College of Science & Engineering

INSPIRING ACHIEVEMENT

Port of Townsville Inshore Dolphin Monitoring Program Report

Analysis of the second field season (June - July 2020)

(Photo Daniella Hanf, CEBEL, Flinders University ©)

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Disclaimer:

Executive Summary

Background

The Port of Townsville Limited (POTL) Inshore Dolphin Monitoring Program (IDMP) was introduced as part of their environmental approval under the Commonwealth *Environment Protection and Biodiversity Conservation Act 1999* (EPBC Act) for the Townsville Port Channel Upgrade Project (CU Project). The aims of the IDMP are to establish baseline information and monitor and report on changes beyond natural spatial and temporal variation in the distribution, abundance, habitat use and behaviour of Australian snubfin dolphins (*Orcaella heinsohni*) and Australian humpback dolphins (*Sousa sahulensis*) in association with the CU Project construction activities. The IDMP will be implemented over pre-, during and post-CU Project construction activities. Pre-construction monitoring began in June 2019 following the approved study design and methods outlined in the IDMP scope of work developed for the CU-Project (Parra et al. 2019). In this report, we 1) summarise the results of the IDMP data collected during boat and land-based surveys in 2020, 2) compare these to previous results obtained during preconstruction monitoring in 2019, and 3) report on any changes, beyond natural spatial and temporal variation, in coastal dolphin abundance and distribution since 2019.

Methods

As in 2019, the IDMP methodology integrated boat and land-based surveys. The boat-based surveys involved 12 people (four per research vessel), and the land-based surveys involved a team of two to three people per shift. We made efforts to employ a balanced team or skilled professionals for key roles, assisted by local university students for which we provided training and mentoring. As a result of COVID-19 travel restrictions, most of our team were local graduate students, and the remainder were professionals from interstate.

Sampling began on the 22nd of June and ended on the 28th of July 2020. Vessel surveys were conducted in Cleveland Bay and Halifax Bay during daylight hours (i.e. between 07:00 and 18:00) and in suitable weather conditions. We used three vessels simultaneously to cover inshore and offshore areas of both bays to collect data on inshore dolphin occurrence, undertake photo-identification, and record environmental parameters (i.e. water depth, sea surface temperature, turbidity, and salinity) associated with dolphin sightings and study area. Updated capture-recapture histories of distinctive individuals from photo-identification data and estimates of the marked proportion of individuals in the population for 2019 and 2020 were used to estimate abundance of snubfin and humpback dolphin in Cleveland Bay and Halifax Bay using capture-recapture population models. As in previous year access to Bowling Green Bay was not feasible, due to boat-ramp inaccessibility at Cape Fergusson due to floods and rain earlier in February-March 2019.

Species distribution modelling methods were used to model the distribution of snubfin and humpback dolphin occurrence (presence/absence) and group size across the study area as a function of spatial-temporal covariates. The predicted probability of occurrence and group sizes were multiplied to give a prediction of relative density of snubfin and humpback dolphins in Cleveland Bay and Halifax Bay. We employed two complimentary quantitative methods (Structural Similarity Index and likelihood-ratio statistic) to investigate differences between the spatial distribution of dolphins in 2019 (preconstruction baseline) and 2020.

The land-based observation point we used during 2019 on Berth 11 (within the Port of Townsville) to conduct visual observations of dolphin presence/absence around the port area was not available this year due to shipping activities, and a three-week maintenance shutdown of the ship loader. Thus, this year we conducted visual land-based observations from an alternative site located close by (~400m away) at the entrance of Berth 11, to a radius ≤ 1 km around the observation point. Although the visual area covered this year overlapped partly with the area covered in 2019, the visible area was markedly reduced as observers were closer to sea level (the 2020 entranceway observation point is LAT +8.22m above water while the observation point on Berth 11 wharf used in 2019 is LAT+9.5m above water)), and their range of view was restricted by the berth structure itself and the eastern and western side of the rock wall under construction as part of the perimeter of the 62ha Port Reclamation Area at the eastern end of the Port.

As per last year, visual scans every 15 min were used to record presence or absence of dolphins, their group size, age composition, behaviour, the number and types of boats traversing the area, the presence or absence of maintenance dredging not associated with CU Project (i.e. routine dredging carried out every year to remove material that has drifted into the channel over time and limits the access of ships) and the rock wall construction activities associated with CU Project (i.e. rock dumping). Land-based survey data was analysed using descriptive statistics (e.g. total dolphin counts by species, and their behavioural composition) and further summarised by a range of covariates (i.e. hours of day, presence of boats, presence of maintenance dredging, and rock dumping). For statistical tests, we used Bayesian p-values to assess overall differences in dolphin occurrence between 2019 and 2020, and assess dolphins' patterns of occurrence in relation to boats, dredging and rock dumping activities.

Results

Vessel survey overview

A total of 1849.6 km (1013.9 km in Cleveland Bay and 835.7 km in Halifax Bay) were surveyed on transect over 13 days between June 22nd and July 27th, 2020, completing six survey repeats of Cleveland Bay and Halifax Bay (Fig. 4, Table 2).

We recorded a total of 86 dolphin groups (including both on and off effort sightings), consisting of 30 snubfin, 55 humpback and one bottlenose dolphin group. Snubfin and bottlenose dolphins were sighted less frequently than humpback dolphins, in both Cleveland and Halifax bays. Fifty-two individual snubfin dolphins and 56 individual humpback dolphins were photo-identified on and off effort during sampling in 2020. No bottlenose dolphins were photo-identified. Three snubfin and five humpback dolphins were photo-identified at both sites.

Abundance

Using closed population models, we estimated the total number of snubfin dolphins using Cleveland Bay at 143 (95% CI = 47-435) individuals and at 73 (95% CI =38-140) individuals for Halifax Bay (Table 9). The total population size of humpback dolphins was estimated at 50 (95% CI = 31-81) individuals for Cleveland Bay and at 74 (95% CI = 51-107) individuals for Halifax Bay (Table 9). The number of snubfin dolphins captured in Cleveland Bay in 2020 over the secondary samples were relatively few for capture-recapture modelling, resulting in low capture probabilities (Table 7) and thus the wide confidence interval around the 2020 abundance estimate. There is considerable overlap in the confidence intervals of abundance estimates from 2019 and 2020, suggesting there has been no major changes in the abundance of either species.

Given the small numbers of bottlenose dolphins encountered we were not able to generate estimates of abundance for this species.

Spatial distribution

The species distribution models of both snubfin and humpback dolphins for Cleveland and Halifax Bays in 2020 showed a consistent and high probability of occurrence in waters close to the mainland coast (snubfin: ~2-3km , humpback: ~4-8km from mainland coast) and lower occupancy further offshore (Figs. 6-7). Areas of higher probability of both snubfin and humpback dolphin occurrence (>50%) in Cleveland Bay were mainly located between the Port of Townsville and Alligator and Crocodile Creeks to the east, and along the West Channel between Magnetic Island and Cape Pallarenda (Figs. 6-7). In Halifax Bay, both species were more likely to occur in the central (Bohle River to Toolakea) and northern inshore areas (off and west of Toomulla) (Figs. 6-7). Spatial models of relative density generally followed the same pattern as their occurrence, with areas of high occurrence also characterized by high density of dolphins. For humpback dolphins, distance to rivers, space (in general, unexplained), distance to land, and year (as an interaction) were the dominating covariates explaining their spatial distribution (Fig. 8). For snubfin dolphins, an unexplained spatial patterning variable was the dominating covariate (Fig. 8).

Comparison of the spatial predictions of species distribution models maps, using the Structural Similarity (SSIM) index, indicated there were no major changes in the spatial distribution of snubfin and humpback dolphins in the study area between 2019 and 2020 (Table 10) .The generalized likelihood-ratio test indicated marginal but important interannual differences in the spatial processes influencing dolphin’s spatial distribution related to year.

Patterns of attendance to the port area

We conducted 948 visual scans over 18 days from the land-based observation point at the entrance to Berth 11. Snubfin dolphins were seen on 9 days and present in 34 scans, humpback dolphins were observed on 4 days and present in 7 scans, and bottlenose dolphins were not seen on any day. Snubfin and humpback dolphins were observed throughout different times of the day, engaged mainly in foraging behaviours (Fig. 9a). Snubfin dolphin sightings peaked in the morning between 9:00-11:00, while humpback dolphin sightings peaked between 11:00-13:00 (Fig. 9b). No dolphins were observed within the body of water being enclosed by the rock wall under construction.

There were less observations of both species in comparison to 2019 and statistical analysis showed snubfin and humpback dolphin occurrence around the port was lower in 2020 (Table 12). Snubfin dolphins seemed to become absent as the number of boats increased, while humpback dolphins appeared to shift their behavior from foraging at low-boat presence, to travelling at high-boat presence (Figs. 11). Both species presence did not seem to be affected by maintenance dredging activities (Table 12). Snubfin dolphins' patterns of occurrence around the port did not seem to be affected by rock-dumping activities associated with the rock wall construction. In contrast, the occurrence of humpback dolphins around the port decreased during rock dumping activities (Table 13). However, interpretation should be taken with caution as the number of humpback dolphins sighted during non-rock-dumping activities was low (n =7) .

Discussion and conclusions

Despite some logistical constraints due COVID 19, the 2020 monitoring of inshore dolphins proceeded well, and we were able to gather important data on the distribution and abundance of snubfin and humpback dolphins in Cleveland and Halifax Bays for comparison with baseline data collected in 2019 under pre-construction conditions of CU Project.

The abundance estimates for snubfin and humpback dolphins in Cleveland and Halifax Bays and their predominant inshore spatial distribution in 2020 were relatively similar to 2019, indicating no substantial changes in their population demographics and spatial habitat use. Snubfin dolphins in Cleveland Bay showed low capture probabilities (Table 7) which resulted in an estimate of abundance with a wide 95% confidence interval (143, 95% CI = 47-435). Despite the uncertainty associated with the abundance estimates of snubfin dolphins in Cleveland Bay, others were reliable and had good precision associated with them and showed overlap around confidence intervals with previous year. Thus, there is no indication of a substantial change or a decreasing trend in population size.

Based on the land-based observations it appears the overall dolphin occurrence around the port area decreased in comparison to 2019. Patterns of snubfin dolphin occurrence around the port do not seem to be affected by maintenance dredging or rock-dumping activities. Although humpback occurrence showed no difference with dredging their occurrence decreased with rock-dumping activities. The low number of dolphin observations in 2020 may be a result of dolphins using the waters around the port less frequently or simply a result of the lower vantage point used for observations during 2020. The latter seems more likely, given the sightings and the dolphins high probabilities of occurrence in areas around the port revealed by boat surveys and species distribution models.

In summary, the estimates of abundance and spatial distribution obtained for Cleveland and Halifax bay during 2020 showed similar patterns to those obtained in 2019. Although both species continue to be sighted around the port of Townsville, there was a decrease in their frequency of occurrence in this area. We believe this is likely a result of restricted visibility associated with the low vantage point used this year for land-based observations, rather than an impact from construction activities. We strongly recommended that the observation point for the remainder of the project stays fixed on the elevated point at Berth 11 to facilitate future comparisons.

1. Introduction

The Townsville Port Channel Upgrade Project (CU Project) is a joint project of the Queensland and Australian Governments and Port of Townsville Limited (POTL). The CU project is the first stage of the long-term Port Expansion Project and will be delivered over a period of six years from 2018 to 2023. The expansion of the Port of Townsville is needed to accommodate forecast growth in trade at the port and address current capacity constraints. As part of the environmental approvals under the Commonwealth *Environment Protection and Biodiversity Conservation Act 1999* (EPBC Act) for the CU project, POTL was required to develop and implement an Inshore Dolphin Monitoring Program (IDMP).

The aims of the IDMP are to establish baseline information and monitor and report on changes, beyond natural spatial and temporal variation, in the distribution, abundance, habitat use and behaviour of the Australian snubfin dolphin (*Orcaella heinsohni*) and the Australian humpback dolphin (*Sousa sahulensis*) in association with the CU Project construction activities. Both species are listed as: Matter of National Environmental Significance (NES) under the EPBC Act; 'Vulnerable' by the International Union for Conservation of Nature (IUCN) (Parra et al. 2017a, Parra et al. 2017b); 'Near Threatened' in the Action Plan for Australian Mammals 2012 (Woinarski et al. 2014); and 'Vulnerable' in Queensland, under the *Nature Conservation Act 1992*. The IDMP will be implemented over pre-, during and post-CU Project construction activities. The findings from the IDMP will be used to inform management decisions for the project on an ongoing basis.

The specific objectives of the Inshore Dolphin Monitoring Program are to:

1. Objective One: Develop an Inshore Dolphin Monitoring Program consistent with the Coordinated National Research Framework to inform the Conservation and Management of Australia's Tropical Inshore Dolphins (Department of the Environment, 2015), or subsequent

document; and that provides consistent and scientifically valid monitoring methodologies to be able to determine trends and identification of stressors with the potential to cause adverse impacts for these species. This program is to cover pre-, during and post-construction timescales as separate identified study stages and reporting deliverables.

2. Objective Two: Provide a baseline assessment on the distribution, abundance and habitat use of the Australian snubfin dolphin and the Australian humpback dolphin species in areas of Cleveland Bay that may be directly or indirectly impacted by the CU Project and adjacent non-impacted sites.

3. Objective Three: Monitor and report on changes, beyond natural spatial and temporal variation, to the population and behaviour of the Australian snubfin dolphin and the Australian humpback dolphin throughout construction, pile driving operations and dredging activities for the CU Project, and a sufficient period of time post-construction to identify any changes in population and behaviour of the identified dolphin species as a result of the said activities.

4. Objective Four: Provide recommendations on key areas of adverse impact and potential mitigation measures, including the identification of residual adverse impacts in Cleveland Bay which cannot be managed.

5. Objective Five: Contribute to improving public awareness during the works on the inshore dolphin populations in Cleveland Bay.

The IDMP of snubfin and humpback dolphins for the CU project commenced in July 2019. The 2019 inshore dolphin surveys constituted the pre-construction phase as no construction activity occurred during this period. The 2020 inshore dolphin surveys corresponded with early construction activities of the rock wall that will form the perimeter of the 62ha Port Reclamation Area as part of the Channel Upgrade project. Construction activities associated with these included the placement of four different types of rock material: primary armour, secondary armour, core rock and ballast rock to the North of the existing East Port, at the mouth of Ross River. in line with the scope of work, the objective of this report is to provide a summary of the fieldwork conducted and the results of the 2020 inshore dolphin monitoring program, and report on any changes, beyond natural spatial and temporal variation, in coastal dolphin abundance and distribution since 2019.

Opportunistic sightings of other marine mammals (i.e. bottlenose dolphins, dugongs and humpback whales) were recorded during surveys and are presented in this report as point distribution maps.

2. Methods

2.1 Data collection

2.1.1 *Scientific permits and animal ethics*

The 2020 inshore dolphin monitoring program was conducted under Scientific Permit G19/42001.1 issued by the Great Barrier Reef Marine Parks Authority, permit SPP19-001808 from the Queensland Department of Environment and Science, and Animal ethics approval E477/18 from the Animal Ethics Committee of Flinders University.

2.1.2 *Training*

All IDMP personnel received boat and land safety induction and were trained in survey techniques and protocols on 17 and 18 June 2020, which involved testing all boat and land-based equipment and data collection procedures.

2.1.3 *Vessel-based survey methods*

As described in detail in the IDMP developed for the CU-Project, the boat-based methods have been built on a Robust Design sampling structure (Pollock et al. 1990, Kendall 2013) of one primary sample per year (June-July), consisting of six secondary samples (i.e. a complete survey) at Cleveland Bay and Halifax Bay (Fig. 1). Access to Bowling Green Bay was not feasible due to the February-March 2019 storm damage to Australian Institute of Marine Science's (AIMS) boat ramp at Cape Ferguson. The closest other available boat ramps required considerable travel time by road (over an hour) and rivers (over 30mins) and were highly tide dependant, thus making it impractical and unsafe to conduct vessel-based surveys in this bay under the planned allotted time.

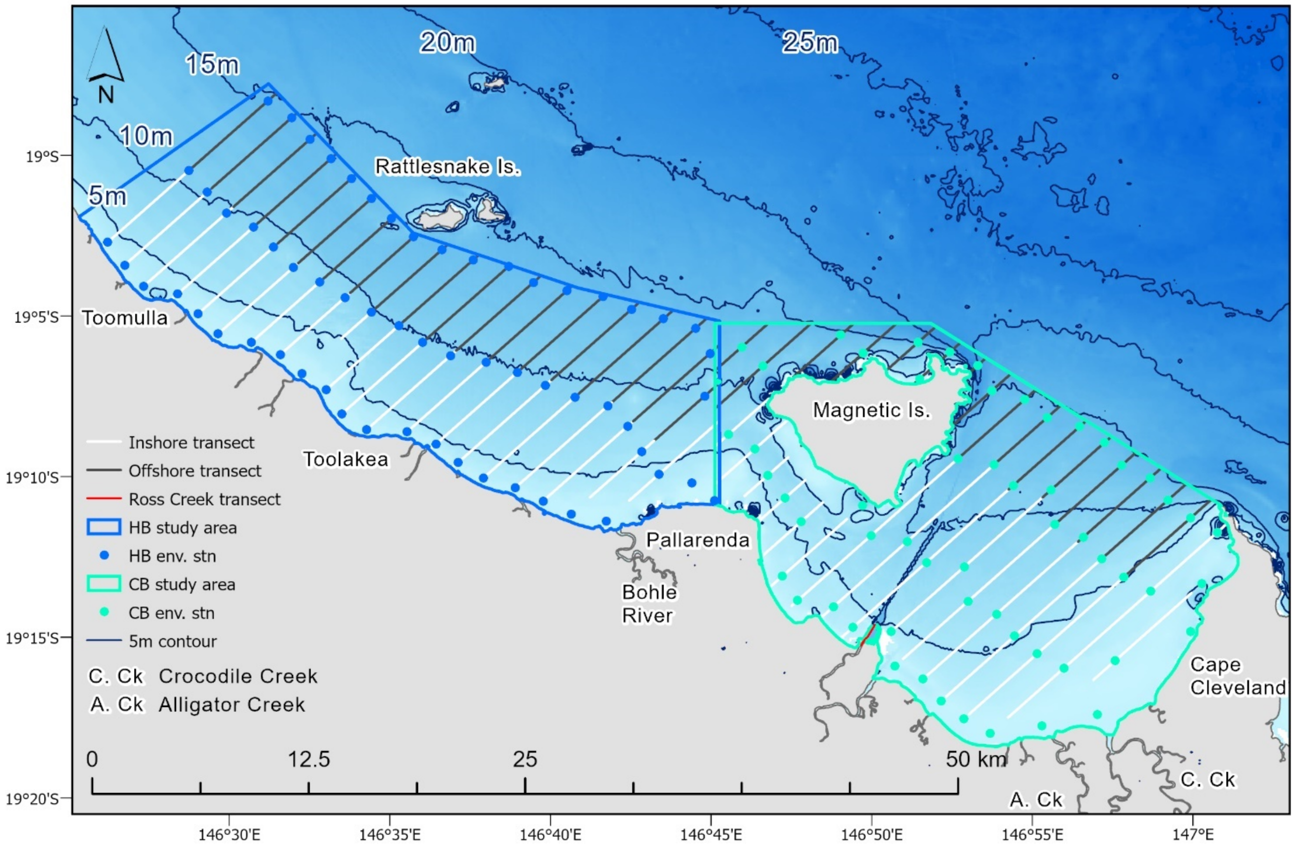


Figure 1. Map of Cleveland and Halifax Bays study areas including inshore and offshore transect, Ross Creek transect, and environmental stations.

Sampling methods followed standard procedures applied in capture-recapture studies of inshore dolphin studies (Parra et al. 2006b, Cagnazzi et al. 2011). We used automated survey design algorithms (Strindberg and Buckland 2004) implemented in the software program Distance (Thomas et al. 2009) to design a systematic random line transect survey with regular line spacing (1.6 km apart and at 45º to the shore) covering both inshore and offshore areas within each of the survey sites (Fig. 1). Systematic line spacing results in even spatial distribution of sampling effort, uniform coverage probability and better information on dolphin's spatial distribution and environmental variables than random designs (Du Fresne et al. 2006, Thomas et al. 2007). Survey priority was given to inshore areas over offshore areas depending on weather conditions, as both snubfin and humpback dolphins occur mainly in inshore areas in the region.

We used the same three rigid hull inflatable boats (RHIBs) (i.e. RV Coda, Koopa and Manta, Fig. 2) as in 2019 to simultaneously survey different areas of each bay during June-July 2020 and complete a full survey of each bay within one day. All surveys were conducted in mostly good sighting conditions (Beaufort Sea State ≤ 3 and no rain) between 07:00 and 18:00, depending on suitable conditions. A crew of three observers and a skipper systematically searched for dolphins forward of each vessel's beam with the naked eye. Once an individual or group of dolphins was sighted, on-transect effort was suspended and the dolphins were approached slowly (<5 knots) to within 5-10m to carry out photo-identification and record GPS location, species identification, group size (minimum, best and maximum estimates), group age composition (calf, juvenile, adult as defined by Parra et al. 2006a), and predominant group behaviour (Mann 1999a). Groups were defined as dolphins with relatively close spatial cohesion (i.e. each member within 100 m of any other member) involved in similar (often the same) behavioural activities. Photographs of individual animals were taken using Nikon D750 digital SLR cameras fitted with 50-500 telephoto zoom lenses.

After all, or most individuals in the group were photographed or dolphins were lost, transect effort resumed at the location on the transect line where the dolphins were first sighted. Data on environmental variables (water depth, sea surface temperature, turbidity, and salinity) were collected in situ using a U-52 Horiba multi-parameter water quality meter at the location where each group of dolphins was first encountered, at set points along the transect line, and at the beginning and end of each transect leg (i.e. environmental stations, Fig. 1). All data on survey conditions, survey effort and marine mammal sightings were recorded in handheld tablets using CyberTracker software (http://www. cybertracker.org/).

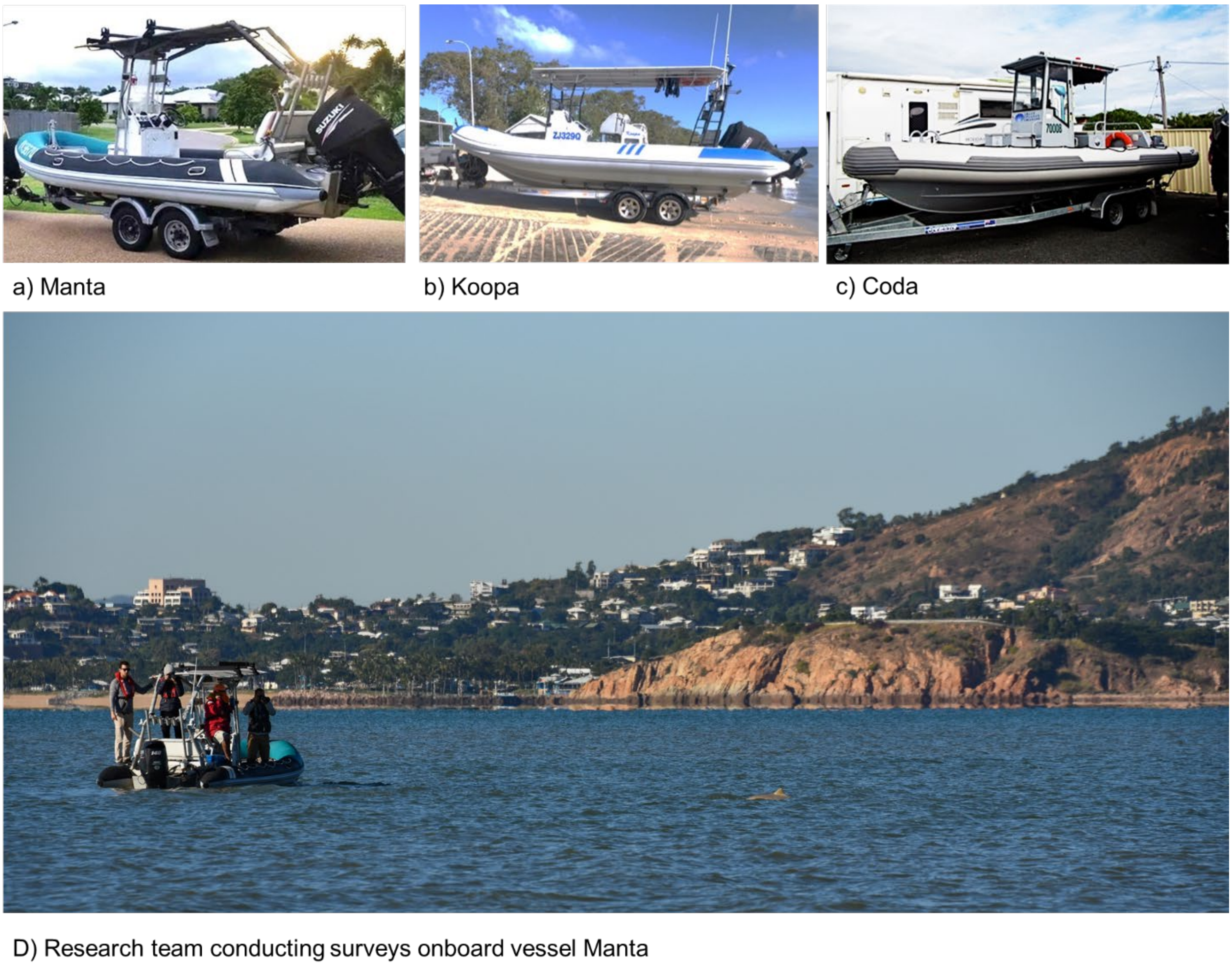


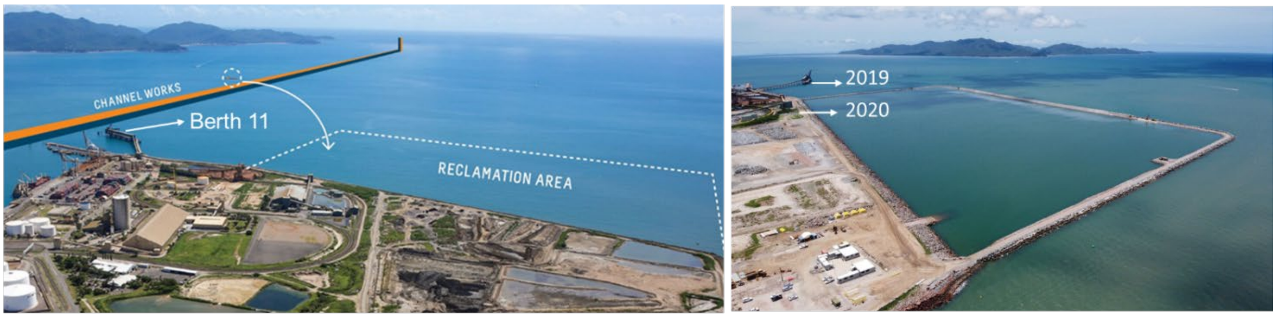
Figure 2. Rigid hull inflatable boats a) RV Manta, b) RV Koopa and c) RV Coda used for boat-based surveys of inshore dolphins in the Townsville region during June and July 2020.

Research team conducting surveys of inshore dolphins in Cleveland Bay onboard vessel Manta (d).

2.1.4 *Land-based survey methods*

This field season, land-based observations of dolphin presence/absence around the port were carried out at the entrance to Berth 11 within the Port of Townsville, whereas in 2019 they were conducted at the end of the berth from an elevated vantage point on berth 11 (LAT + 9. 5m abovewater) (Fig. 3). The 2019 land-based observation point on Berth 11 was not accessible this year due to shipping activities, and a three-week maintenance shutdown of the ship loader. Thus, this year we conducted visual land-based observations from an alternative site located about 400m south of 2019 observation point at the entrance of Berth 11, to a radius ≤ 1 km around the observation point. Although the visual area covered this year overlapped partly with the area covered in 2019, the visible area was markedly reduced as observers were closer to sea level (LAT + 8.22m above water) and their range of view was impeded by the Berth 11 structure itself, and the eastern and western side of the rock wall that was under construction as part of the perimeter of the 62ha Port Reclamation Area at the eastern end of the Port. This area also coincides with the CU project area for land reclamation and widening of the channel at the harbour entrance (Fig. 3). The coastal waters adjacent to the Port of Townsville have previously been identified as a dolphin high use area (Parra 2006). Conducted over time, this method will enable us to determine the dolphins' occurrence (presence/absence) in this area and assess their response to CU project construction activities that occur within this area (Pirotta et al. 2013).

Visual scan sampling every 15 min was used to record the occurrence (presence/absence) of dolphins (Altmann 1974, Mann 1999b), and covered a radius of approximately 1km around the observation point at the entrance of Berth 11. Observations were conducted by a team of two trained observers doing one or two three-hour shifts per day between 07:00 and 17:00. Visual observations were mostly undertaken during good weather conditions (i.e. Beaufort sea state ≤ 3 and no rain). Each observer scanned to the left or the right-hand side of the observation point with the aid of 7 x 50 binoculars and the naked eye. During each visual scan we recorded, within a radius of approximately 1km around the observation point, the presence or absence of dolphins, their group size, age composition, behaviour, the number and types of boats traversing the area, and the presence or absence of CU construction activities including dredging and rock dumping.



a) Berth 11 b) Observation points

Figure 3. a) Location of Berth 11 within the Port of Townsville and b) land observation points on Berth 11 in 2019 and at entrance to Berth 11 in 2020.

2.2 Data analysis: Population demographics

2.2.1 *Photo-identification*

Capture-recapture histories of distinctive individuals were used to estimate abundance of Australian snubfin and humpback dolphins in 2019 and 2020 using capture-recapture population models (Williams et al. 2002, Amstrup et al. 2005). An individual was considered 'captured' when it was first photo-identified, and 'recaptured' when photo-identified thereafter. Individual snubfin and humpback dolphins were identified based on the unique natural marks on their dorsal fins (Parra and Corkeron 2001, Parra et al. 2006a). All photographs taken during boat surveys were examined and subjected to a strict quality and distinctiveness grading protocol before matching and cataloguing to minimise misidentification (Hunt et al. 2017). Only high-quality photographs of distinctive individuals were used in analyses. We used DISCOVERY (version 1.2.) software to process, match, catalogue and manage all the photo-identification data (Gailey and Karczmarski 2012).

Both "on effort" and "off effort" sightings were combined and included in capture- recapture (CR) analyses. Capture history data were analysed using CAPTURE within the program MARK (White and Burnham 1999).

2.2.2 *Capture-recapture models*

Capture-recapture methods (Williams et al. 2002, Amstrup et al. 2005) can be used to estimate population sizes and rates of apparent survival (alive and in the area), temporary emigration and movement between sites. The Multistate Closed Robust Design model (MSCRD, Brownie et al. 1993, Nichols and Coffman 1999, Kendall and Nichols 2002, Kendall 2013) will be fitted to estimate these parameters. As indicated in 2019 report, the MSCRD will require, however, data from a minimum of three yearly samples. Until there are sufficient data to build an MSCRD model, closed population models will be fitted to the data from each year to estimate abundance of each species in Cleveland Bay and Halifax Bay. The estimates provided by these models will be updated with the MSCRD when data from the first three years become available.

2.2.3 *Goodness of fit of closed population models*

Program CAPTURE (Otis et al. 1978) estimates a suite of eight alternative closed population models and also performs goodness of fit (GOF) tests. The models vary according to whether capture probabilities vary by time, differ between first and subsequent captures (indicating a behavioural response to first capture) or vary among individuals (individual heterogeneity). The GOF tests are designed to detect time (t), behaviour (b) and heterogeneity (h) effects and combinations of them. Given a set of data, CAPTURE can be tasked to select the appropriate model given the results of the GOF tests.

2.2.4 *Model selection – AIC*

In general, the modelling process involves fitting a set of models with alternative parameter structures and comparing them for fit to data and parsimony. Models were compared with the Akaike Information Criterion corrected for small sample sizes (AICc, Burnham and Anderson 2002), with smaller values of AICc indicating better fitting models, and with AICc weights, which measure the relative likelihoods of the models in the set. When one model in the set had a clearly lower AICc than all others and attracted the major proportion of the AICc weight, the parameter estimates from this 'best' model are reported; when several models have similar AICc values and shared the AICc weight, model-averaging may be applied (Buckland et al. 1997) whereby a weighted average of the parameter estimates from several models are reported.

2.2.5 *Estimating the total population size*

Not all individuals have sufficiently distinctive marks to support unambiguous identification. Only distinctively marked individuals may be considered to be captured in photographs and capture-recapture models can only yield estimates of the number of distinctively marked members in a population. This estimate may be adjusted to yield an estimate of total population size by dividing by an estimate of the proportion of distinctively marked individuals in the population as described below.

For each species, the number of individuals depicted by good quality photographs (P_t) and, of those, the number that depicted a distinctively marked individual (P_m) was recorded for each group encounter. A mixed effects binary logistic model was fitted to the distinctiveness data on individuals with good quality photographs (1 = distinctively marked, 0 = not distinctively marked) with group and individual within group as random factors to estimate the marked proportion (M_p) of the population. Between-group variation may arise with natural variation in the proportion of distinctive to non-distinctive individuals. The model separates this variance from the variance associated with the estimated population proportion (Brooks et al. 2017).

The total abundance (N_{total}) of each population for any sampling period may be estimated by dividing the estimated abundance of marked dolphins ($\hat{N}_{marked}$) by the estimated marked proportion ($\hat{M}_p$):

$$\hat{N}_{total} = \hat{N}_{marked} \big/ \hat{M}_p \text{, with } \hat{\mathrm{S}}\mathrm{E}(\hat{N}_{total}) = \hat{N}_{total} \sqrt{Var(\hat{N}_{marked}) \big/ \left(\hat{N}_{marked}\right)^2 + Var(\hat{M}_p) \big/ \left(\hat{M}_p\right)^2}$$

Log-normal confidence intervals for abundance estimates may be calculated following Burnham et al. (1987):

$$\hat{N}_{lower} = \hat{N} \big/ C \text{ and } \hat{N}_{upper} = \hat{N} \cdot C, \text{ where } C = \exp\left(z_{\alpha/2} \sqrt{\log_e \left[1 + \left(\hat{S}E(\hat{N}) \big/ \hat{N} \right)^2 \right]} \right)$$

2.3 Data analysis: Spatial distribution

2.3.1 *Modelling framework*

Our goal was to model dolphin's spatial distribution in the study area before (2019) and after (2020) CU project construction activities began to assess if there were any differences in the spatial distribution patterns of snubfin and humpback dolphins between years. At a mature stage of the project, with more data, the goal of the analysis will be inference about the spatial distribution of dolphins, especially in relation to human disturbances. Currently, there were only 8 observations of rock dumping activities during the boat-based data-collection, therefore we do not address this modelling objective in this report. Instead, the goals of the 2020 modelling exercise were to:

1. Estimate covariates' importance (i.e., relative variable importance).

2. Assess models' predictive performance (e.g., ROC-AUC and PR-AUC scores).
3. Examine differences in species' spatial distribution between survey year 2019 and 2020.

As was detailed in the previous report, the modelling framework used for species distribution modelling was the high-performance "boosting" technique (Bühlmann and Yu 2003, Schmid and Hothorn 2008), specifically emulating the works of Kneib et al. (2009) and Hothorn et al. (2010). The method is an ensemble method that automatically performs model selection among different sub-models, such as spatial splines, temporal splines, spatial autocorrelation, and linear effects, etc. The method also addresses many common data-challenges, including small samples size and high-dimensionality ("small-n high-p problem"), and high multicollinearity among spatial covariates (Oppel et al. 2009, Schmid et al. 2010, Bühlmann et al. 2013, Mayr et al. 2014). It is also related to other high-performance methods (Meir and Rätsch 2003, Chen and Guestrin 2016) and can decompose variation into spatial, temporal, and observational covariates, as motivated by Hothorn et al. (2010).

Species distribution models for 2019 and 2020 incorporated 11 sub-components, representing different groupings of covariates and wrapped in different sub-models (Table 1). According to the boosting methodology, only important sub-models are selected, and the unimportant sub-models are either shrunk to have only a small contribution to the models' predictions, or they are ignored altogether. The various components were:

1: Main-effect penalized least squares, one for each covariate representing weather conditions, ecological variables, and boats.

2: Interaction penalized least squares, one for each covariate representing ecological variables and boats, including an interaction with “year” (i.e., different slops and intercepts for 2019 and 2020).

3: Decision-tree (1), including covariates for weather conditions.

4: Decision-tree (2), including covariates for ecological variables and boats.

5: Decision-tree (3), including covariates for ecological variables and boats, plus “year” as a (potential) interacting covariate.

6: Main-effect univariate splines for time-of-day and time-of-year.

7: Interaction univariate splines for time-of-day and time-of-year, including “year” as an interaction term (i.e., different marginal effects for each year).

8: Main-effects bivariate splines for large-scale spatial trends.

9: Interaction bivariate splines for large-scale spatial trends; including “year” as an interaction term (i.e., different marginal spatial trends per year).

10: Spatial-autocorrelation effects (Matern radial basis function).

11: Spatial-autocorrelation effects with an interaction with “year” (i.e., a different spatial field per year).

Table 1. Covariates considered for the species distribution modelling of Australian Snubfin and humpback dolphins in Cleveland and Halifax Bays in 2019 and 2020, with columns indicating the: i) type of sub-model used for each covariate group within the larger ensemble-of-models, ii) the data-source for training the ensemble and iii) data source at prediction locations (how the covariate was extrapolated outside the points of data-collection).

Sub-models	Model type	Covariate	Covariate description	Source at training	Source at prediction
1,2, & 3	Main Effect PLS, Interaction PLS, and Decision trees	BSS	Beaufort Sea-State (BSS), 5-point ordinal scale	In-situ estimate	Constant, average conditions
		Swell	Estimated swell height	In-situ estimate	Constant, average conditions
		Visibility	Visible distance, 3-point ordinal scale	In-situ estimate	Constant, average conditions
		Glare	Glare intensity, 4-point ordinal scale, summed two sides	In-situ estimate	Constant, average conditions
1,2,4 & 5	Main Effect PLS, Interaction PLS, and Decision trees	SST	Sea surface temperature (SST) from multiparameter water sensor	In-situ measurement	Interpolated spatial surface
		Salinity	Conductivity from multiparameter water sensor	In-situ measurement	Interpolated spatial surface
		Turbidity	Turbidity from multiparameter water sensor	In-situ measurement	Interpolated spatial surface
		River Distance	Log-distance to coastal waterways/estuaries	GIS, derived (Dyall et al. 2004)	Same as training
		Reef Distance	Log-distance to reefs	GIS, derived (Beaman 2012)	Same as training
		Seagrass Distance	Log-distance to seagrass meadows	GIS, derived (McKenzie et al. 2014)	Same as training
		Foreshore Distance	Log-distance to foreshore ecotypes	GIS, derived (Beaman 2012)	Same as training

Sub-models	Model type	Covariate	Covariate description	Source at training	Source at prediction
		Land Distance	Log-distance to land	GIS, derived (Beaman 2012)	Same as training
		Bathymetry	Average depth	GIS, bathymetric DEM (Whiteway 2009, Beaman 2010)	Same as training
		Boats Total	Counts of all boats in vicinity	In-situ counts	Interpolated spatial surface
		Boats Small	Counts of all boats in vicinity, small size	In-situ counts	Interpolated spatial surface
		Boats Medium	Counts of all boats, medium size	In-situ counts	Interpolated spatial surface
		Boats Large	Counts of all boats, large and industrial and ferries	In-situ counts	Interpolated spatial surface
		Boats Fishing	Counts of all fishing boats and trawlers	In-situ counts	Interpolated spatial surface
		Boats Recreational	Counts of all recreational and sailing boats	In-situ counts	Interpolated spatial surface
		Boats Industrial	Counts of all barges, trawlers, tugs and other industrial	In-situ counts	Interpolated spatial surface
6, 7	Main-effect splines, and Interaction splines	Time-of-day	Metric time at observations	In-situ measurement	Constant, average conditions
		Day-of-Year	Julian-day	In-situ measurement	Constant, average conditions
8,9	Main-effect bivariate splines, Interaction bivariate splines	Space X & Y	UTMs used in spatial spline	GIS	Same as training
10,11	Radial basis functions	Space X & Y	UTMs used in spatial covariance function	GIS	Same as training

2.3.2 *Main Effects and Interactions*

Some of the covariates are represented in more than one sub-model, especially regarding “main effects” versus “interaction” effect with year. During the automatic model-selection and regularization, the model selects the best combination of main-effects and interaction effect. For example, the penalized least-squares sub-models can represent a univariate main-effect with no interactions; or they can have an interaction with “year”, such that the slope and intercepts vary per year. Those sub-models that include “year” as an interacting categorical variable have more penalization than the “main effects” learners. This means that the automatic mode-selection should only select the higher-order interactions if the extra complexity is warranted and there is some important difference between years 2019 vs 2020, in terms of dolphin spatial distribution.

In other words, the boosting automatic model-selection mechanism is implicitly testing whether “year” is an important covariate in explaining dolphins’ spatial distribution. If there was no important difference between dolphins’ spatial distribution between 2019 vs 2020, then the model-selection should favour the more parsimonious “main effect” sub-models that lack year as an interacting covariate. This will be important in latter tests on differences between 2019 and 2020.

2.3.3 *Model Parsimony, Hyperparameters and Regularization*

The automatic model-selection and shrinkage mechanism improves model predictive performance by only giving high weight to the most important sub-models and shrinking the weights of unimportant sub-models so that they have a small overall effect. This is also known as l1-regularization (which is equivalent to the Lasso). Therefore, the final model is much more parsimonious and has a much lower complexity than the full theoretical model which includes all sub-models.

The degree of shrinkage/regularization was controlled by several hyperparameters. These are explained in the following list. The values for each of these hyperparameters was tuned via 10-fold cross-validation, such that the model with the best predictive performance, according to the 10-fold cross-validation log-likelihood, was selected as the final model used for inference.

The list of pertinent hyperparameters were:

- the number of boosting iterations m (aka the "early stopping" parameter). The more iterations meant more complex models, and fewer boosting iterations meant more shrinkage and fewer selected sub-models.
- the learning-rate (aka "shrinkage" rate) which down-weights the contribution of any individual submodel. This was fixed to a single value per species (0.01-0.03), after manually experimenting with different values to get final models that had between 1000-3000 boosting iterations. A lower shrinkage rate meant that the model required more boosting iterations and has a smoother surface; a higher shrinkage rate meant the model required fewer boosting iterations and produced a less-smooth surface. A smaller rate is generally preferable but comes at high computational cost (time and electricity).
- Max-depth of decision-trees, which could take on values of [2, 3, or 4]. This hyperparameter was only relevant for the decision-tree sub-models (No.: 3, 4 and 5). The maximum tree depth (maxdepth) controlled the degree of interaction among covariates and the number of partitions of the covariate space. A small maxdepth meant that only two-way interactions were allowed, and there were only three splits of the covariate space (per boosting iteration). A higher maxdepth allowed higher-order interactions and allowed many more splits of the covariate space.

- Minimum test-statistic threshold (i.e., mincriterion, in the mboost R-library) which could take on values [0.4, 0.5, or 0.65]. This hyperparameter was only relevant to the decision-tree sub-models (No: 3, 4 and 5). It controlled the hurdle rate for testing whether a split in the covariate space was significant enough to continue growing a decision tree. Lower values allowed the trees to grow longer (more interactions and more splits); higher values prevented the tree from growing too long and prevented unimportant splits from entering the model.
- Degrees-of-freedom of the main-effects spatial splines, which could take on values [8,10,12, or 14]. This hyperparameter was only relevant to the main-effect spatial spline (sub-model No.8). A higher degree-of-freedom allowed a more flexible spatial surface, while lower values resulted in less spatial complexity.
- Degrees-of-freedom of the spatial splines with year-interactions. These values were related to the degrees-of-freedom of the main-effects spatial splines, by being fixed to according to a formula: 2-times minus 2 of the degrees-of-freedom of the main-effects spatial splines. The motivation for this formulation the following: the interaction models must have less than 2x the degrees of freedom of the main-effects models, otherwise the model-selection mechanism would always select the sub-model with the higher degree-of-freedom and lead to overfitting.
- Degrees-of-freedom of the main-effects of the spatial-autocorrelation radial basis function (for sub-model No.10) which could take on values [9, 12, 14, or 16]. Higher values allowed more "wiggly" auto-correlation effects, and lower values enforced smoother auto-correlation effects.
- Degrees-of-freedom of the spatial-autocorrelation radial basis function with year-interactions (sub-model No.11). These values were fixed to 2-times minus 2 of the degrees-of-freedom main-effects spatial-autocorrelation radial basis function (for

sub-model No.10). Like the spatial splines, this interaction sub-model needed to have less than 2x the degrees-of-freedom of its main-effects sister-model.

Other parameters, like the degrees-of-freedom of the penalized least-squares models (sub-models No. 1 and 2) and the degrees-of-freedom of the temporal splines (sub-model No.5) had their values fixed to 1 and 4, respectively, for all models (i.e.,. the recommended default values of the mboost library).

2.3.4 *Modelling differences between 2019 and 2020*

The modelling method is an ensemble approach that combines sub-models according their contribution to the risk-reduction via shrinkage and regularization (i.e., weighting by their ability to explain variation). A nice feature of this automatic model-averaging is that we can embed different sub-models-as-hypotheses: are dolphins' spatial-temporal distribution the same each year? Or do they change one year to the next? These two conjectures can be specified as sub-models.

This is implicitly the point of the detailed description of the different sub-models, especially regarding those that are the same but differ according whether there is a by-year interaction covariate. Consider sub-models (1) versus sub-models (2). The former posit a linear "main effect" response between dolphin occupancy/counts and covariates, whereby this linear response is consistent across years (e.g., dolphins are inversely related to distance-to-reefs, regardless of year), whereas the latter allows the functional relationship to differ each year (e.g., dolphins are inversely related to distance-to-reefs in 2019, and have no relationship in 2020). Likewise, sub-models (6) and (7) specify either a global main-effect or by-year segregated effect regarding the functional relationship between dolphins and time-of-day, respectively. And so forth with sub-models (8) vs. (9), and (10) vs. (11).

In reality, due to the sparsity of positive observations of dolphins, the most "parsimonious" weighting of different sub-models will likely include some shrinkage on both global and by-year interactions, such that the global main-effects describes functional relationships approximately persist across all years (e.g. dolphins favour a certain location / time regardless of year), and the by-year sub-models describe marginal variations.

2.3.5 *Model outputs: RVIs and AUC statistics*

After tuning the hyper-parameters, we trained a final model for each species. These final models were used for inference, including estimating the relative variable importance ("contribution to risk-minimisation"; Elith et al. 2008) as well as spatial prediction of dolphin locations and abundance.

Model performance was assessed by statistics including the area under the receiver-operator curve (cv-ROCAUC) and the area under the precision-recall curve (cv-PRAUC) (Fielding and Bell 1997, Harrell Jr 2015). For the AUC statistics, values above 0.5 to 1 are considered improvement over random classification.

2.3.6 *Differences spatial patterns between survey year 2019 and 2020*

We employed two complimentary quantitative methods to investigate differences between the spatial distribution of dolphins in year 2019 (our putative baseline year) and 2020.

The first method used the a descriptive statistical called the Structural Similarity Index (Wang et al. 2004), which provided a measure of the spatial correlation between two spatial distribution maps. The SSI statistic varies between -1 and 1, where 1 indicates high spatial correlation between two maps (i.e. the spatial structure of the underlying map is identical) and -1 indicates complete dissimilarity between the spatial structure of the underlying maps. We calculated the SSI statistics between spatial distribution maps generated for 2019 versus

2020. We repeated the calculation at several spatial resolutions (100m, 500m, 1000m). A high SSI would mean that there is a high similarity between two years, after removing variation explained by temporal effects (time-of-day, time-of-year) or factors affecting observational errors (glare, BSS, swell). The statistic is purely descriptive, without any notion of significance testing or hypothesis testing.

The second method used a likelihood-ratio statistic (Royall 1997) between two models, per species: the best model according to hyperparameter tuning, versus a reduced model which dropped the interaction covariate “year as factor”. See Table 1 for a description of the 11 different sub-models and which covariates they include. The “year as covariate” is included in sub-models 2,5,7,9 and 11, which allows for marginals differences between years 2019 and 2020 in terms of how dolphins respond to different effects. By removing the interaction covariate “year”, and measuring the change in likelihood, we have a formal measure for evaluating the hypothesis: “is there an important difference between models that allow inter-annual differences, versus a model that did not?”

A high likelihood-ratio (much greater than 1) between the reduced model and the full model is evidence that the model *without* interannual differences is best, whereas a low likelihood-ratio (much less than 1) is evidence that the model *with* interannual differences is best, while a likelihood ratio close to 1 would mean that there is little difference. We used 10-fold cross-validation to approximate the “expected likelihood” (rather than the within-sample likelihood), such that the likelihood calculations were evaluated by training the model on10-different 90% subsets of the data, and estimating the likelihood on the hold-out sample. It should be noted that the AIC is famous for approximating the expected likelihood (i.e., minimising the AIC maximises the expected likelihood, Akaike 1974, Akaike 1998).

Although p-values are unnecessary for inference on the expected likelihood (much like the AIC), we nonetheless approximated a p-value via our 10-fold cross-validation, defined as: the number of CV-runs were the reduced model had a higher likelihood on the hold-out sample than the full-model. This approximate p-value can take on multiples of 0.1 (i.e., 0, 0.1, 0.2, …., 1).

2.3.7 *Spatial predictions*

Using the best model (according to cross-validation) we produced three types of spatial partial plots. The first partial plot was the probability of occurrence (presence/absence) of snubfin and humpback dolphins. The second partial plot was the expected conditional group size. The predicted probability of occurrence and group sizes were then multiplied to give a prediction density of snubfin and humpback dolphins in Cleveland Bay and Halifax Bay.

2.3.8 *Spatial Interpolation*

As was performed in the previous report, as a pre-processing step prior to the species distribution model spatial predictions, we needed to interpolate values of some of the covariates (i.e., generate spatial maps). This was necessary for those covariates which were estimated or measured in-situ during the boat surveys (such as SST, turbidity, salinity, boats total, boats small, boats medium, boats large, boats fishing, boats recreational, and boats industrial). Being measure/estimated in a point-wise fashion, they have no natural map that we can use for the species distribution mode spatial prediction.

As we did in the previous report, the spatial interpolations were conducted by pooling two spatial modelling techniques:

- GAMs: model-averaging of spatial GAMs; and
- Component-wise boosting.

Each covariate was modelled according to both modelling techniques, and their spatial predictions were averaged. Both techniques allowed decomposition of variation into spatial components and temporal components. Only the spatial components were used for generating the spatial interpolations (in other words, all temporal effects were set to their mean-value across the entire spatial survey area).

Regarding missing data, we employed a two-round approach. During round #1, all rows of data that had missing data were deleted, and an initial working-model was made for SST, turbidity, salinity and all the boat-covariates, for a total of 10 models (one per covariate that required interpolation). The missing values of these covariates were then imputed using the Round #1 models, and a second round of models were run, conditional on the imputed values from Round 1 (thereby allowing us to use all rows of data). The Round 2 models were then used to interpolate the values of the covariates across the study area, for both 2019 and 2020.

2.3.9 *Spatial Interpolation by GAMs*

The spatial interpolation by GAMs consisted of running 262 models and model-averaging their predictions by AIC weights. We used the R-package mgcv (Wood 2003). The different models consisted of different combinations of the following terms/sub-models:

1. year-as-factor (i.e., different intercepts per year)
2. two of the following main-effects using thin-plate shrinkage splines:

    - spline(bathymetry)
    - spline(distance to rivers)
    - spline(distance to reefs)
    - spline(distance to nearshore)
    - spline(distance to land)
    - spline(SST)
    - spline(salinity)

   - spline(turbidity)

3. one of the following soap-film spatial smooths:

   - spline(latitude, longitude) , i.e., main-effect spatial spline
   - spline(latitude, longitude, interaction=year), i.e., interaction with year

4. one of the following bivariate splines:

   - spline(time-of-day, time-of-year), i.e., main-effect temporal spline
   - spline(time-of-day, time-of-year, by=year), i.e., interaction with year

It should be noted that the GAM method benefitted from the soap-film spatial smooth that respects maritime boundaries and islands (unlike generic kriging methods or generic bivariate splines).

It should be noted that there were additional, more-complex models that were possible, such models with bivariate interactions among covariates, but these often-had difficulty converging and failed. Nonetheless, given the small amount of data, it is reasonable to bias the models to only those that have a small amount of complexity (i.e., a few number of covariates and degrees-of-freedom), and use model-averaging to weight models according to their predictive performance.

The models for SST, salinity, and turbidity used a Gaussian distribution (sometimes the values were log-transformed and mean-centred in order to get approximately normally-distributed values), whereas the boat covariates (boats total, boats small, boats medium, boats large, boats fishing, boats recreational, boats industrial) were modelled according to a zero-inflated Poisson distribution (used to model count data that have many zero counts).

The final model was combined by discarding models with less than 5% AIC model-weights and weighting the remaining predictions according to their AIC model-weights.

2.3.10 *Spatial Interpolation by Boosting*

The second interpolation method was boosting. The technique was identical to that used for species distribution modelling for snubfin and humpbacks, but excluded all covariates relating to weather conditions (e.g., BSS, glare), thereby focusing on large-scale spatial processes for interpolation, and not intra-day weather variation.

The interpolated covariates SST, salinity, and turbidity were run using a Gaussian distribution, whereas the boat covariates (boats total, boats small, boats medium, boats large, boats fishing, boats recreational, boats industrial) were modelled according to a zero-inflated Poisson distribution.

2.4 Data analysis: Patterns of attendance to the port area

2.4.1 *Land-based surveys*

We have analysed the land-based survey data using a combination of descriptive statistics. This report provides the following descriptive statistics: total dolphin counts by species, and their behavioural compositions (resting, foraging, socialising, and travelling). These dependent variables are further summarised by covariates, including hours of day, presence of boats, presence of dredging, presence of rock dumping, as well as an overall comparison of the 2019 vs 2020 counts of dolphins. The later represent our primary inferential tool for testing whether there have been any changes on dolphin occurrence around the port area due to boats and CU construction activities.

For statistical tests, we used a method called the Bayesian p-value (Gelman et al. 1996). We used the occurrence records of 2019 as a type of “null model” (characterising pre-construction conditions) and calculated Bayesian p-values which compared dolphin presence in 2020 to those of 2019. Low Bayesian p-values suggest that the presence of dolphins was lower than what would be expected according to the 2019 null-model, while high Bayesian p-values suggest that the 2020 data is consistent with the 2019 null-model.

Likewise, we used the presence/absence of dolphins during non-dredging/dumping periods in 2019 as the "null model" (characterising normal conditions of the dolphins) and calculated the probability of seeing dolphin counts as low as that observed during dredging/dumping activities. Low Bayesian p-values provide evidence that the counts of dolphins were lower during human activities (i.e., a low-probability events according to the null-models), while high Bayesian p-values suggest that the counts during human activities were no different than under normal background conditions.

$$\underbrace{\pi(\theta^{\varnothing}|\boldsymbol{y}) \propto \underbrace{\left(\prod_{i=1}^{N^{\varnothing}_{\text{scans}}} \text{Bern}(y_i|\theta^{\varnothing})\right)}_{\text{likelihood}} \underbrace{\text{Beta}(1,1)}_{\text{prior}}}_{\text{null model: probability of dolphin occurences during non-dredging}}$$

$$p_{\text{Bayes}} = \sum_{\tilde{n}=0}^{\tilde{n}_{\text{dredge}}} \left(\int_{\pi(\theta^{\varnothing})} \pi(\tilde{n}|\theta^{\varnothing})d\theta\right) = \underbrace{\sum_{\tilde{n}=0}^{\tilde{n}_{\text{dredge}}} \underbrace{\left(\int_{\pi(\theta^{\varnothing})} \text{Bin}(\tilde{n}; N^{\text{dredge}}_{\text{scans}}, \theta^{\varnothing})d\theta\right)}_{\substack{\text{probability of } \tilde{n} \text{ occurrences of dolphins} \\ \text{during } N_{\text{scans}} \text{ and given null model } \theta^{\varnothing}}}}_{\text{sum over: less than or upto } n_{\text{dredge}} \text{ occurrences}}$$

where:

$\boldsymbol{y}$:= occurrences of dolphins during normal non-dredging scans

$\theta^{\varnothing}$:= estimated probability of dolphins occurrences during non-dredging scans

$N^{\varnothing}_{\text{scans}}$:= number of scans with no dredging

$N^{dredge}_{\text{scans}}$:= number of scans with dredging

$\tilde{n}_{\text{dredge}}$:= observed number of occurrences of dolphins during dredging

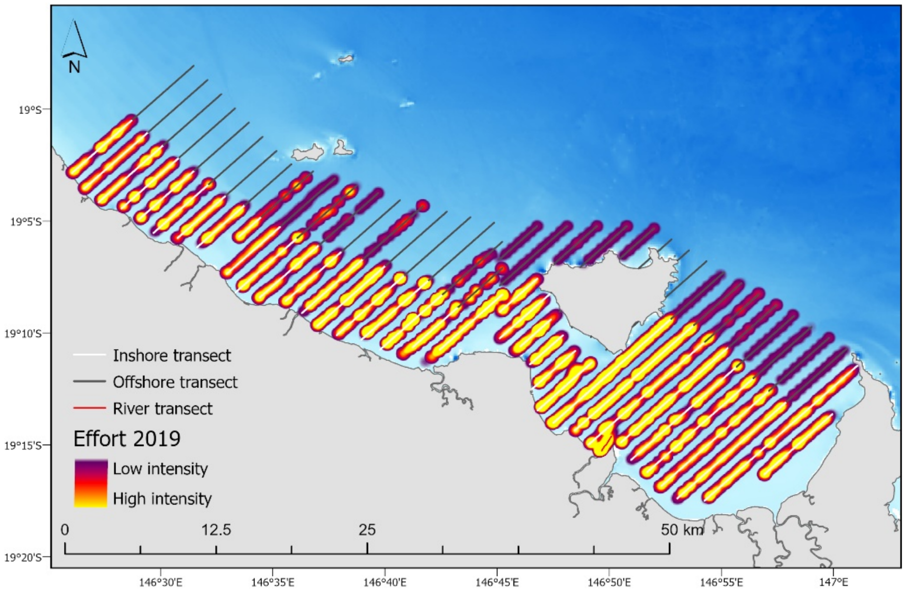
The above formalism is specific to the calculation of Bayesian p-values for binary-occurrences. For counts/abundances, the same framework applies, but instead uses a Poisson-Gamma distribution as the null model.

3. Results

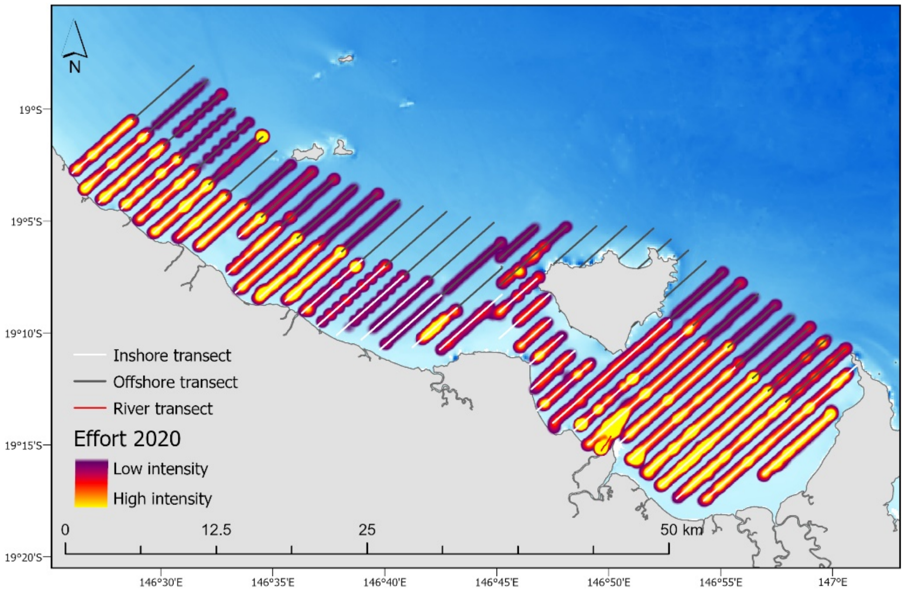
3.1 Population demographics

3.1.1 *Vessel based survey effort*

We surveyed a total of 1849.6 km on transect effort over 13 days between June 22nd and July 27th, 2020, covering 1013.9 km in Cleveland Bay and 835.7 km in Halifax Bay (Fig. 4, Table 2). As planned, we completed six survey repeats of each bay, each representing a secondary period. Similar to last year, survey effort was higher in inshore areas (1598.6 km, including 8.4 km of survey effort at the mouth of the Ross Creek) than in offshore areas (251 km) due to the poor weather conditions encountered often in offshore areas (Beaufort sea state > 4). The vessel survey effort in 2020 was comparable to the survey effort in 2019, in which we completed 1767.1 km on transect effort over 15 days, covering 936.3 km in Cleveland Bay and 830.8 km in Halifax Bay.



a) Survey effort 2019



b) Survey effort 2020

Figure 4. Map of survey area showing survey transects (solid black lines) and realized survey effort (light blue to dark red) in Cleveland and Halifax Bay in a) June-July 2019. and b) 2020. Survey intensity scale represents the relative amount of times a transect was visited, as an approximate visual indicator of observational intensity (for data-summary purposes only).

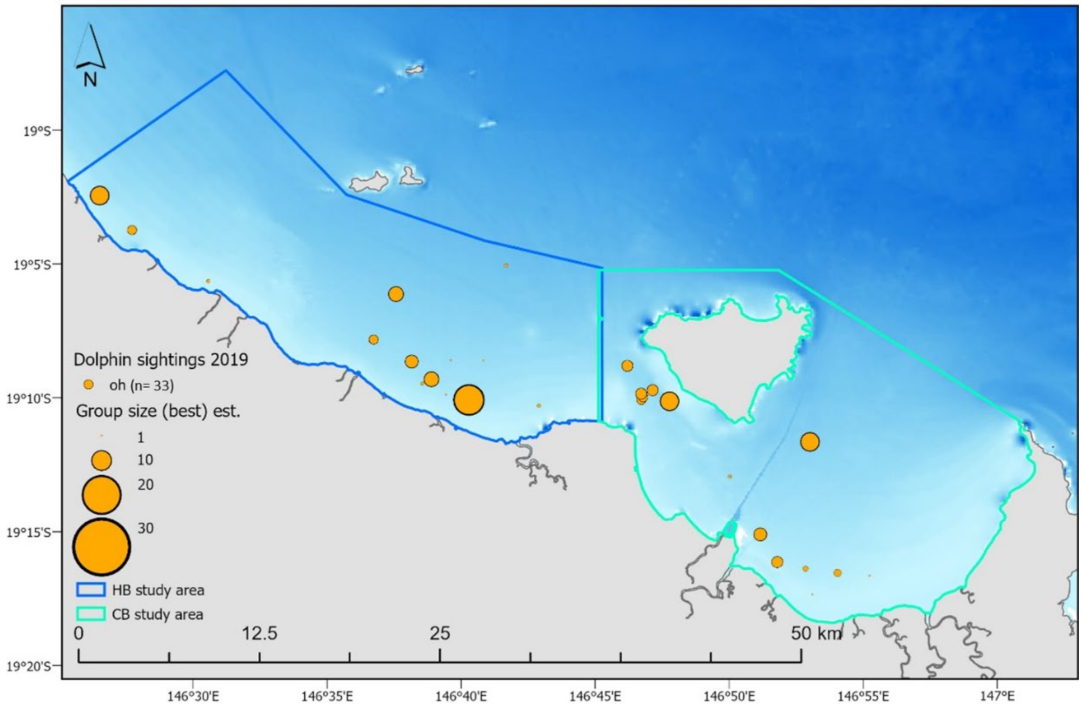
Table 2: Summary of boat-based survey effort (total length of transects completed on effort) and sea state conditions encountered in Cleveland Bay (CB) and Halifax Bay (HB) during each complete survey (secondary period) in the 2020 primary sample (June-July).

Study area	Sec. period	Date/s	Inshore	Offshore	Beaufort Sea State		
			Transect length (km)	Transect length (km)	min	max	mode
Cleveland Bay	1	22/06	146.2	27.5	0	3	1
	2	25/06	172.8	6.5	1	4	2
	3	04/07	122.2	10.7	1	4	2
	4	15/07	146.2	0	0	3	2
	5	17/07	146.2	11.2	0	4	2
	6	19/07	146.2	78.2	0	3	2
	Total		879.8	134.1	-	-	-
Halifax Bay	1	23/06	121.2	0	0	4	1
	2	12/07	121.2	57	0	2	2
	3	16/07	116.1	0	0	4	2
	4	18/07	121.2	0	1	3	2
	5	26/07	121.2	57.5	0	2	2
	6	27/07	117.9	2.4	1	2	2
	Total	-	718.8	116.9	-	-	-
	Grand total		1598.6	251			

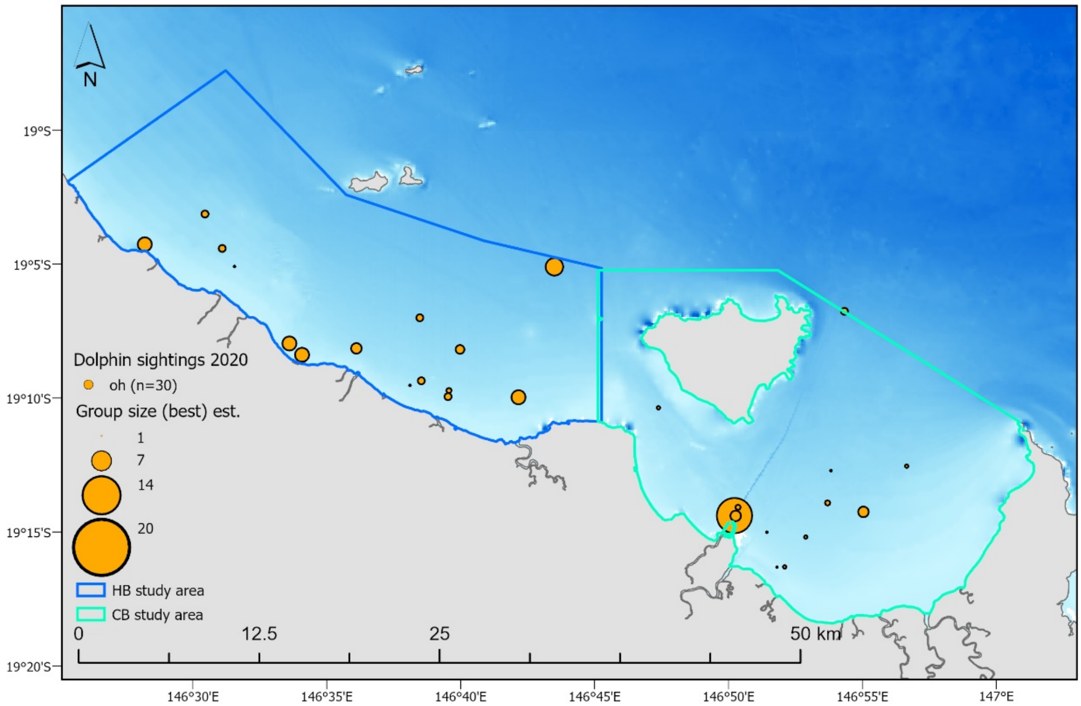
3.1.2 *Dolphin sightings, encounter rates and group sizes*

The vessel surveys in 2020 resulted in a total of 86 dolphin group sightings (including both on and off effort sightings) (Fig. 5a-f, Table 3). This consisted of 30 groups of snubfin dolphins, 55 groups of humpback dolphins, one bottlenose dolphin group, and included six mixed species groups of snubfin and humpback dolphins. Other marine mammals sighted during 2020 surveys included humpback whales and dugongs (Fig 5g-h). Encounter rates (Number of dolphin groups/km) of snubfin, humpback, and bottlenose dolphins over the whole study area (i.e. including both bays) were similar between 2019 and 2020 (Table3). However, encounter rates of snubfin, humpback, and bottlenose dolphin groups per bay were lower in 2020 than in 2019 (Table 3).In 2020, we sighted a total of 14 groups of Snubfin dolphins in Cleveland Bay (0.01 dolphin group/km) and 16 in Halifax Bay (0.02 dolphin group/km). Groups of humpback dolphins were sighted in higher numbers than snubfin dolphins, with 26 groups sighted in Cleveland Bay (0.03 dolphin group/km) and 29 in Halifax Bay (0.03 dolphin group/km) (Table 3). Only one bottlenose dolphin group was recorded in Halifax Bay.

Groups of snubfin dolphins varied in size from 1 to 20 individuals, with a mean (± SD) group size of 4.7 ± 3.9 (based on best estimates of group size). The group size of humpback dolphins ranged from 1 to 20 individuals, with a mean (± SD) group size of 4.7 ± 4.1. As per last year, groups of all dolphin species were composed mainly of adult individuals and contained similar numbers of juveniles and calves (Table 4).

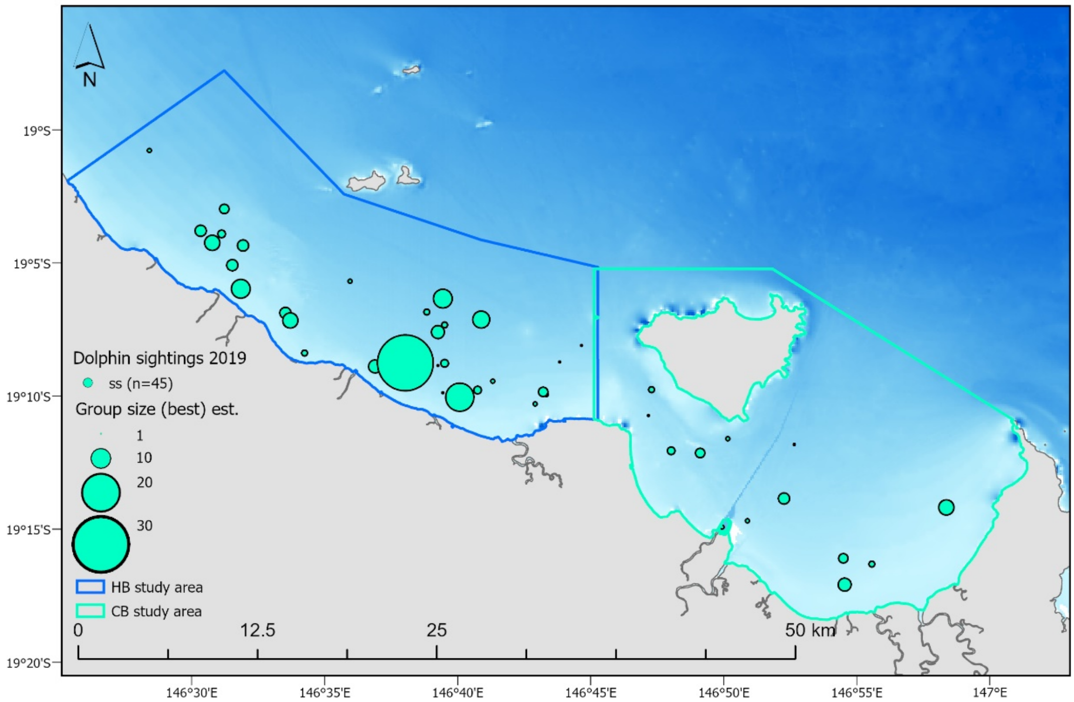


a) Snubfin dolphin sightings 2019.

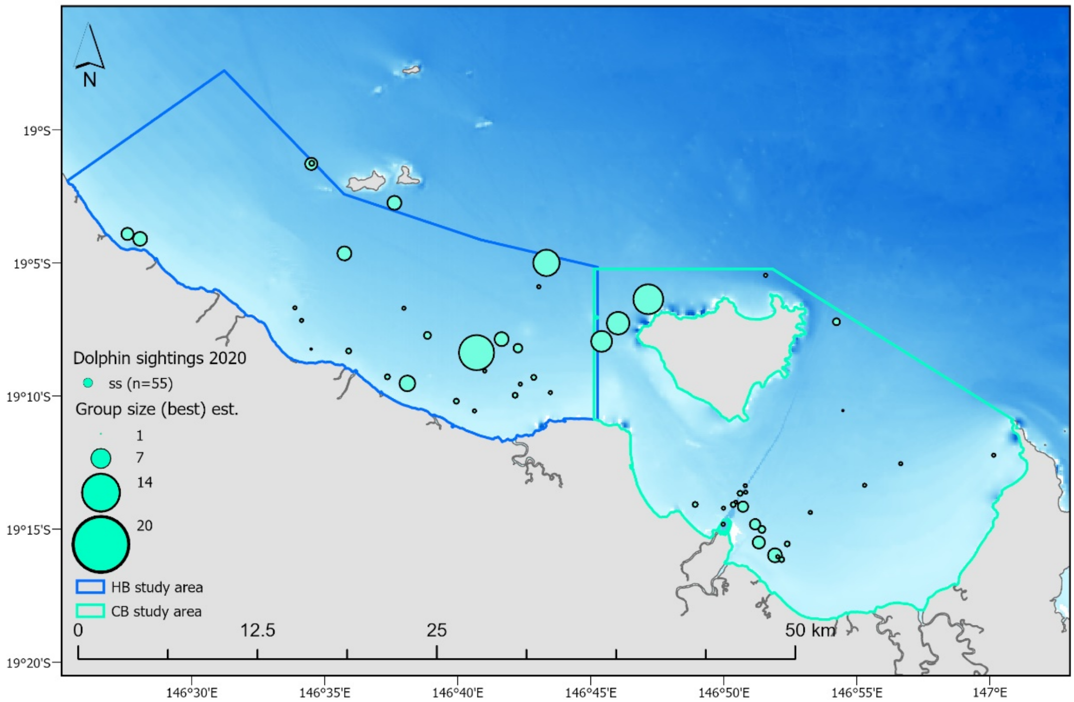


b) Snubfin dolphin sightings 2020.

Figure 5. Location and group sizes of Australian snubfin dolphins (a-b), Humpback dolphins (c-d), bottlenose dolphins (e-f) and other marine mammals (g-h) sighted in 2019 and 2020, during boat surveys in Cleveland and Halifax Bays.

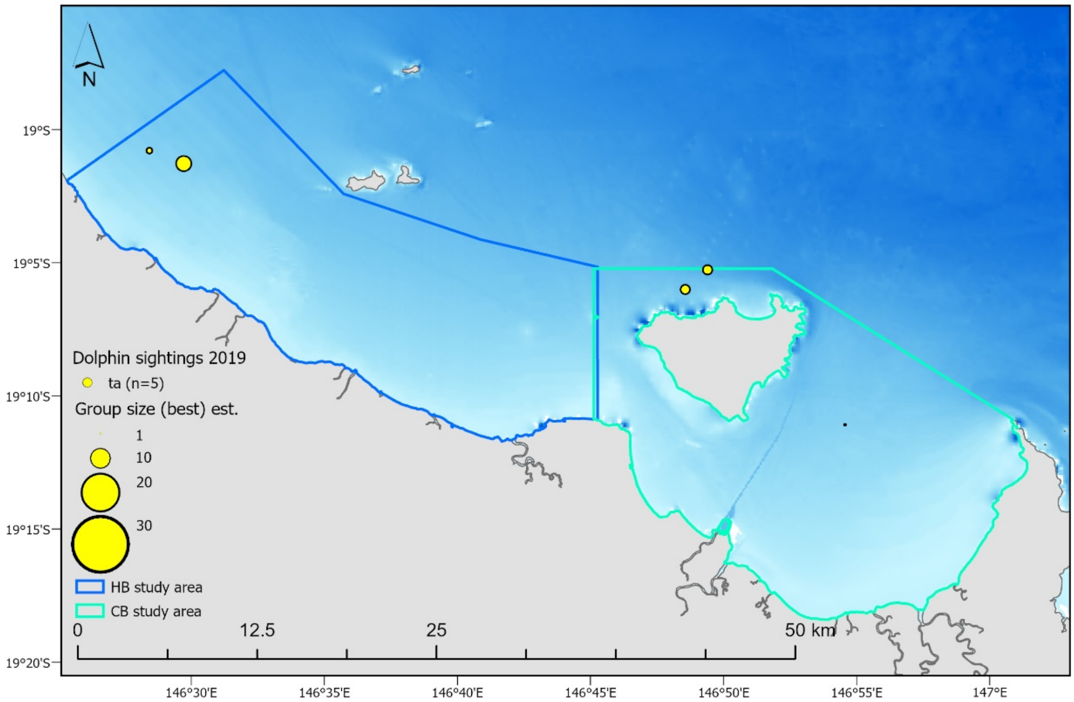


c) Humpback dolphin sightings 2019.

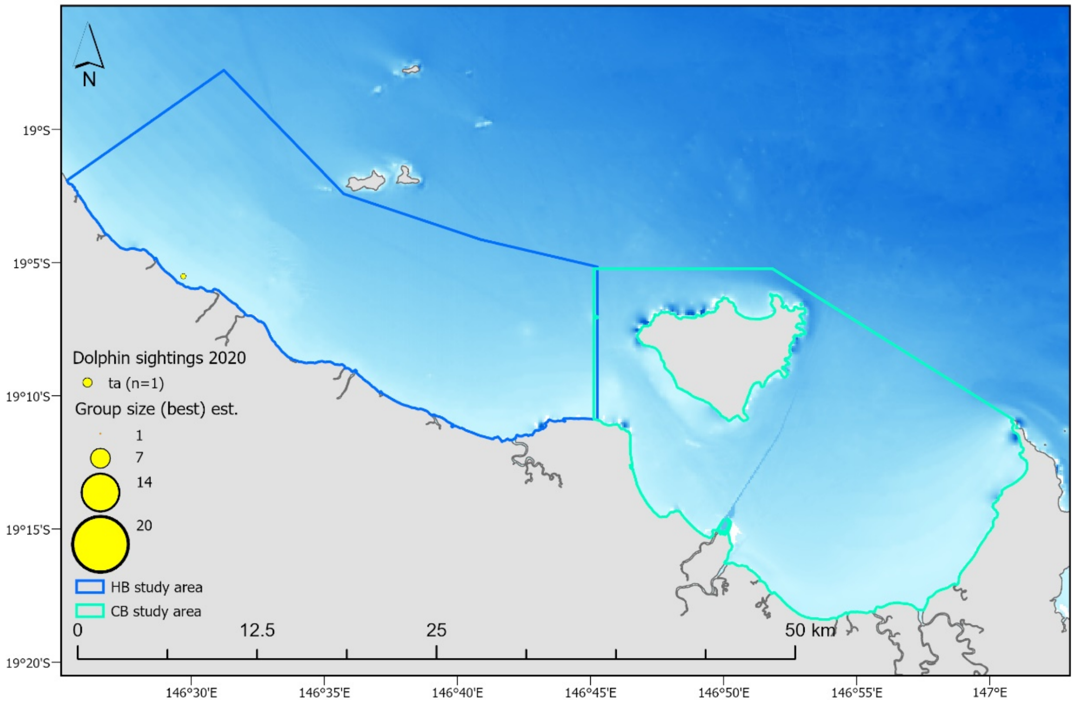


d) Humpback dolphin sightings 2020.

Figure 5 (continued). Location and group sizes of (a-b) Australian snubfin dolphins, (c-d) Humpback dolphins, (e-f) bottlenose dolphins and (g-h) other marine mammals sighted in 2019 and 2020, during boat surveys in Cleveland and Halifax Bays.

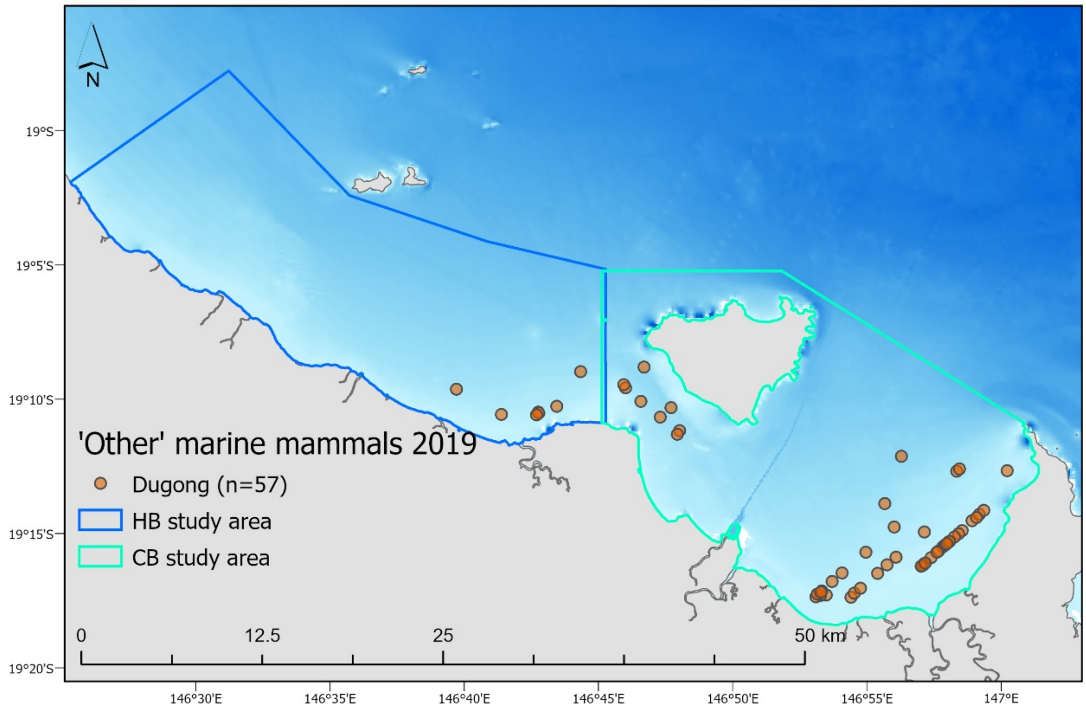


e) Bottlenose dolphin sightings 2019.

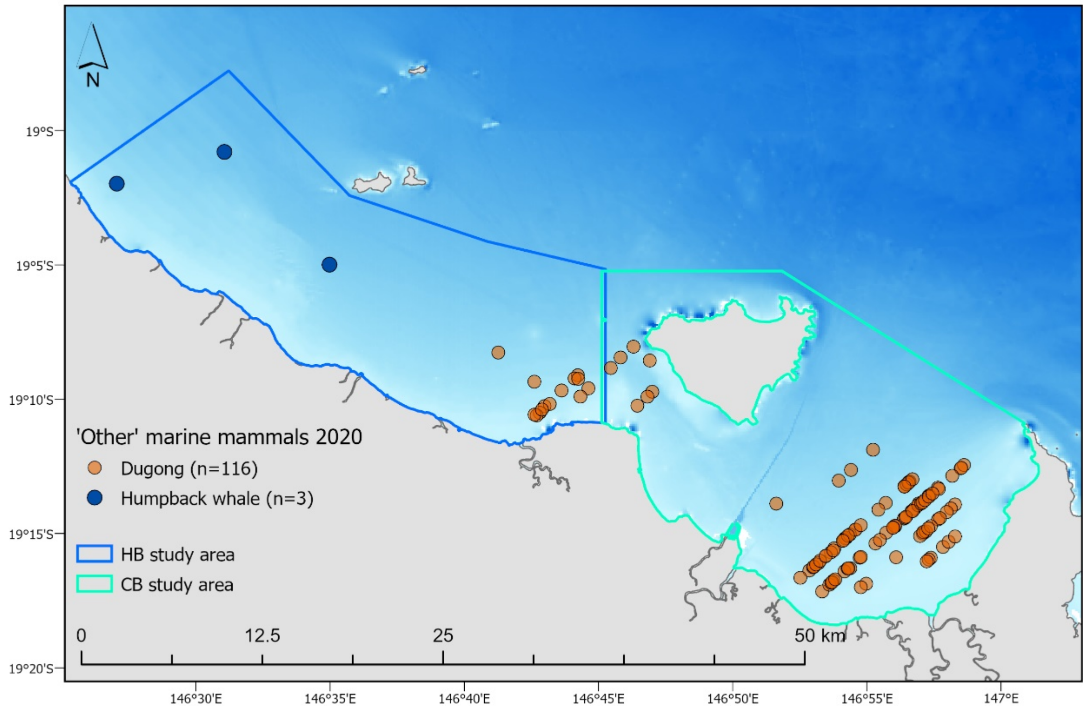


f) Bottlenose dolphin sightings 2020.

Figure 5 (continued). Location and group sizes of (a-b) Australian snubfin dolphins, (c-d) Humpback dolphins, (e-f) bottlenose dolphins and (g-h) other marine mammals sighted in 2019 and 2020, during boat surveys in Cleveland and Halifax Bays.



g) Other marine mammal sightings 2019.



h) Other marine mammal sightings 2020.

Figure 5 (continued). Location and group sizes of (a-b) Australian snubfin dolphins, (c-d) Humpback dolphins, (e-f) bottlenose dolphins and (g-h) other marine mammals sighted in 2019 and 2020, during boat surveys in Cleveland and Halifax Bays.

Table 3. Number (n) and encounter rate (total number of dolphin groups sighted per km of transect surveyed) of snubfin, humpback and bottlenose dolphins in Cleveland and Halifax Bays during 2019 and 2020 boat surveys.

Year	Species	Cleveland Bay		Halifax Bay		Total	
		n	Number of dolphin groups/km	n	Number of dolphin groups/km	n	Number of dolphin groups/km
2019	**Snubfin**	17	0.07	16	0.07	33	0.02
	Humpback	13	0.05	32	0.15	45	0.03
	Bottlenose	3	0.01	2	0.01	5	0.003
2020	**Snubfin**	14	0.01	16	0.02	30	0.02
	Humpback	26	0.03	29	0.03	55	0.03
	Bottlenose	0	0	1	0.001	1	0.001

Table 4. Group size and age composition of snubfin, humpback and bottlenose dolphins encountered during boat-based surveys in the Townsville region in 2019 and 2020.

Year	Species	Group size			Group age composition			
		Min	Max	Mean (SD)	Mean proportion of adults, juveniles, calves (%)			No. groups with juvenile or calf present
					A	J	C	
2019	Snubfin	1	16	4.7 (3.6)	77	11	10	15 (45%)
	Humpback	1	30	5.18 (4.9)	77	11	10	28 (62%)
	Bottlenose	1	8	4.4 (2.6)	67	10	10	4 (80%)
2020	Snubfin	1	20	4.7 (3.9)	83	6	10	15 (50%)
	Humpback	1	20	4.7 (4.1)	75	13	12	32 (58%)
	Bottlenose	3	3	3 (NA)	NA	NA	NA	1 (100%)

3.1.3 *Photo-identification and capture-recapture data*

Thirty-five individual snubfin and 49 individual humpback dolphins were captured (i.e., photo-identified) on-effort during sampling in 2020 (Table 5). When off-effort captures were included, these numbers increased to 52 snubfin and 56 humpback dolphins. No bottlenose dolphins were photo-identified.

Twelve snubfin dolphins were captured on-effort in Cleveland Bay and 24 in Halifax Bay (Table 5). One individual snubfin dolphin was captured on effort and three were captured on-effort plus off-effort at both sites When off-effort captures were included, the number captured in Cleveland Bay increased by 14 to 26, and the number captured in Halifax Bay increased by five to 29. Twenty-six humpback dolphins were captured on-effort in Cleveland Bay and 28 in Halifax Bay (Table 5). Five individuals were captured on-effort and eight on-effort plus off-effort at both sites. When off-effort captures were included, the number captured in Halifax Bay increased by ten to 38.

The immediate objective is to assess, for snubfin and humpback dolphins, whether the (re)capture data on the originally-planned six secondary samples (PS_SS) are suitable or whether they would be better collapsed to three secondary samples (PS_SS3) for analysis, and whether using the off-effort together with the on-effort data would provide better data for analysis.

Considering the originally planned six secondary samples (PS_SS) and on-effort only captures, there were no captures in at least one of the six secondary samples, and very small numbers of captures (≤ 3) in one or more of the samples for both species on most sites (Table 5). Including the off-effort captures increased these numbers somewhat but some zero and very small numbers of captures remained.

Secondary samples with zero or very small numbers of captures contribute no or very little information to capture-recapture models. Thus, the data from the originally planned six secondary samples were inadequate to support informative capture-recapture population models. Fortunately, an even number of secondary samples was planned in anticipation of small numbers of captures being made to allow a strategy of collapsing each consecutive pair of secondary samples into one (1&2=1, 3&4=2, 5&6=3) to increase the per secondary sample numbers of captures (Table 5).

There were no zero but some very small (≤ 3) numbers of captures in the on-effort only data in the three new secondary samples (PS_SS3): there were as few as three captures of snubfin dolphins in one sample in Cleveland Bay, one capture of a humpback dolphin in one sample in Cleveland Bay and three captures of humpback dolphins in one sample in Halifax Bay (Table 5). Inclusion of the off-effort captures removed all instances of zero captures and most very small (≤ 3) numbers of captures in the three secondary sample data, although there were only two captures of humpback dolphins in one sample in Cleveland Bay.

The three secondary sample data generally constituted adequate numbers of captures for analysis, especially if the off-effort captures were included. That only two humpback dolphins were captured on-and off-effort in Cleveland Bay in the first secondary sample makes this sample somewhat deficient, although there were good numbers in secondary samples two and three. Overall, although sufficient for estimates to be obtained, the number of snubfin dolphins captured in Cleveland Bay in 2020 over the secondary samples (PS_SS3) were relatively few for capture-recapture modelling and a wide confidence interval is expected to be associated with the respective abundance estimate .

If the spatial distribution of off effort captures were correlated with the spatial habitat use of sub-groups of dolphins, inclusion of the off-effort data might have introduced heterogeneity of capture probabilities into the data. This question is addressed in the section on goodness of fit.

Table 5. Number of individual dolphins identified and number of captures by year, species, bay, on and off effort, and secondary sample. PS_SS refers to the originally planned six secondary samples; PS_SS3 refers to three secondary samples as collapsed from PS_SS (1 & 2 =1, 3 & 4 = 2, 5 & 6 = 3).

Year	Species	Bay	Effort	No of Individuals identified	PS_SS						PS_SS3		
					p1s1	p1s2	p1s3	p1s4	p1s5	p1s6	p1s1	p1s2	p1s3
2019	Snubfin	Cleveland	On only	27	7	3	9	0	13	2	10	9	14
			On + off	27	7	3	9	0	13	6	10	9	14
		Halifax	On only	36	11	1	10	0	11	11	11	10	21
			On + off	37	11	1	10	0	11	11	12	10	21
	Humpback	Cleveland	On only	13	0	3	10	1	0	0	3	11	0
			On + off	19	3	3	11	3	5	0	6	13	5
		Halifax	On only	46	4	18	2	8	9	21	20	10	29
			On + off	46	4	19	2	8	9	21	21	10	29
	Bottlenose	Cleveland	On only	5	0	0	0	5	0	0	0	5	0
			On + off	5	0	0	0	5	0	0	0	5	0
		Halifax	On only	0	0	0	0	0	0	0	0	0	0
			On + off	2	0	1	0	0	1	0	1	0	1
2020	Snubfin	Cleveland	On only	12	6	0	2	1	4	0	6	3	4
			On + off	26	6	0	2	10	4	7	6	11	11
		Halifax	On only	24	0	6	5	8	8	8	6	12	16
			On + off	29	0	6	7	8	11	8	6	13	19
	Humpback	Cleveland	On only	26	1	0	8	6	17	5	1	11	21
			On + off	26	1	2	8	6	17	8	2	11	21
		Halifax	On only	28	1	15	2	3	10	0	16	3	10
			On + off	38	3	15	4	9	10	5	18	10	15

3.1.4 *Goodness of fit*

The CAPTURE preferred models (Table 6) indicate that sufficient evidence was not found to require models which accommodate either behavioural response to first capture or individual heterogeneity of capture probabilities for snubfin dolphins in Cleveland Bay or humpback dolphins in Halifax Bay for either the on-effort only or on-plus off-effort data. However, evidence of individual heterogeneity was detected for snubfin dolphins in Halifax Bay and humpback dolphins in Cleveland Bay. That the same models were preferred for both the on-effort only and on-plus off-effort data indicates that inclusion of the off-effort data had not introduced the observed heterogeneity effects.

Table 6. Program CAPTURE-preferred models for the capture-recapture data on each species in each bay and for the on-effort only and on-plus off-effort captures. Model M0 has a constant capture probability, model Mt has capture probability varying by secondary sample (PS_SS3) while model Mh attempts to adjust for the observed heterogeneity (Chao 1987).

Year	Species	Bay	On + Off Effort	On Effort Only
2019	Snubfin	Cleveland	M0	M0
		Halifax	M0	M0
	Humpback	Cleveland	Mt	NA*
		Halifax	Mt	Mt
2020	Snubfin	Cleveland	M0	M0
		Halifax	Mh	Mh
	Humpback	Cleveland	Mh	Mh
		Halifax	M0	Mt

*NA indicates that CAPTURE would not run as there were too few data in only two non-zero samples.

3.1.5 *Models*

Closed population models were run in Program Mark (V8.1, White and Burnham 1999) on the three-secondary sample (PS_SS3) on- plus off-effort capture-recapture data on snubfin and humpback dolphins in Cleveland and Halifax Bays. The data displaying heterogeneity effects were analysed using the model of Chao (1987) to correct for the observed heterogeneity. The models with the lower AICc was chosen for interpretation. The parameter estimates, their standard errors and 95% confidence intervals are shown in Table 7.

Table 7. Parameter estimates, their standard errors (SE) and 95% confidence intervals (lower and upper limits) from closed population models fitted to the on- plus off-effort data on snubfin and humpback dolphins in Cleveland and Halifax Bays in 2019 and 2020. Parameters p_1, p_2 and p_3 are capture probabilities in the first, second and third secondary samples respectively, N_m is the estimate of the "marked" population size. The models used for each analysis are indicated in parentheses.

Year	Species	Bay	Parameter	Estimate	SE	L95%CI	U95%CI
2019	Snubfin	Cleveland	p_1	0.20	0.069	0.10	0.37
			p_2	0.20	0.069	0.10	0.37
			p_3	0.20	0.069	0.10	0.37
			N_m (M0)	54	16.36	36	108
		Halifax	p_1	0.13	0.056	0.06	0.29
			p_2	0.11	0.049	0.05	0.25
			p_3	0.23	0.088	0.11	0.45
			N_m (M0)	89	28.69	56	180
	Humpback	Cleveland	p_1	0.20	0.093	0.07	0.44
			p_2	0.43	0.154	0.18	0.72
			p_3	0.17	0.083	0.06	0.39
			N_m (Mt)	30	8.68	22	62
		Halifax	p_1	0.29	0.073	0.17	0.45
			p_2	0.14	0.047	0.07	0.26
			p_3	0.41	0.090	0.25	0.59
			N_m (Mt)	71	12.00	57	107
2020	Snubfin	Cleveland	p_1	0.08	0.05	0.02	0.25
			p_2	0.08	0.05	0.02	0.25
			p_3	0.08	0.05	0.02	0.25
			N_m (M0)	121	74.76	51	396
		Halifax	p_1	0.22	NA	NA	NA
			p_2	0.22	NA	NA	NA
			p_3	0.22	NA	NA	NA
			N_m (Mh)	62	20.99	40	132
	Humpback	Cleveland	p_1	0.28	NA	NA	NA
			p_2	0.28	NA	NA	NA
			p_3	0.28	NA	NA	NA
			N_m (Mh)	42	10.26	32	76
		Halifax	p_1	0.29	0.08	0.16	0.47
			p_2	0.29	0.08	0.16	0.47
			p_3	0.29	0.08	0.16	0.47
			N_m (Mt)	62	11.56	47	96

Note: 1) N.A. Standard errors are not provided for the average capture probability from the Chao (1987) model in CAPTURE.

2) Model M0 has a constant capture probability, model Mt has capture probability varying by secondary sample (PS_SS3) while model Mh attempts to adjust for the observed heterogeneity (Chao 1987).

3.1.6 *Total population sizes*

The numbers of snubfin and humpback dolphins estimated to have used Cleveland and Halifax Bays during the sampling periods in 2019 and 2020 are summarised in this section. Both the estimated sizes of the marked and total populations are reported. Whereas in 2019 an attempt was made to estimate the sizes of the total populations of adult dolphins, the present estimates refer to the total populations including juveniles and calves (i.e. we have taken into account the proportion of all marked individuals in the population not just adults). This has reduced the estimated marked proportions from those previously reported for 2019, but the new abundance estimates provide a better representation of the total number of individuals in the study area. The estimates of the marked proportions of snubfin and humpback dolphins in the 2019 and 2020 samples are reported with their associated standard errors (SE), and lognormal 95% confidence intervals (lower and upper limits) are reported in Table 8. Estimates of the marked proportions of dolphins were used to estimate the total population sizes shown in Table 9. The estimated proportions of marked dolphins for 2020 were 0.85 (SE=0.035) for the snubfin population and 0.84 (SE=0.027) for the humpback population.

Snubfin dolphins were more abundant in Cleveland Bay than Halifax Bay, while humpback dolphins were more abundant in Halifax Bay than Cleveland Bay. The total number of snubfin dolphins using Cleveland Bay in 2020 was estimated at 143 (95% CI = 47-435) individuals and at 73 (95% CI =38-140) individuals for Halifax Bay (Table 9). The total population size of humpback dolphins was estimated at 50 (95% CI = 31-81) individuals for Cleveland Bay and 74 (95% CI = 51-107) individuals for Halifax Bay. As expected, the wide confidence interval associated with the abundance estimate for snubfin dolphins in Cleveland Bay reflects their low capture probabilities ($p = 0.08$) in the first, second and third secondary samples in 2020.

In 2019 both snubfin and humpback dolphins were more abundant in Halifax Bay than in Cleveland Bay (Table 9). This year snubfin dolphins were more abundant in Cleveland than Halifax Bay while humpback dolphins were again more abundant in Halifax than in Cleveland Bay (Table 9). However, there is considerable overlap in the confidence intervals of these abundance estimates, suggesting there has been no major changes in the abundance of either species

Table 8. Estimated proportions of marked snubfin and humpback dolphins in the 2019 and 2020 samples.

Year	Species	Estimate	SE	Lower 95% CI	Upper 95% CI
2019	Snubfin	0.79	0.029	0.73	0.85
	Humpback	0.70	0.034	0.63	0.76
2020	Snubfin	0.85	0.035	0.77	0.91
	Humpback	0.84	0.027	0.78	0.88

Table 9. Estimated numbers in the marked and total populations of snubfin and humpback dolphins that used Cleveland and Halifax Bays during the sampling periods in 2019 and 2020 with their associated standard errors (SE), coefficients of variance (CV) and lognormal 95% confidence intervals (lower and upper limits).

			Marked population					Total population				
Year	Species	Bay	Estimate	SE	CV	L95%CI	U95%CI	Estimate	SE	CV	L95%CI	U95%CI
2019	Snubfin	Cleveland	54	16.36	0.30	36	108	68	20.72	0.30	38	122
		Halifax	89	28.69	0.32	56	180	112	36.32	0.32	60	208
	Humpback	Cleveland	30	8.68	0.29	22	62	43	12.63	0.29	25	76
		Halifax	71	12.00	0.17	57	107	102	17.85	0.18	73	143
2020	Snubfin	Cleveland	121	74.76	0.62	51	396	143	88.19	0.62	47	435
		Halifax	62	20.99	0.34	40	132	73	24.85	0.34	38	140
	Humpback	Cleveland	42	10.26	0.24	32	76	50	12.45	0.25	31	81
		Halifax	62	11.56	0.19	47	96	74	14.03	0.19	51	107

3.2 Spatial distribution modelling

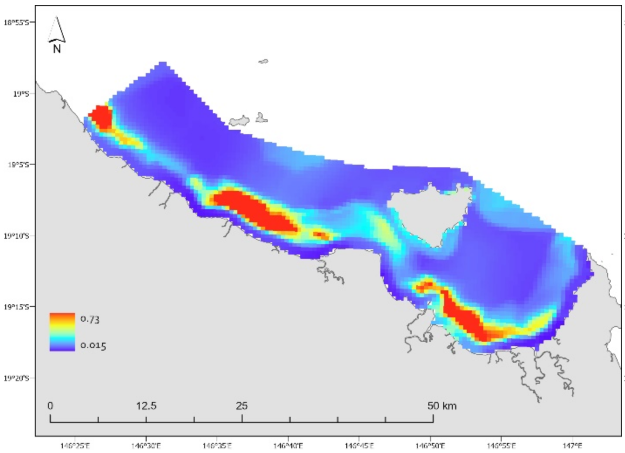
3.2.1 *Model performance and spatial predictions*

There were 45 encounters of humpbacks in 2020 with associated estimates of group size and measurement of environmental conditions that were used for the species distribution modelling. Their median and mean groups sizes were 4.00 and 5.02 (SD 4.88), respectively. The total counts of humpback dolphins (i.e., the sum of all groups) was 226. The number of points comprising the pseudo-zeros used for the species distribution model was 581. Compared to the previous field season, the 2019 number of encounters, median and mean group sizes were: 45, 4.00, and 5.13 (SD 5.16) respectively.

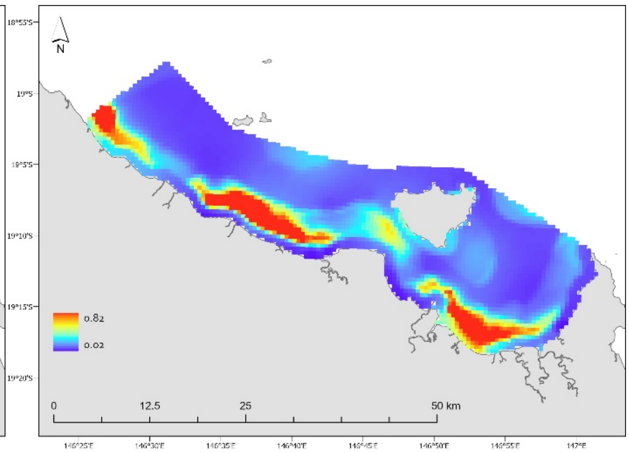
For snubfins in 2020, there were 31 encounters with associated estimates of group size and measurement of environmental conditions that were used for the species distribution modelling. Their median and mean groups sizes were 5.00 and 4.74 (SD 3.60), respectively. The total counts (sum of all groups) was 147. The number of points comprising the pseudo-zeros for the species distribution model was 595. Compared to the previous field season, the 2019 number of encounters, median and mean group sizes were: 31, 5.00, and 4.77 (SD 3.62) respectively.

Overall, the species distribution models of snubfin and humpback dolphin occurrence had good predictive performance. The final model for humpbacks had the following tuned hyper-parameters: 1996 boosting iterations, a learning rate of 0.018, a decision-tree maximum depth of 4, mincriterion-statistic of 0.4, and spatial degrees-of-freedom of 12 (bivariate spatial splines) and 14 (spatial-auto-correlation). This model had good predictive performance, with a cv-ROC-AUC value of 0.905 (out of 1) and cv-precision-recall-AUC of 0.568. The hyperparameters of the final model for snubfins was similar to that for humpback, but ran for 1237 boosting iterations, and had a learning-rate of 0.022. The cv-ROC-AUC statistic for snubfins was 0.909 (out of 1) and had an cv-precision-recall-AUC of 0.464, indicating slightly weaker overall predictive performance compared to the humpbacks' model.

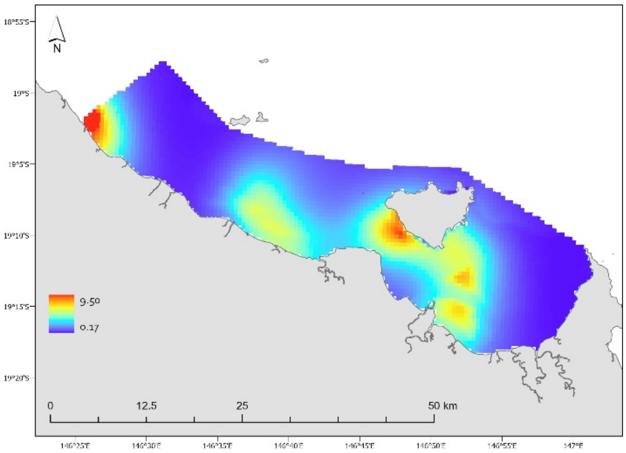
The spatial partial plots of humpback and snubfin dolphin across the survey area are shown in Figures 6 and 7 respectively. These plots show the probability of occurrence (Figs. 6a-b and 7a-b) and the conditional group size (i.e., the total number dolphins at an encounter, conditional on the group actually being present) (Figs. 6c-d and 7c-d) per year. These two components, the occupancy, and conditional counts, make up the two components of the zero-inflated Poisson model. The plots also show the integration of the two processes, the expected counts, which is the probability of occupancy multiplied by the conditional counts (Figs. 6e-f and 7e-f) per year. Note that the influence of temporal covariates (time-of-day, day-of-year) and environmental conditions (swell, BSS, glare, visibility) have been set to their global averages.



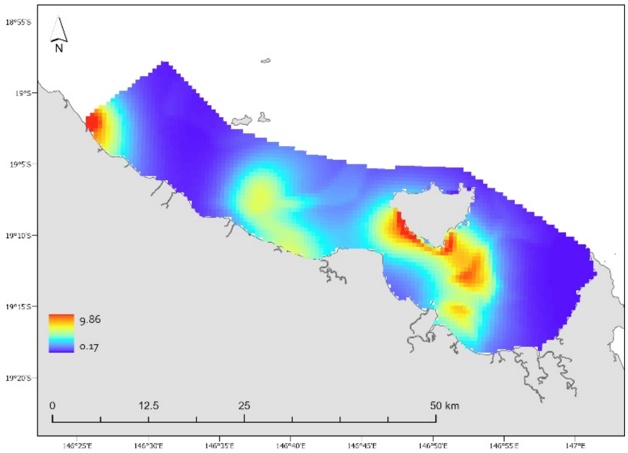
a) 2019



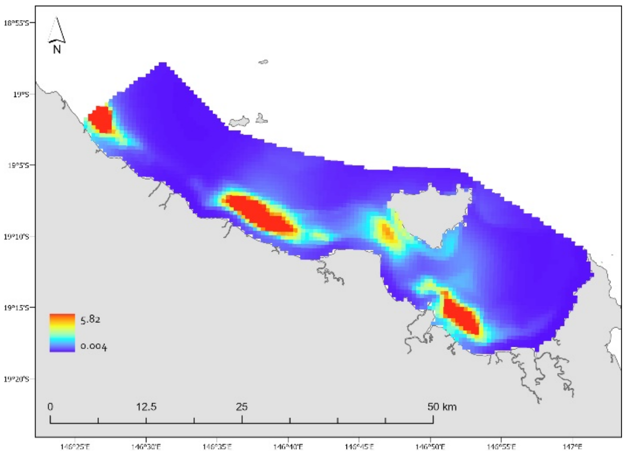
b) 2020



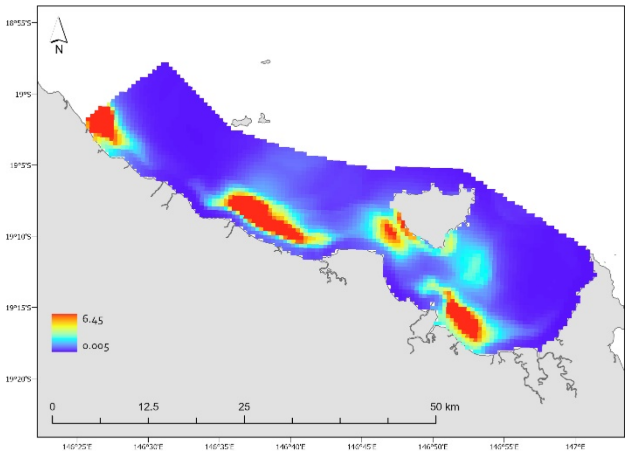
c) 2019



d) 2020

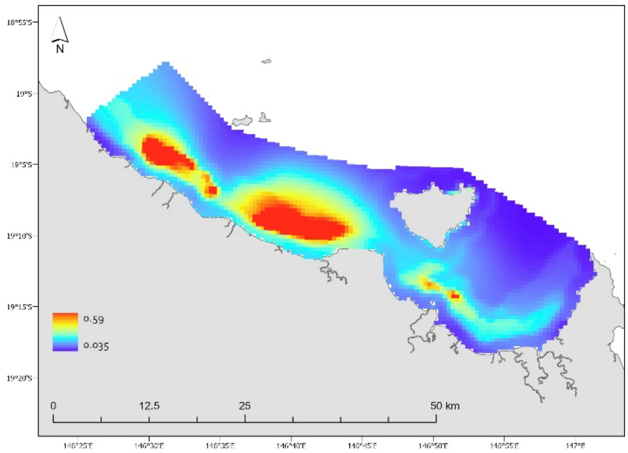


e) 2019

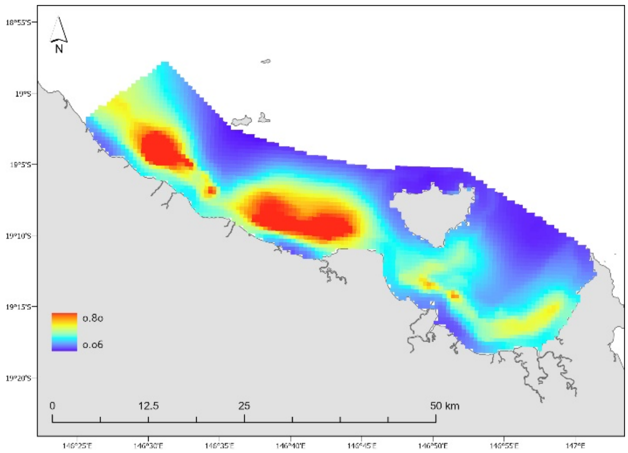


f) 2020

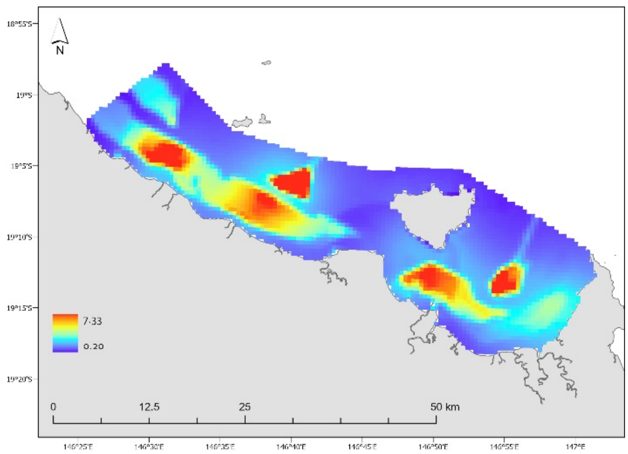
Figure 6. Spatial partial plots of snubfin dolphins from ensemble-modelling of species distribution across the survey area based on data collected in in 2019 and 2020: (a-b) shows how the probability of dolphins' presence/absence varies spatially over the study area (c-d) shows how group size varies spatially, and (e-f) shows the relative density (probability of occupancy times group size) of snubfin dolphins across the bays in 2019 and 2020.



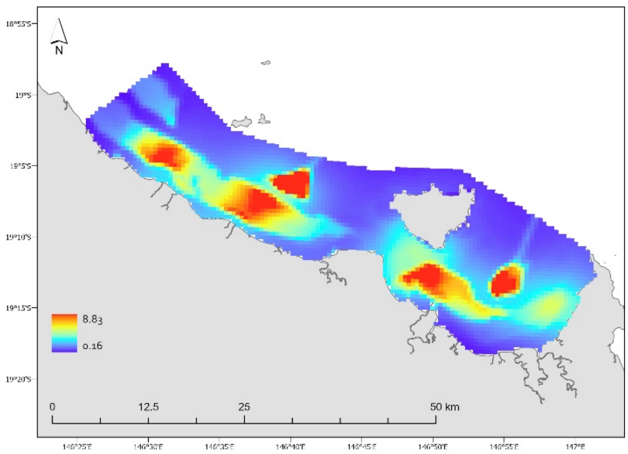
a) 2019



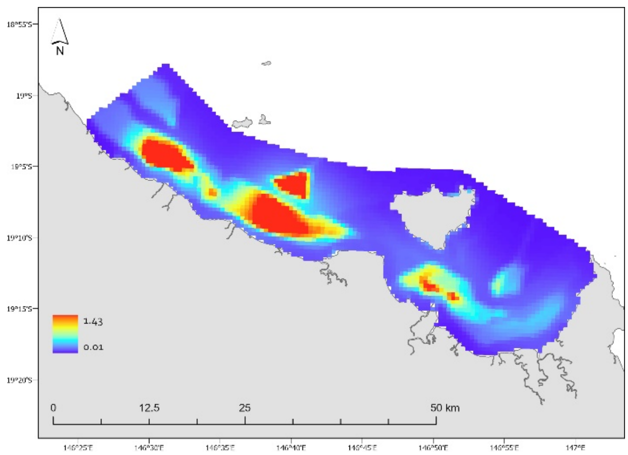
b) 2020



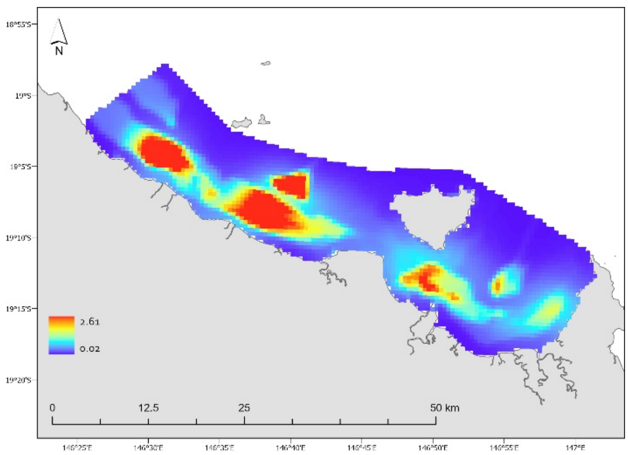
c) 2019



d) 2020



e) 2019



f) 2020

Figure 7. Spatial partial plots of Australian humpback dolphins from ensemble-modelling of species distribution across the survey area based on data collected in 2019 and 2020: (a-b) shows how the probability of dolphins' presence/absence varies spatially over the study area, (c-d) shows how group size varies spatially, and (e-f) shows the relative density (probability of occupancy times group size) of humpback dolphins across the bays.

The species distribution models of both snubfin and humpback dolphins for Cleveland and Halifax Bays in 2020 showed a consistent and high probability of occurrence in waters close to the mainland coast (within 8km) and lower occupancy further offshore (Figs. 6 and 7). This pattern of occurrence was very similar to the one observed in 2019 (Figs. 6 and 7).

In Cleveland Bay, spatial predictions for 2020 showed that snubfin dolphins had a higher probability of occurrence (>50%) in coastal waters (~2-3km from mainland coast) between the Port of Townsville and Alligator and Crocodile Creeks to the east, and along the West Channel between Magnetic Island and Cape Pallarenda (Fig. 6b). In Halifax Bay, snubfin dolphins were more likely to occur in the central (Bohle River to Toolakea) and northern inshore areas (off and west of Toomulla) (Fig. 6b). The spatial predictions of group size and relative density were patchier, but reflected a similar pattern, with high-density hotspots in areas of high occurrence in Both Cleveland and Halifax Bays (Fig. 6d). The patterning of occupancy and relative density were similar in magnitude between 2019 and 2020, but the high-density areas were slightly more expansive in area in 2019 (Fig. 6).

In 2020 humpback dolphins showed have a consistent and high probability of occurrence (>50%) in waters close to mainland coast (~4 – 8km), with lower occurrence further offshore (Fig 7b). This was consistent along the shoreline of both Cleveland and Halifax Bays, except off the tip of Cape Cleveland in Cleveland Bay (Fig. 7b). Areas of high occurrence probability for humpback dolphins in Cleveland Bay were mainly located close to shore between the Ross river mouth and Kissing Point. In Halifax Bay, high occurrence areas were more widespread, extending from Cape Pallarenda to Toolakea and coastal waters off Toomulla (Fig. 7b). Their relative density generally followed the same pattern as the occurrence, however, there were two patches of high-count density that may reflect and increased grouping behaviour offshore (Fig. 7d). These patches occurred to the west of Magnetic Island by 8-12km in Halifax Bay, and in the centre of Cleveland Bay (Fig.7d).

Comparing 2019 and 2020 species distribution models, we see almost the same spatial patterning, except that the probability of occupancy was much greater and more extensive in 2020 (Fig. 7).

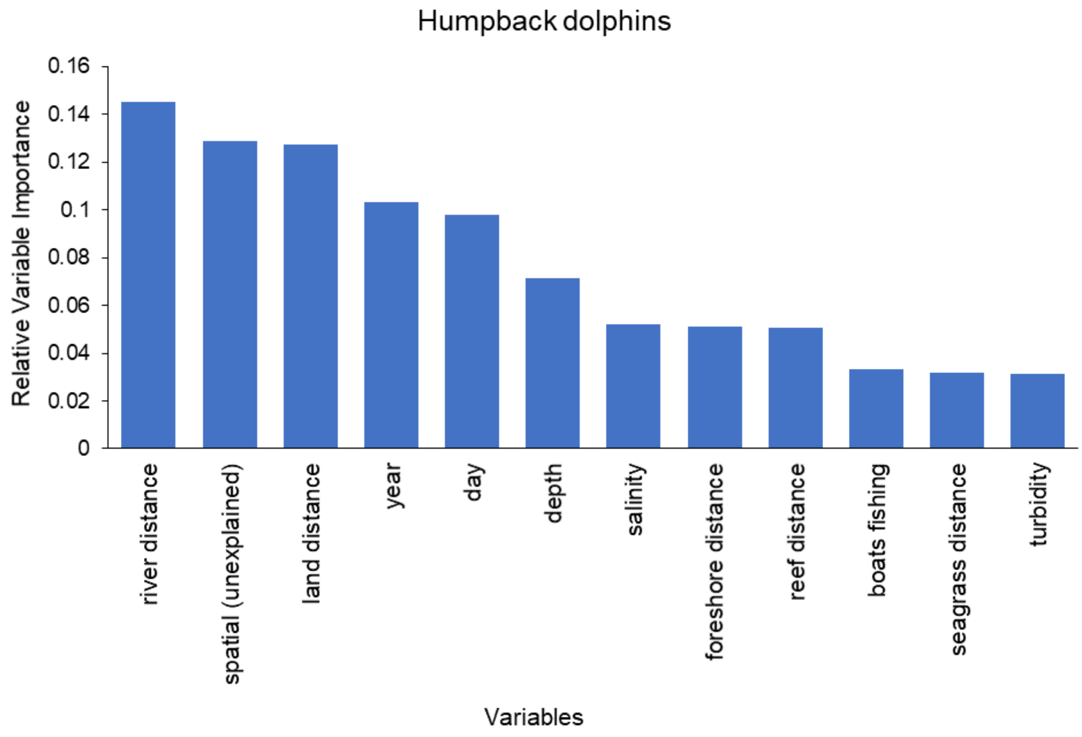
3.2.2 *Relative Variable Importance*

The relative variable importance values (RVI) are shown in Figure 8. The RVIs measure how much each covariate contributes to the reduction in the model risk-function (negative log-likelihood). In other words, it indicates what are the most relevant predictor variables for snubfin and humpback dolphin spatial distribution patterns.

For humpback dolphins, there was not one dominating covariate. The top 5 covariates/processes all had RVIs between 8-15% which were: *distance to rivers*, *space* (in general, unexplained), *distance to land*, and *year* (as an interaction covariate), and *time-of-day*. The high RVI allotted to unexplained spatial variation (12%, rank 2nd RVI), suggests that a lot of the spatial variation was not captured by known covariates. The high allocation to "year" as an interactive covariate (10%, rank 4th RVI) suggests that there was some interannual variation in the spatial distribution patterns of humpback dolphins between 2019 and 2020. The low allocation of RVI to the number of boats (various classes of boats), such as "fishing boats" (3%, rank 10th) suggests that there was no large and measurable interaction between boating activities and dolphin's occurrence.

The RVI statistics for snubfins was dominated by one large spatial process: an unexplained spatial patterning that accounted for 48% of the explained risk-reduction. In other words, we do not know what is driving the snubfin's spatial distribution (even if we can model it). The remaining covariates were all less than 7.1% of the explained risk-reduction. Notably, "year" as an interactive covariate had only 5% RVI, suggesting that interannual variation is less prevalent among Snubfins, or that their spatial distribution changed only slightly between 2019 and 2020.

As was mentioned in the previous report, one should keep-in-mind that ensemble-modelling plus the existence of multi-collinearity among environmental predictors means that it is difficult to assign RVI to any one particular covariate, if it has a lot correlation with other covariates (Bühlmann et al. 2013). However, correlation is not a problem for prediction and species distribution model interpolation, only for attributing explained variation to unique features.



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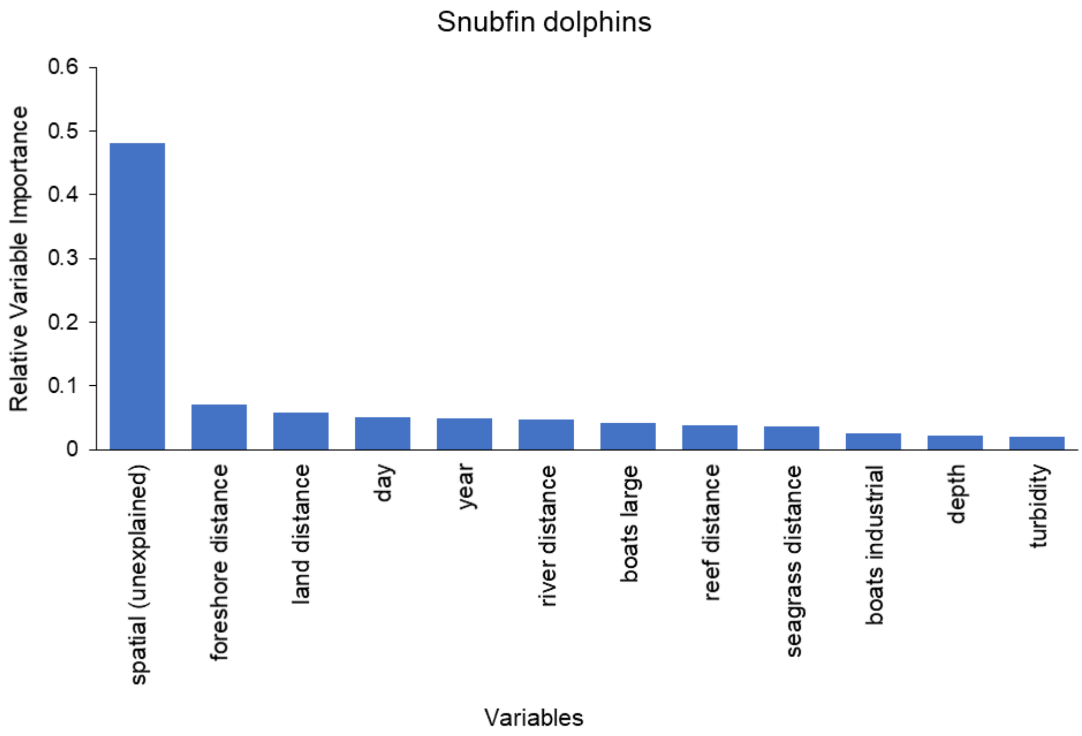


b)

Figure 8. The relative variable importance (contribution to risk-minimisation) of each covariate considered in ensemble species distribution modelling of a) Australian humpback and b) snubfin dolphins based on data collected in 2020.

3.2.3 *Differences between spatial patterns between survey years 2019 and 2020*

Structural Similarity Indices

We calculated SSI values which compared the species distribution model maps in 2019 vs 2020, at multiple spatial resolutions (Table 10). Overall, the SSI showed high spatial correlation (SSI > 0.5) for both species, indicating there were no major changes in the spatial distribution of snubfin and humpback dolphins in the study area between 2019 and 2020. The species distribution model of humpback dolphins had lower SSIs than snubfins, and the SSI statistic decreased as the spatial resolution increased from 100m to 1000m. This suggests broader scale processes are more different between 2019 and 2020 than smaller scale processes (although the correlation is still positive and relatively high ~0.5). In contrast, the snubfin SSI statistics were uniformly high, suggesting a strong correlation and similar spatial distribution in 2019 and 2020. Together the SSI statistics reveal that the snubfins had a consistent spatial patterning across the years, while humpbacks had slightly less interannual correlation, especially at larger scales.

Table 10. Structural Similarity Indices (SSI) between species distribution models of Australian snubfin and humpback dolphins in 2019 and 2020 in the Townsville region.

Species	Spatial Resolution of Predictions (m)		
	100	500	1000
Humpback dolphin	0.75	0.67	0.52
Snubfin dolphin	0.88	0.88	0.85

Likelihood Ratio

The generalized likelihood-ratio between (best) full model and the reduced model (that dropped “year” as a covariate) for humpbacks was 2.04^{-18} which was far less than 1. Using the cross-validation results to approximate a p-value, this p-value was approximately 0.000. For snubfins, the likelihood ratio was 3.95^{-22}, and had an approximate p-value of 0.100. Therefore, for both species, there was strong evidence that the best model should include year as an interaction-covariate, and that there were important interannual differences in the spatial processes influencing dolphin’s spatial distribution. Examination of the species distribution model maps between 2019 and 2020, suggest that the occurrences were slightly more expansive in 2019 for snubfin and more expansive in 2020 for humpback dolphins, but overall dolphins were spatially distributed over similar areas across years (Figs. 6 and 7).

3.3 Patterns of attendance to the port area

3.3.1 *Land based survey effort*

We were able to conduct land-based observations on 18 days between the 22nd of June and the 28th of July, completing a total of 948 scans (compared to 870 scans in 2019) (Table 11). Out of the 18 days surveyed humpback dolphins were seen on 4 days, snubfin dolphins on 9 days, and bottlenose dolphins on 0 days. Similar to last year, there were more observations of snubfins (present in 34 scans) than humpbacks (present in 7 scans) (Table 11). Overall, however, there were less observations of both species in comparison to 2019. In 2019, out of 17 days surveyed, humpback dolphins were sighted on 10 days (over 20 scans), snubfin dolphins on 9 days (over 50 scans), and bottlenose dolphins on one day (over 1 scan). No dolphins were observed within the body of water being enclosed by the rock wall under construction.

3.3.2 *Overall difference in dolphin occurrence between year 1 (2019) and year 2 (2020)*

The quantitative assessment of differences between dolphin occurrence between 2019 and 2020 suggest that there was a significant difference (Table 12). The Bayesian P-values were 0.02 for snubfins, and 0.01 for humpbacks. This assessment is interpreted as the following: assuming the 2019 period served as a null-model of the occupancy, there is a low probability (Bayesian p-value) that the realised counts of dolphins in 2020, of either species, were consistent with the null models. Overall, there was a decrease in the number of snubfin and humpback dolphins that were observed from land-based surveys during 2020.

Table 11. Survey effort and dolphins observed from entrance to Berth 11 at the Port of Townsville during June-July 2020. BSS= Beaufort Sea State at which observations were conducted.

Date	Number of scans	Number of scans with humpback dolphins present	Number of scans with snubfin dolphins present	Number of scans with bottlenose dolphins present	BSS min	BSS Max	BSS Mode
2020-06-22	48	0	0	0	1	2	1
2020-06-23	48	0	0	0	1	3	1
2020-06-24	42	0	0	0	1	4	1
2020-06-25	48	0	0	0	1	4	2
2020-07-04	48	4	0	0	1	3	1
2020-07-11	48	0	0	0	1	3	2
2020-07-12	50	0	0	0	1	3	1
2020-07-15	48	0	7	0	1	3	1
2020-07-16	54	0	4	0	1	4	1
2020-07-17	50	0	6	0	0	4	1
2020-07-18	62	0	0	0	1	4	1
2020-07-19	62	0	0	0	0	3	1
2020-07-20	54	0	8	0	1	4	1
2020-07-21	40	0	0	0	1	3	2
2020-07-25	60	0	0	0	1	3	1
2020-07-26	60	2	3	0	1	2	1
2020-07-27	64	0	3	0	0	3	1
2020-07-28	62	1	3	0	1	3	1
TOTAL	948	7	34	0			

Table 12. Comparison of dolphin occurrences between 2019 and 2020 by Bayesian P-values.

Species	Year	Number of Scans	N occurrences of dolphins	Bayesian P-value
Snubfin	2019	869	49	
	2020	948	34	0.02
Humpback	2019	869	19	
	2020	948	7	0.01

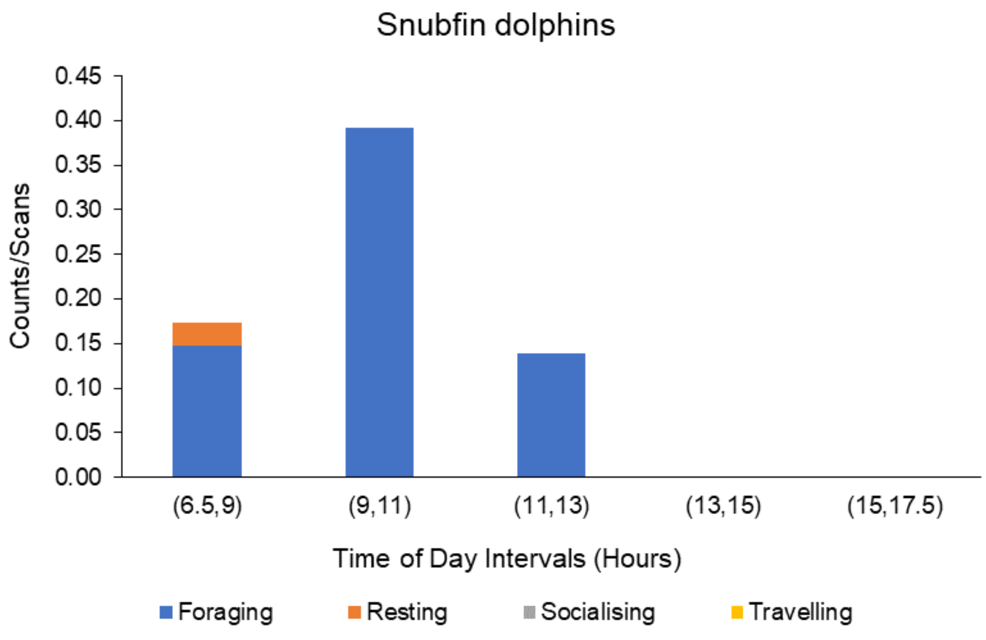
3.3.3 *Diel and behavioural patterns observed*

Both snubfin and humpback dolphins were observed mainly foraging around the port (Table 13). Snubfin dolphin sightings peaked in the morning at 9:00-11:00 and were absent in the afternoon from 13:00 onwards (Fig. 9). Humpback dolphin sightings peaked between 11:00-13:00, were also observed in the afternoon (13:00-17:00), but not seen in the early morning (7:00-9:00) (Fig. 9). Throughout the morning hours snubfin dolphins were seen foraging, whereas humpbacks were observed socializing in the morning (9:00-11) and mostly foraging from 11:00 onwards (Fig. 9).

For comparison across both survey years (2019 and 2020), the pooled distribution of species counts by time-of-day, and by behavior, are also shown in Fig 10. The pooled estimates likewise reveal that snubfin dolphins spend most of their time foraging and travelling in the morning between 7-11, whereas humpbacks are more consistent across the day, in both foraging and travelling.

Table 13. The total number of scans where either species was present (and behaviour could be determined) during 2020 land-station surveys, and the proportion of times they were observed engaged in foraging, resting, socializing and travelling behavior. The pooled numbers for survey years 2019 and 2020 are also shown below.

Species	Year	Number of Scans with Species Present	Foraging	Resting	Socialising	Travelling
Snubfin	2020	29	0.97	0.03	0.00	0.00
Humpback	2020	7	0.71	0.00	0.29	0.00
Snubfin	Pooled 2019/20	76	0.75	0.03	0.03	0.20
Humpback	Pooled 2019/20	25	0.56	0.00	0.08	0.36



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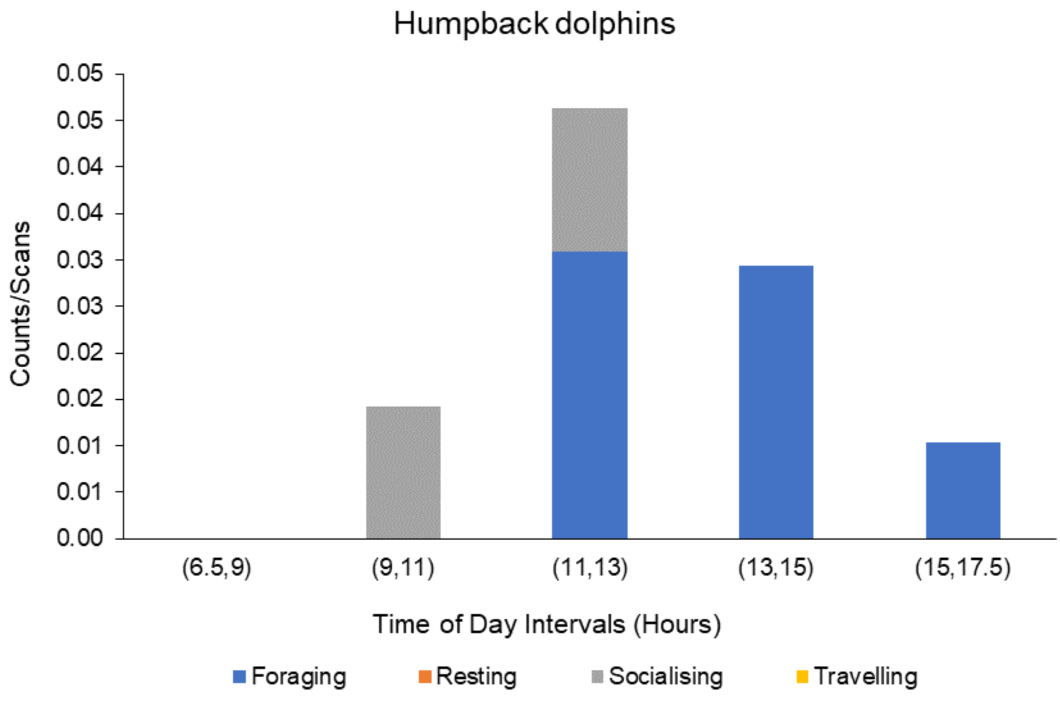
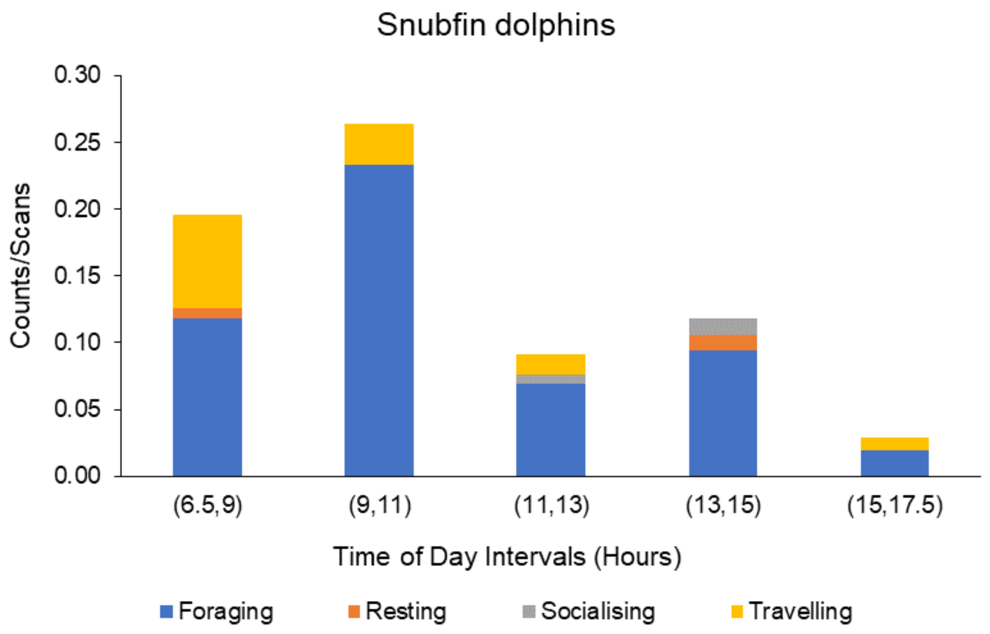


b)

Figure 9. a) Australian Snubfin and b) humpback dolphin observations by time of day (approximately 2 hourly bins) in 2020. Bar height represents densities of counts (number of dolphin's groups seen divided by number of scans); bar compositions represent proportion time observed in various behaviours.



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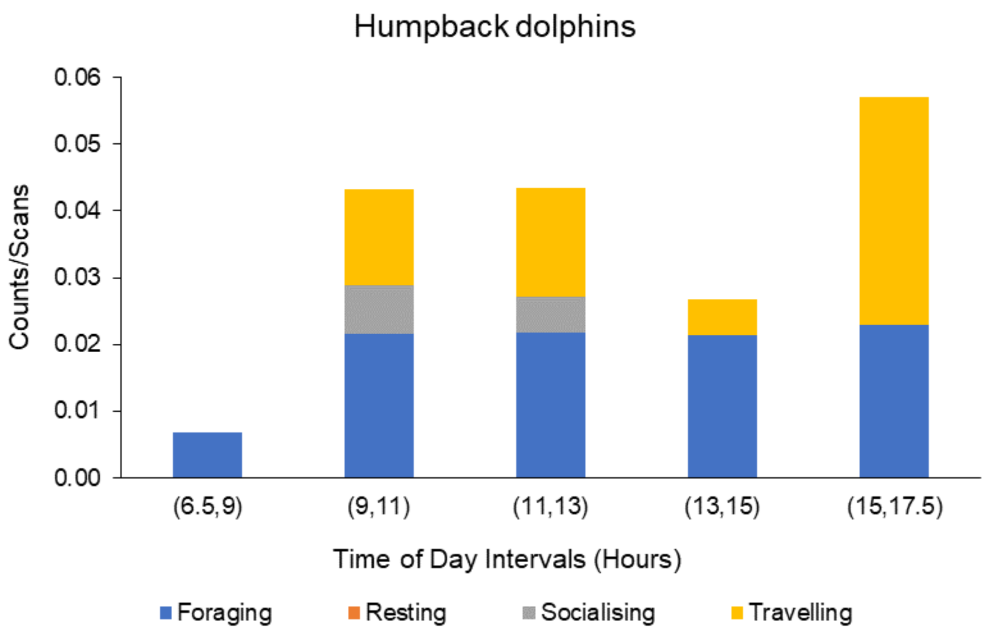
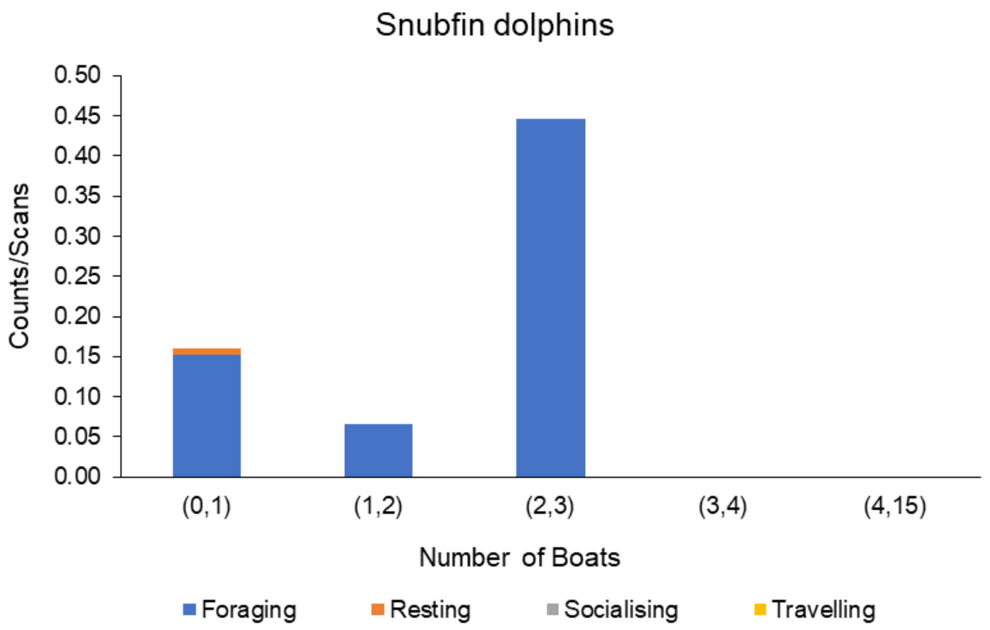


b)

Figure 10. Pooled observations (2019 and 2020) of a) snubfin and b) humpback dolphins by time of day (2 hourly bins). Bar height represents densities of counts (number of dolphin groups seen divided by number of scans); bar compositions represent proportion time observed in various behaviours.

3.3.4 *Dolphins patterns of occurrence in relation to boats, dredging and rock dumping*

In relation to the presence of boats in 2020, snubfin dolphins seemed to become absent as the number of boats increased (Fig. 11a). This was very different from the pooled counts of boats and behaviours (pooled for both 2019 and 2020), where the differences in behaviours and counts was not obviously related to the number of boats present (Fig. 12a). Humpback dolphins appeared to shift their behavior from foraging at low-boat presence, to travelling at high-boat presence. This pattern seemed pronounced during the 2020 survey year (Fig. 11b) but was not so obvious when compared to the pooled distribution of boats and behaviours across both 2019 and 2020 (Fig. 12b). In the latter case, the heterogeneity of all behaviours seemed to be greater as the number of boats increased.



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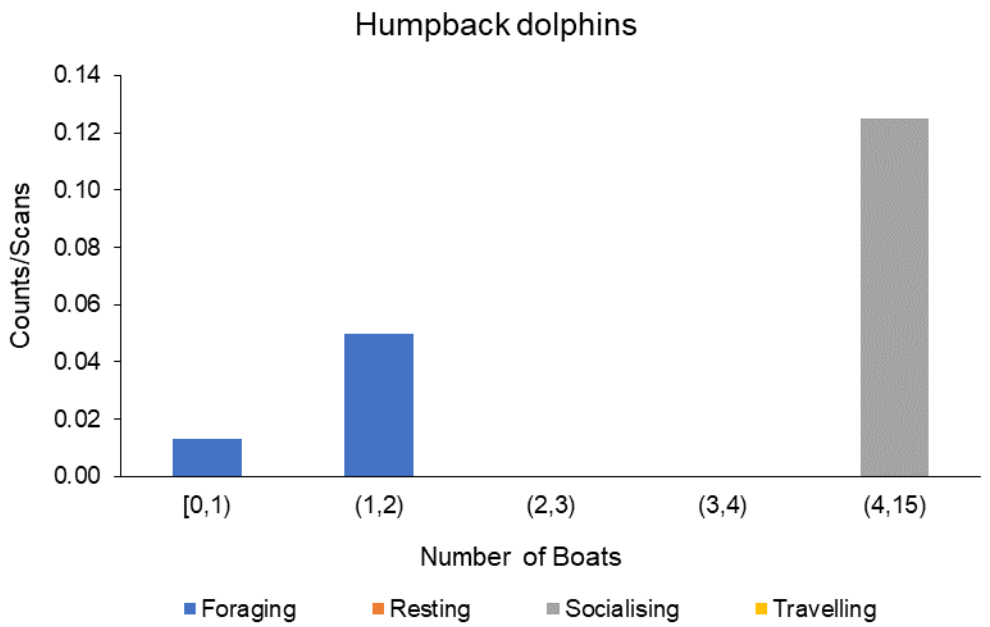
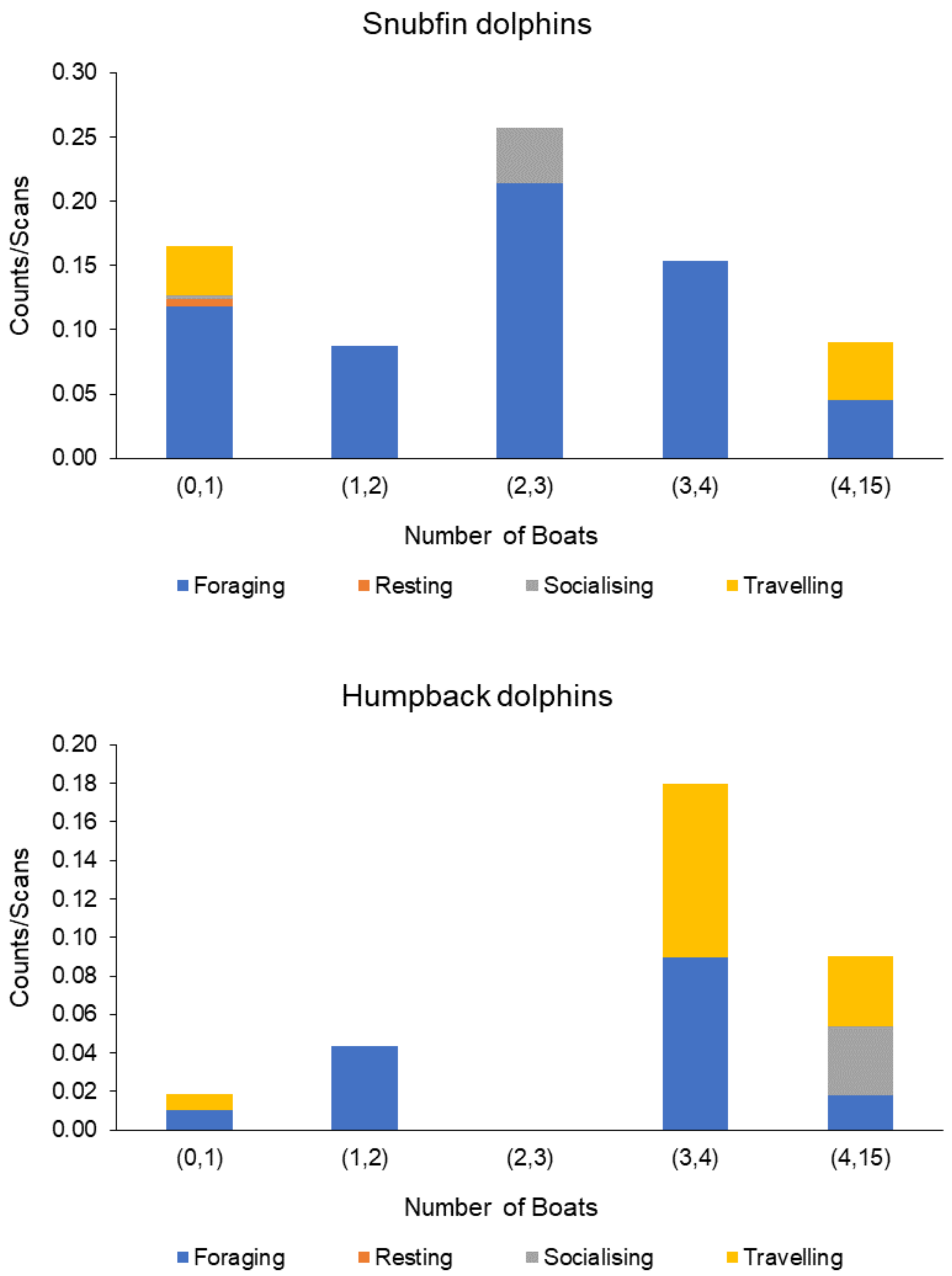


b)

Figure 11. Counts of a) snubfin and b) humpback dolphins groups observed and their behaviours, stratified by the number of boats present, for the 2020 survey-year. Bar height represents densities of counts (number of dolphin groups seen divided by number of scans).



b)

Figure 12. Counts of a) snubfin and b) humpback dolphins groups observed and their behaviours, stratified by the number of boats present, and pooled across survey years 2019 and 2020. Bar height represents densities of counts (number of dolphin groups seen divided by number of scans).

Out of 948 scans carried out from Berth 11, maintenance dredging by the trailing suction hopper dredger (TSHD) Brisbane was recorded during three scans. While there were no observations of dolphins, of either species, during the dredging activities (Table 14), the high P-Bayes statistics suggest that the probability of observing no-dolphins was consistent with the background/null distribution of dolphin-occupancy during normal non-dredging scans. In other words, the absence of dolphins during dredging cannot be considered unusual.

Table 14. Land-based occurrences of snubfin and humpback dolphins from Berth 11 during dredging and non-dredging operations in 2020 (*top*) as well as pooled across survey-years 2019 and 2020 (*bottom*).

Species	Year	Dredging Presence	N-scans	N Occurrences of Dolphins	P-Bayes
Snubfin	2020	no	945	34	NA
		yes	3	0	0.89
Humpback	2020	no	945	7	NA
		yes	3	0	0.98
Snubfin	Pooled 2019 and 2020	no	1805	83	NA
		yes	12	0	0.57
Humpback	Pooled 2019 and 2020	no	1805	26	Na
		yes	12	0	0.84

The above results were similar to the statistics from the 2019 analyses. When we pooled counts of dredging and dolphin counts across both 2019 and 2020, the Bayesian P-statistics are lower (i.e., more concerning) but not low enough to conclude that the counts were inconsistent with the null-model (no-dredging). Note that in 2019 and 2020 no capital dredging occurred, dredging activities were limited to maintenance dredging.

Rock-dumping activities were present during 401 of the visual scans in 2020. There were no rock-dumping activities during 2019. Table 15 shows the Bayesian P-values comparing counts of dolphins when dumping was present vs the null-model (no rock-dumping present). Snubfins had a high p-value (0.98) suggesting no differences in the patterns of their occurrence in relation to rock dumping. In contrast, humpbacks dolphins had a very small p-value (0.01) suggesting that their patterns of occurrence around the port were different from the null-model. The occurrence of humpback dolphins around the port appears to have decreased during rock dumping activities (0 occurrence of humpbacks during all the rock-dumping activities, versus 7 occurrences during non-rock-dumping scans). However, interpretation should be taken with caution as the number of humpback dolphins sighted during non-rock-dumping activities was low (n =7) .

Table 15. Land-based occurrences of snubfin and humpback dolphins from Berth 11 during rock dumping and non-dumping scans in 2020.

Species	Rock-Dumping Present	Number of Scans	N occurrences of dolphins	Bayesian P-value
Snubfin	no	542	14	NA
	yes	397	20	0.98
Humpback	no	542	7	NA
	yes	397	0	0.01

4. Discussion and conclusions

4.1 Survey effort

The 2020 early-construction monitoring of inshore dolphins for the Port of Townsville proceeded well despite some weather and logistical constraints, largely surrounding COVID-19 travel related restrictions on staffing. As planned, we were able to repeat six full surveys of Cleveland and Halifax Bay between June-July. Most survey effort focused on inshore waters due to predominant unfavourable conditions (Beaufort Sea State > 4) encountered in offshore transects, which was similar to 2019.

As in previous year, we were not able to survey Bowling Green Bay because boat-ramp at Cape Fergusson is still not accessible due to floods and rain in February and March 2019. We do not foresee Bowling Green bay been accessible in the future and given the two years of monitoring already underway we recommend continuing to focus survey effort on Cleveland Bay and Halifax Bay.

4.2 Estimates of Abundance

Adequate data were available to obtain estimates of abundance for snubfin and humpback dolphins in Cleveland Bay and Halifax Bay using closed capture-recapture population models. The total number of snubfin dolphins using Cleveland Bay and Halifax Bay in 2020 was estimated at 143 (95% CI = 47-435) and 73 (95% CI =38-140) individuals, respectively (Table 9). The total population size of humpback dolphins was estimated at 50 (95% CI = 31-81) individuals for Cleveland Bay and 74 (95% CI = 51-107) individuals for Halifax Bay (Table 9). In the future, similar data collected over three years will support the use of Multistate Closed Robust Design models (MSCRD) to estimate rates of apparent survival (alive and in the area), temporary emigration and potentially also movement between sites in addition to population sizes.

In comparison to last year, our 2020 abundance estimates indicated that snubfin and humpback dolphins were more abundant in Cleveland Bay and less so in Halifax Bay than in 2019 (Table 9). There was considerable overlap in the confidence intervals around the estimates across years however, suggesting that there has been no major change in the abundance of either species in Cleveland or Halifax Bay. Some of the abundance estimates for 2020, particularly the one for snubfin dolphins in Cleveland Bay, should be interpreted with caution due to potential biases because of low and heterogeneous capture probabilities.

In contrast to 2019, heterogeneity in capture probabilities was observed in the 2020 data for snubfin dolphins in Halifax Bay and humpback dolphins in Cleveland Bay. Heterogeneous and low capture probabilities are a common problem in many capture—recapture studies, particularly of species occurring at low densities such as humpback and snubfin dolphins, and can lead to biased estimates of abundance when using models assuming no heterogeneity (Otis et al. 1978, Amstrup et al. 2005). Therefore, we used models that incorporate heterogeneity of capture probability and corrected for the observed heterogeneity (Chao 1987). In 2020, the estimated capture probabilities ranged from 0.22 to 0.29 except for snubfin dolphins in Cleveland Bay which were 0.08. Capture probabilities greater than 0.20 are adequate to support reliable population size estimates with relatively good precision while a capture probability of 0.08 is not. Consequently, while the estimates for humpback dolphins in both bays and snubfin dolphins in Halifax Bay are considered reliable (CVs ranging from 0.19 to 0.34), the estimate of the number of snubfin dolphins in Cleveland Bay (143, 95% CI = 47-435) is questionable (CV=0.62). The uncertainty that their low capture probability generates is reflected in the wide 95% confidence interval. The low capture probabilities of snubfin dolphins in 2020 can stem from spatial aspects of sampling (e.g. dolphins occurred in lower density and were not encountered often within the area sampled), sampling (e.g. failure to obtain good quality photographs of individuals within each group encountered) and behaviour (animal encountered were difficult to approach, animals spending more time outside than inside study area). The low capture probabilities encountered this field season are likely a result of a combination of all these factors.

The confidence intervals around future population size estimates from an MSCRD model may be narrower than those obtained from closed population models due to parameter sharing and a higher data to parameters ratio. The use of the planned MSCRD model in the future and the estimation of apparent survival, temporary emigration, and especially movements between sites, in addition to abundance will depend highly on obtaining as good or better capture probabilities as those obtained here.

In summary, despite some uncertainty associated with 2020 abundance estimates due to low capture probabilities (snubfin dolphins in Cleveland Bay) and heterogeneity effects (snubfin dolphins in Halifax Bay and humpback dolphins in Cleveland Bay), abundance estimates of snubfin and humpback dolphin in Cleveland and Halifax bay fall within the range of past estimates and do not show a decreasing trend in population size.

4.3 Spatial distribution

The species distribution models of both snubfin and humpback dolphins for 2019 and 2020 in both Cleveland and Halifax Bays showed a consistent and high probability of occurrence in waters close to the coast and lower occupancy further offshore (Figs. 6-7). Their relative density generally followed the same pattern as their occurrence, with areas of high occurrence also being the most with high density of dolphins. The high use of inshore waters in Cleveland Bay and Halifax Bay by snubfin and humpback dolphins corroborates what has been observed in previous studies (Parra 2006, Nagombi 2018), indicating the continued importance of coastal habitats for these species.

Comparison of the spatial predictions of species distribution models maps using the Structural Similarity (SSIM) index revealed a strong correlation across years (Table 10). This indicated that there were no major changes in the spatial distribution of snubfin and humpback dolphins in the study area between 2019 and 2020. The generalized likelihood-ratio showed that the best model should include year as an interaction-covariate, and that there were marginal but important interannual differences in the spatial processes influencing dolphin's spatial distribution. Such marginal variations per year are expected given the seasonally dynamic nature of the covariates involved in the models and the distributional dynamics of highly mobile species such as dolphins.

4.4 Patterns of attendance to the port area

Land-based observations from the entrance to Berth 11 within the Port of Townsville in 2020 were feasible throughout the day on good weather conditions. It is important to note, as we mentioned earlier, that during 2020 we used a different observation point than 2019. Although the new observation point is relatively close to the one used in 2019 (~400m away), it is not as high above sea level (LAT +8.22m above water) as the one use during 2019 (LAT+9.5m above water) and thus observers visibility was reduced. Thus, the result of our comparisons and inferences regarding dolphin's presence/absence around the port in 2020 and 2019 should be taken with caution, as we cannot separate the effect the new observation point may have on dolphin observations. It is strongly recommended that the observation point for the remainder of the project stays fixed on the elevated point at Berth 11 used in 2019 as to not compromise any future comparisons.

Both snubfin and humpback dolphins were observed in inshore waters adjacent to the Port (Table 11). Despite similar observation effort across years, comparison of dolphin occurrences between 2019 and 2020 revealed significant differences, with less observations of both species in 2020 (Table 12). The low number of dolphin observations in 2020 may be a result of dolphins using the waters around the port less frequently or simply a result of the lower vantage point used for observations during 2020. The latter seems more likely, given the sightings and the dolphins high probabilities of occurrence in areas around the port revealed by boat surveys (Fig. 5) and species distribution models (Fig. 6).

As in previous year, both species were observed mainly foraging (Table 13) around the port throughout different hours of the day, with snubfin dolphin sightings peaking in the morning at 9:00-11:00 and humpback dolphins sightings peaking towards midday between 11:00-13:00 (Fig. 9). In relation to the presence of boats in 2020, snubfin dolphins seemed to become absent as the number of boats increased , while humpback dolphins appeared to shift their behavior from foraging at low-boat presence, to travelling at high-boat presence (Fig.11). This pattern seemed pronounced during the 2020 survey year but was not so obvious when compared to the pooled distribution of boats and behaviours across both 2019 and 2020 (Fig. 12).

While there were no observations of dolphins, of either species, during the maintenance dredging activities (Table 14), the probability of observing no-dolphins was consistent with the background/null distribution of dolphin-occupancy during normal non-dredging scans. Therefore, the absence of dolphins during dredging cannot be considered unusual.

Snubfin dolphins' patterns of occurrence around the port did not seem to be affected by rock-dumping activities associated with the rock wall construction (Table 15). In contrast, the occurrence of humpback dolphins around the port decreased during rock dumping activities (Table 15). Due to the differences in the location of the observation point we cannot be certain the decrease in sightings of humpback dolphins is a result of rock-dumping activities.

Despite the limitations involved due to the change in the spatial location of our observation point, land-based observations together with vessel observations and species distribution models corroborated the frequent occurrence and use by both dolphin species of the coastal waters around the Port of Townsville, mainly for foraging and travelling activities as has been shown in the past (Parra 2006, Nagombi 2018).

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