetties. The number of presence cells was small but consistent across years, eliminating any biases associated with variations in sampling size (**Table 9**).

The Evaluation of ROC and TSS indicated that most models performed better than random (**Table 10**) for each year, although more than half of the FDA and MAXENT models exhibited poor performance in Year 3. After excluding the poorly performing algorithm runs, the ensemble model outperformed all single SDMs, achieving a ROC value of 0.92 and TSS value ranging from 0.69 to 0.77, indicating good to excellent model performance across all years.

Table 9. Statistic summary of the predictive performance for yearly SDMs run for dolphins in Cockburn Sound. The two metrics used for evaluation were the area under curve of the receiver operating characteristic (ROC) metric and the True Skill Statistic (TSS). Selection of the pseudo-absence cells was repeated 10 times (i.e. total of 10 datasets tested).

Period	Nb presence cells	Nb pseudo-absence cells per dataset	ROC		TSS	
			Range	Median	Range	Median
Year 1	20	60	0.63-1	0.87	0.25-1	0.73
Year 2	19	57	0.60-1	0.90	0.27-1	0.77
Year 3	18	54	0.57-1	0.82	0.14-1	0.60
Year 4	21	63	0.55-1	0.84	0.10-1	0.63

8.8.2 Variable importance and response curves

SDMs consistently identified water depth as one of the most important variables shaping the dolphin distribution in Cockburn Sound, except for Year 2 where water visibility took precedence (**Table 10**). Additionally, slope emerged as an important variable Year 3. Interestingly, in Year 4, the distance to recreational boat ramps/commercial jetties had a strong influence on dolphin distribution compared to water depth (**Table 10**).

The response curves of the ensemble models across the years revealed that the highest probability of dolphin occurrence was associated with shallow waters (< 10 m), high water visibility (Year 2), moderate to higher slope, and proximity to recreational boat ramps/commercial jetties (Year 4) (**Figure 25**).

Table 10. Importance of the predictor variables used in the SDMs of Indo-Pacific bottlenose dolphins in Cockburn Sound by Year (Year 1: June 2011-May 2015; Year 2: June 2012-May 2013; Year 3: June 2013-May 2014; Year 4: May 2014-June 2015). SDMs algorithms were classification tree analysis (CTA); flexible discriminant analysis (FDA); generalised additive model (GAM); generalised boosted model (GBM); generalised linear model (GLM), multivariate adaptive regression splines (MARS); maximum entropy (MAXENT) and random forest (RF). Variable importance is presented as the mean value over 10 runs performed for each algorithm and for 10 datasets of randomly selected pseudo-absence cells. The number of runs of each algorithm that was included in the ensemble is indicated in subscript (i.e. runs meeting the ROC ≥0.7 and TSS ≥0.4 thresholds). Variables of greatest influence are highlighted in bold.

Year	Algorithms	Explanatory variables						
		Substrate type	SST	Water depth	Visibility	Slope	Distance to coast	Distance to ramps/jetties
Year 1	CTA^{94}	0.03	0.03	**0.80**	0.02	0.13	0.03	0.06
	FDA^{88}	0.15	0.08	**0.65**	0.01	0.10	0.09	0.03
	GAM^{100}	0.31	0.28	**0.56**	0.28	0.13	0.31	0.50
	GBM^{100}	0.00	0.04	**0.68**	0.04	0.12	0.06	0.04
	GLM^{98}	0.12	0.03	**0.71**	0.06	0.08	0.21	0.08
	MARS^{93}	0.32	0.09	**0.41**	0.15	0.06	0.21	0.18
	MAXENT^{100}	0.25	0.40	**0.48**	0.26	0.39	0.39	0.25
	RF^{100}	0.09	0.07	**0.20**	0.03	0.06	0.06	0.04
	Ensemble	0.04	0.03	**0.71**	0.01	0.03	0.09	0.04
Year 2	CTA^{92}	0.00	0.15	0.22	**0.41**	0.10	0.07	0.15
	FDA^{85}	0.01	0.10	0.17	**0.43**	0.07	0.14	0.16
	GAM^{77}	0.17	0.37	0.37	**0.59**	0.35	0.33	0.33
	GBM^{100}	0.00	0.07	0.12	**0.27**	0.10	0.05	0.10
	GLM^{89}	0.03	0.23	0.17	**0.41**	0.11	0.06	0.09
	MARS^{94}	0.01	0.10	0.22	**0.40**	0.11	0.18	0.17
	MAXENT^{100}	0.18	0.29	0.32	**0.47**	0.35	0.31	0.37
	RF^{100}	0.00	0.07	0.09	**0.14**	0.05	0.06	0.08
	Ensemble	0.00	0.06	0.09	**0.25**	0.02	0.03	0.04

Table 10. *Ongoing*

Year	Algorithms	Explanatory variables						
		Substrate type	SST	Water depth	Visibility	Slope	Distance to coast	Distance to ramps/jetties
Year 3	CTA[87]	0.01	0.11	0.26	0.17	**0.36**	0.18	0.20
	FDA[33]	0.05	0.09	**0.31**	0.13	0.20	0.12	0.23
	GAM[87]	0.23	0.25	0.34	**0.36**	0.21	0.21	0.35
	GBM[94]	0.01	0.09	0.17	0.11	**0.31**	0.11	0.09
	GLM[69]	0.15	0.07	**0.51**	0.18	0.13	0.07	0.15
	MARS[81]	0.04	0.15	0.20	0.10	0.28	0.20	**0.35**
	MAXENT[47]	0.09	0.04	**0.53**	0.14	0.11	0.08	0.14
	RF[100]	0.01	0.06	**0.11**	0.09	0.10	0.08	0.09
	Ensemble	0.02	0.01	**0.31**	0.12	**0.20**	0.04	0.16
Year 4	CTA[76]	0.00	0.08	0.28	0.09	0.24	0.07	**0.39**
	FDA[62]	0.07	0.08	**0.44**	0.04	0.29	0.02	0.14
	GAM[97]	0.39	0.11	**0.48**	0.26	0.29	0.23	0.26
	GBM[100]	0.00	0.09	0.12	0.06	0.12	0.06	**0.26**
	GLM[88]	0.17	0.04	0.22	0.01	0.26	0.05	**0.57**
	MARS[88]	0.15	0.03	**0.54**	0.10	0.16	0.11	0.22
	MAXENT[98]	0.25	0.30	0.44	0.35	**0.48**	0.29	0.46
	RF[100]	0.03	0.08	0.07	0.05	**0.16**	0.05	0.14
	Ensemble	0.14	0.03	**0.25**	0.01	**0.22**	0.02	**0.37**

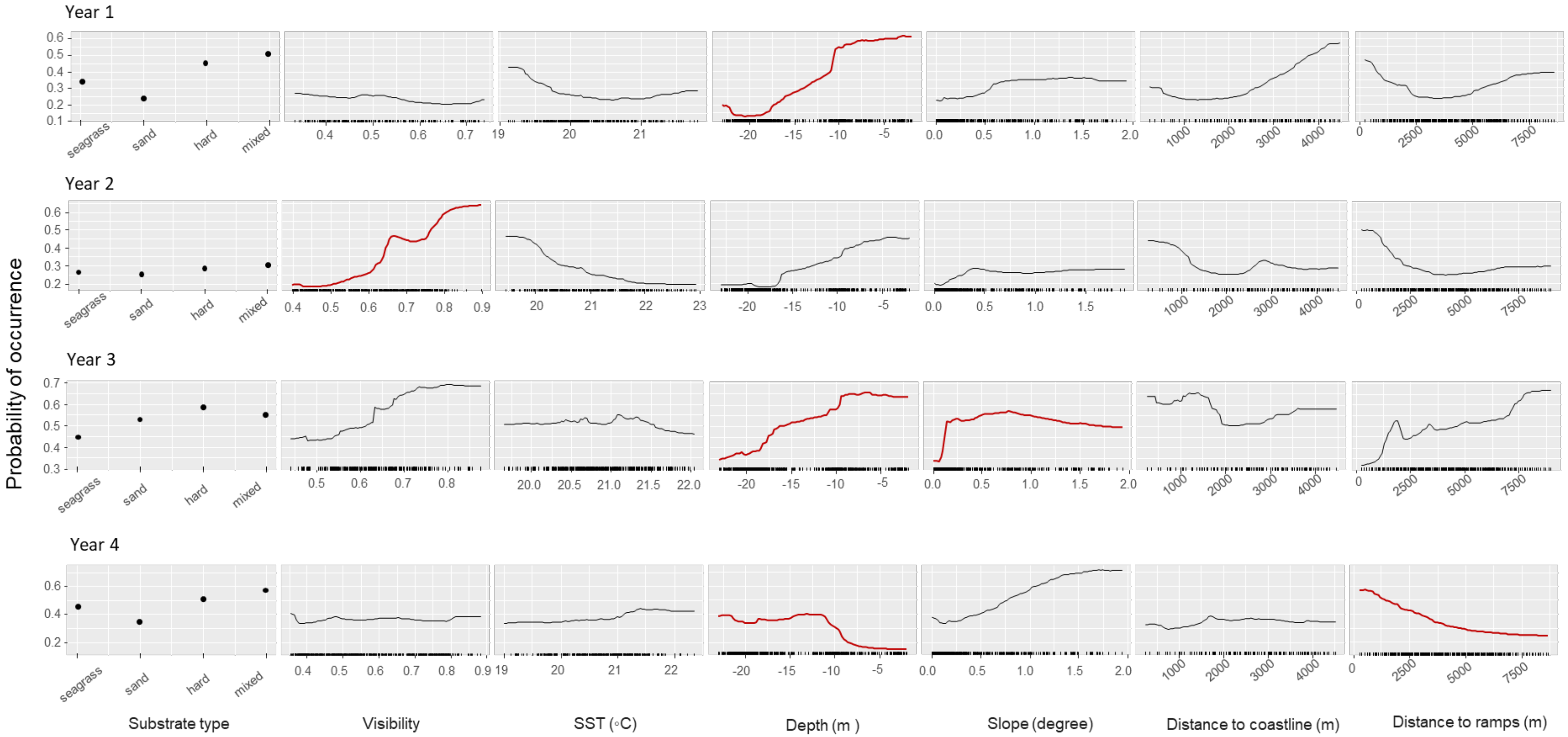

Figure 25. Response curves of the yearly presence of dolphins in relation to the explanatory variables obtained for the ensemble SDMs run for distribution mapping of Indo-Pacific bottlenose dolphins in Cockburn Sound. Year 1: June 2011-May 2015; Year 2: June 2012-May 2013; Year 3: June 2013-May 2014; Year 4: May 2014-June 2015. Curves highlighted in red identified the biggest influential variable(s) for each year.

8.8.3 Distribution and maps

In all four years, the highest concentration of cells with moderate to very high probabilities of dolphin occurrence were observed along the edges of Cockburn Sound (**Figure 26**). These areas extended across the Kwinana Shelf and were present to the north and south of Garden Island, including a portion of Mangle Bay. Conversely, the lowest probabilities of occurrence were primarily concentrated within the central basin of the sound, spanning from the northern to the southern regions (**Figure 26**).

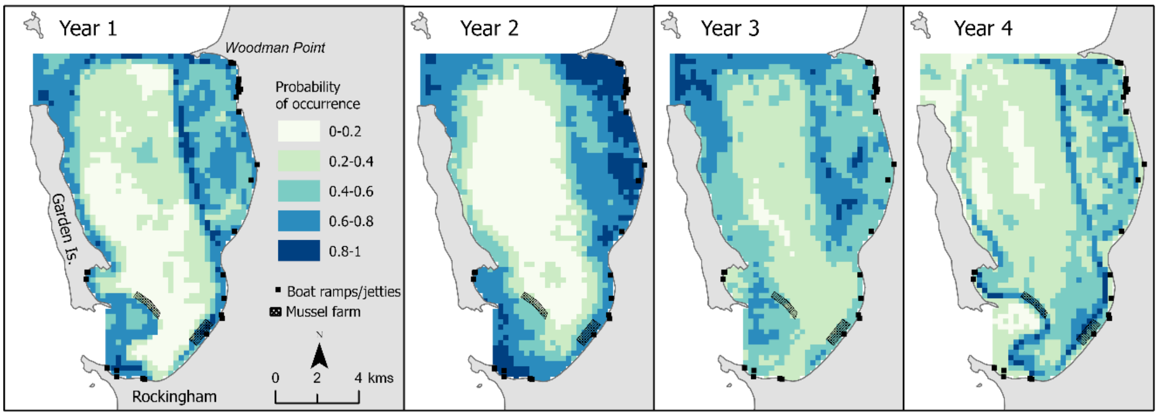

Figure 26. Yearly ensemble models of Indo-Pacific bottlenose dolphin probability of occurrence in Cockburn Sound. Colours as shown in the legend indicate the probability of occurrence of dolphins: very low (0-0.2); low (0.2-0.4); moderate (0.4-0.6); high (0.6-0.8); very high (0.8-1).

8.9 Appendix 9. Results of behaviour ensemble SDMs for dolphins in Cockburn Sound

8.9.1 Statistical summary of the models

The Cockburn Sound SDMs for the entire study period utilised six explanatory variables: substrate type, SST, water depth, slope, distance to the coastline and distance to recreational boat ramps/commercial jetties. Separate SDMs were run for foraging, resting, and travelling behaviours. Unfortunately, the sample size for socialising behaviour was insufficient for testing.

Evaluation of ROC and TSS metrics demonstrated that most models performed better than random (**Table 11**), except for MAXENT algorithms in the resting behaviour category most likely due to the limited sample size. However, after removing the poorly performing algorithm runs, the ensemble models consistently outperformed all single SDMs. The ensemble model exhibited a ROC ranging from 0.86 to 0.94 and a TSS ranging from 0.61 to 0.75, indicating good to excellent model performance across all three behaviours.

Table 11. Statistic summary of the predictive performance for SDMs run using sightings of dolphins foraging, resting, and travelling behaviours in Cockburn Sound. The two metrics used for evaluation were the area under curve of the receiver operating characteristic (ROC) metric and the True Skill Statistic (TSS). Selection of the pseudo-absence cells was repeated 10 times (i.e. total of 10 datasets tested).

Behaviour	Nb presence cells	Nb pseudo-absence cells per dataset	ROC		TSS	
			Range	Median	Range	Median
Foraging	49	147	0.59-1	0.80	0.17-1	0.51
Resting	19	57	0.72-1	0.90	0.45-1	0.76
Travelling	39	117	0.61-1	0.80	0.21-1	0.52

8.9.2 Variable importance and response curves

For all three behaviours examined, the SDMs consistently identified water depth as the most influential variable in shaping the distribution of dolphins in Cockburn Sound (**Table 12**). However, the response curves revealed some variations in the optimal probability of dolphin occurrence. When resting, the highest probability was observed in areas with a depth shallower than 7 m (**Figure 27**). For foraging, the peak probability occurred around 10 m depth, while for travelling, the probability extended across a broader range of depths from 5 to 15 m.

Additionally, the distance to recreational boat ramps/commercial jetties emerged as an influential variable specifically for foraging behaviour (**Table 12**). The probability of dolphins engaging in foraging was higher in waters located either in close proximity to the ramps/jetties or at the significant distance from them (beyond 7,500 m; **Figure 27**).

Table 12. Importance of the predictor variables used in the SDMs of Indo-Pacific bottlenose dolphins in Cockburn Sound by behaviour (foraging; resting; travelling). SDMs algorithms were classification tree analysis (CTA); flexible discriminant analysis (FDA); generalised additive model (GAM); generalised boosted model (GBM); generalised linear model (GLM), multivariate adaptive regression splines (MARS); maximum entropy (MAXENT) and random forest (RF). Variable importance is presented as the mean value over 10 runs performed for each algorithm and for 10 datasets of randomly selected pseudo-absence cells. The number of runs of each algorithm that was included in the ensemble is indicated in subscript (i.e. runs meeting the ROC ≥0.7 and TSS ≥0.4 thresholds). Variables of greatest influence are highlighted in bold.

Behaviour	Algorithms	Explanatory variables					
		Substrate type	SST	Water depth	Slope	Distance to coastline	Distance to ramps/jetties
Foraging	CTA^{73}	0.10	0.23	**0.46**	0.14	0.15	**0.27**
	FDA^{70}	**0.25**	0.10	**0.25**	0.12	0.18	**0.26**
	GAM^{95}	0.06	0.11	0.28	0.09	0.20	**0.58**
	GBM^{100}	0.02	0.21	**0.27**	0.10	0.12	0.15
	GLM^{53}	**0.27**	0.15	**0.33**	0.09	0.07	0.12
	$MARS^{88}$	0.11	0.16	0.24	0.07	**0.30**	**0.52**
	$MAXENT^{94}$	**0.24**	0.23	0.22	0.23	**0.24**	**0.25**
	RF^{100}	0.08	0.11	**0.16**	0.10	**0.17**	**0.17**
	Ensemble	0.09	0.14	**0.20**	0.06	0.15	**0.38**
Resting	CTA^{100}	0.02	0.05	**0.87**	0.03	0.02	0.08
	FDA^{100}	0.08	0.10	**0.74**	0.04	0.08	0.10
	GAM^{100}	0.17	0.25	**0.73**	0.17	0.26	**0.45**
	GBM^{100}	0.02	0.13	**0.67**	0.08	0.08	0.09
	GLM^{100}	0.08	0.11	**0.75**	0.06	0.09	0.08
	$MARS^{100}$	0.12	0.18	**0.64**	0.12	0.19	**0.20**
	$MAXENT^{100}$	0.24	**0.41**	**0.63**	0.36	0.36	0.35
	RF^{100}	0.05	0.09	**0.42**	0.07	0.07	0.08
	Ensemble	0.02	0.07	**0.85**	0.02	0.03	0.05

Table 12. *Ongoing*

Behaviour	Algorithms	Explanatory variables					
		Substrate type	SST	Water depth	Slope	Distance to coastline	Distance to ramps/jetties
Travelling	CTA[63]	0.00	0.12	**0.82**	0.11	0.07	0.05
	FDA[60]	0.03	0.00	**0.86**	0.06	0.11	0.03
	GAM[86]	0.11	0.08	**0.65**	0.09	0.16	0.16
	GBM[100]	0.00	0.10	**0.67**	0.11	0.13	0.08
	GLM[96]	0.05	0.04	**0.79**	0.10	0.17	0.07
	MARS[88]	0.02	0.07	**0.78**	0.10	0.13	0.09
	MAXENT[87]	0.15	0.19	**0.63**	0.27	0.28	0.31
	RF[100]	0.02	0.08	**0.38**	0.08	0.15	0.12
	Ensemble	0.00	0.01	**0.93**	0.04	0.10	0.01

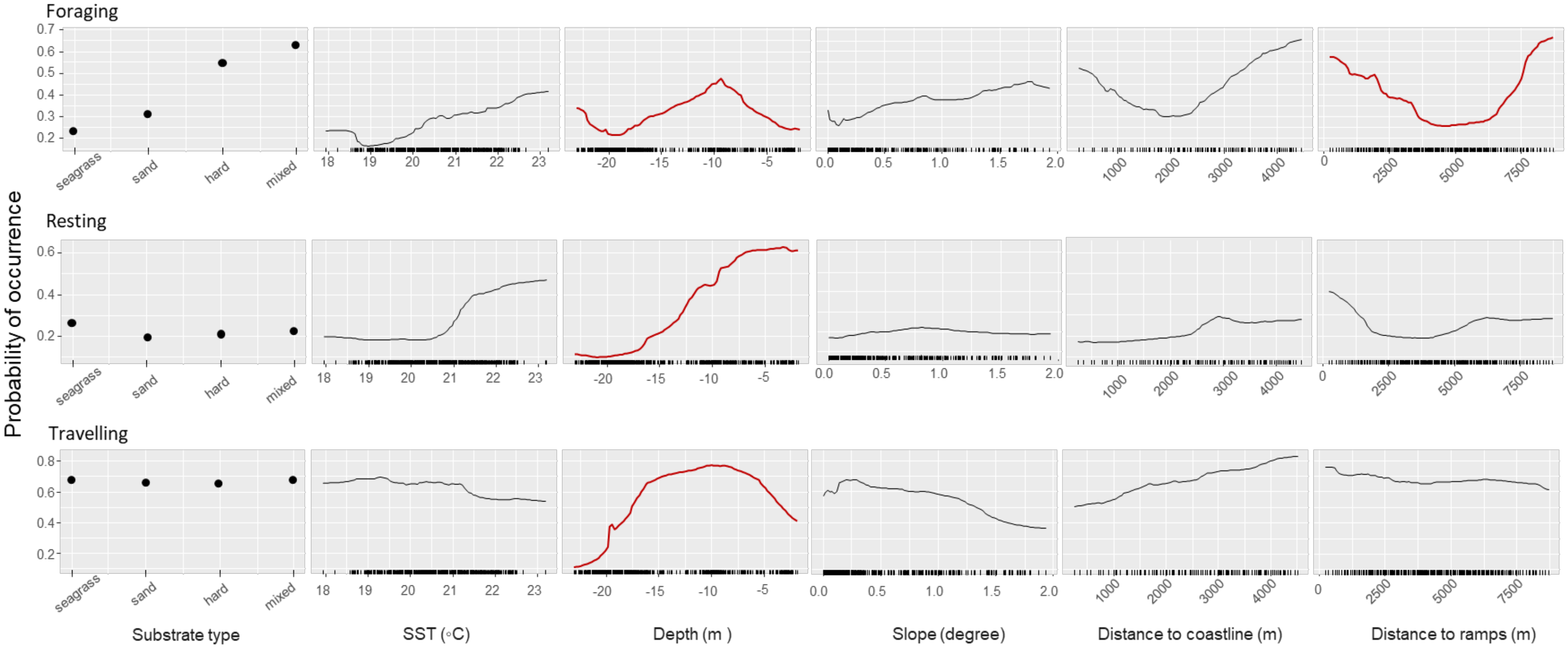

Figure 27. Response curves of the presence of dolphins in relation to the explanatory variables obtained for the ensemble SDMs run for each behaviour distribution mapping of Indo-Pacific bottlenose dolphins in Cockburn Sound. Behaviour tested were foraging, resting, and travelling. Curves highlighted in red identified the biggest influential variable(s) in each behaviour.

8.9.3 Distribution and maps

Overall, there was significant overlap in the areas of suitable habitat for all three behaviours examined. Specifically, moderate to very high probabilities of dolphin occurrence were consistently identified across the Kwinana Shelf and along the coastal edge spanning from Woodman Point to Point Peron. These favourable areas were also observed between the Causeway bridge and the mussel farm, as well as along Garden Island. In contrast, the central basin of Cockburn Sound was deemed not suitable for dolphins to rest, while low occurrence of dolphins foraging was still identified (**Figure 28**).

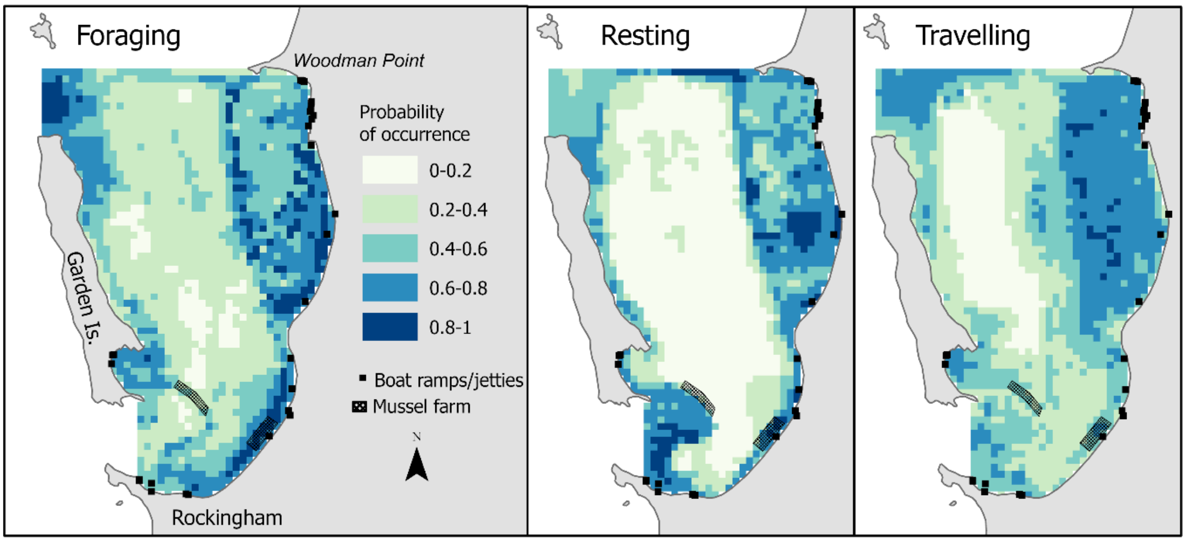

Figure 28. Behaviour specific (foraging, resting, travelling) of the ensemble models of Indo-Pacific bottlenose dolphin probability of occurrence in Cockburn Sound. Colours as shown in the legend indicate the probability of occurrence of dolphins: very low (0-0.2); low (0.2-0.4); moderate (0.4-0.6); high (0.6-0.8); very high (0.8-1).

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