INSPIRING ACHIEVEMENT

Port of Townsville Inshore Dolphin Monitoring Program Report

Analysis of the fifth field season (June - July 2023)

(Photo CEBEL, Flinders University ©)

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Executive Summary

This report presents the results of the Inshore Dolphin Monitoring Program (IDMP) for the Port of Townsville Limited (POTL) Channel Upgrade Project (CU Project). The data collected in 2023 during boat and land-based surveys were summarized and compared to previous years (2019-2022). The study investigated any changes in coastal dolphin abundance and distribution beyond natural spatial and temporal variations since 2019.

As in previous years, in 2023 the IDMP methodology involved boat-based photo-identification surveys of dolphins in Cleveland and Halifax Bays and visual land-based surveys of dolphins from Berth 11 within the Port of Townsville in Cleveland Bay. Data analysis of dolphin sighting data collected during boat surveys involved capture-recapture and species distribution modelling methods to assess differences in population demographics and spatial patterns across survey years (2019-2023). Land-based survey data was analysed using Bayesian p-values and Generalized Additive Models (GAMs) to assess overall differences in dolphin occurrence across all four years (2019-2023) in relation to anthropogenic activities associated with the CU project in Cleveland Bay and that coincided with the dolphin monitoring, including rock dumping (associated with rock wall construction in 2020), capital dredging (i.e., dredging carried out by a backhoe dredger in 2022 and 2023), and pile driving (2022). We also assessed the dolphins' patterns of occurrence in relation maintenance dredging (2019, 2020 and 2023) not associated with CU Project (i.e., routine dredging carried out by a trailing suction hopper dredger every year to remove material that has drifted into the channel over time and limits the access of ships).

Three vessels undertook simultaneous, predetermined line-transect surveys over 14 days between June 9 and July 7, 2023, covering 1229.9 km in Cleveland Bay and 1075.5 km in Halifax Bay between. We observed a total of 31 groups of snubfin dolphins (2 in Cleveland

Bay and 29 in Halifax Bay), 50 groups of humpback dolphins (26 in Cleveland Bay and 24 in Halifax Bay) and 21 groups of bottlenose dolphins (2 in Cleveland Bay and 19 in Halifax Bay). Ten individual snubfin and 51 humpback dolphins were photo-identified in Cleveland Bay, and 52 snubfin and 40 humpback dolphins were photo-identified in Halifax Bay in 2023. At the same time, we completed a total of 19 days of visual survey scans from the land-based observation point on Berth 11. Humpback dolphins were observed on 16 days. Snubfin and bottlenose dolphins were not seen on any day.

The total estimated abundance of snubfin dolphins in Cleveland Bay was stable over the first three years of monitoring with 31 in 2019, 42 in 2020, and 34 in 2021. During 2022 and 2023 we had very few sightings of snubfin dolphins in Cleveland Bay and therefore the abundance estimates obtained for these years from the modelling are unreliable and likely to overestimate the abundance. A model that assumed the probability of capture in these years was the same as the mean from the first three years failed to yield an estimate for 2022 and estimated 15 snubfin dolphins for 2023. The estimated total abundance of snubfin dolphins in Halifax Bay decreased from 56 in 2019 to 36 in 2020 and 33 in 2021 before increasing to 117 in 2022 and falling to 76 in 2023. The number of humpback dolphins present in Cleveland Bay increased from 19 in 2019 to 33 in 2020 and 2021 and increased again to 49 in 2022 and 90 in 2023 (Fig. 9). Humpback dolphin numbers were higher in Halifax Bay than in Cleveland Bay in most years, with 65 in 2019, 53 in 2020, 42 in 2021, and 77 in 2022. However, in 2023, Cleveland Bay had more humpback dolphins than Halifax Bay, with an estimated 90 individuals.

Snubfin dolphin numbers in Halifax Bay rose sharply in 2022 and 2023 due to increased movements from Cleveland Bay, reduced emigration, and immigration from outside the region. However, the simultaneous drop in population estimates between 2022 and 2023 indicates that many dolphins first identified in 2023 were already present but undetected, meaning the surge in first captures reflects both true immigration and a lag in detection rather than a sudden population increase.

The decrease in the number of sightings of snubfin dolphins in Cleveland Bay and relative increase in Halifax Bay over the last two years are reflected in their space use. Species distribution models of the spatial occurrence of snubfin dolphins and their relative density showed a marked departure from earlier years: with low occupancy and density in the region north and to the east of Port of Townsville, along the shore of Cleveland Bay, and a new elongated narrow band of moderate occupancy and density along the entire coast of Halifax Bay. In contrast, humpback dolphins continue to show high occupancy and density to the north and to the east of Port of Townsville, along the shore of Cleveland Bay, as well as a large expanse of high-occupancy and density between Saunders Beach and Cape Pallarenda in Halifax Bay. Generalised likelihood ratio tests to evaluate whether the disturbance covariates had an important contribution to the snubfin and humpback dolphins distributions, provided evidence that some disturbances had some effect. Based on RVI values both capital and maintenance dredging appear to have a small influence on snubfin dolphins spatial distribution, and counts of large boats, fishing boats and maintenance dredging on humpback dolphins spatial distribution. Covariate interaction plots suggested that snubfin dolphin density increased with proximity to maintenance dredging but also increased with greater distance from capital dredging. For humpback dolphins, covariate interaction plots indicated that their density increased with a higher number of large boats, decreased with more fishing boats, and increased with greater distance from maintenance dredging. Thus, why we may see a decrease in snubfin dolphins occurrence and density in Cleveland Bay where capital dredging took place.

The quantitative assessment of differences in snubfin dolphins patterns of attendance to the port area between 2023 and all previous years suggest that 2023 was quite different than the first three years of monitoring (2019-2021) and more similar to 2022. As in 2022, the number of encounters of snubfin dolphins was lower than expected based on previous years. In contrast, the number of encounters of humpback dolphins around the port were in line (or greater) than the expectations of previous years. The analysis of dolphin presence with respect to disturbances around the port indicated that: 1) snubfin dolphin occurrence decreased when capital dredging was present and/or active but increased during rock dumping; 2) humpback dolphin occurrence decreased when rock dumping was active but increased with both construction and maintenance dredging.

Overall, the available data from both boat and land-based observations indicate that the occurrence and abundance of snubfin dolphins in Cleveland Bay and their pattern of attendance to the port area decreased in 2022 and 2023 in comparison to previous years, while their presence and abundance has increased in Halifax Bay. In contrast, humpback dolphin abundance and occurrence have increased in Cleveland Bay while remaining relatively stable in Halifax bay over the study period.

The changes in population demographic parameters and patterns of attendance of snubfin dolphins to the port area coincided with CU capital dredging and piling activities in Cleveland Bay in 2022 and 2023. The data indicates snubfin dolphins decline in presence and numbers is correlated with capital dredging being present and/or active. It is important to note that these correlations do not imply causation. Our comparisons are informed on correlations between species abundance, occurrence and construction activities related to CU project, which may be causal but may also be contingent on a variety of extrinsic (e.g., climate, competitive exclusion, or dispersal limitation) and intrinsic factors (e.g., diet, habitat specialization) that could influence a species' occurrence and that are not accounted for in this study. Moreover, temporal delays in marine mammals' response to pressures are often expected, and changes in population abundance, distribution and behavior often lag several years behind habitat loss or degradation caused by environmental and anthropogenic disturbances. Therefore, the reduction in the abundance of snubfin dolphins in Cleveland Bay and their declined presence around the port area observed in 2022 and 2023 could also represent a delayed response to habitat loss following the completion of the rock wall construction for the 62-ha port reclamation area at the eastern end of the Port in 2021. As we gather more data over the next years (post construction activities) we will be able to assess if such changes are temporary and further elucidate the seasonally dynamic nature of the covariates involved in the models and the distributional dynamics of these highly mobile species.

1. Introduction

The Townsville Port Channel Upgrade Project (CU Project) is a jointly funded 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 2024. 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.

IDMP of snubfin and humpback dolphins for the CU project commenced in June 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 the initial marine construction activities of the rock wall which was completed in 2021 and formed 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. Pile driving activities for the CU Project started in 2021 and were limited to the development of the temporary unloading facility (TUF), mooring infrastructure for the discharge of dredge material from barges to the reclamation area and for the re-alignment of the channel navigational beacons. TUF piling was intermittent from Aug 2021 to Early Jan 2022, and beacon piling (20mins per day and not on consecutive days) was carried out in June/July 2022 and Feb 2024.BCapital dredging activities (using a backhoe dredge) associated with the widening of the shipping channel started in 2022 in Cleveland Bay. 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 2023 inshore dolphin monitoring program, and report on any changes, beyond natural spatial and temporal variation, in coastal dolphin abundance and distribution in association with the CU Project 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 2023 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 inductions and were trained in survey techniques and protocols between the 29th and the 31st of May 2023, 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).

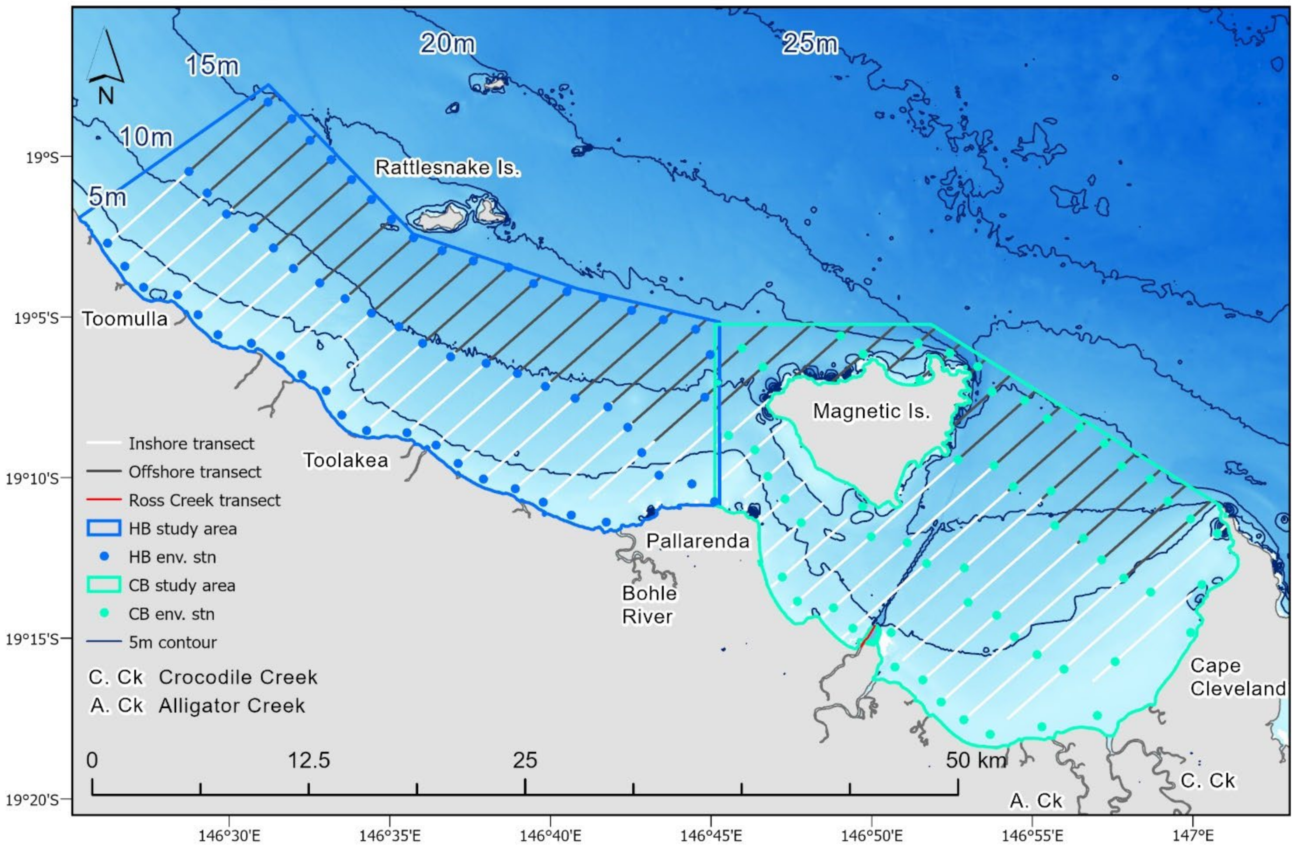


Figure 1. Map of Cleveland and Halifax Bays study areas including inshore and offshore transects, Ross Creek transect, and environmental stations.

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 dolphins' 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.

As in previous years, we used three rigid hull inflatable boats (RHIBs) (Fig. 2) to simultaneously survey different areas of each bay during June-July 2023 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/).

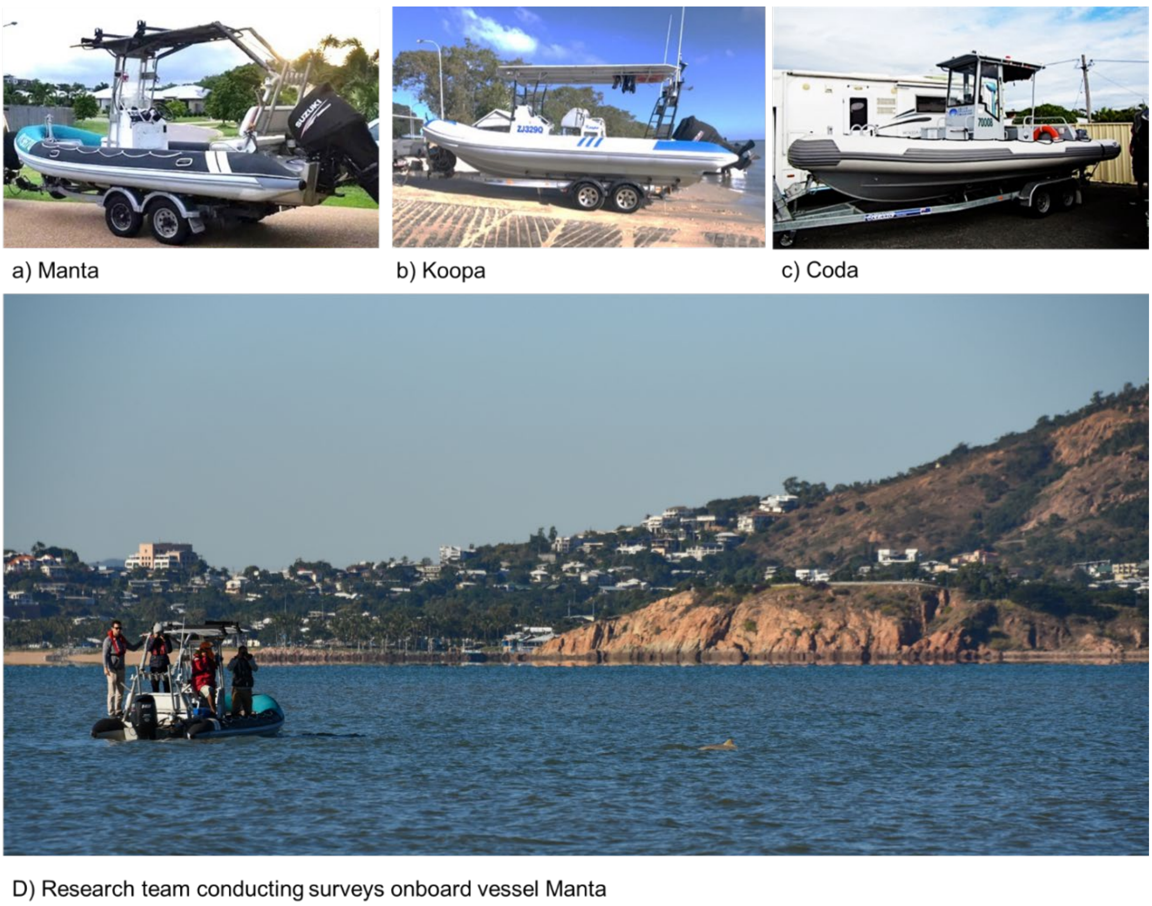


Figure 2. Rigid hull inflatable boats a) RV Manta, b) RV Koopa and c) RV Coda used for boat-based surveys of inshore dolphins in the Townsville region during June and July 2023.

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

2.1.4 *Land-based survey methods*

Land-based observations of dolphin presence/absence around the port were mostly carried out from Berth 11, an elevated platform (LAT + 9. 5m above water) within the Port of Townsville (Fig. 3). Berth 11 offers a reasonable vantage point over coastal waters adjacent to the Port of Townsville that were previously identified as a dolphin high use area (Parra 2006). This area also coincides with the CU project area for land reclamation and widening of the channel at the harbour entrance (Fig. 3). Land-based observations of dolphin presence/absence around the port in 2020 were carried out at the entrance to Berth 11 (~400m south of original observation point) due to shipping activities, and a three-week maintenance shutdown of the ship loader. 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 including capital dredging, rock dumping and pile driving operations (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 Berth 11. Observations were conducted by a team of two-three trained observers doing one or two three-hour shifts per day between 06:00 and 18:00 depending on weather conditions. 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, presence/absence of maintenance dredging (i.e., routine dredging, not associated with CU construction activities, carried out by a trailing suction hopper dredger every year to remove material that has drifted into the channel over time and limits the access of ships), and the presence or absence of CU construction activities including rock dumping (associated with rock wall construction in 2020), capital dredging (i.e., dredging carried out by a backhoe dredger in 2022), and piling (beacon pile driving carried out in June/July 2022).

a) Berth 11 b) Researchers conducting observations

Figure 3. Location of (a) land observation point on Berth 11 within the Port of Townsville, and (b) researchers conducting dolphin surveys from the berth.

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 across all years of study 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 the program MARK (White and Burnham 1999).

Note that as we add a new year to the dataset the capture-recapture models are updated and thus the corresponding population demographic estimates for every year. Furthermore, every year the photo-identification catalogue is revised and corrected for any misidentification error (i.e., false negative: one individual is identified as two, false positive: two individuals are identified as one).

2.2.2 *Capture-recapture models*

The Multistate Closed Robust Design model (MSCRD, Brownie et al. 1993, Nichols and Coffman 1999, Kendall and Nichols 2002, Kendall 2013) was employed for analysis of the capture-recapture data to estimate abundance, apparent survival, and movements between sites and temporary emigration between primary samples. The MSCRD extends the Closed Robust Design model (CRD, Pollock 1982, Kendall and Nichols 1995, Kendall et al. 1995, Kendall et al. 1997) to include multiple states following the multistate model for recapture data (Arnason 1972, 1973, Brownie et al. 1993, Schwarz et al. 1993).

The MSCRD model provides estimates of:

1. Apparent survival ($\hat{\phi}$) between primary samples (probabilities of being alive and present in the sample area) for both sites.

2. Movements between sites (ψ MS) and temporary emigration (ψ TE) between primary samples (probabilities of movement between states). Temporary emigration is included among the movements in the MSCRD by defining an 'unobservable' state for dolphins that are temporarily absent (offshore or elsewhere) during a primary sample. There are two parameter estimates for temporary emigration in any primary sample: the probability of being absent from the sampling area in that primary sample (emigration) and the probability of returning in that primary sample after an absence (reimmigration).

3. Abundance at each primary sample (N, number present on a site) for both sites.

With two sites, three states were defined: two observable states on the two sites (CB and HB) and one unobservable state (U) for temporary absence from both sites. Dolphins may move between all three states (or stay where they were) between consecutive pairs of primary samples, with such movements being modelled as transition probabilities.

Different patterns or structures of temporary emigration may be estimated by applying constraints to the corresponding temporary emigration and (re) immigration parameters. An implication of estimating these separately is that the probability of emigration in an interval is related to the probability of emigration in the previous interval or has a Markovian temporal structure. When the probability of emigration in an interval is equal to the probability of staying away after a previous absence, whether an animal comes or goes is a random process and the temporary emigration structure is referred to as 'random'. When the probability of emigration in an interval is equal to the probability of immigration after a previous absence there is an even flow of animals into and out of the sample area and the temporary emigration structure is referred to as 'even flow'. Kendall (2013) may be the most accessible account of these temporary emigration structures.

Capture-recapture studies typically yield an estimate of apparent survival or the probability of both remaining alive and available for recapture in the sample area. Estimates of the probability of remaining alive (biological survival) must be made by other means. If estimates of both apparent and biological survival are available however, an estimate may be made of the probability of permanent emigration from the sample area. More formally, an estimate of the probability of permanent emigration $\hat{E}$ may be derived as $\hat{E} = 1 - \frac{\hat{\phi}}{\hat{S}}$ where $\hat{\phi}$ is an estimate of the probability of apparent survival and $\hat{S}$ is an estimate of the probability of biological survival.

Life history data on Australian inshore dolphins that might support an estimate of the rate of biological survival for a species are extremely limited. Studies on the Indo-Pacific humpback dolphin (*Sousa chinensis*) in the Pearl River Estuary in southern China (Huang et al. 2012) yielded an estimate of biological survival of 0.97 (95% CI = 0.96-0.98) per annum. The Indo-Pacific humpback dolphin is a close relative of the Australian humpback dolphin and the biological survival rates of the two species may be expected to be similar. The adult survival rate for the Australian snubfin dolphin (*Orcaella heinsohni*) was reported as 0.95 per annum by Taylor et al. (2007).

2.2.3 *MCRD Data preparation*

The MSCRD requires data identifying whether each individual dolphin was or was not captured in each combination of primary and secondary sample (PS x SS). There were many examples of the same dolphins having been captured more than once in the same primary and secondary samples. These repeat captures arose from the simultaneous operation of three boats and because of within-day movement of dolphins between the transects where they were first captured to other transects being surveyed later in the day. There was a mixture of captures made ‘on-effort’ (while following the pre-defined transects) and captures made ‘off-effort’ on transit between transects. Repeat captures in the same primary and secondary samples were redundant and deleted from the data prior to model fitting. Deletions were made in two steps: when repeat captures were made both on- and off-effort, the on-effort captures were retained; and among the remaining captures, the capture made first was retained.

The MSCRD models the data from both sites simultaneously and requires that no dolphin is recorded as having been captured on both sites in the same primary sample. There were a few examples of dolphins having moved between the sites within a primary sample and having been captured on both. The capture histories for these dolphins were modified to show all captures within each primary sample as having been made on the site where they were first captured.

The survey design specified six secondary samples (SS) on each site in each primary sample (PS). Pairs of secondary samples were taken consecutively on each site. The numbers of captures in the original six secondary samples (SS) were sometimes zero or very small. In response to this event, the data were collapsed from six (SS) to three secondary samples (SS3) by recording whether each dolphin was or was not captured within each consecutive pair of secondary samples.

2.2.4 *Goodness of fit*

It is necessary to assess whether the data collected are consistent with the statistical model proposed for their analysis, i.e., to assess the goodness of fit of the data to the model. We used program U-CARE (Choquet *et al*. 2005) for goodness of fit tests. The tests were performed on data collapsed to primary samples; for models for a single site, the tests assume a Cormack-Jolly-Seber (CJS; Lebreton *et al*. 1992) type of model, and for MSCRD models they assume a multistate version of the model that allows for transitions between states (JollyMove; Brownie *et al*. 1993). If there is significant lack of fit, it is necessary to adjust the estimates using an estimate of the variance inflation factor $\hat{c}$ and a version of AIC_c for over dispersed data ($QAIC_c$; Burnham and Anderson 2002). The variance inflation factor $\hat{c}$ was estimated as the ratio of the overall test statistic for the model from U-CARE and the model degrees of freedom.

2.2.5 *Model selection – AIC*

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

2.2.6 *Estimating the total population size*

Not all individuals have sufficiently distinctive marks to support unambiguous identification. Only distinctively marked individuals may 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 binary logistic model was fitted to the data on distinctive and non-distinctive dolphins to estimate the marked proportion ($\widehat{M}_p$) of the population for each species.

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

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

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

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

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. We aim to gather quantitative indicators of differences in the spatial distribution of snubfin and humpback dolphins across years. We use a large collection of quantitative methods to do this, from descriptive statistics to likelihood ratio tests. Note that as we add a new year to the dataset the species distribution models are updated, while considering interannual variation, and so are the corresponding spatial predictions and related statistics for every year.

We also aimed to evaluate whether CU project construction activities (e.g., rock dumping, capital dredging, pile driving) were important predictors of dolphin's spatial distribution.

Our evaluations were primarily through model-based inference and descriptions of models' behaviour. We did the following:

1. Estimated covariates' "Relative Variable Importance" for a range of human-activities (boats presence, presence of anthropogenic disturbances) and environmental covariates (SST, salinity).
2. Calculated likelihood-ratios between models with anthropogenic disturbances vs models without.
3. Marginal plots of covariates' functional relationship with species' abundances
4. Assessed models' predictive performance (e.g., ROC-AUC and PR-AUC scores).

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, 2020, 2021, 2022 and 2023 incorporated 9 sub-components, representing different groupings of covariates, and wrapped in different functional forms (Table 1). The method is supposed to only select the most important sub-models. The unimportant sub-models are either “shrunk” to have only a small contribution to the overall ensemble’s prediction, 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 slopes and intercepts for 2019, 2020, 2021, 2022 and 2023).
3. Decision-tree (1), including covariates for weather conditions.
4. Decision-tree (2), including covariates for ecological variables, boats, and the distance-to-disturbance covariates (rock dumping, capital dredging and piling).
5. The same as base-learner #2 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).

One difference between this year’s analysis and previous years’ analyses was our decision to discard the radial basis function (to model small-scale spatial autocorrelation). These were discarded because: i) they become computationally infeasible with more interaction terms (per year effects); ii) they were not selected in past-years' best models (particularly 2022), and iii) they are functionally similar to bivariate spatial splines.

Table 1. Covariates considered for the species distribution modelling of Australian Snubfin and humpback dolphins in Cleveland and Halifax Bays between 2019 and 2023 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), 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 (indicative reef outline as mapped by GBRMPA)	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 (Euclidean distance to only mainland 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 (Euclidean distance to coastal boundary, including mainland and large islands)	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 (< 5m)	In-situ counts	Interpolated spatial surface
		Boats Medium	Counts of all boats, medium size (5-10m)	In-situ counts	Interpolated spatial surface
		Boats Large	Counts of all boats, large size (> 10m)	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 motorboats and sailing boats	In-situ counts	Interpolated spatial surface
		Boats Industrial	Counts of all barges, tugs, tankers, ferries, and cruise ships	In-situ counts	Interpolated spatial surface
		Rock Dumping	Log-distance to rock dumping during days of activity in 2020; otherwise max distance	GIS, derived	Interpolated spatial surface
		Piling	Log-distance to piling locations during days of activity in 2022; other max distance	GIS, derived	Interpolated spatial surface
		Maintenance Dredging	Log-distance to maintenance dredging locations during 2019 and 2020; other max distance	GIS, derived	Interpolated spatial surface
		Capital dredging	Log-distance to construction during days of activity in 2022 and 2023; other max distance	GIS, derived	Interpolated spatial surface
		Min distance to disturbance	Minimum distance over rock dumping, piling, and dredging (capital and maintenance).	GIS, derived	Interpolated spatial surface
		Pointwise disturbance	Binary indicator of onboard records of disturbances being present	In-situ measurement	Set to 0

Sub-models	Model type	Covariate	Covariate description	Source at training	Source at prediction
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

2.3.2 *Main Effects and Interactions*

Some of the covariates are represented in more than one sub-model, especially as different sub-models represent “main effects” versus “interaction effects” 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, in terms of dolphin spatial distribution.

2.3.3 *Disturbances*

There were multiple distance-to-disturbance covariates that were introduced this year. In past reports, the presence of such disturbances were simply recorded in-situ, but such information was difficult extrapolate to a broader spatial field.

Using GIS and UTM coordinates, we mapped these disturbances to specific points, and approximate times (based on data provided by the Port of Townsville), allowing use to calculate each dolphin sighting (and null-points’) distance to the disturbance on specific dates.

These disturbance covariates included:

- distance to rock dumping, present in June-July of 2020. This activity was related to CU project and occurredimmediately adjacent to the port lands.
- distance to piling activities present intermittently between 28/06/2022 to 9/07/2022. Piling occurred at a few distinct locations with known dates along the

channel stretching from the Port of Townsville to the south-east region of Magnetic Island.

- distance to capital dredging (BHD), occurring intermittently in the winters of 2022 and 2023 on known dates, along the channel stretching from the Port of Townsville to the south-east region of Magnetic Island.
- Minimum distance to disturbance. This spatial covariate was the minimum of all the above covariates when they were available.
- distance to maintenance dredging (TSHD) present during 24/05/2019 to 09/06/2019 and from 1/06/2020 to 29/06/2020). These activities occurred along the channel stretching from the Port of Townsville to the south-east region of Magnetic Island.

Distances to the disturbances were calculated for each dolphin observation and each null-point. The distances were “marine distances”, such that they accounted for islands and mainland obstructions. See Fig. 4 for an example of the shortest distance between a dolphin located north of Magnetic Island, and a disturbance.

During time-intervals in which a disturbance was not occurring, we set the covariate’s value to the maximum over the study area. In other words, when a disturbance wasn’t present, it was recorded as being maximally distant. This was necessary to fill null-values with a proper metric. Years without a particular construction activity provide a reference point for comparison. Including non-disturbance years prevents bias in the dataset by ensuring that the model is not only capturing responses to disturbance, allowing us to assess whether any observed changes in dolphin distribution were temporary or persistent, whether changes are potentially due to CU construction activities or just part of the dolphins' natural behavior.

All the distances were logged and then re-scaled to zero-mean and unit-variance.

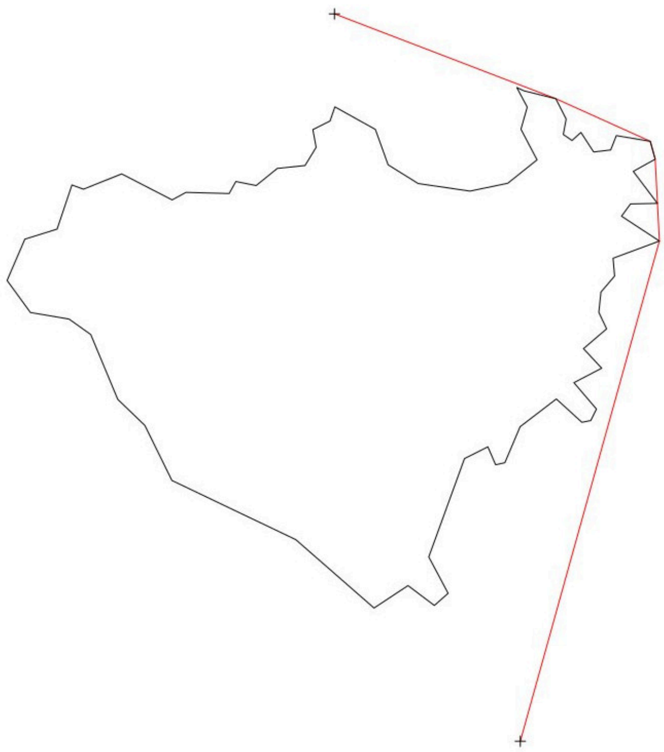


Figure 4. Demonstration of the shortest-distance path between a disturbance point to the south-east of Magnetic Island, and a dolphin point to the north of Magnetic Island, whereby the straight-line is obstructed by the island. These shortest marine paths were used for the distance-to-disturbance covariates.

2.3.4 *Model Parsimony, Hyperparameters and Regularization*

The automatic ensemble-building and shrinkage mechanism theoretically improves model predictive performance by 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 ensemble is more parsimonious than the full theoretical model which could include 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 hyperparameters with the best predictive performance, according to the 10-fold cross-validation log-likelihood, was selected as the final model used for inference.

The 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 (0.01-0.12), after manually experimenting with different values to get final models that had between 1000-6000 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 [3, 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.
- Bucket weight i.e., the minimum weight of terminal leaves in the decision-trees, which could take on values in the range of [2,6]. Lower values allow fitting more granular

variation, at the risk of overfitting. Higher values require patterns to have more support in terms of the number of points on either side of a split, at the risk of underfitting rare but important patterns.

- Minimum test-statistic threshold (i.e., mincriterion, in the mboost R-library) which could take on values [0.4, 0.5, 0.6, 0.7, 0.75, 0.8 0.85]. 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 [12 - 38]. 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, could take on values in the range [18, 40] In previous years, these values were fixed as a multiple of the main effects. In either case, the values were higher to absorb per-year marginal variation above-and-beyond the variation that is common to all years (which should be explained by the main-effect spatial base-learner).
- Degrees-of-freedom of the main-effects of the spatial-autocorrelation radial basis function (for sub-model No.10) which could take on values [12 - 36]. Higher values allowed “wigglier” 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). which could take on values [12 – 36]. In previous

years, these values were fixed as a multiple of the main effects, but were allowed to vary somewhat independently in this study.

- K-knots in spatial splines, i.e., the number of basis functions underlying a spline. This could take on values between 20 to 36. Higher values allow more granular spatial processes, at the risk of overfitting noise, while lower values force fitting more large and systemic patterns, at the risk of underfitting local spatial variation.
- 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).

2.3.5 *Relative Variable Importance*

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, and used for conducting comparative likelihood-ratio tests.

2.3.6 *Covariate Partial Plots*

Whereas RVIs and likelihood ratio tests can help quantify the importance of a covariate upon a species’ distribution, they do not provide a sense of the functional-relationship or direction of the relationship between a covariate and the response variable. With traditional linear models, one can look at the direction and magnitude of coefficients to inference such relationships, but these are unavailable for machine-learning methods. Furthermore, the high-dimensional interactions that are present in machine-learning models means that a single covariate can rarely be interpreted in isolation, but must be observed as party to multiple two- or three-way interactions with other covariates.

Therefore, we made marginal plots of the two-way interactions between the high-RVI covariates and the (predicted) response variable. From these non-linear interactions, we looked for patterns in the relationship and magnitude of relationship between species' predicted abundance and the underlying covariates.

A pair's marginal plot was created by first fixing the values of all other covariates to their 2023 mean-values, and then varying the pair's values uniformly throughout its empirical range (in 2023), to get a 2D surface. The 2D surface was truncated to minimum convex hull of a pair's empirical values (effectively excluding combinations of values that do not exist in reality, like maximum depth and zero distance to land).

2.3.7 *AUC statistics*

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.

2.3.8 *Likelihood-Ratios: Inference about disturbances*

In order to evaluate whether the disturbance covariates had an important contribution to the species' distributions, we used generalised likelihood ratios (Royall 1997) to compare two models per species: the best model according to hyperparameter tuning *vs.* a reduced model which dropped all the disturbance covariates (e.g., distance to rock dumping, distance to dredging, etc).

When the likelihood ratio between the reduced model and the full model is very high (>>1), it is evidence that the disturbance covariates are not significant contributions to the SDM. When the likelihood ratio between the reduced model and the full model is very low (<<1), it is evidence that the disturbance covariates are significant. Furthermore, the degree of significance is monotonic with respect to a decrease in the likelihood ratio, allowing us to compare between species and answer the question: “are disturbances more or less significant for snubfins or humpbacks?”

We used a 5-times 10-fold cross-validation to approximate the “expected likelihood” (as opposed to the within-sample likelihood), such that the likelihood calculations were evaluated by training the model 5-times on 10-fold subsets of the data, and then estimating the likelihood on the hold-out samples. The mean over the cross-validation runs (aka CV-likelihood) was our estimate for the expected likelihood. 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). Therefore, by comparing two models by their CV-likelihoods, we are essentially conducting the same type of model comparison as minimising the AIC (albeit, with a different approximation of the expected likelihood).

We also computed CV p-values to contextualise our confidence in the conclusions of the likelihood ratio. The CV p-values were the proportion of the 5-times CV-runs in which the reduced model was better than the best-model. For example, if the reduced model defeats the best model 0 times, then our p-value would be 0.0. If the reduced model defeats the best model in all CV-runs, then the p-value would be 1.0. The approximate p-value can take on multiples of 0.2 (i.e., 0, 0.2, …., 1.0). Low p-values mean that the full-model can be rejected with more confidence that the conclusion is robust to multiple realisations of the data.

2.3.9 *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 plot is the expected counts of animals in groups if the group is present. This is not to be confused with abundance, because a very sparsely distributed population which aggregates into large herds/pods could have the same abundance as an evenly distributed population with small group sizes. The third spatial partial plot was the product of the probability of occurrence and group sizes, which yields a predicted density of snubfin and humpback dolphins in Cleveland Bay and Halifax Bay.

2.3.10 *Spatial Interpolation of In-Situ Covariates*

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 model spatial prediction.

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

- Generalised additive models GAMs: model-averaging of spatial GAMs; and
- component-wise boosting.

Each in-situ 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 all years.

2.3.11 *Spatial Interpolation by Generalised additive models (GAMs)*

The spatial interpolation by GAMs consisted of running multiple 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. three of the following main-effects using thin-plate shrinkage splines: spline(bathymetry), spline(distance to rivers), spline(distance to reefs), spline(distance to seagrass), spline(distance to nearshore), spline(distance to land), spline(SST), spline(salinity), and spline(turbidity). Only three combinations of covariates were tested, in which covariate-sets were selected based on minimizing in-group correlation among the covariates.
3. one of the following soap-film spatial smooths: spline(latitude, longitude) as a main-effect spatial; and spline(latitude, longitude, interaction=year) as a per-year interaction.

4. one of the following bivariate splines: spline(time-of-day, time-of-year) as a main-effect temporal spline; and spline(time-of-day, time-of-year, by=year) as a per-year interaction spline.

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 Poisson distribution (note: in past years we tried to interpolation-GAMS with a zero-inflated Poisson distribution, but these proved computationally infeasible with more data).

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.

2.3.12 *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.

2.3.13 *Spatial Interpolation of Distance-to-Disturbances*

Although the disturbances (piling, rock dumping, capital dredging) were literally spatial fields, we transformed them into spatial fields by calculating distances each marked point of a disturbance, from every grid-cell in the study area. This was necessary in order to incorporate such covariates that were used during model training into the SDM.

The spatial field of each disturbance was calculated by a two-step process. First, we generated ~500 points systematically across the study area’s marine space. At each point, we calculated the (log) distance to a disturbance. If a disturbance was a linear feature (like the maintenance dredging) or was multiple points (like piling), we took the minimum distance. The assumption behind using the minimum distance is that a dolphin’s response is likely strongest to the nearest disturbance source. Secondly, we used these points as inputs to a high-capacity spatial spline model, whose response variable was the distance-to-disturbance. Finally, using the trained model, we interpolated to all the remaining grids in the study area. An example of the 2022 distance-to-capital dredging is shown in Fig.

5. This figure shows how far different locations in the study area were from the dredging activities that occurred that year.

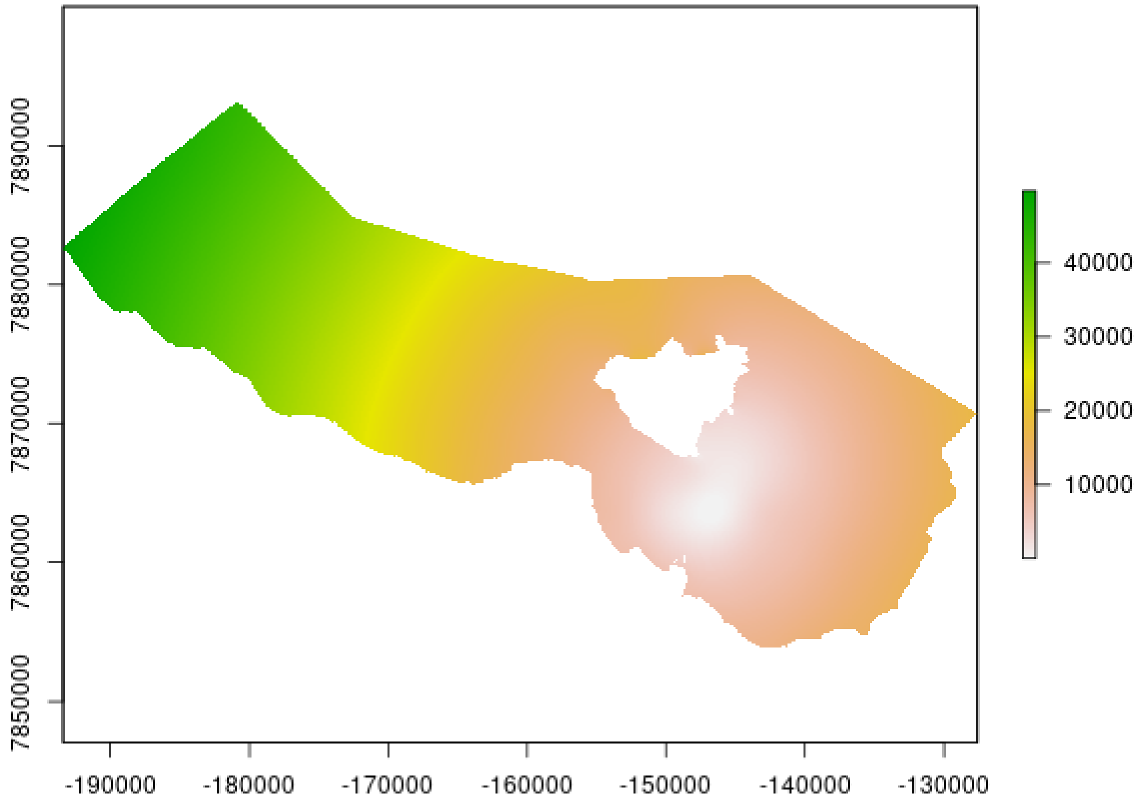


Figure 5. Example of spatial field representation of distance to capital dredging in 2022. The X and Y axes represent UTM coordinates (Universal Transverse Mercator projection). The colours represent the distance in meters from the dredging activities. Green areas: Farthest from the dredging activity. Yellow areas: Intermediate distances. Pink areas: Closest to the dredging activity. The scale bar on the right shows values ranging from low (white) to high (green). These values correspond to the distance in meters from the dredging location.

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, and statistical ensemble-modelling.

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 counts of dolphins in 2023 vs 2019 , 2023 vs 2020, and 2023 vs 2021. 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 2023 to those of previous years. 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 2023 data is consistent with the 2019 null-model.

Likewise, we used the presence/absence of dolphins during no-capital dredging , no-maintenance dredging, no-rock dumping and no-piling periods across all years as the “null model” (characterising normal conditions of the dolphins) and calculated the probability of seeing dolphin counts as low as that observed during capital dredging, maintenance dredging rock dumping, and piling activities. Low Bayesian p-values provide evidence that the counts of dolphins were lower that what would be expected according to the null models of no capital dredging, no maintenance dredging, no-rock dumping and no-piling periods (i.e., a low-probability events according to the null-models), while high Bayesian p-values suggest that the counts during disturbance 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:

$$\begin{aligned}
\boldsymbol{y} &:= \text{occurrences of dolphins during normal non-dredging scans} \\
\theta^{\varnothing} &:= \text{ estimated probability of dolphins occurrences during non-dredging scans} \\
N^{\varnothing}_{\text{scans}} &:= \text{number of scans with no dredging} \\
N^{dredge}_{\text{scans}} &:= \text{number of scans with dredging} \\
\tilde{n}_{\text{dredge}} &:= \text{observed number of occurrences of dolphins during dredging}
\end{aligned}$$

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.

2.4.2 *Land-Station Ensemble Modelling*

We used the R-package mgcv to model the presence/absence of snubfin and humpback dolphins per scan, as an ensemble of GAMs. In particular, we used logit-binomial response variable (i.e., presence/absence) and included various environmental predictors and anthropogenic indicators modelled as linear effects, including wind, BSS, swell, visibility, glare, boats small, boats medium, boats large, boats fishing, boats recreational, boats total, boats industrial, dredging (both construction and maintenance dredging), rock dumping, and piling (aggregated as a single binary indicator). Unexplained temporal variation was modelled as three covariates: year-as-a-factor, time-of-day (as a 6-degree spline), time-of-day with an interaction with year (as an 18-degree bivariate spline), and julian-day-of-year (as a 6-degree spline) and julian-day-of-year (as an 18-degree bivariate spline).

Due to the large number of related/overlapping covariates, we performed multi-model inference, capping the number of linear covariates at 3. We used the AIC to approximate posterior-model probabilities (a.k.a, AIC-weights). The weights were used for two purposes: i) to calculate model-averaged regression-coefficients/marginal-effects and frequentist p-values for different covariates); and ii) for calculating the posterior inclusion probabilities (a.k.a, sum-of-AIC weights). The former is for estimating effects-sizes and performing significance tests, while the latter have a Bayesian interpretation: what is the probability that covariate X is important for dolphins' presence/absence.

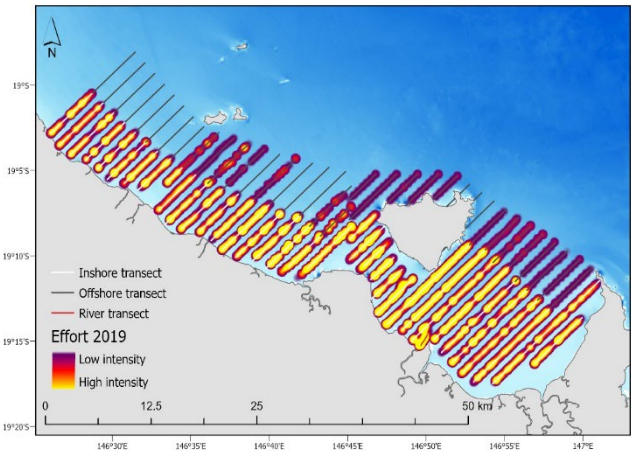
We also estimated the model-averaged time-series of dolphin probability of occupancy (on the logit-scale) across years 2019, 2020, 2021, 2022 and 2023.

3. Results

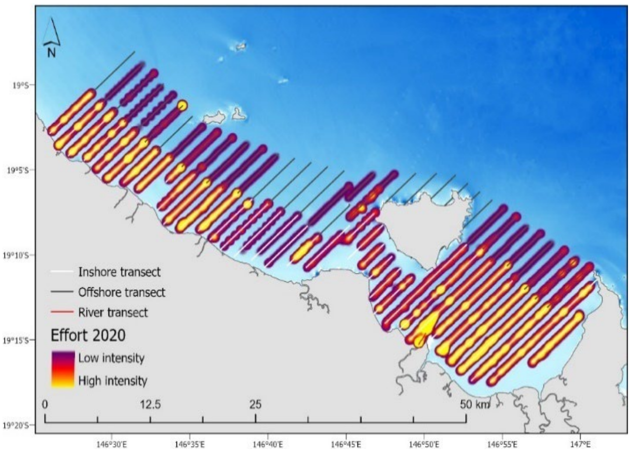
3.1 Population demographics

3.1.1 *Vessel based survey effort*

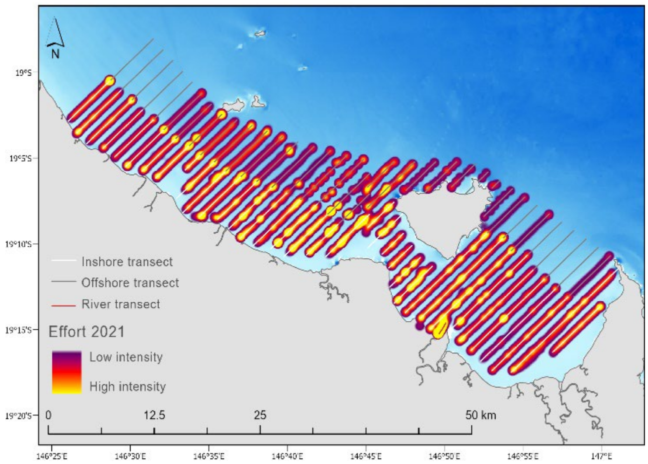
We surveyed a total of 2305.4 km on transect effort over 14 days between June 9 and July 7, 2023, covering 1229.9 km in Cleveland Bay and 1075.5 km in Halifax Bay (Fig. 6, Table 2). As planned, we completed six survey repeats of each bay (plus an additional; seven repeat), each representing a secondary period. Like last year, survey effort was higher in inshore areas (1849 km) than in offshore areas (456.5 km) due to the poor weather conditions encountered often in offshore areas (Beaufort sea state > 4).



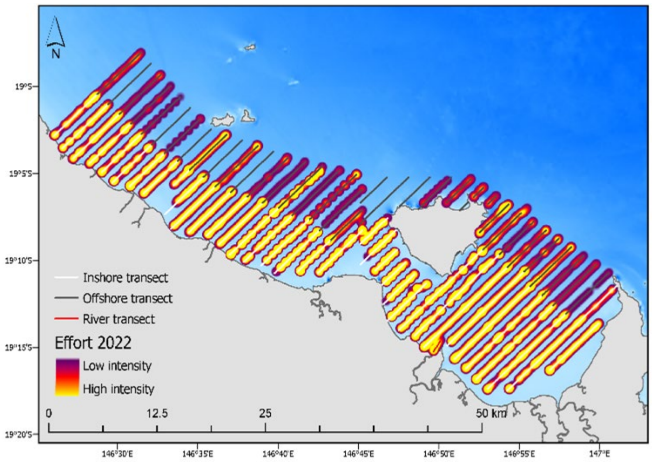
a) 2019



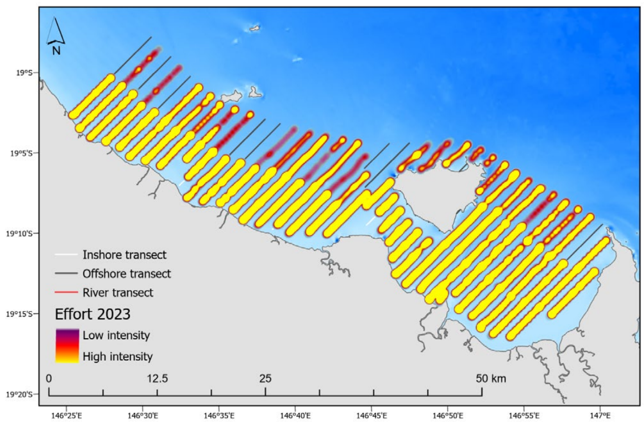
b) 2020



c) 2021



d) 2022



e) 2023

Figure 6. 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 June-July a) 2019, b) 2020, c) 2021, d) 2022 and e) 2023. Survey intensity scale represents the relative number 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 2023 primary sample (June-July).

Study area	Sec. period	Date/s	Inshore	Offshore	Total	Beaufort Sea State		
			Transect length (km)	Transect length (km)	Transect length (km)	min	max	mode
Cleveland Bay	1	09/06	144.8	25.9	170.7	0	3	1
	2	14/06	133.1	20.4	153.5	1	3	2
	3	18/06	144.8	1.4	146.2	1	3	2
	4	23/06	144.8	50.7	195.5	0	2	2
	5	26/06	144.8	41.7	186.5	1	3	2
	6	28/06	144.8	57.5	202.3	0	2	1
	7	05/07	144.8	30.4	175.2	0	3	2
	Total	-	1001.9	228.0	1229.9	-	-	-
Halifax Bay	1	13/06	121.2	40.7	161.9	1	3	2
	2	15/06	121.2	0.0	121.2	1	3	2
	3	19/06	121.2	41.5	162.7	1	3	2
	4	24/06	120.5	17.5	138.0	0	2	0
	5	27/06	120.5	30.5	151.0	0	3	2
	6	29/06	121.2	50.4	171.6	0	3	2
	7	06/07	121.2	47.9	169.1	0	2	2
	Total	-	847.1	228.5	1075.5	-	-	-
	Grand total	-	1849.0	456.5	2305.4	-	-	-

3.1.2 *Dolphin sightings, encounter rates and group sizes*

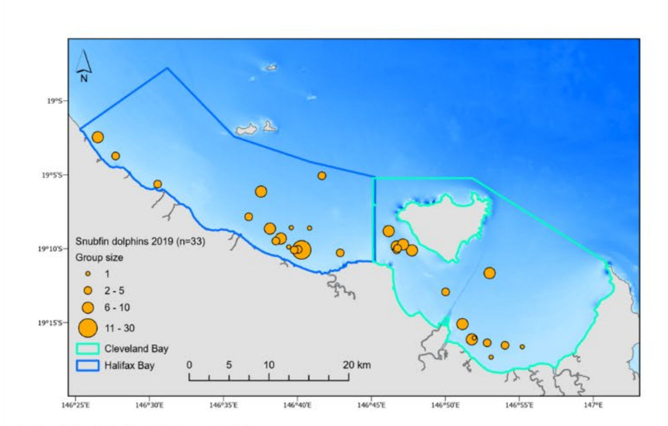
The vessel surveys in 2023 resulted in a total of 102 dolphin group sightings (including both on and off effort sightings) (Fig. 7e, Table 3). This consisted of 31 groups of snubfin dolphins (Fig. 7e), 50 groups of humpback dolphins (Fig. 7j) and 21 groups of bottlenose dolphins (Fig 7o). Other marine mammals sighted during 2023 surveys included dugongs (Fig 7t). In 2023, we only sighted a total of 2 groups of snubfin dolphins in Cleveland Bay (0.0016 dolphin group/km), while 29 were sighted in in Halifax Bay (0.0270 dolphin group/km). A total of 26 groups of humpback dolphins were sighted in Cleveland Bay (0.0211 dolphin group/km) and 24 in Halifax Bay (0.0223 dolphin group/km) (Table 3). Bottlenose dolphin groups were sighted 2 times in Cleveland Bay (0.0016 dolphin group/km) and 19 (0.0177 dolphin group/km) in Halifax Bay in 2023 (Table 3).

Encounter rates (number of dolphin groups/km) of snubfin dolphins in Cleveland Bay declined over time, with the highest value in 2019 (0.0182 groups/km) and the lowest in 2022 (0.0019 groups/km) and 2023 (0.0016 groups/km). In Halifax Bay, encounter rates remained stable between 2019 (0.0193 groups/km) and 2020 (0.0191 groups/km), decreased in 2021 (0.0140 groups/km), increased in 2022 (0.0214 groups/km) and 2023 (0.0270 groups/km) (Table 3).

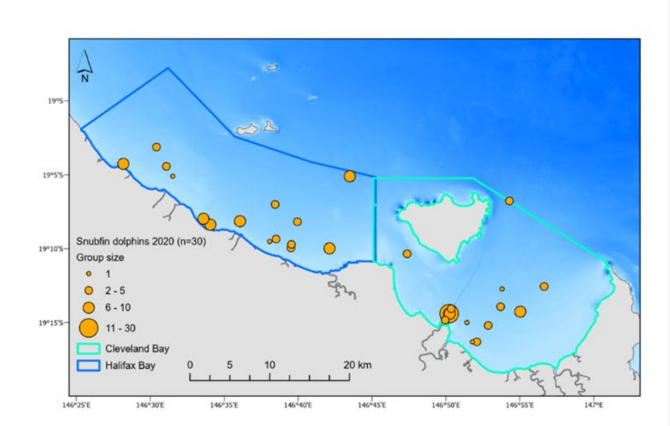
In Cleveland Bay, humpback dolphin encounter rates increased from 2019 (0.0139 groups/km) to 2020 (0.0256 groups/km), declined in 2021 (0.0219 groups/km) and 2022 (0.0185 groups/km), and rose again in 2023 (0.0211 groups/km). In Halifax Bay, rates were highest in 2019 (0.0385 groups/km), decreased in 2020 (0.0347 groups/km) and 2021 (0.0169 groups/km), increased in 2022 (0.0259 groups/km), anmd then decreased in 2023 (0.0223 groups/km) (Table 3).

In Cleveland Bay, bottlenose dolphins were rarely recorded: encounter rates declined from 2019 (0.0032 groups/km) to zero in 2020, increased in 2021 (0.0030 groups/km) and 2022 (0.0039 groups/km),and dropped in 2023 (0.0016 groups/km). In Halifax Bay, encounter rates decreased from 2019 (0.0024 groups/km) to 2020 (0.0012 groups/km), increased in 2021 (0.0100 groups/km), rose slightly in 2022 (0.0101 groups/km), and peaked in 2023 (0.0177 groups/km) (Table 3).

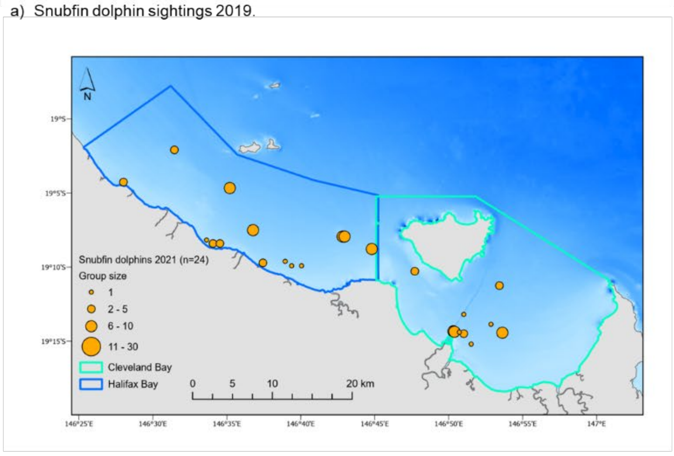
Groups of snubfin dolphins in 2023 varied in size from 1 to 24 individuals, with a mean (± SD) group size of 5.5 ± 4.4 (based on best estimates of group size) (Table 4). The group size of humpback dolphins ranged from 1 to 25 individuals, with a mean (± SD) group size of 3.9 ± 3 Bottlenose dolphin groups ranged from 1 to 15 individuals (mean ± SD = 5.3. ± 2.9) (Table 4).



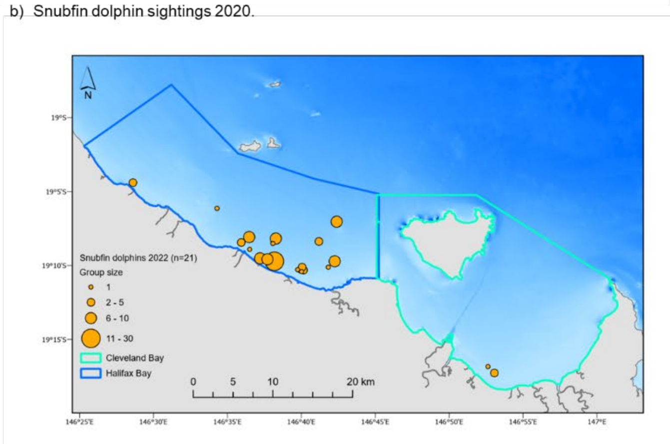
a) Snubfin dolphin sightings 2019.



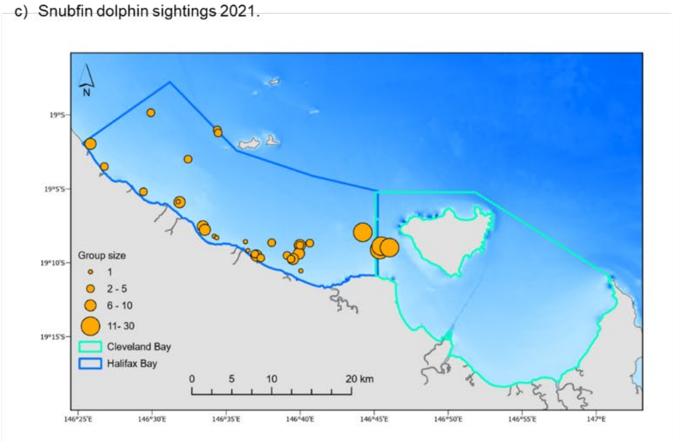
b) Snubfin dolphin sightings 2020.



c) Snubfin dolphin sightings 2021.

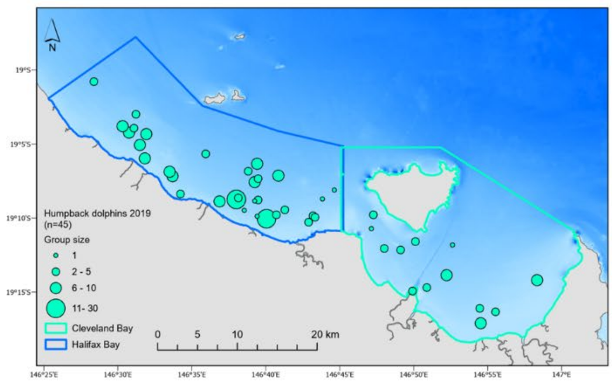


d) Snubfin dolphin sightings 2022.

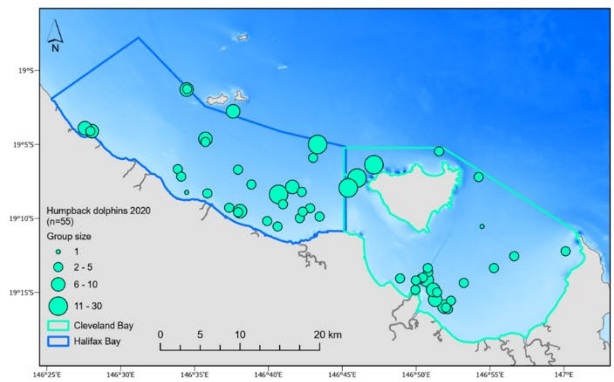


e) Snubfin dolphin sightings 2023.

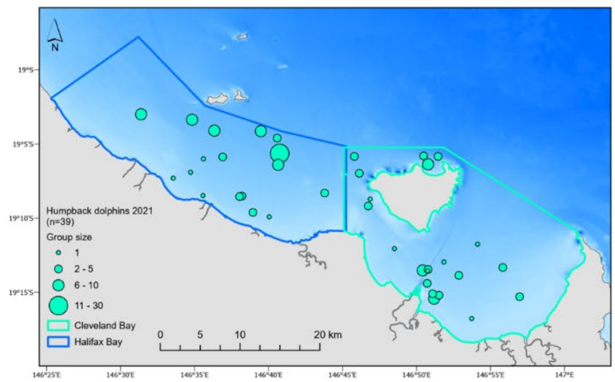
Figure 7. Location and group sizes of Australian snubfin dolphins (a-e), humpback dolphins (f-j), bottlenose dolphins (k-o) and other marine mammals (p-t) sighted in 2019, 2020, 2021, 2022 and 2023 during boat surveys in Cleveland and Halifax Bays.



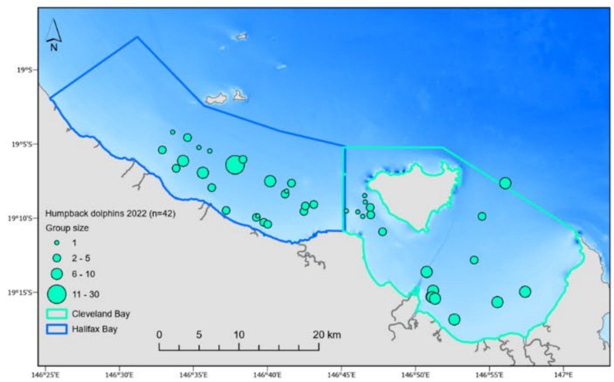
f) Humpback dolphin sightings 2019.



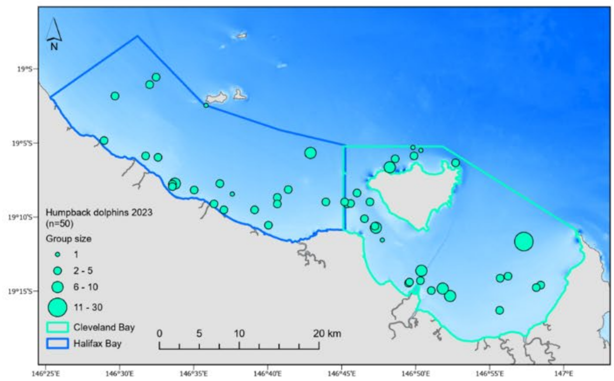
g) Humpback dolphin sightings 2020.



h) Humpback dolphin sightings 2021.

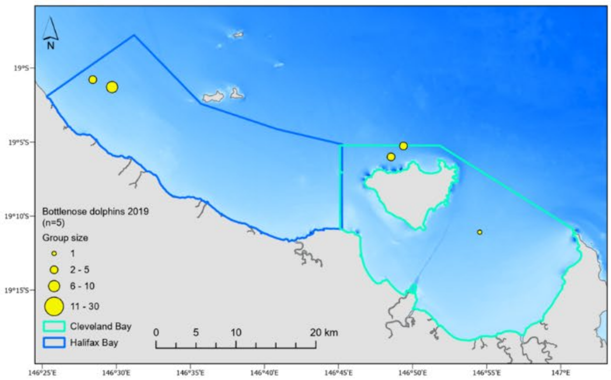


i) Humpback dolphin sightings 2022.

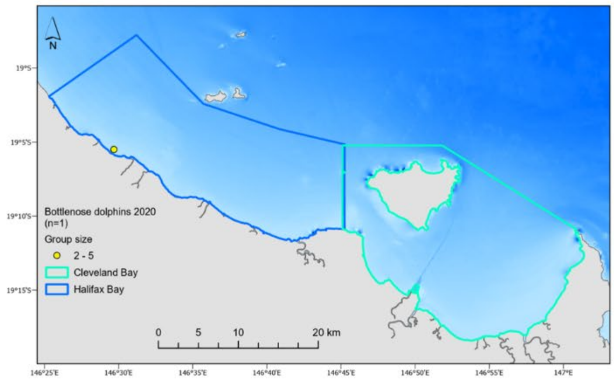


j) Humpback dolphin sightings 2023.

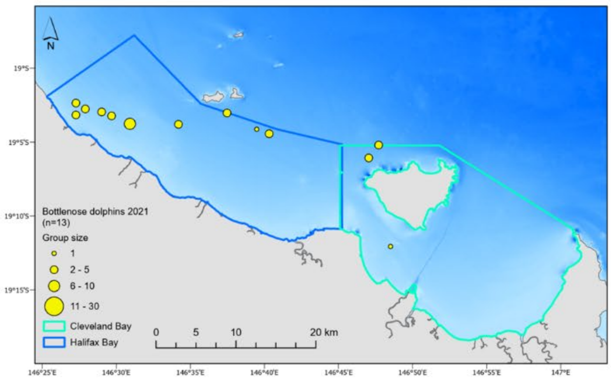
Figure 7 (continued). Location and group sizes of Australian snubfin dolphins (a-e), humpback dolphins (f-j), bottlenose dolphins (k-o) and other marine mammals (p-t) sighted in 2019, 2020, 2021, 2022 and 2023 during boat surveys in Cleveland and Halifax Bays.



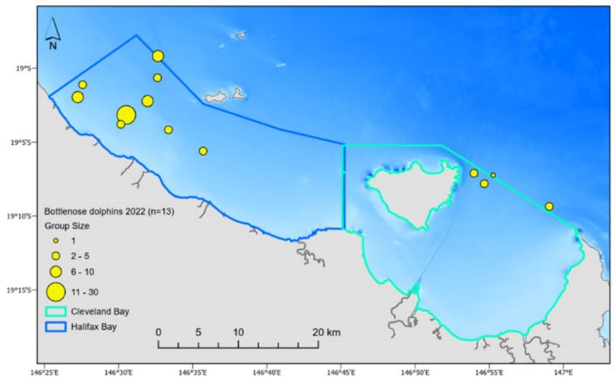
k) Bottlenose dolphin sightings 2019.



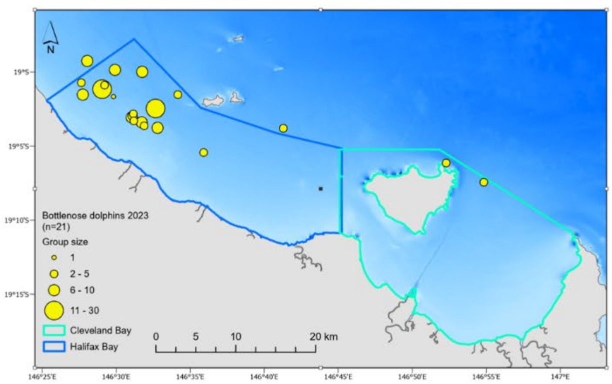
l) Bottlenose dolphin sightings 2020.



m) Bottlenose dolphin sightings 2021.

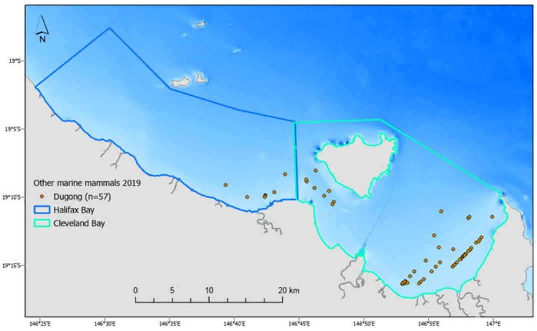


n) Bottlenose dolphin sightings 2022.

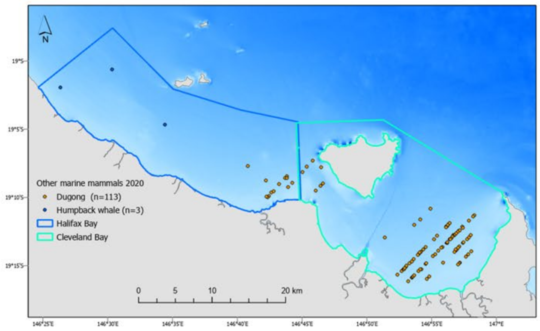


o) Bottlenose dolphin sightings 2023.

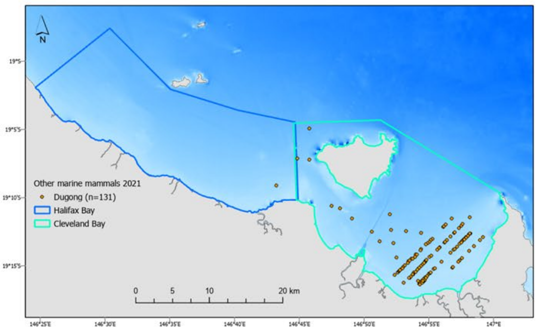
Figure 7 (continued). Location and group sizes of Australian snubfin dolphins (a-e), humpback dolphins (f-j), bottlenose dolphins (k-o) and other marine mammals (p-t) sighted in 2019, 2020, 2021, 2022 and 2023 during boat surveys in Cleveland and Halifax Bays.



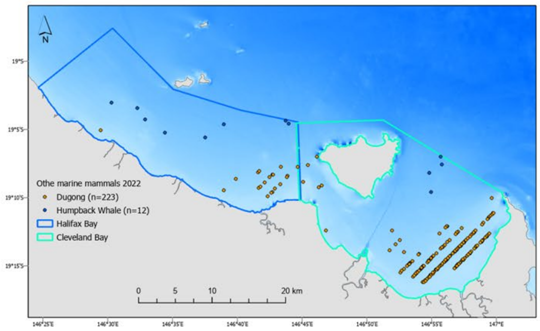
p) Other marine mammal sightings 2019.



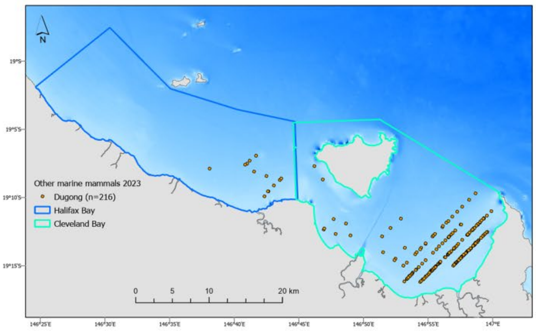
q) Other marine mammal sightings 2020.



r) Other marine mammal sightings 2021.



s) Other marine mammal sightings 2022.



t) Other marine mammal sightings 2023.

Figure 7 (continued). Location and group sizes of Australian snubfin dolphins (a-e), humpback dolphins (f-j), bottlenose dolphins (k-o) and other marine mammals (p-t) sighted in 2019, 2020, 2021, 2022 and 2023 during boat surveys in Cleveland and Halifax Bays.

Table 3. Number of dolphin groups (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, 2020, 2021, 2022 and 2023 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	0.0182	16	0.0193	33	0.0187
	Humpback	13	0.0139	32	0.0385	45	0.0255
	Bottlenose	3	0.0032	2	0.0024	5	0.0028
2020	Snubfin	14	0.0138	16	0.0191	30	0.0162
	Humpback	26	0.0256	29	0.0347	55	0.0297
	Bottlenose	0	0.0000	1	0.0012	1	0.0005
2021	Snubfin	10	0.0100	14	0.0133	24	0.0117
	Humpback	22	0.0219	17	0.0162	39	0.0190
	Bottlenose	3	0.0030	10	0.0095	13	0.0063
2022	Snubfin	2	0.0019	19	0.0214	21	0.0110
	Humpback	19	0.0185	23	0.0259	42	0.0219
	Bottlenose	4	0.0039	9	0.0101	13	0.0068
2023	Snubfin	2	0.0016	29	0.0270	31	0.0134
	Humpback	26	0.0211	24	0.0223	50	0.0217
	Bottlenose	2	0.0016	19	0.0177	21	0.0091

Table 4. Group size and age composition of snubfin, humpback and bottlenose dolphins encountered during boat-based surveys in the Townsville region in 2019, 2020, 2021, 2022 and 2023.

Year	Species	Group size			Group age composition			
		Min	Max	Mean (SD)	Mean proportion of adults, juveniles, calves (%) A	J	C	No. groups with juvenile or calf present
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%)
2021	Snubfin	1	12	4.1 (2.8)	81	10	8	13 (54%)
	Humpback	1	20	4 (3.6)	84	9	6	17 (43%)
	Bottlenose	1	10	3.5 (2.3)	63	23	14	10 (77%)
2022	Snubfin	1	26	4.6 (5.1)	83	6	11	6 (30%)
	Humpback	1	20	3.7 (2.8)	77	12	11	22 (52%)
	Bottlenose	1	16	4.9 (2.9)	76	20	4	9 (69%)
2023	Snubfin	1	24	5.5 (4.4)	87	2	11	14 (45%)
	Humpback	1	25	3.9 (3)	70	15	15	35 (70%)
	Bottlenose	1	15	5.3 (2.9%)	75	13	12	15 (71%)

3.1.3 *Photo-identification and capture-recapture data*

One hundred and seventeen individual snubfin and 170 individual humpback dolphins have been identified since sampling began in 2019 and the most recent survey in 2023 (Table 5). Table 5 shows the numbers of snubfin and humpback dolphins captured and first identified in each bay in each year. The total numbers of each species captured and first captured in each year irrespective of the sites in which they were captured are also shown. These totals are not always equal to the sums of the numbers identified in each of the two bays. This is because some dolphins were captured in both bays in the same years and are not counted twice in the totals. It is pertinent to note that because a dolphin may have been first identified in a certain year should not be taken to mean that they were not present in previous years only that, if they were present in previous years, they were not captured. Captured or not, their numbers are represented in the model estimates. In 2023, 10 individual snubfin and 51 humpback dolphins were photo-identified in Cleveland Bay, and 52 snubfin and 40 humpback dolphins were photo-identified in Halifax Bay (Table 5).

Table 5. Numbers of individual snubfin and humpback dolphins captured and first identified in each bay in each year from 2019 to 2023. The total numbers captured and first identified in each year irrespective of the sites on which they were captured are also shown.

Species	Bay	Number captured/First captures				
		2019	**2020**	**2021**	**2022**	**2023**
Snubfin	**Cleveland**	28/28	26/8	15/5	1/0	10/4
	Halifax	38/38	26/10	16/2	42/26	52/21
	Total	57/57	49/14	29/4	43/26	54/16
Humpback	**Cleveland**	16/16	25/16	25/9	29/13	51/32
	Halifax	42/42	39/25	29/8	32/20	40/24
	Total	54/54	56/30	50/11	58/29	82/46

Although some dolphins first captured in a given year may have been present but undetected in earlier years, the sharp increase in new identifications is notable. In particular, large numbers of snubfin dolphins were first captured in Halifax Bay in 2022 and 2023, while humpback dolphins showed a marked increase in new identifications in Cleveland Bay in 2023. These spikes in first captures suggest that immigration into the study area may have occurred in recent years, particularly for snubfins in Halifax Bay and humpbacks in Cleveland Bay..

The MSCRD analyses all data on each species captured in both bays in all five years. Previous reports have demonstrated that no biases were introduced by the inclusion of off-effort data. Thus, we use both on-effort and off-effort data for the MSCRD analyses of each species. Good data for both bays in all four years are required for the model to return reliable estimates for each species. This was not the case for snubfin dolphins in 2022 or 2023, with only one having been captured in Cleveland Bay in 2022 and ten having been captured all on one day in 2023. How these deficiencies were managed in the analysis is subsequently discussed in detail. Considering the combined on- and off-effort data (Table 6) in the original six secondary samples (PS_SS) data for both species, there were many zero or very low numbers of captures in both bays in all years. Models using these data would return many poorly or improperly estimated parameters, i.e., with large or zero standard errors. 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 6). As a result, the data were collapsed to three secondary samples (PS_SS3) for MSCRD analyses of both dolphin species.

Table 6. Number of individual snubfin and humpback 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	No. of Individuals identified	Effort	PS_SS						PS_SS3		
					s1	s2	s3	s4	s5	s6	S1	S2	S3
2019	Snubfin	Cleveland	27	On only	8	3	9	0	12	6	11	9	13
			28	On + off	8	3	9	11	12	6	11	15	13
		Halifax	36	On only	13	1	11	0	12	10	14	11	20
			38	On + off	13	1	11	2	12	10	14	13	20
	Humpback	Cleveland	12	On only	3	3	9	3	0	0	6	10	0
			16	On + off	3	3	10	5	5	0	6	12	5
		Halifax	42	On only	4	19	1	10	9	17	20	11	25
			42	On + off	4	19	1	10	9	17	20	11	25
2020	Snubfin	Cleveland	26	On only	6	0	2	10	4	7	6	11	11
			26	On + off	6	0	2	10	4	7	6	11	11
		Halifax	26	On only	0	6	7	8	10	8	6	15	18
			26	On + off	0	6	7	8	10	8	6	15	18
	Humpback	Cleveland	25	On only	1	2	8	6	16	8	3	11	20
			25	On + off	1	2	8	6	16	8	3	11	20
		Halifax	39	On only	3	16	5	10	13	5	19	14	18
			39	On + off	3	16	5	10	13	5	19	14	18
2021	Snubfin	Cleveland	15	On only	4	7	1	1	3	0	11	2	3
			15	On + off	4	7	1	1	3	0	11	2	3
		Halifax	16	On only	0	6	4	1	1	6	6	5	7
			16	On + off	0	6	4	1	1	6	6	5	7
	Humpback	Cleveland	23	On only	11	3	0	9	10	2	13	9	11
			25	On + off	11	3	0	9	10	7	13	9	14
		Halifax	28	On only	16	1	5	2	0	11	17	7	11
			29	On + off	16	1	5	2	0	12	17	7	12
2022	Snubfin	Cleveland	1	On only	0	0	0	0	0	1	0	0	1

Year	Species	Bay	No. of Individuals identified	Effort	PS_SS						PS_SS3		
					s1	s2	s3	s4	s5	s6	S1	S2	S3
			1	On + off	0	0	0	0	0	1	0	0	1
		Halifax	40	On only	0	4	12	1	13	17	4	13	25
			42	On + off	0	4	13	4	13	17	4	16	25
	Humpback	Cleveland	21	On only	0	0	16	6	3	5	0	19	6
			29	On + off	6	1	16	6	3	11	7	19	11
		Halifax	31	On only	0	2	0	9	4	21	2	9	22
			32	On + off	3	2	0	9	4	21	4	9	22
2023	Snubfin	Cleveland	10	On only	0	0	0	0	0	10	0	0	10
			10	On + off	0	0	0	0	0	10	0	0	10
		Halifax	40	On only	1	0	6	4	6	27	1	10	33
			52	On + off	1	1	7	8	6	34	2	19	40
	Humpback	Cleveland	47	On only	10	2	4	0	23	14	10	4	36
			51	On + off	11	2	6	9	23	19	11	9	38
		Halifax	30	On only	0	3	6	11	9	10	3	15	17
			40	On + off	0	4	8	11	9	18	4	17	24

3.1.4 *Goodness of fit*

The goodness of fit test statistics from U-Care were, for the snubfin data $\chi^2 = 6.711$, $df = 12.00, p = 0.876$ and, for the humpback data $\chi^2 = 6.973, df = 15, p = 0.961$ indicating no evidence of lack of fit between the models and the data for either species. Consequently, no adjustment was made to $\hat{c}$ (i.e., $\hat{c} = 1$) and AIC_c was used for model comparisons.

3.1.5 *Models*

Capture probabilities were highly variable over years and secondary samples (PS_SS3) for both species and displayed no evident pattern for either. Consequently, capture probability was fitted as fully time varying by year and secondary sample (PS_SS3) in all models except as described below. The apparent survival, movement and temporary emigration parameters refer to the intervals between years (2019 to 2020, 2020 to 2021, 2021 to 2022, and 2022 to 2023). In principle, separate estimates may be obtained for each interval. These parameters were typically estimated with wide confidence intervals and were often fitted as constant over intervals (yielding averages for the three intervals). This was a practical way of obtaining useful and reasonably reliable estimates of meaningful parameters given limited numbers of captures.

Exceptions to fitting the apparent survival, movement, and temporary emigration parameters as constant over intervals were made in response to the near absence of snubfin dolphins in Cleveland Bay in 2022 with only one having been captured, and limited captures (10) in 2023 which all occurred on only one day. The approach to fitting these models is described subsequently.

It is likely that very few snubfin dolphins visited the Bay during the sampling period in 2022, with very few sightings from either the vessel surveys (2 sightings) or land-based surveys (one sighting). The absence of snubfin dolphins in Cleveland Bay in 2022, following estimates of approximately 30-40 in previous years, may have been due to a decrease in their apparent survival (due to deaths or permanent emigration from the Bay), an increase in their rate of movement from Cleveland to Halifax Bay, or an increase in their temporary emigration from the Townsville area (absent from both Cleveland and Halifax Bays).

While more snubfin dolphins were captured in Cleveland Bay in 2023 than 2022, that they were all captured on only one day is problematic for the analysis. Since capture-recapture models rely on recaptures across multiple sampling events to estimate population size, the anomalous capture pattern in 2023 affects not only the 2023 estimates but also the 2022 estimates. If capture probability in 2023 was artificially inflated on one day, it could lead to misleading estimates of survival and movement, making 2022's population size estimates unreliable as well. Capture-recapture models assume that, within a given season, the population size remains relatively stable. However, if all captures in 2023 occurred on a single day, it suggests that either: 1) The dolphins were not consistently present throughout the season (i.e., temporary emigration), or 2) Sampling conditions or effort were significantly different on that particular day compared to the rest of the season. Either scenario contradicts the assumption of a constant number of dolphins in Cleveland Bay. If the high number of captures in 2023 were due to a temporary aggregation event rather than a true reflection of the population size, the model could overestimate the population for that year. Conversely, if the model assumes that dolphins were equally available for capture throughout the season, but in reality, they were not, then it could underestimate capture probability and inflate the population estimate.

Although the global goodness of fit test found no evidence of lack of fit of the data to the model, the pattern of captures in 2023 would be very unlikely to have occurred if the assumptions of the model were met, notably that the number of snubfin dolphins in

Cleveland Bay was constant throughout the season. Consequently, not only are the estimates for snubfin dolphins in 2022 suspect but so also are the estimates for 2023.

Although changes in the estimates of the apparent survival, movement, and temporary emigration parameters in the MSCRD model might theoretically describe the events underlying the changes in capture rates in 2022 and 2023 from those in 2019, 2020 and 2021, the capacity of the model to detect such changes as significant effects is limited by the volume of data. There is very little information in the data for Cleveland Bay in 2022 with only one capture, and the information in the ten captures in 2023 is unreliable as described above.

Captures were made on only one day in both 2022 and 2023. The capture probability for these years was modelled as having been constant over secondary samples to allow the models to run and estimates to be produced. While we might suspect that there was an increase in movements out of Cleveland Bay to Halifax Bay or that there was an increase in temporary emigration from Cleveland Bay between 2021 and 2022, and that there may have been an increase in movements from Halifax Bay or return from temporary emigration between 2022 and 2023, there are not sufficient or sufficiently reliable data for these affects to be reliably estimated.

While estimates from models with the capture probabilities in Cleveland Bay modelled as constant over secondary samples are reported here, the estimated numbers of snubfin dolphins in Cleveland Bay in 2022 and 2023 are considered unreliable. As a check on the bias involved, the best fitting model was refitted with the mean (= ~ 0.3) of the estimated capture probabilities from 2019 to 2021 for snubfin dolphins in Cleveland Bay in 2022 and 2023. This model did not estimate the number for 2022 and returned one as the number captured and estimated 15 snubfin dolphins in Cleveland Bay in 2023.

To obtain evidence of increased movement from Cleveland to Halifax Bay between 2021 and 2022, the rate of movement was fitted as equal between 2019 to 2020 and 2020 to 2021, different between 2021 and 2022 and zero between 2022 and 2023 (there was only one to move). In respect of movements in the other direction, from Halifax Bay to Cleveland Bay, the rates were fitted as equal between 2019 to 2020 and 2020 to 2021, zero between 2021 and 2022 (only one was found in Cleveland Bay in 2022) and different between 2022 and 2023.

With only one snubfin dolphin captured in Cleveland Bay in 2022, reliable estimates cannot be obtained for movement from Halifax Bay to Cleveland Bay between 2021 and 2022 nor between Cleveland Bay and Halifax Bay between 2022 and 2023. These constraints also apply to temporary emigration from Cleveland Bay between 2022 and 2023 and re-immigration to Cleveland Bay between 2021 and 2022. All models were fitted with these parameters set to zero. Models with movements between bays or temporary emigration fitted as constant over intervals without these constraints may produce apparently reasonable estimates but these are more cleanly estimated with the constraints applied.

Attempts to model variation in temporary emigration movements over time yielded very small estimates of emigration with very wide confidence intervals in all periods. One model with temporary emigration was found to yield reasonable estimates: this model had temporary emigration from Cleveland Bay only, between 2019 to 2020 and 2020 to 2021 for both emigration and re-immigration, emigration between 2021 and 2022, and re-immigration between 2022 and 2023. All attempts to model temporary emigration from and to Halifax Bay produced estimates that were either very small with a large standard error (emigration) or very large with a standard error of zero (re-immigration) indicating improper estimation.

Consequently, temporary emigration from and to Halifax Bay was fixed at zero and not estimated in all models.

Subject to the constraints described above, movements between sites were modelled as constant over time and of even flow (equal in both directions), random (complementary between directions) or Markovian (flows in the two directions independent) forms. Apparent survival was modelled as constant over time and either equal or different between sites. Models that generated improper estimates or which attracted less than one percent of the AIC weight were eliminated leaving a final set of six models for averaging.

For humpback dolphins, apparent survival was fitted as equal or different for the two sites, movement between sites was fitted as equal or different in both directions, and temporary emigration was fitted as zero for Cleveland Bay and equal or different from and to Halifax Bay. Even flow structures were clearly superior to random structures and only these and the Markovian structures (different between directions) were included in the final set of models. The final model set for averaging included six models.

3.1.6 *Australia snubfin dolphin: population parameters 2019-2023*

Six models fitted to the snubfin dolphin data were considered to have yielded reliable estimates of all population parameters, except for abundance. Model averaged estimates of the parameters are reported in Table 7.

The proportion of snubfin dolphins bearing distinctive marks was estimated at 0.90 with SE = 0.012. This was employed together with the estimated sizes of the marked populations to calculate estimated total population sizes (Table 7). The total population sizes are plotted with their 95% confidence intervals for Cleveland and Halifax Bays in each year 2019 to 2023 in Figure 8. The total estimated abundance of snubfin dolphins in Cleveland Bay was reasonably consistent over the first three years of survey at 31 in 2019, 42 in 2020 and 34 in 2021 (Fig. 8). The number of captures declined sharply in 2022, with a slight recovery in 2023. However, as previously discussed, the abundance estimates for these years (Table 7) are considered unreliable, with wide confidence intervals and likely overestimation. A model that assumed the probability of capture in these years was the same as the mean from the first three years failed to yield an estimate for 2022 and estimated 15 for 2023. The estimated total abundance of snubfin dolphins in Halifax Bay decreased from 56 in 2019 to 36 in 2020 and 33 in 2021 before increasing greatly to 117 in 2022 and falling to 76 in 2023 (Table 7, Fig. 8).

Estimates for the average rate of apparent survival (alive and remaining in the bay) of snubfin dolphins in the intervals between consecutive years between 2019 and 2023 were very similar for the two bays and quite high at an average of 0.855 (95% CI = 0.71 – 0.93). With an estimated rate of biological survival of snubfin dolphins of 0.95 pa (Taylor et al. 2007), the estimated rate of permanent emigration is 10% pa, i.e., 10% have left each Bay, have not moved to the other, and are not expected to return.

The rate of movement between Cleveland Bay and Halifax Bay between 2019 and 2020, and 2020 and 2021 was 0.16. This increased to 0.40 between 2021 and 2022 while movement out of Cleveland Bay could not be estimated between 2022 and 2023 with only one dolphin captured in Cleveland Bay in 2022. The rate of movement from Halifax Bay to Cleveland Bay between 2019 and 2020, and 2020 and 2021 was similar to the rate of movement in the other direction at 0.18. While the rate of movement from Halifax Bay to Cleveland Bay between 2021 and 2022 could not be estimated with only one dolphin captured in Cleveland Bay in 2022, the rate decreased to 0.08 between 2022 and 2023. Although data limitations have posed difficulties for estimation, these estimates provide the first evidence of movement out of Cleveland to Halifax Bay in the year before 2022 and indicate that the rate of return from Halifax to Cleveland Bay was only moderate between 2022 and 2023. It may be pertinent that the estimates supporting these conclusions were yielded by models from which the estimated number present in Cleveland Bay in 2022 is likely to be too high (as described above) and the estimate of movement out of Cleveland into Halifax Bay between 2021 and 2022 (0.40) may be too low.

The capacity of the models to estimate temporary emigration was severely limited by the very small numbers present in Cleveland Bay in 2022 and 2023 and relatively small numbers of captures generally. It was not possible to estimate temporary emigration from and to Halifax Bay, and the estimates for temporary emigration from and to Cleveland Bay were near zero.

Table 7. Australian snubfin dolphin: Multistate Closed Robust Design (MSCRD) model averaged estimates of population parameters, their standard errors (SE) and 95% confidence intervals (lower and upper limits) for Cleveland Bay (CB) and Halifax Bay (HB). All estimates are probabilities except population sizes.

Parameter*	Bay	Year	Estimate	SE	LCI	UCI
Apparent survival (φ)	CB	2019-2023	0.85	0.06	0.71	0.93
Apparent survival	HB	2019-2023	0.86	0.04	0.75	0.93
Movement between sites (ψMS)	CB to HB	2019-2021	0.16	0.05	0.08	0.30
	CB to HB	2021-2022	0.40	0.15	0.17	0.70
Movement between sites	HB to CB	2019-2021	0.18	0.06	0.09	0.33
	HB to CB	2022-2023	0.08	0.08	0.01	0.42
Temporary emigration from (ψTE)	CB	2019-2021	0.01	0.05	0.00	0.99
	CB	2021-2022	0.00	0.00	0.00	0.00
Temporary emigration from	HB	NIL (fixed)	NA	NA	NA	NA
Return of previously emigrated dolphins to (ψTE)	CB	2019-2021	0.01	0.05	0.00	0.99
Return of previously emigrated dolphins to	CB	2022-2023	0.00	0.00	0.00	0.00
Marked population size (N_{marked})	CB	2019	28	3.42	21.61	35.00
Marked population size	CB	2020	38	7.72	22.65	52.92
Marked population size	CB	2021	31	9.48	12.50	49.66
Marked population size SEE TEXT	CB	2022	14	20.13	-25.59	53.32
Marked population size SEE TEXT	CB	2023	33	17.37	-1.31	66.79
Marked population size	HB	2019	50	9.53	31.73	69.09
Marked population size	HB	2020	32	4.00	24.37	40.04
Marked population size	HB	2021	30	8.72	13.02	47.20
Marked population size	HB	2022	105	23.71	58.97	151.91
Marked population size	HB	2023	68	10.22	48.20	88.27
Total population size (N_{total})	CB	2019	31	3.82	24	40
Total population size	CB	2020	42	8.60	28	63
Total population size	CB	2021	34	10.54	19	62
Total population size	CB	2022	16 *	22.37	2	124
Total population size	CB	2023	37 *	19.31	14	97
Total population size	HB	2019	56	10.61	38	81
Total population size	HB	2020	36	4.47	28	45
Total population size	HB	2021	33	9.70	19	58
Total population size	HB	2022	117	26.39	75	181
Total population size	HB	2023	76	11.40	56	101

*Parameters:

- N_{marked}: estimate of the "marked" population size.
- N_{total}: estimate of the total population size considering proportion of unmarked animals in the population.
- φ: estimate of apparent survival.
- ψ_{MS}: estimate of transition probability/movement between sites.
- ψ_{TE}: estimate of temporary emigration.

* These estimates are considered unreliable. See text.

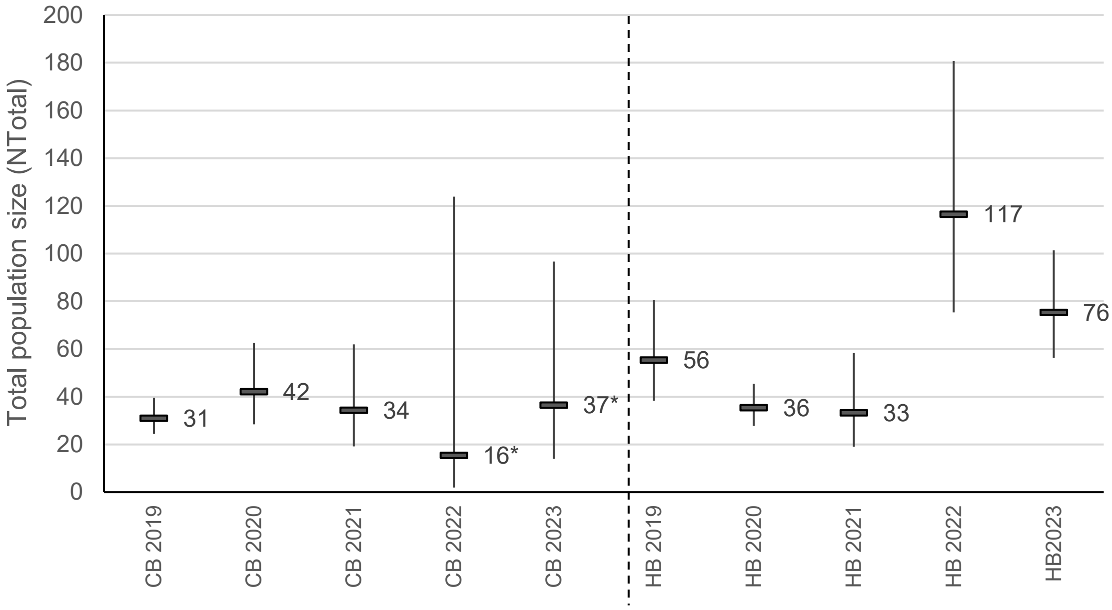


Figure 8. Estimates of the total population size of Australian snubfin dolphins with 95% confidence intervals in Cleveland (CB) and Halifax Bays (HB) for the years 2019 to 2023. The estimates for Cleveland Bay in 2022 and 2023 are considered unreliable (*) and likely overestimated (see text).

3.1.7 *Australian humpback dolphin: population parameters 2019-2023.*

Six models for the humpback data were considered to have yielded reliable estimates of all parameters. Model averaged estimates of the parameters are reported in Table 8.

The proportion of humpback dolphins bearing distinctive marks was estimated at 0.88 with SE = 0.011. This was employed together with the estimated sizes of the marked populations to estimate total population sizes (Table 8). The total population sizes are plotted with their 95% confidence intervals for Cleveland and Halifax Bays for the years 2019 to 2023 in Figure 9. The number of humpback dolphins present in Cleveland Bay increased from 19 in 2019 to 33 in 2020 and 2021 and increased again to 49 in 2022 and 90 in 2023 (Fig. 9).

There were more humpback dolphins present in Halifax than Cleveland Bay in most years, with 65 in 2019, 53 in 2020, 42 in 2021, and 77 in 2022 (Fig. 9, Table 8). However, in 2023, Cleveland Bay had more humpback dolphins than Halifax Bay, with an estimated 90 individuals (Fig. 9, Table 8). It appears that as suggested from the relatively large numbers of humpback dolphins first identified in both bays in the last two years (Table 5) that there may have been immigration into both bays in these years.

Estimates for the average rate of apparent survival (alive and remaining in the bay) in the intervals between consecutive years between 2019 and 2023 were reasonably high and the same for both bays at 0.86 pa (Table 8). With an estimated rate of biological survival of humpback dolphins of 0.97 pa, the estimated rate of permanent emigration was 11.3% pa from both bays. Dolphins that have permanently emigrated from each Bay have not moved to the other and are not expected to return.

The average rates of movement between the Bays in the intervals between consecutive years between 2019 and 2023 were equal in both directions at 0.18 pa (i.e. approximately 18% of the marked individuals in one bay moved to the other bay between any two consecutive years, Table 8). That's a substantial proportion (18%) in the context of ecological and demographic processes, especially for species like dolphins that often show strong site fidelity.

Estimates of temporary emigration from each Bay differed at zero for Cleveland Bay and at 0.27 pa for Halifax Bay; suggesting that while all humpback dolphins present in Cleveland Bay during one sampling season were estimated to also be present in the next, about 27% of humpback dolphins present in one sampling season in Halifax Bay were absent for the duration of the next. Return of previously emigrated humpback dolphins to a Bay was estimated at zero for Cleveland Bay and at 0.28 pa for Halifax Bay.

Table 8. Australian humpback dolphins: Multistate Closed Robust Design (MSCRD) model averaged estimates of population parameters, their standard errors (SE) and 95% confidence intervals (lower and upper limits) for Cleveland Bay (CB) and Halifax Bay (HB). All estimates are probabilities except population sizes.

Parameter*	**Bay**	**Year**	**Estimate**	**SE**	**LCI**	**UCI**
Apparent survival (φ)	CB	2019-2023	0.86	0.04	0.75	0.93
Apparent survival	HB	2019-2023	0.86	0.06	0.69	0.95
Movement between sites (ψ_{MS})	CB to HB	2019-2023	0.18	0.04	0.12	0.26
Movement between sites	HB to CB	2019-2023	0.18	0.03	0.12	0.25
Temporary emigration from (ψ_{TE})	CB	2019-2023	0.00	0.00	0.00	0.00
Temporary emigration from	HB	2019-2023	0.27	0.09	0.13	0.47
Return of previously emigrated dolphins to (ψ_{TE})	CB	2019-2023	0.00	0.00	0.00	0.00
Return of previously emigrated dolphins to	HB	2019-2023	0.28	0.15	0.08	0.64
Marked population size (N_{marked})	CB	2019	17	2.07	13.43	21.56
Marked population size	CB	2020	29	4.01	21.28	37.01
Marked population size	CB	2021	29	3.60	22.39	36.52
Marked population size	CB	2022	43	7.57	28.46	58.15
Marked population size	CB	2023	79	12.30	55.20	103.42
Marked population size	HB	2019	57	9.60	37.87	75.51
Marked population size	HB	2020	47	7.56	31.96	61.60
Marked population size	HB	2021	37	6.06	24.75	48.51
Marked population size	HB	2022	68	18.40	32.10	104.24
Marked population size	HB	2023	74	18.28	37.81	109.46
Total population size (N_{total})	CB	2019	19	2.36	15	25
Total population size	CB	2020	33	4.58	25	43
Total population size	CB	2021	33	4.11	26	42
Total population size	CB	2022	49	8.62	35	69
Total population size	CB	2023	90	14.02	66	122
Total population size	HB	2019	65	10.94	47	90
Total population size	HB	2020	53	8.62	39	73
Total population size	HB	2021	42	6.91	31	58
Total population size	HB	2022	77	20.93	46	130
Total population size	HB	2023	84	20.80	52	136

*Parameters:
- N_{marked}: estimate of the “marked” population size.
- N_{total}:estimate of the total population size taking into account proportion of unmarked animals in the population.
- φ: estimate of apparent survival.
- ψ_{MS}: estimate of transition probability/movement between sites.
- ψ_{TE}: estimate of temporary emigration.

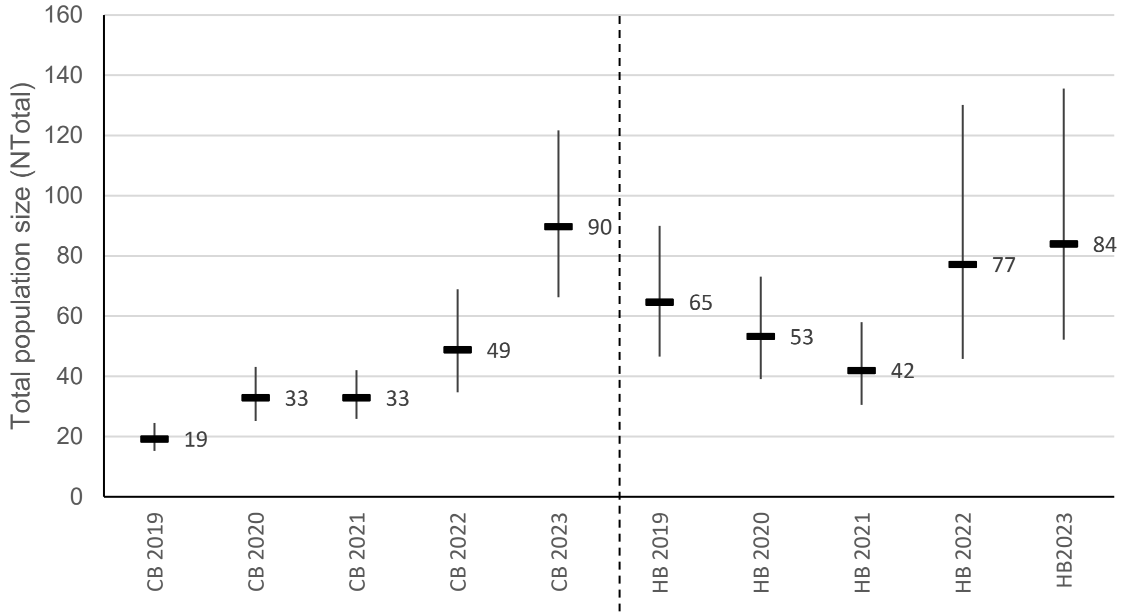


Figure 9. Estimates of total population size with 95% confidence intervals of Australian humpback dolphins in Cleveland (CB) and Halifax Bays (HB) for the years 2019 to 2023.

3.2 Spatial distribution modelling

3.2.1 *Model performance and spatial predictions*

There were 31 encounters of snubfin dolphins and 50 of humpback dolphins in 2023. There were 783 points used as pseudo-zero encounters for the SDM of snubfin dolphins and 764 for humpback dolphins.

Overall, the final ensemble models for generating species distribution plots for 2023 had good predictive performance but had slightly lower performance in comparison to 2021. The ensemble model for humpback dolphins obtained a global cv-ROC-AUC of 0.833 (down slightly from last year's value of 0.840) and a cv-precision-recall-AUC of 0.38 (compared to last year's performance of 0.462). For snubfins, the global cv-ROC-AUC was 0.833 (compared to last year's 0.853); the cv-precision-recall-AUC was 0.217 (compared to last year's 0.300).

The per-year predictive performance (cv-ROC-AUC) for humpback dolphins, using the 2023 ensemble model, were: 0.86, 0.95,0.77,0.76, and 0.69 for survey-years 2019 to 2023, respectively. These values were nearly the same as previous models' per-year values, with 2023 being a drag on performance. The per-year predictive performance (cv-ROC-AUC) for humpback dolphins, using the 2023 ensemble model, were: 0.86, 0.91, 0.74, 0.83, and 0.79 for survey-years 2019, 2020, 2021, 2022, and 2023 respectively. These values were lower for 2019 and 2020 compared to past years' models, but higher for 2021 and 2022. The model struggled with 2023's data, but less so than the 2020 dataset.

3.2.2 *Relative Variable Importance*

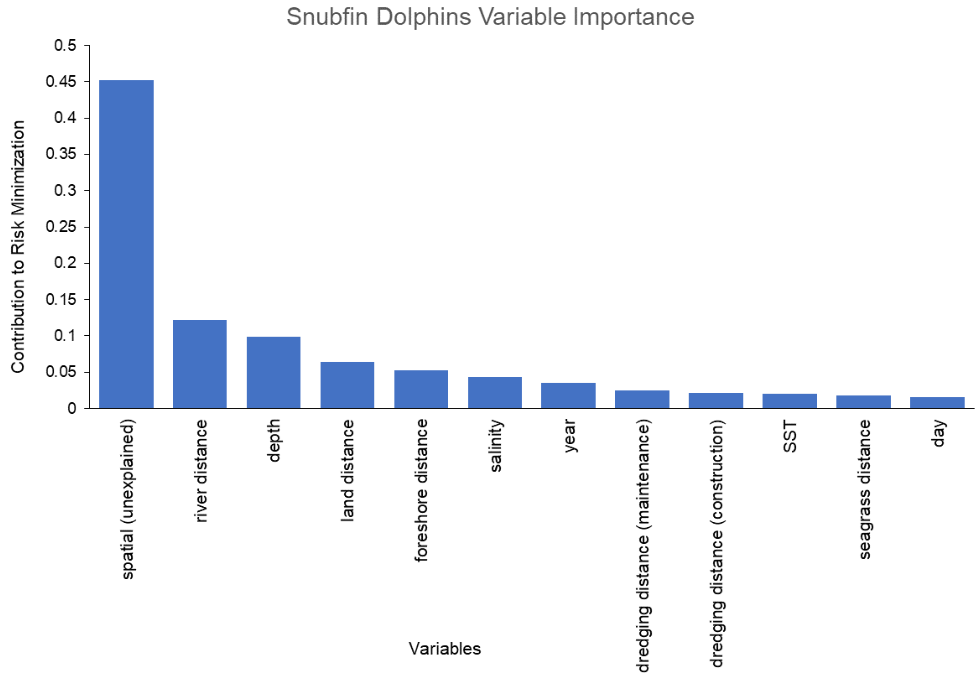
The relative variable importance values (RVI) are shown in Figure 10. The RVIs measure how much each covariate contributes to the reduction in the model risk-function (negative log-likelihood). In other words, it indicates which predictors are responsible for the model's overall goodness-of-fit.

For snubfin dolphins, the order of RVIs was: an unexplained spatial process (45%), log-distance to rivers (12%), depth (9.9%), log-distance to land (6.6%), log- distance to foreshore (5.3%), salinity (4.2%), year as a categorical variable (3.5%), log-distance to maintenance dredging (2.5%), log-distance to capital dredging (2.1%), SST (1.7%), log-distance to seagrass (1.7%), and Julian day (1.6%). For those covariates with a contribution greater than 5%, the ordering of covariates was similar to last year's models, however, the unexplained spatial processed was more predominant this year than last year (32% RVI in 2022).

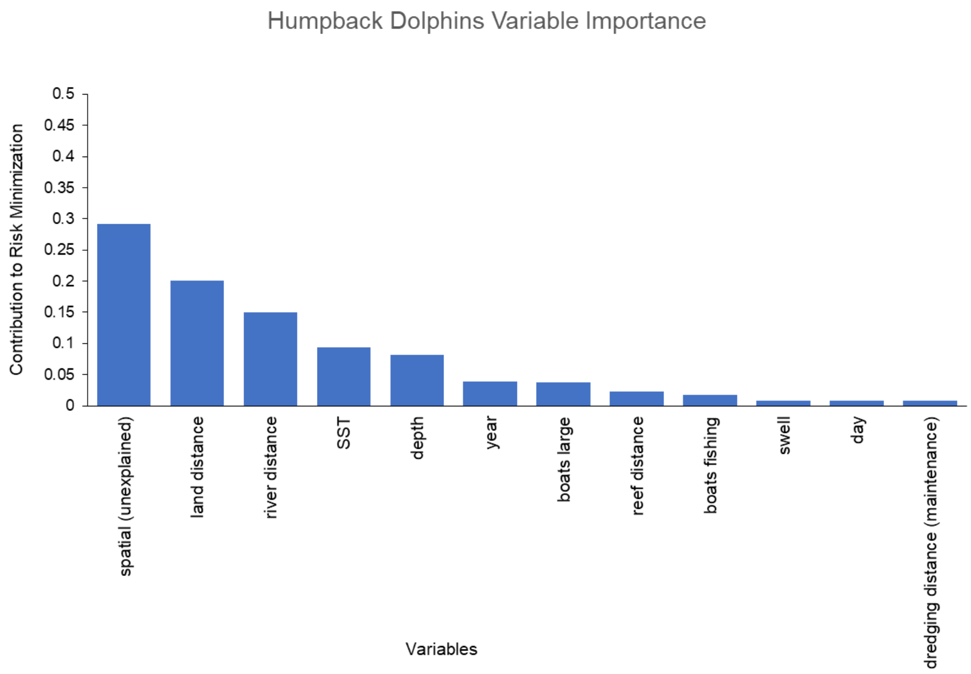
For humpbacks, the most important variable was an unexplained spatial process (i.e., spatial base-learners), accounting for 29% of risk-minimisation. Thereafter, the most important variables were log-distance to land (20%), then log-distance to rivers (15%), SST (9.3%), depth (8.2%), year as a categorical variable (3.8%), counts of large boats (3.7%), log-distance to reefs (2.2%), counts of fishing vessels (1.7%), swell (0.9%), Julian day (0.9%) and log-distance to maintenance dredging (0.8%). All covariates thereafter had RVIs of less than 0.7%.

To help intuit the significance of covariates with a small RVI, one can benchmark them against year-as-a-categorical variable: at ~3.5% RVI for either species, its influence can be readily visualised and understood as the variation between the per-year SDM plots. Year was used as a benchmark as it is a biologically intuitive, moderately influential factor (≈3.5% variation for both species), providing a clear reference point against which less intuitive predictors can be compared. Since the RVI for 'log-distance to maintenance dredging' in snubfin dolphins is around 2.5%, which is similar in magnitude to the 3.5% RVI of the year-as-a-categorical variable, this suggests that the influence of distance to maintenance dredging on snubfin dolphin distribution is almost as important as the variation in species distributions between years. This comparison helps to convey that while the effect of log-distance to maintenance dredging is slightly smaller, it has a similar level of influence on species distribution as temporal factors (like year).

As mentioned in past reports, the presence of multi-collinearity among covariates means that it is difficult to uniquely assign RVI to any one particular covariate (Bühlmann et al. 2013), especially when there is a highly flexible non-linear spatial spline that can act as a “catch-all” representation of the spatial variation that would otherwise be more causally related to other interpretable covariates.



a)



b)

Figure 10. The relative variable importance (contribution to risk-minimisation) of each covariate considered in ensemble species distribution modelling of a) Australian snubfin and b) humpback dolphins based on data collected in 2023.

3.2.3 *Likelihood Ratio Tests Disturbance Covariates*

We used a 5 times10-fold cross-validation to compare the CV-likelihood of the base-model versus a reduced model that dropped the five disturbance covariates (distance to piling, distance to rock dumping, distance to capital dredging, distance to maintenance dredging, and minimum distance to any disturbance. Note that, within this set of covariates, only maintenance dredging is classified as a non-CU activity. Likelihood ratios above 1 indicate support for the reduced model without the disturbance covariates, whereas ratios below 1 indicate support for the full model that includes the disturbance covariates.

The CV-likelihood ratio for humpbacks was $2.4^{-33} << 1$, with a cross-validation p-value of 0.2. This indicates substantial support for the full model and provides strong evidence that the disturbances had some effect. Taken together with the RVI results, the effect may be mostly driven by the role of maintenance dredging. The cross-validation p-value suggests that a “no effect” null-model cannot be ruled out completely.

The CV-likelihood ratio for snubfin dolphins was 0.055 <1, with a cross-validation p-value of 0.2. This indicates solid support for the full model and provides evidence that the disturbances had some effect. In particular, based on the RVI results, it is likely that dredging (both maintenance and construction) was responsible for these results. The cross-validation p-value suggests that a “no effect” null-model cannot be ruled out completely.

3.2.4 *Covariate Two-Way Interaction Partial Plots*

We used partial plots of two-way interactions to understand the marginal functional relationship between species’ abundance and pairs of interacting covariates. These were done exclusively through two-way interaction plots (Fig. 11), due to the inherent interactive nature of the underlying machine-learning method.

There are too many plots to present here (they are available upon request). Instead, we subjectively describe the functional relationships simple as large increase, moderate increase, small increase, small decrease, moderate decrease, and large decrease, in additional to any other notes.

Snubfin Functional Relationships with Covariates (2023)

- Distance to rivers – strong decrease. (i.e., density of species increases as distance to river decreases).
- Depth – moderate decrease (i.e., density of species increases as water depth decreases).
- Distance to land – moderate increase (i.e., density of species increases as distance to land increases).
- Distance to foreshore – moderate decrease (i.e., density of species increases as distance to shore decreases).
- Salinity – small increase (i.e., density of species increases as salinity increases).
- Distance to maintenance dredging – small decrease (i.e., density of species increases as distance to maintenance dredging decreases).
- Distance to capital dredging – small increase (i.e., density of species increases as distance to capital dredging increases).
- SST – small increase (i.e., density of species increases as SST increases).
- Distance to seagrass – small increase (i.e., density of species increases as distance to seagrass increases).
- Julian day of year – small increase (i.e., density of species increases as Julian day increases).

Humpback Functional Relationships with Covariates (2023)

- Distance to land – strong increase (i.e., density of species increases as distance to land increases).
- Distance to rivers – strong decrease (i.e., density of species increases as distance to river decreases).
- Large boats – moderate increase (i.e., density of species increases as number of large boats increases).
- Distance to reefs - moderate increase (i.e., density of species increases as distance to reefs increases, only present among a few interactions).
- SST – small increase (i.e., density of species increases as SST increases).
- Depth – small decrease (i.e., density of species increases as water depth decreases).
- Fishing boats – small decrease (i.e., density of species increases as number of fishing boats decreases, depends on interaction with large boats).
- Swell – small increase (i.e., density of species increases as swell increases)
- Julian day – small increase (i.e., density of species increases as Julian day increases).
- distance to maintenance dredging (Year 3) – small increase (i.e., density of species increases as distance to maintenance dredging increases).

The reader should note that the relationships could change under multi-way interactions and different years.

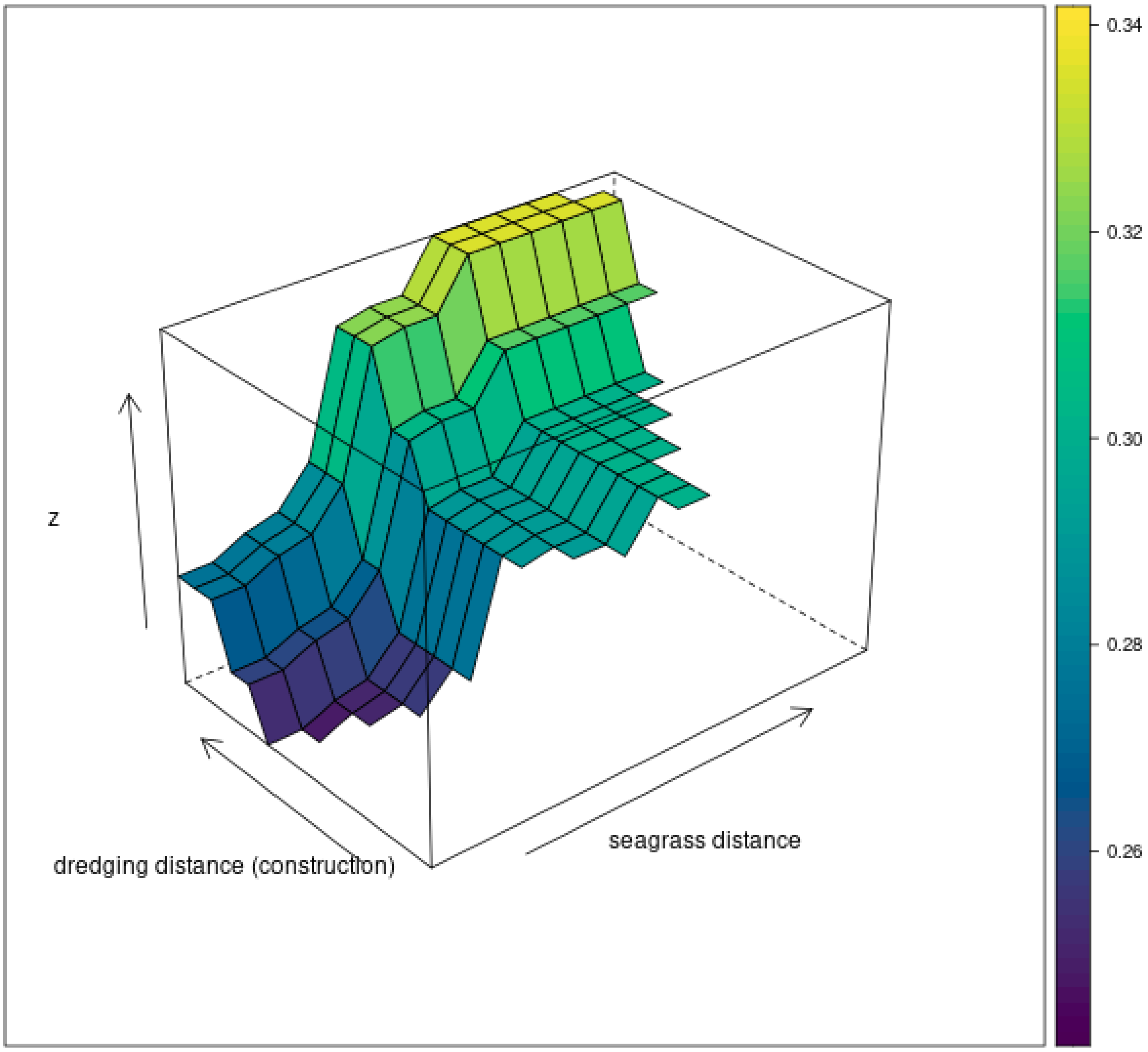


Figure 11. Example of two-way marginal plot for snubfin's (predicted) functional relationship with distance to capital dredging (BHD) and distance to seagrass.

3.2.5 *Plots and Summaries of Spatially Varying SDM Components*

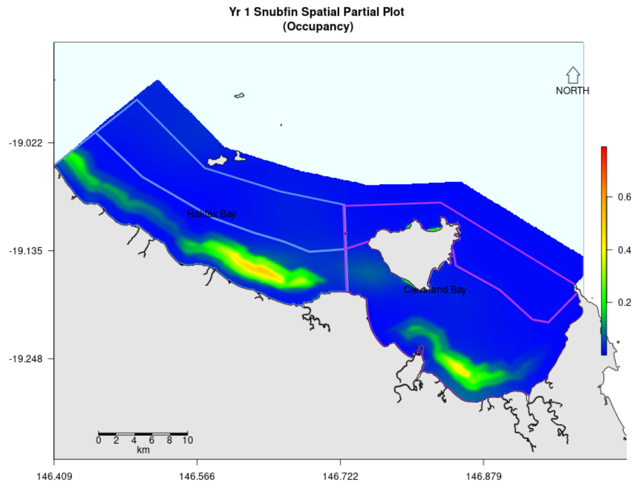
The spatial partial plots of snubfin and humpback dolphins across the survey area are shown in Figures 12 and 13 respectively. These plots show the probability of occurrence (Figs. 12a-e and 13a-e) and the conditional group size (i.e., the size of an encounter, if a group is present) per year (Figs. 12f-j and 13f-j). These two components, the occupancy, and conditional counts, constitute the zero-inflated Poisson bivariate distribution. The plots also show the integration of the two processes, the expected counts, which is the probability of occupancy multiplied by the conditional counts per year (Figs. 12k-o and 13k-o). Note that the influence of temporal covariates (time-of-day, day-of-year) and environmental conditions (swell, BSS, glare, visibility) have been removed by conditioning the plots on the global averages of temporal-covariates. For those years in which a log-distance-to-disturbance was present (like distance-to-maintenance dredging or distance-to-rock dumping), the SDM the model is conditioned on the disturbance being present.

The 2023 spatial occurrence of snubfin dolphins (Fig 12e) and their relative density (Fig 12o) shows a marked departure from earlier years: for instance, prior years had a high occupancy and high-density region north and to the east of Port of Townsville, along the shore of Cleveland Bay, which has disappeared in 2023 (Fig. 12e). In contrast, the 2023 spatial occupancy distribution and relative density shows a new elongated narrow band of moderate-occupancy and density along the entire coast of Halifax Bay, whose past-year equivalent was more broken and separated along the HB shore (Fig. 12e).

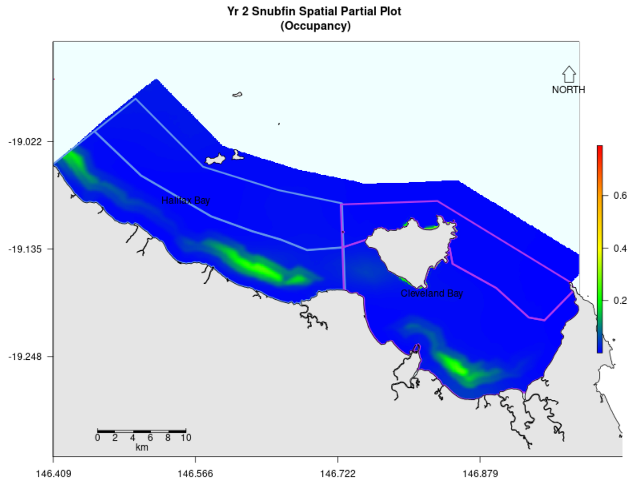
The spatial occupancy (Fig 13e) and relative densities of humpback dolphins (Fig. 13o) seem to exhibit a similar patterning that was present in 2022 (albeit at much lower absolute densities). There was high occupancy and density to the north and to the east of Port of Townsville, along the shore of Cleveland Bay , as well as a large expanse of high-occupancy and density between Saunders beach and Cape Pallarenda along the shore of Halifax Bay (Fig. 13e). Unlike snubfins, humpbacks were consistently present in Cleveland Bay in all years, particularly around the Port Townsville and to the east of the port (Fig 13).

Regarding the decomposition of the expected counts into its occupancy and conditional group-size components, there were some interesting contrasts between species. For humpbacks, the conditional group-size exhibited erratic spatial-variation across the offshore regions, especially in 2020, 2021 and 2022. Group-sizes in 2022 were high around the Port of Townsville, and small between Port of Townsville and Magnetic, in the vicinity where dredging occurred.

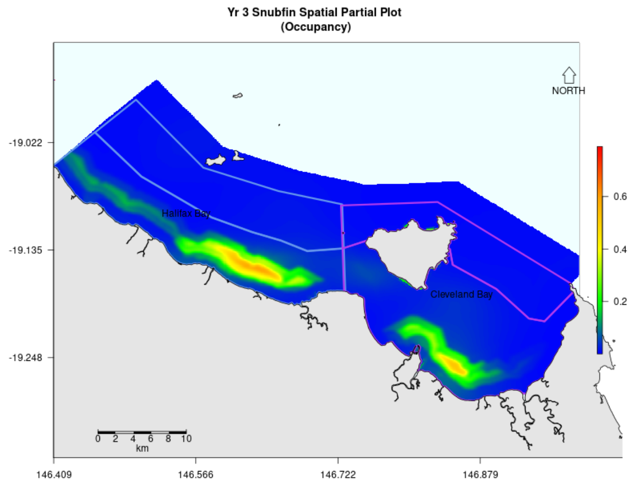
For snubfins, the occupancy component was roughly in-line with the expected counts, and was clearly the dominant component, whereas the conditional group-size component was more uniform across space. Two exceptional areas of very high conditional group-size (particularly in 2022, but also somewhat in 2023) were: i) to the west of Magnetic Island on the nearshore boundary between Cleveland and Halifax Bay; and ii) between Port Townsville and Magnetic Island, in the vicinity of capital dredging and piling activities (both of which were present in 2022). For the latter region, it could be that the disturbances induced a behavioural response associated with grouping, such as fast-travelling and less foraging.



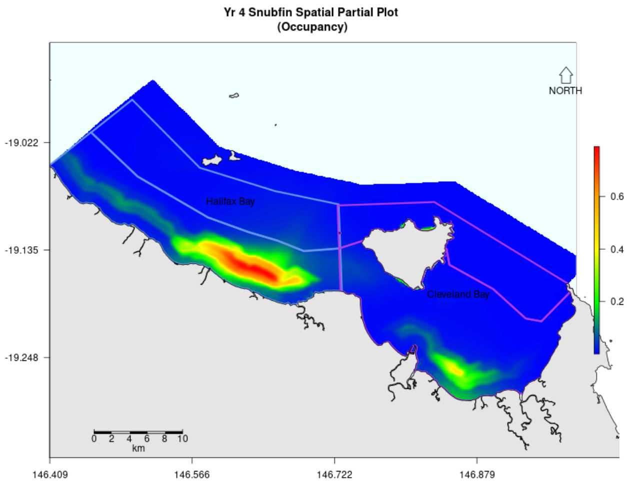
a) 2019



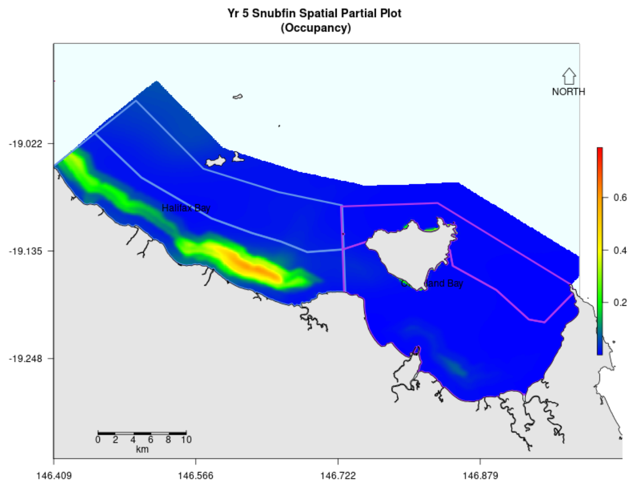
b) 2020



c) 2021

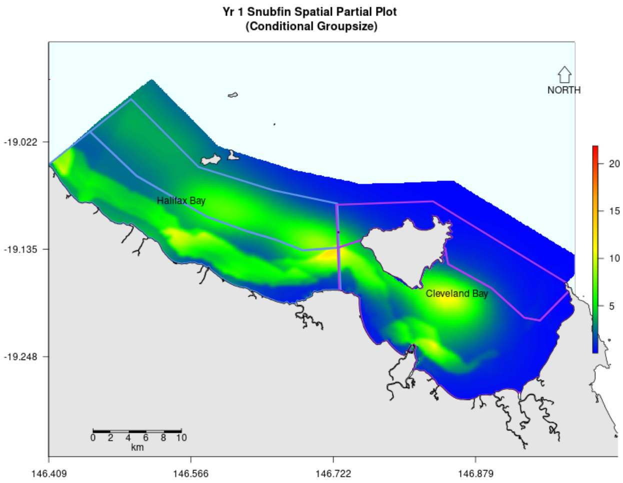


d) 2022

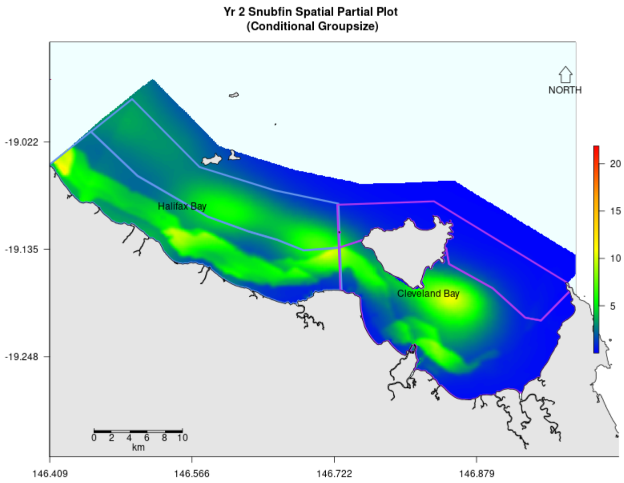


e) 2023

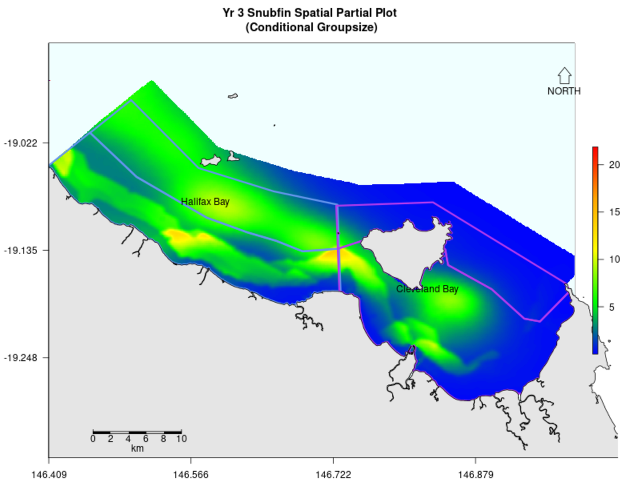
Figure 12. Spatial partial plots of Australia snubfin dolphins from ensemble-modelling of species distribution across the survey area based on data collected in 2019, 2020, 2021, 2022 and 2023: (a-e) shows how the probability of dolphins' presence/absence varies spatially over the study area, (f-j) shows how expected group size varies spatially (conditional on being present), and (k-o) shows the relative density function of dolphins across the bays.



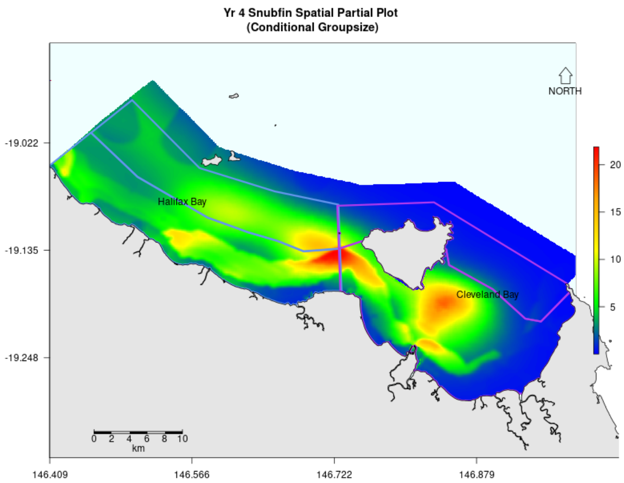
f) 2019



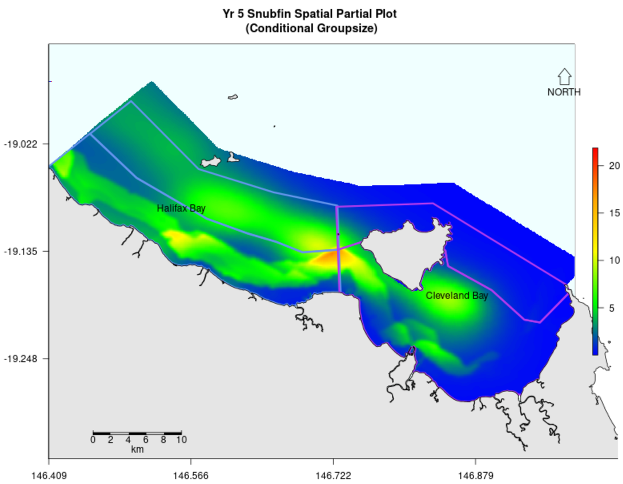
g) 2020



h) 2021

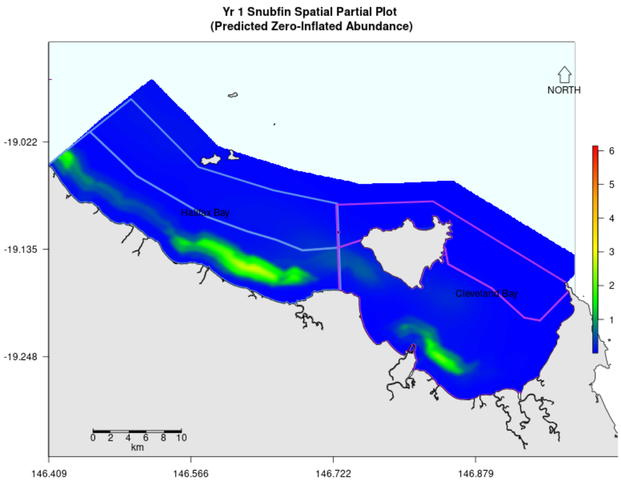


i) 2022

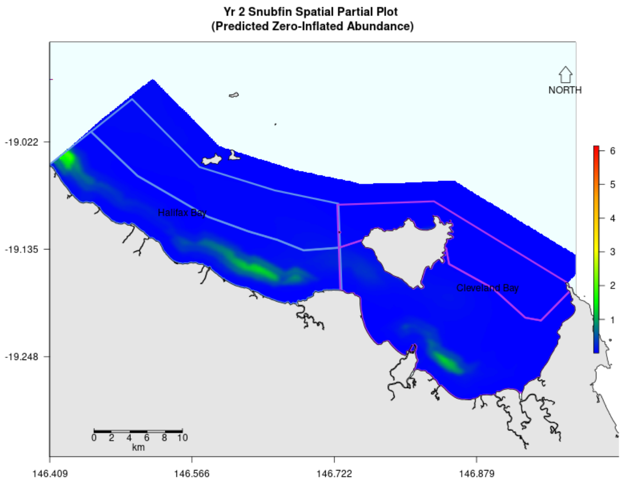


j) 2023

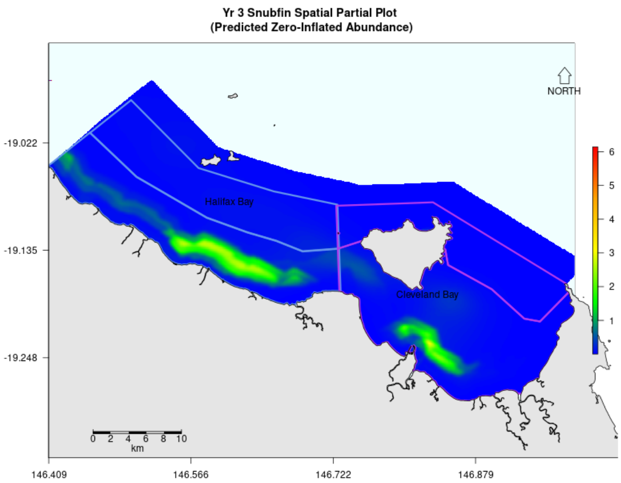
Figure 12 (continued). Spatial partial plots of Australia snubfin dolphins from ensemble-modelling of species distribution across the survey area based on data collected in 2019, 2020, 2021, 2022 and 2023: (a-e) shows how the probability of dolphins' presence/absence varies spatially over the study area, (f-j) shows how expected group size varies spatially (conditional on being present), and (k-o) shows the relative density function of dolphins across the bays.



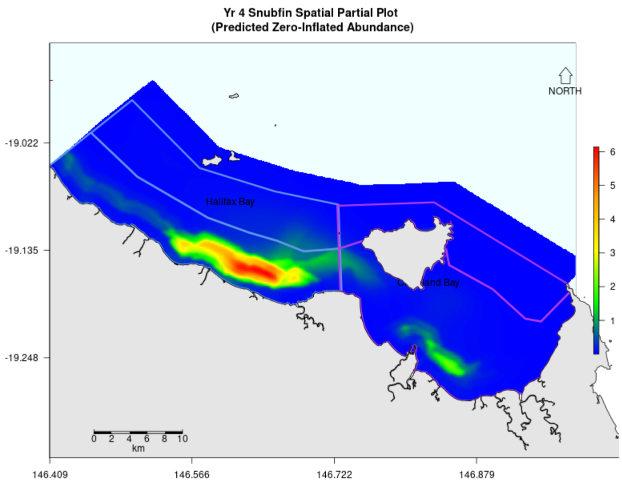
k) 2019



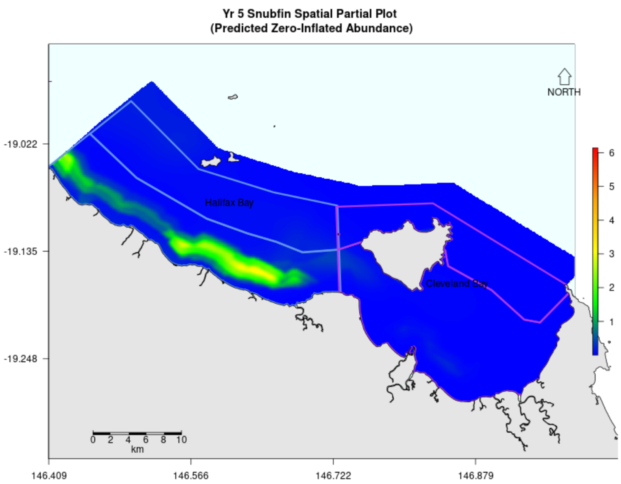
l) 2020



m) 2021

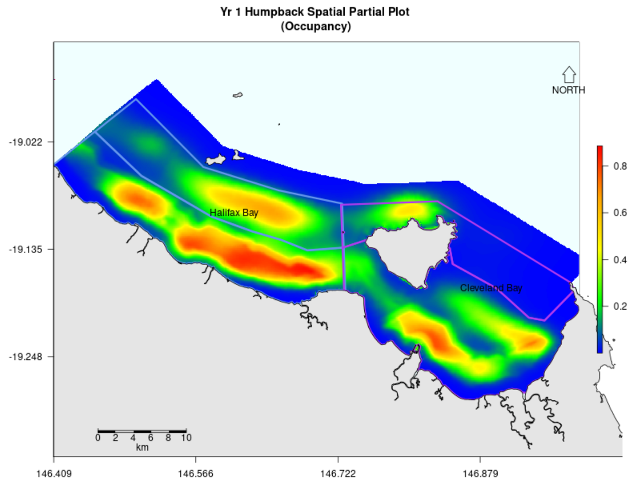


n) 2022

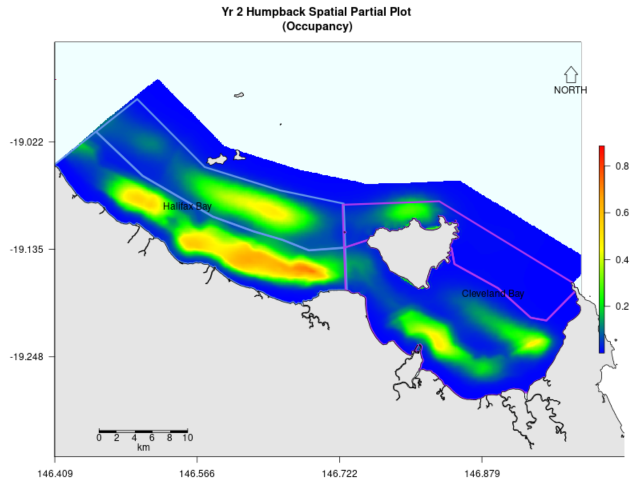


o) 2023

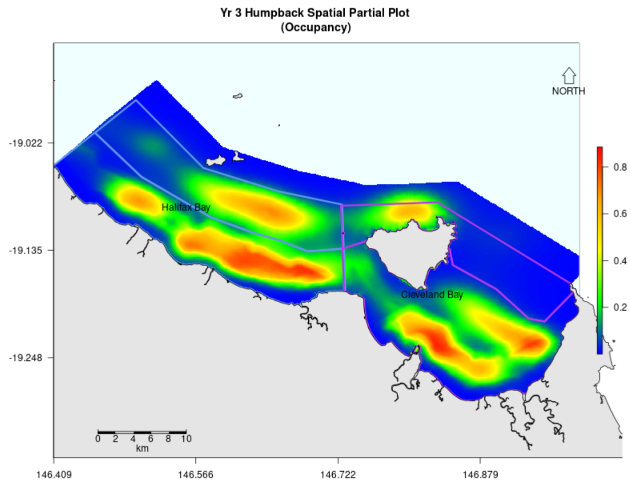
Figure 12 (continued). Spatial partial plots of Australia snubfin dolphins from ensemble-modelling of species distribution across the survey area based on data collected in 2019, 2020, 2021, 2022 and 2023: (a-e) shows how the probability of dolphins' presence/absence varies spatially over the study area (f-j), shows how expected group size varies spatially (conditional on being present), and (k-o) shows the relative density function of dolphins across the bays.



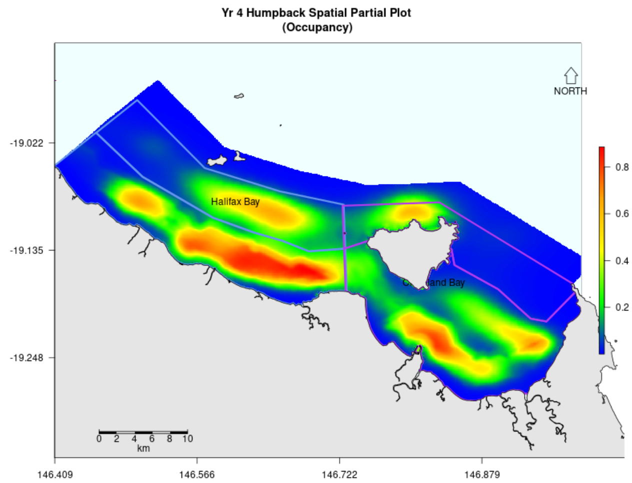
a) 2019



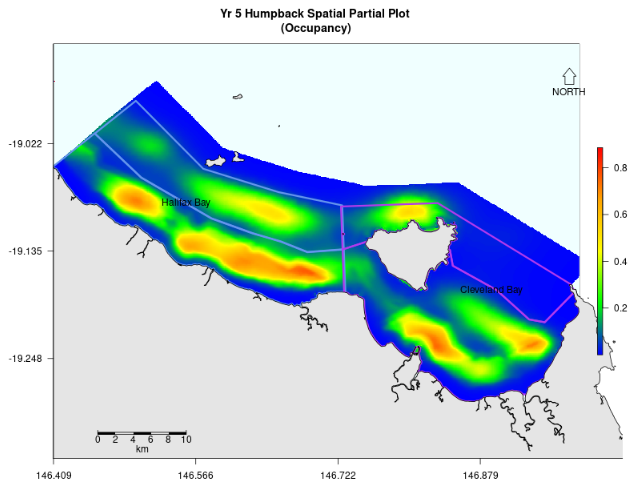
b) 2020



c) 2021

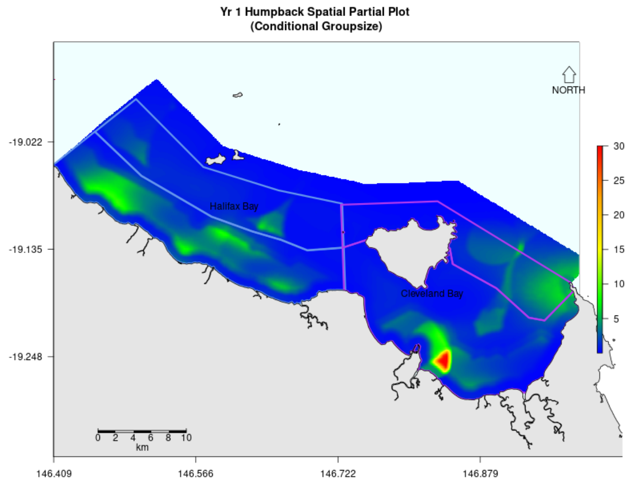


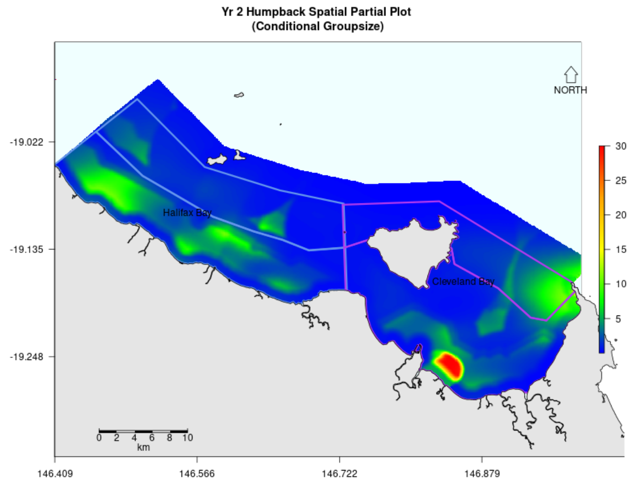
d) 2022



e) 2023

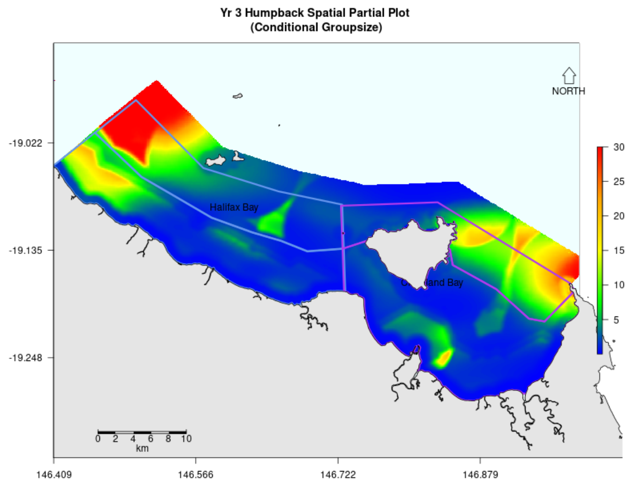
Figure 13. Spatial partial plots of Australia humpback dolphins from ensemble-modelling of species distribution across the survey area based on data collected in 2019, 2020, 2021, 2022 and 2023: (a-e) shows how the probability of dolphins' presence/absence varies spatially over the study area (f-j), shows how expected group size varies spatially (conditional on being present), and (k-o) shows the relative density function of dolphins across the bays.

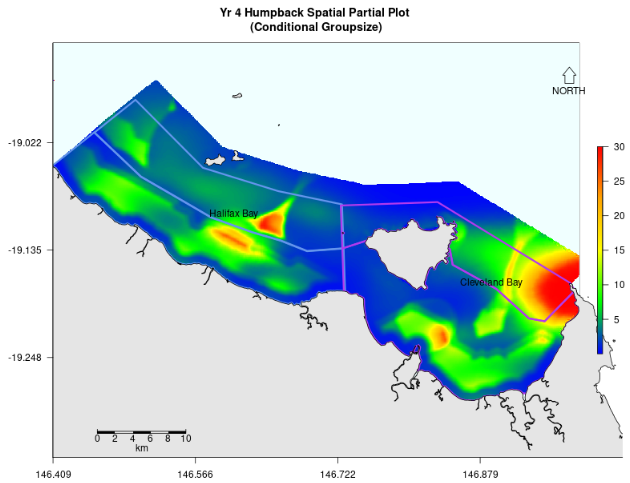




f) 2019

g) 2020





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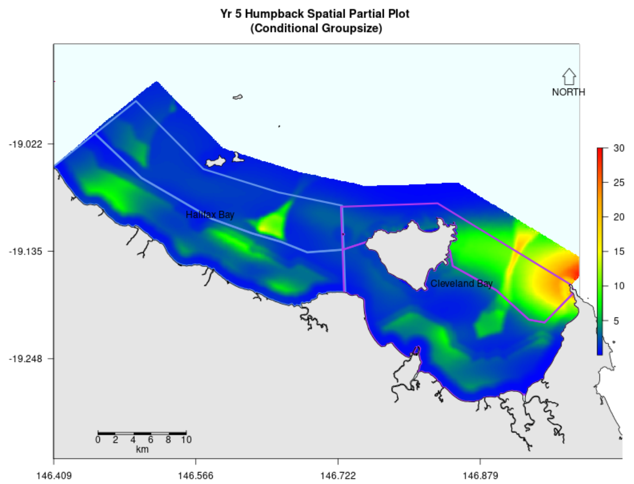
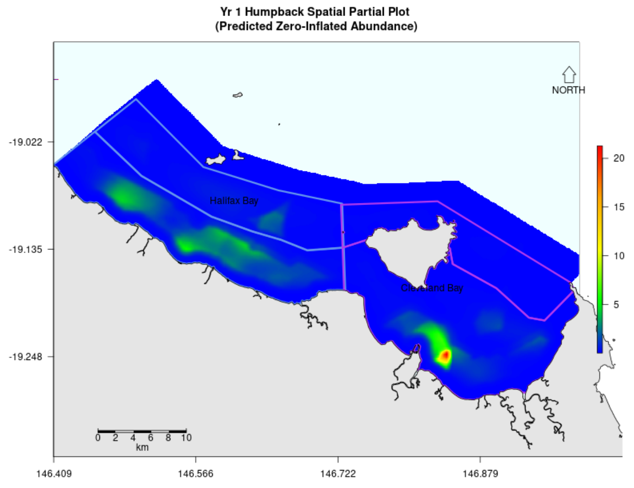
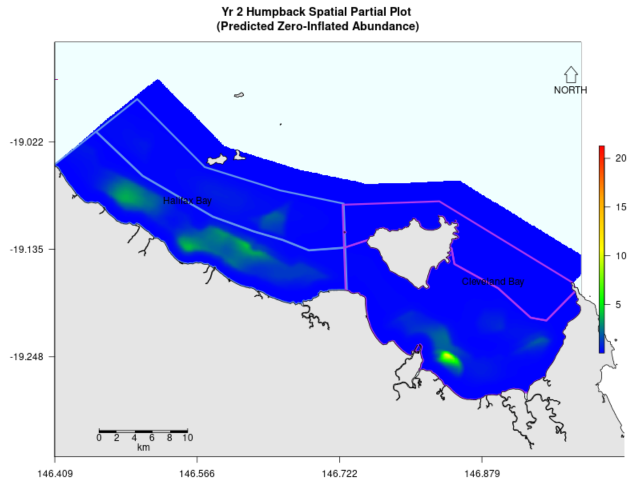


j) 2023

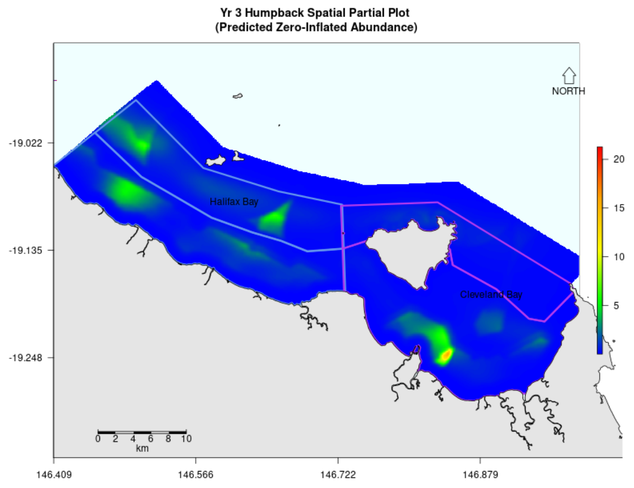
Figure 13 (continued). Spatial partial plots of Australia humpback dolphins from ensemble-modelling of species distribution across the survey area based on data collected in 2019, 2020, 2021, 2022 and 2023: (a-e) shows how the probability of dolphins' presence/absence varies spatially over the study area (f-j), shows how expected group size varies spatially (conditional on being present), and (k-o) shows the relative density function of dolphins across the bays.



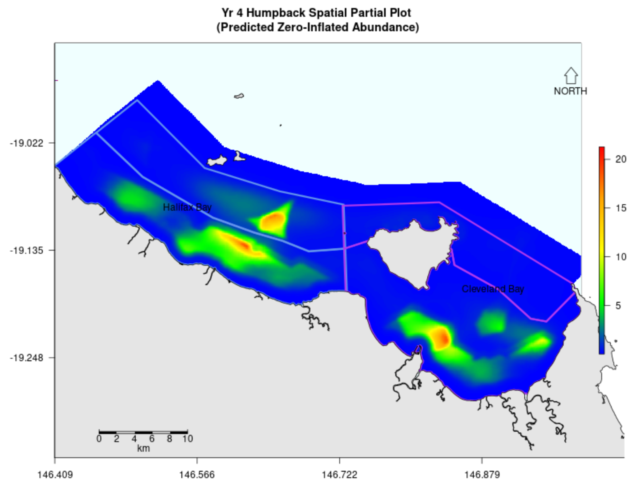
k) 2019



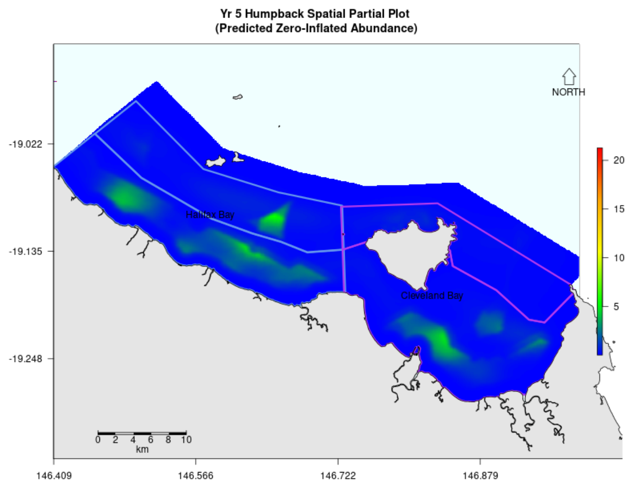
l) 2020



m) 2021



n) 2022



o) 2023

Figure 13 (continued). Spatial partial plots of Australia humpback dolphins from ensemble-modelling of species distribution across the survey area based on data collected in 2019, 2020, 2021, 2022 and 2023: (a-e) shows how the probability of dolphins' presence/absence varies spatially over the study area (f-j), shows how expected group size varies spatially (conditional on being present), and (k-o) shows the relative density function of dolphins across the bays.

For snubfins, Table 9a shows the average predicted values (for predicted occupancy and expected) across the spatial plots and stratified by bay (Cleveland Bay vs. Halifax Bay), inshore vs. offshore, and by year. Table 9b shows the same for humpback dolphins. The 2023 values were very low in Cleveland Bay's inshore water. For example, the expected occupancy was down to 0.01, a 3 to 6-fold reduction compared to prior years. Halifax Bay's inshore water, however, attained their highest values across the study-years, in both occupancy and expected counts.

For humpbacks, the 2023 year obtained values for occupancy and expected counts that were the median across years, for most strata, but down starkly compared to the bumper year of 2022. In other words, the values are neither high nor low compared to past years.

Table 9. Summaries of a) snubfin dolphins and b) humpback dolphins predicted occupancy and expected counts, by strata.

a) Snubfin dolphins

	Expected Occupancy				**Expected Counts**			
	Halifax Bay		**Cleveland Bay**		**Halifax Bay**		**Cleveland Bay**	
Year	inshore	offshore	inshore	offshore	inshore	offshore	inshore	offshore
2019	0.08	0.02	0.05	0.02	0.42	0.07	0.16	0.02
2020	0.04	0.01	0.03	0.01	0.19	0.03	0.07	0.01
2021	0.09	0.01	0.06	0.01	0.43	0.07	0.19	0.01
2022	0.14	0.02	0.04	0.01	0.95	0.11	0.17	0.02
2023	0.11	0.02	0.01	0.01	0.56	0.08	0.03	0.01

b) Humpback dolphins

	Expected Occupancy				**Expected Counts**			
	Halifax Bay		**Cleveland Bay**		**Halifax Bay**		**Cleveland Bay**	
Year	inshore	offshore	inshore	offshore	inshore	offshore	inshore	offshore
2019	0.34	0.23	0.2	0.09	0.99	0.25	0.58	0.04
2020	0.22	0.14	0.09	0.05	0.77	0.21	0.3	0.02
2021	0.29	0.22	0.25	0.11	0.75	1.07	0.62	0.31
2022	0.33	0.19	0.22	0.11	2.01	1.19	1.54	0.22
2023	0.26	0.17	0.18	0.09	0.81	0.42	0.5	0.19

3.3 Patterns of attendance to the port area

3.3.1 *Land based survey effort*

During the 2023 field season, there were 19 days of land-based surveys, conducted between June 2nd and July 11th. There was a total of 1164 scans (compared to 870 scans in 2019, 948 in 2020, 1533 in 2021, and 1490 scans in 2022; Table 10). No snubfin nor bottlenose dolphins were seen, as compared to just one observation of a snubfin dolphin in 2022. Humpbacks were observed on 16 of the 19 survey-days.

Table 10. Survey effort and dolphins observed from Berth 11 at the Port of Townsville during June-July 2023. 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
2/06/2023	68	2	0	0	1	3	2
3/06/2023	66	2	0	0	1	3	1
4/06/2023	66	2	0	0	2	4	2
13/06/2023	66	1	0	0	1	2	1
14/06/2023	66	3	0	0	1	4	1
15/06/2023	66	1	0	0	1	3	1
16/06/2023	66	4	0	0	1	3	3
19/06/2023	56	3	0	0	1	3	2
20/06/2023	66	4	0	0	1	4	1
26/06/2023	4	0	0	0	1	2	1
27/06/2023	66	0	0	0	0	2	1
28/06/2023	66	1	0	0	0	2	1
29/06/2023	66	0	0	0	1	3	2
30/06/2023	56	1	0	0	1	5	3
5/07/2023	66	1	0	0	0	3	1
6/07/2023	66	6	0	0	0	3	1
8/07/2023	66	6	0	0	1	4	3
10/07/2023	66	10	0	0	1	4	1
11/07/2023	56	6	0	0	1	4	1
Total	**1164**	**53**	**0**	**0**			

3.3.2 *Overall difference in dolphin occurrence between years*

For snubfin dolphins, the Bayesian p-value for 2019 (baseline) vs 2023 was 0, indicating that encounters of snubfin dolphins in 2023 were lower than expected (recall that a small p suggests inconsistency between baseline and 2023). Bayesian p-values for 2020 vs 2023, and 2021 vs 2023 were also approximately 0, indicating that encounters of snubfin dolphins were lower in 2023 than expected based on previous years. The 2023 vs. 2022 p-value was moderate at 0.32, but there was only one snubfin observation in 2022, and 0 in 2023, making the comparison sparse.

In contrast, for humpbacks dolphins, the Bayesian p-values for 2019 (baseline) vs 2023, 2020 vs 2023, and 2021 vs 2023 were all greater than 0.998 (Table 11), i.e., the number of encounters of humpback dolphins were in line (or greater) than the expectations of previous years. The 2023 vs. 2022 humpback p-value was 0.6, suggesting moderate alignment with the expectations of 2022.

Table 11. Comparison of dolphin occurrences between 2023 and all other years and corresponding Bayesian P-values.

a) 2019-2023

Species	Year	Number of Scans	N occurrences of dolphins	Bayesian P-value
Snubfin	2019	867	49	0.00
	2023	1164	0	
Humpback	2019	867	19	1.00
	2023	1164	53	

b) 2020-2023

Species	Year	Number of Scans	N occurrences of dolphins	Bayesian P-value
Snubfin	2020	948	34	0.00
	2023	1164	0	
Humpback	2020	948	7	1.00
	2023	1164	53	

c) 2021-2023

Species	Year	Number of Scans	N occurrences of dolphins	Bayesian P-value
Snubfin	2021	1533	27	0.00
	2023	1164	0	
Humpback	2021	1533	32	1.00
	2023	1164	53	

d) 2022-2023

Species	Year	Number of Scans	N occurrences of dolphins	Bayesian P-value
Snubfin	2022	1490	1	0.32
	2023	1164	0	
Humpback	2022	1490	65	0.60
	2023	1164	53	

3.3.3 *Diel and behavioural patterns observed*

There were no observations of snubfins in 2023, from the land station, and so no behavioural analyses could be performed.

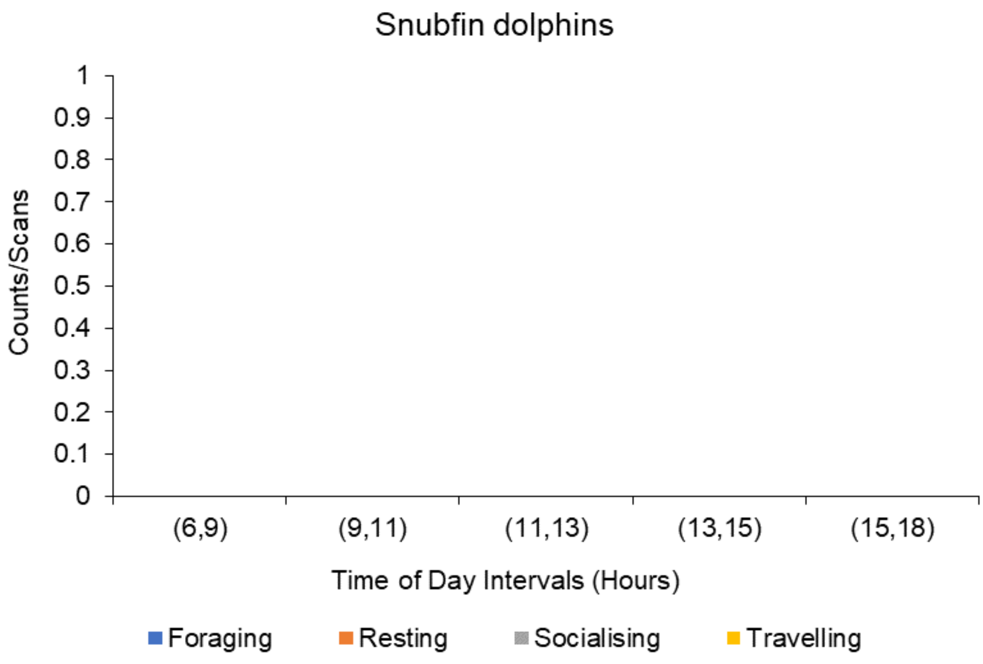
In 2023, humpback dolphins were mainly observed foraging (48%; Table 12), followed by travelling (35%). These behaviours were especially dominant in the morning (Fig. 14b), both in terms of absolute number of encounters, as well as proportion of time, especially during 9:00 am to 11:00 am, and encounters fell-off sharply after 15:00. Other behaviours such as resting and socialising showed no discernible pattern.

The behavioural summaries were also made by pooling all survey years together, from 2019 to 2023 (Fig. 15). The pooled behavioural summaries of snubfins (from 2019 to 2023) showed that they spent the overwhelming majority of their time foraging, with most encounters occurring evenly between 6:00 to 11:00, followed by a sharp drop-off in encounters thereafter (Fig 15a).The pooled summaries suggest that humpback dolphins had a morning-peak in foraging and travelling activities between 9:00-11:00, and more uniform activity in the hours of 6:00 to 9:00, and 11 through to 15:00, with a sharp decline after 15:00 (Fig. 15b).

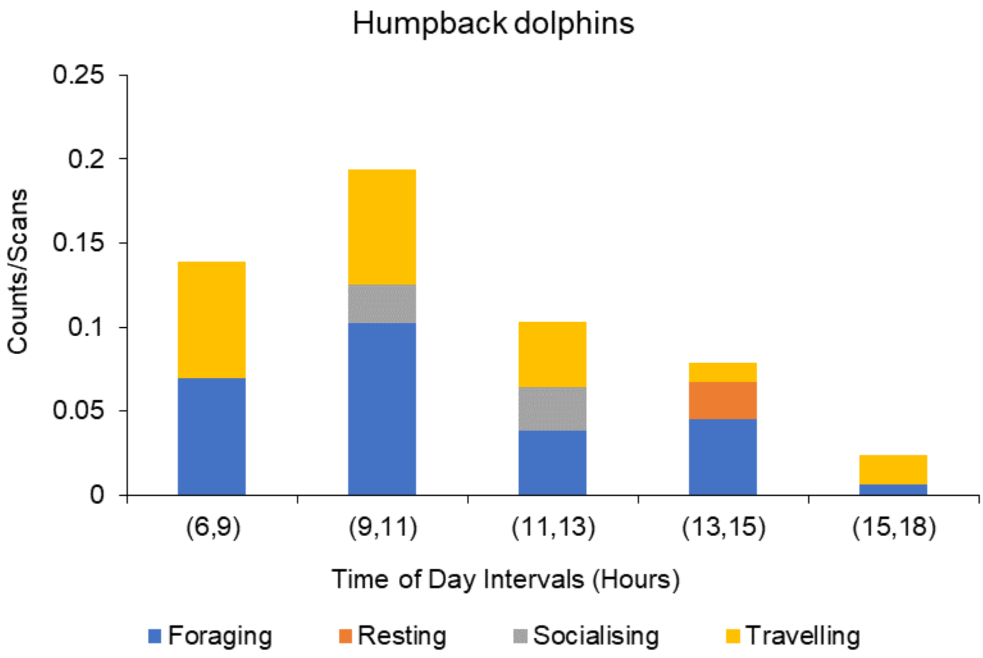
Table 12. The total number of scans where either species was present (and behaviour could be determined) during land-station surveys from 2019 to 2023, and the proportion of times they were observed engaged in foraging, resting, socializing, and travelling behavior. The aggregated numbers for all survey years ("pooled") are also shown below.

Species	Year	Number of Scans with Species Present	Foraging	Resting	Socialising	Travelling
Snubfin	2019	47	0.62	0.02	0.04	0.32
	2020	29	0.97	0.03	0.00	0.00
	2021	24	0.54	0.00	0.25	0.21
	2022	1	0.00	0.00	0.00	1.00
	2023	0.00	0.00	0.00	0.00	0.00
	Pooled	101	0.69	0.02	0.08	0.21
Humpback	2019	18	0.50	0.00	0.00	0.50
	2020	7	0.71	0.00	0.29	0.00
	2021	29	0.52	0.00	0.31	0.17
	2022	59	0.44	0.02	0.15	0.39
	2023	52	0.48	0.04	0.08	0.40
	Pooled	165	0.49	0.02	0.15	0.35

* Note: discrepancies in counts with other tables due to NA in behaviours

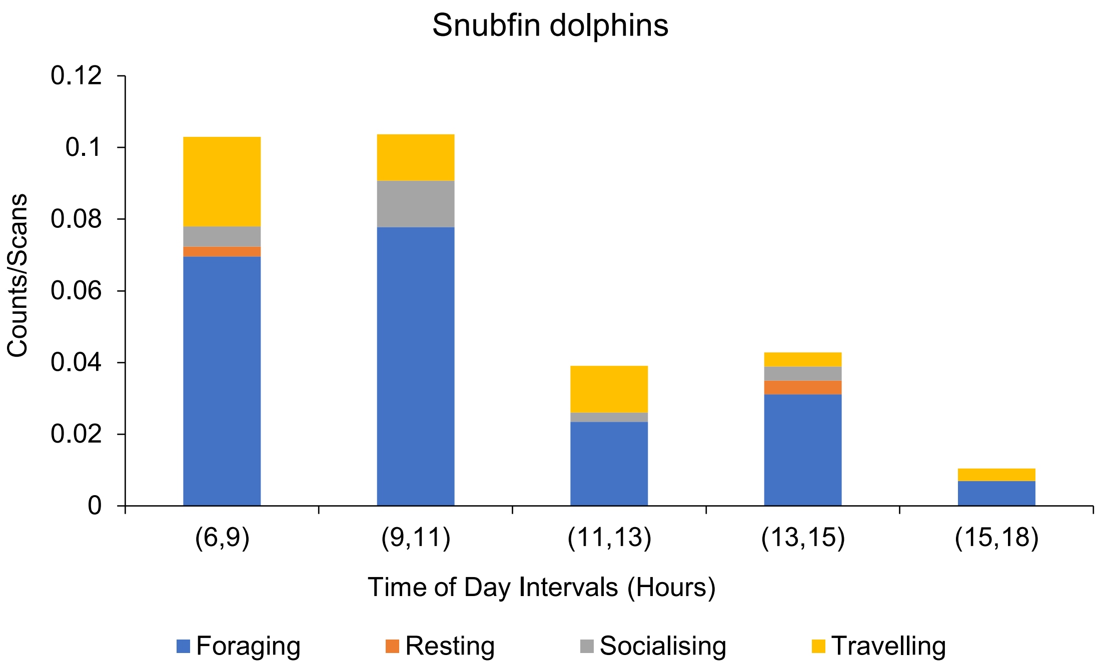


a)

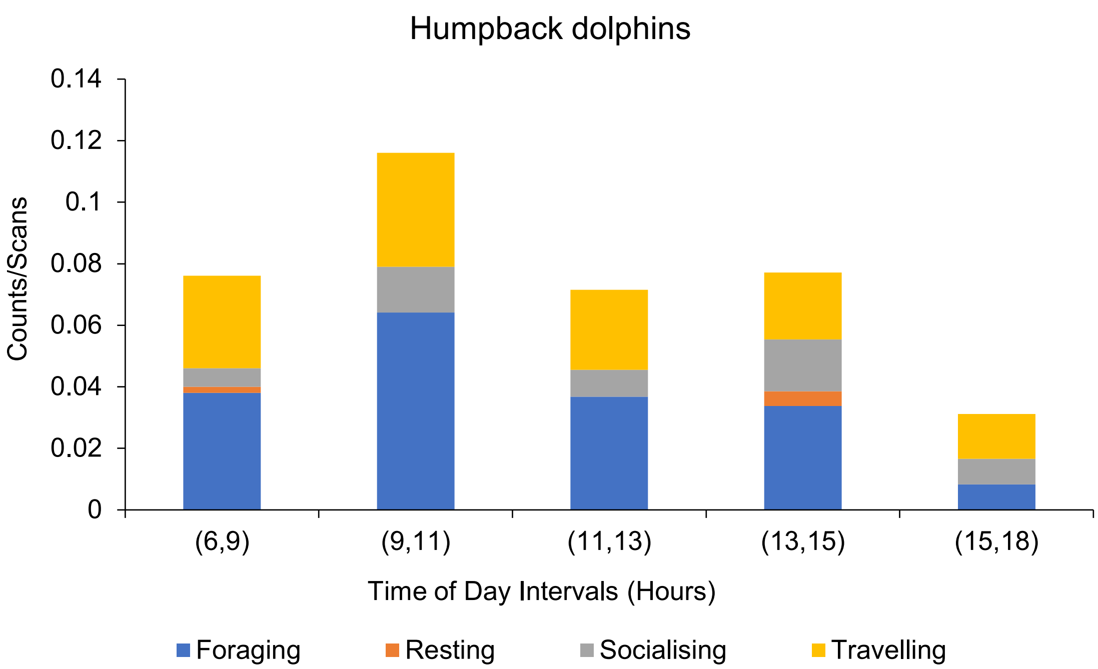


b)

Figure 14. a) Australian snubfin and b) humpback dolphin observations by time of day (2-3 hourly bins) in 2023. 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.



a)



b)

Figure 15. Pooled observations (2019 to 2023 inclusive) of Australian a) snubfin and b) humpback dolphins by time of day (2-3 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.

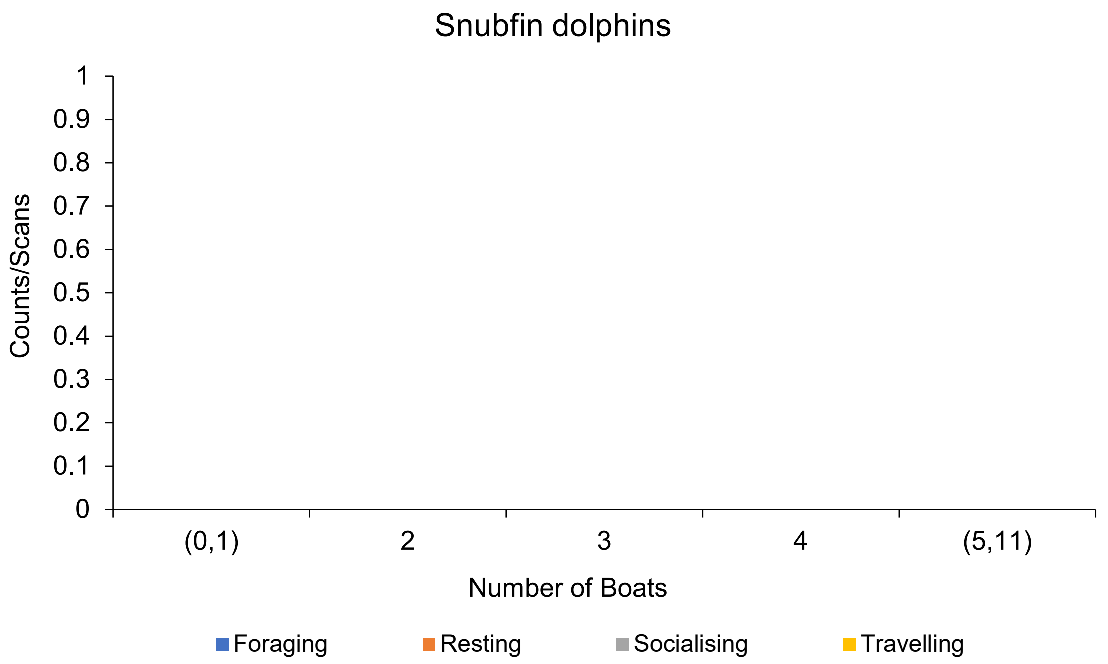
3.3.4 *Dolphins' patterns of occurrence in relation to boats, capital dredging, maintenance dredging and rock dumping*

Boats

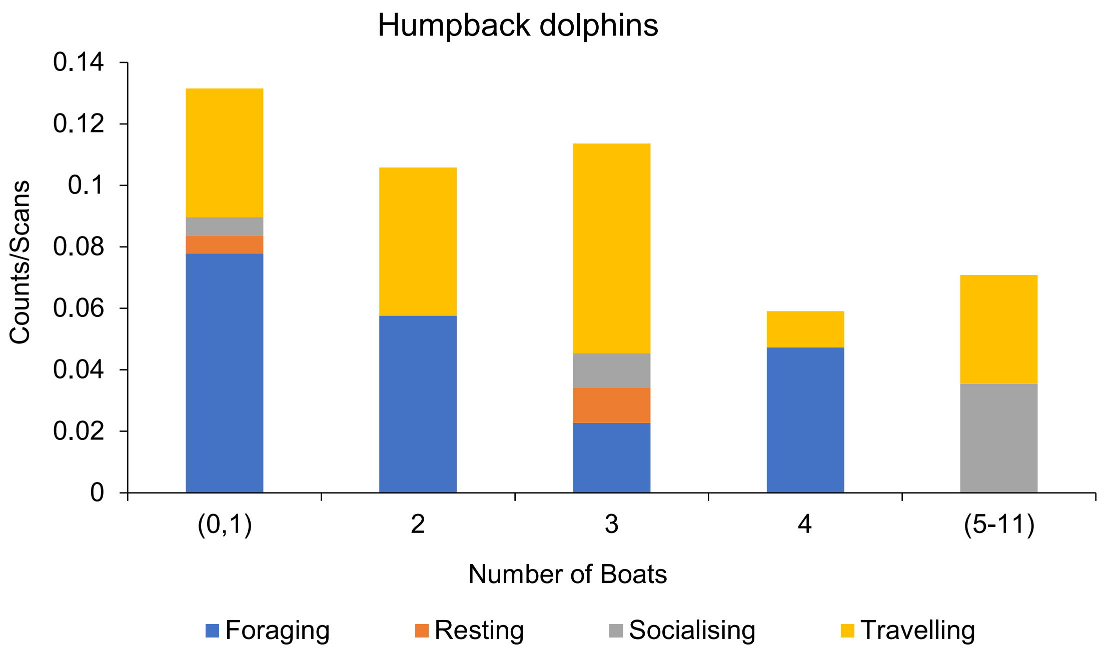
All boats were pooled for analysis given data available. There were no observations of snubfin dolphins from Berth 11 during 2023. The presence and behavioural activity of humpback dolphins observed from Berth 11 in 2023 changed as the number of boats increased (Fig 16b). Humpback dolphin counts tended to decrease with increasing number of boats, and generally dolphins were observed foraging more frequently when there were less boats present and socialising when there were more boats (Fig. 16b).

In the presence of boats overall years, snubfin dolphins had a more marked decline in counts, dropping approximately 37% from 0-1 boats being present to 2-15 boats present (Fig. 17a). There didn't seem to be a consistent pattern in their behaviour in relation to the number of boats present, although at the lowest number of boats they spent the majority of their time foraging (65%), while at the highest number of boats (5-15), they were evenly split between foraging (33%), travelling (33%), and resting (33%).

When considering all years of data pooled together, the counts and behaviour of humpback dolphins changed as the number of boats increase from 0-1 to 5-15 (Fig.17b). The counts of humpbacks decreased by 15% from 0-1 boats to 5-15 boats. The humpbacks spent the majority of their time foraging (52%) and travelling (33%) when there were 0-1 boats; this gradually shifted to more time spent travelling (50%) and socialising (40%) in the presence of 5-15 boats, and very little time spent foraging (10%) (Fig.17b).



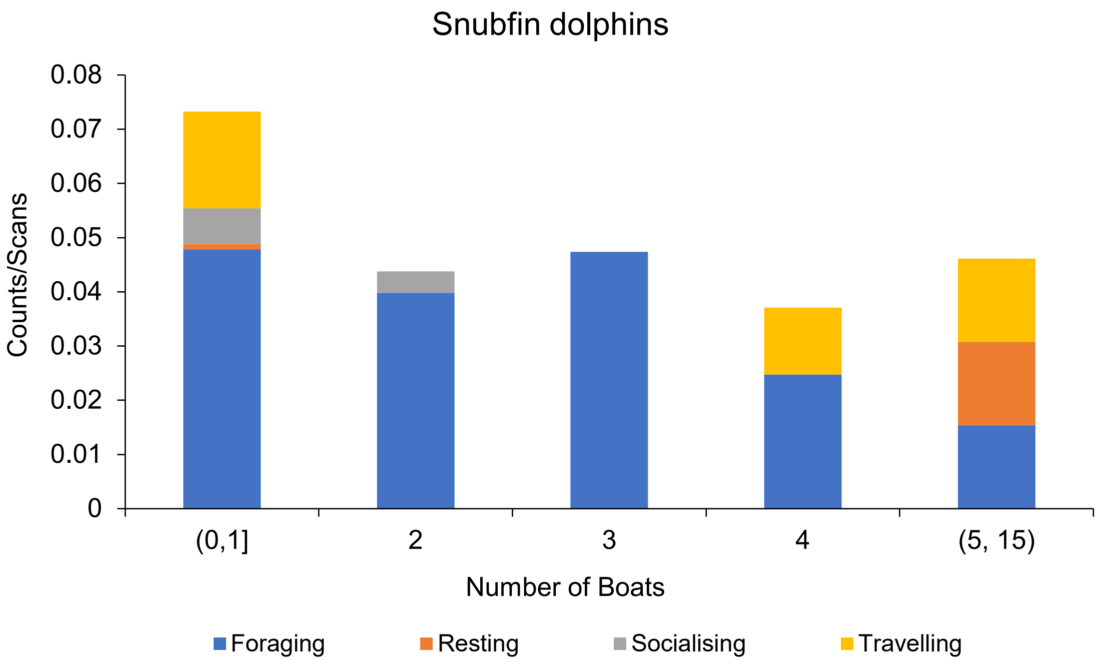
a)



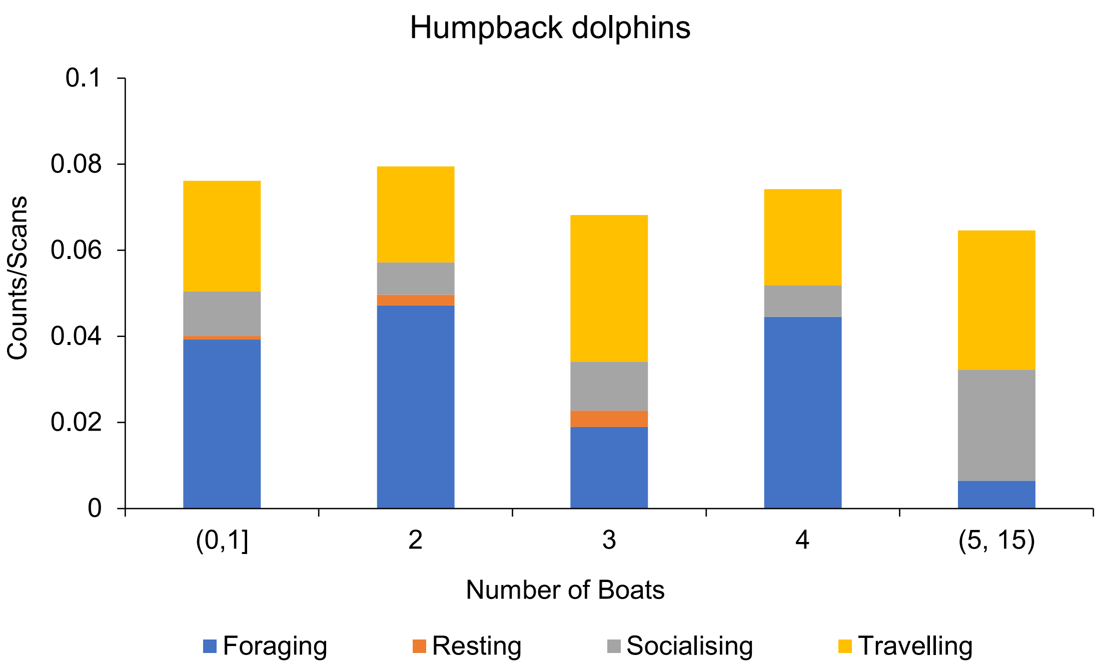
b)

Figure 16. Counts of Australian a) snubfin and b) humpback dolphins groups observed and their behaviours, stratified by the number of boats present, for the 2023 survey-year. Bar

height represents densities of counts (number of dolphin groups seen divided by number of scans).



a)



b)

Figure 17. Pooled observations (2019 to 2023 inclusive) of Australian a) snubfin and b) humpback dolphins by time of day (2-3 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.

Dredging

Regarding the analysis of dolphin presence with respect to maintenance and capital dredging activities, we pooled all years and used the absence of dredging (of all types) as the null-model to calculate Bayesian p-values. For capital dredging, we further analysed the data based on whether the dredging was active (i.e. refers to a period when dredging operations were actively occurring-mechanical removal of sediments, rocks, or debris from the seabed) vs. inactive (periods when dredging operations are not occurring), as well as present (dredging vessel is at the site, regardless of whether it is actively operating) vs. not present (i.e. no dredging vessels are at the site) (Table 13).

Over 5 years of field study, there were a total of 21 scans in which maintenance dredging was present, 1327 scans in which capital dredging was present, and 858 scans in which capital dredging was present and active.

The humpbacks had very high Bayesian p-values for all types of dredging ($p \geq 0.95$) (Table 13). Therefore, their presence/absence patterns were in-line with the no-dredging null model, and may indicate a positive affinity.

For snubfin dolphins, the p-values were high for maintenance dredging (0.99), but very low for capital dredging presence (0.000) and capital dredging activity (0.000), suggesting that capital dredging was associated with low snubfin counts that were inconsistent with the no-dredging null-model. Therefore, maintenance dredging did not appear to affect the presence/absence of snubfin dolphins around the port area, whereas capital dredging may influence their occurrence patterns.

Table 13. Land-based observations of Australian snubfin and humpback dolphins during a) maintenance dredging with trailing suction hopper dredger (THSD); b) presence of capital dredging with backhoe dredger (BHD) versus periods with no dredging (of all types); and c) active versus inactive/non-presence of capital dredging, across all survey years.

a)

Species	Maintenance Dredging (TSHD)	Number of Scans*	Number of Scans with Dolphins Present	Bayesian P-value
Snubfin	no	4654	108	0.99
	yes	21	2	
Humpback	no	4654	74	0.95
	yes	21	1	

b)

Species	Capital dredging (BHD)	Number of Scans*	Number of Scans with Dolphins Present	Bayesian P-value
Snubfin	no	4654	110	0.00
	yes	1327	1	
Humpback	no	4654	75	0.99
	yes	1327	101	

c)

Species	Construction Dredging (BHD)	Number of Scans*	Number of Scans with Dolphins Present	Bayesian P-value
Snubfin	not present/inactive	5144	110	0.00
	active	858	1	
Humpback	not present/inactive	5144	116	0.99
	active	858	60	

* For both types of dredging, the total number of scans does not match the sum of individual scans due to differences in treatments or sets. When analysing presence and absence counts for capital dredging, we

excluded both maintenance and capital dredging from the "no dredging" treatment. The same approach was applied to maintenance dredging. This ensured that the "no dredging" treatment was free from potential confounding effects caused by the presence of another type of dredging.

Rock-Dumping

There were no additional incidences of rock dumping in 2023. All 401 scans in which rock dumping occurred happened in 2020. Therefore, our conclusions are the same as reported previously.

The Bayesian p-value was very high for snubfins (>0.999), suggesting that the presence of snubfins was not out-of-line with the expectations of the non-rock dumping null model, and there may even have been a positive affinity (Table 14). The p-value was very low for humpback dolphins, given that exactly 0 humpbacks were encountered during rock dumping (Table 14). Therefore, the presence or absence of snubfin dolphins around the port area does not seem to be influenced by rock dumping, however it does appear to have influenced humpback dolphin presence/absence.

Piling Activities

There was no additional piling activity in 2023. All 9 scans in which piling occurred were from 2022, and so our conclusions are the same as reported previously.

There were no observed dolphins during any of the 9 piling scans. While this may seem dramatic, due to the few occurrences of piling, the lack of dolphins was actually in-line with the null-model expectations, such that the Bayesian p-values were high (0.763 – 0.844) (Table 15).

Table 14. Land-based observations of snubfin and humpback dolphins during rock dumping and non-rock dumping construction activities across all survey-years.

Species	Rock-Dumping Present	Number of Scans*	Number of Scans with Dolphins Present	Bayesian P-value
Snubfin	no	5601	91	1.00
	yes	401	20	
Humpback	no	5601	176	0.00
	yes	401	0	

Table 15. Land-based observations of snubfin and humpback dolphins during piling and non-pilling activities across all survey years.

Species	Piling Active	Number of Scans*	Number of Scans with Dolphins Present	Bayesian P-value
Snubfin	no	5993	111	0.84
	yes	9	0	
Humpback	no	5993	176	0.76
	yes	9	0	

*The total number of scans does not match the sum of individual scans as there were a few scans where data was missing or dolphin species could not be determined

3.3.5 *GAM regression of dolphin presence/absence in relation to environmental predictors and anthropogenic disturbances (capital dredging, maintenance dredging, rock dumping, and piling)*

The multi-model GAM exercise for the land-station data inference resulted in 8451 different models with different combinations of covariates. This was a 7.4x increase in the number of models examined previously, due to the combinatorial explosion in the number of models by adding the new segregated disturbance covariates, which had previously been rolled-up into a single indicator variable.

For humpback and snubfin dolphins, there was a lot of multi-model uncertainty, especially for snubfin dolphins. In other words, there were a lot of low probability models, including the top models.

For snubfins, the top model, 2nd top model, and 3rd top model had 14.2%, 7.7%, and 5.0% AIC-weights, respectively, indicating high multimodel uncertainty. The top model included covariates: glare, fishing boats, and various non-linear temporal components. The 2nd best model just had glare and various temporal components. The 3rd best model had glare and small-boats plus various temporal components.

For humpbacks, the top model had 25.5% of the AIC-weights. It included covariates: year-as-a-categorical factor, BBS, glare, capital dredging presence, a non-linear time-of-day spline stratified by year, and a non-linear time-of-year spline stratified by year. The 2nd and 3rd best models had 11.8% and 11.5% AIC-weights, respectively. They also included capital dredging, BSS, as well as various temporal components, and the total number of boats.

Due to the high model uncertainty, our primary means of inference was primarily based on model-averaging, such as interpreting the posterior inclusions probabilities (Table 16) to rank the importance of covariates, and the model-averaged coefficients and p-values (Table 17) to interpret effect magnitude and direction and statistical significance.

For snubfin dolphins, all three temporal covariates had an inclusion probability of approximately 1. Glare had an inclusion probability of 0.98. Fishing boats had an inclusion probability of 0.25., followed by capital dredging/active 0.15 No other covariate had an inclusion probability above 0.1.

For humpback dolphins, the highest posterior probabilities (greater than 0.99, or 99% inclusion) were obtained by five covariates including: all the temporal covariates (hour-of-day, Julian day-of-year, year-as-a-categorical variable), the presence of capital dredging, and BSS. The next largest component was from glare, with an inclusion probability of 0.26, followed by total boats at 0.12. All subsequent covariates had inclusion probabilities below 0.1.

Table 16. Model-averaged sum of AIC-weights (aka approximate posterior inclusion probabilities) for covariates predicting the presence/absence of dolphins at land-stations. Inclusion probabilities greater than 0.5 are shown in bold.

Covariate	Humpbacks	Snubfins
wind	0.01	0.05
BSS	**0.99**	0.04
swell	0.06	0.09
visibility	0.02	0.08
glare	0.26	**0.98**
hour	**0.99**	**1.00**
Julian-day-of-year	**1.00**	**1.00**
year-as-a-categorical factor	**1.00**	**1.00**
boats small	0.09	0.09
boats medium	0.05	0.06
boats large	0.10	0.06
boats fishing	0.04	0.25
boats recreational	0.08	0.05
boats total	0.12	0.07
boats industrial	0.05	0.06
capital dredging presence	**1.00**	0.06
capital dredging active	0.00	0.15
maintenance dredging	0.00	0.04
rock dumping	0.00	0.06
piling	0.00	0.04
aggregate disturbance	0.00	0.05

Table 17 shows the estimate of standardised regression coefficients (1 unit change in logit-probability of presence per 1 standardised unit of the covariates), model-averaged over top models with most posterior weights.

For snubfins, only glare had a statistically significant contribution (aside from the temporal covariates). Some of the estimates suffered from singularities and infinities in the MLE variance-covariance matrix (such as the capital dredging and piling covariates), likely due to the paucity of snubfins presence during capital dredging activities, making it impossible to estimate confidence intervals and p-values. Nonetheless, we can still look to the inclusion probabilities for inference about their "significance".

For humpbacks, there were two (non-temporal) covariates that had statistical significant model-averaged effects: BSS and the presence of capital dredging. The negative MLE for BSS suggests that BSS negatively associated with humpbacks. The positive MLE for capital dredging suggests that capital dredging was positively associated humpbacks.

Table 17. Model-averaged and standardised regression effects from an ensemble of GAMs for predicting dolphin presence at land observation stations.

	Snubfin					Humpbacks				
Covariate	**Mean**	**S.E.**	**Lower 95%CI**	**Upper 95%CI**	**P-value**	**Mean**	**S.E.**	**Lower 95%CI**	**Upper 95%CI**	**P-value**
wind	0.00	0.03	0.00	0.00	0.98	0.00	0.02	0.00	0.00	0.95
BSS	0.00	0.03	-0.06	0.00	0.90	**-0.42**	**0.11**	**-0.62**	**-0.21**	**<0.01**
swell	0.01	0.04	-0.01	0.13	0.89	-0.01	0.04	-0.13	0.00	0.87
visibility	-0.01	0.03	-0.10	0.00	0.86	-249.94	Inf	-Inf	Inf	1.00
glare	**0.30**	**0.11**	**0.04**	**0.50**	**<0.01**	0.04	0.08	0.00	0.27	0.61
boats small	0.01	0.04	0.00	0.15	0.83	0.01	0.04	0.00	0.14	0.82
boats medium	0.00	0.03	0.00	0.03	0.96	0.00	0.02	0.00	0.04	0.92
boats large	-0.01	0.04	-0.09	0.00	0.91	0.01	0.05	0.00	0.19	0.82
boats fishing	0.04	0.08	0.00	0.27	0.62	0.00	0.02	0.00	0.00	0.96
boats recreational	0.00	0.02	0.00	0.00	1.00	0.01	0.03	0.00	0.11	0.85
boats total	0.00	0.03	0.00	0.10	0.91	0.01	0.05	0.00	0.20	0.78
boats industrial	0.01	0.06	0.00	0.19	0.89	0.00	0.03	0.00	0.00	0.97
capital dredging presence	-882.00	Inf	-Inf	Inf	1.00	**0.79**	**0.12**	**0.56**	**1.02**	**<0.01**
capital dredging active	3626.00	Inf	-Inf	Inf	0.99	0.00	0.00	0.00	0.00	1.00
maintenance dredging	0.00	0.01	-0.01	0.00	0.94	0.00	0.00	0.00	0.00	1.00
rock dumping	0.01	0.05	0.00	0.19	0.83	0.00	0.00	0.00	0.00	1.00
piling	276.60	Inf	-Inf	Inf	1.00	0.00	0.00	0.00	0.00	1.00
aggregate disturbance	0.01	0.05	0.00	0.17	0.86	0.00	0.00	0.00	0.00	1.00

Regarding interannual differences at the land-station, Table 18 shows the model-averaged estimated per-year effect (on the logit scale). These per-year-effects, however, do not include the positive and negative effects of covariates that may systematically vary by year (such as certain disturbances that only occurred in certain years).

In contrast to last year's report, this year's analyses revealed slightly more distinct and separable estimates per year, as evidence by 95%CI that were just barely overlapping between years.

The estimates and confidence intervals for snubfins (Table 18) had much more erratic estimates that varied a lot. The year with the largest point-wise estimate was 2019 (-3.91), followed by 2021 (-4.40). The years with the lowest estimates were 2022 (-10.26) followed by 2020 (-14.85). 2023 suffered singularities due to the absence of individuals for that year, and which made point-wise estimation difficult.

For humpbacks the 2019 estimate (-4.02) was almost separable from the 2022 estimate (-5.992) and 2023 estimate (-5.68), suggesting systematic differences between such years. The point-wise estimate for 2021 was highest (-3.87), followed by 2019 (-4.02) and 2020 (-5.16), with 2022 (-5.992) and 2023 (-5.676) having the lowest point-wise estimates for humpbacks (Table 18).

Table18. Model-averaged time-series of per-year-effects on snubfin and humpback dolphin probability of occupancy (on the logit-scale) around the Port of Townsville.

	Snubfin dolphins						Humpback dolphins					
Year	**Mean**	**SE**	**Lower 68%CI**	**Upper 68%CI**	**Lower 95%CI**	**Upper 95%CI**	**Mean**	**SE**	**Lower 68%CI**	**Upper 68%CI**	**Lower 95%CI**	**Upper 95%CI**
2019	-3.91	0.52	-4.42	-3.38	-4.96	-2.9	-4.02	0.26	-4.28	-3.76	-4.58	-3.53
2020	-14.85	10.43	-25.3	-4.5	-35.39	4.84	-5.16	0.4	-5.56	-4.77	-5.98	-4.38
2021	-4.4	0.25	-4.65	-4.16	-4.89	-3.91	-3.87	0.37	-4.24	-3.48	-4.62	-3.14
2022	-10.26	4.43	-14.68	-5.86	-18.99	-1.57	-5.99	0.81	-6.8	-5.21	-7.65	-4.41
2023	-Inf	Inf	NA	NA	NA	NA	-5.68	0.47	-6.15	-5.21	-6.6	-4.79

4. Discussion and conclusions

4.1 Survey effort

The 2023 vessel surveys of inshore dolphins for the Port of Townsville proceeded well. As planned, we were able to repeat six full surveys (plus an additional 7^{th}) of Cleveland and Halifax Bay between June-July, and our survey effort over the last five years has been similar across both bays.

4.2 Estimates of abundance, survival, emigration, and movement

Snubfin dolphins

Due to the limited number of encounters and thus individual captures of snubfin dolphins in Cleveland Bay in 2022 (n =1) and 2023 (n =10) adjustments to the Multistate Closed Robust Design model (as mentioned in results section) had to be made to allow estimation of population parameters. Therefore, the abundance estimated for snubfin dolphins for Cleveland Bay in 2022 and 2023, should be taken with caution, as they are likely overestimated (see results) due to the limited number of captures available in both years.

Overall, the estimates of the abundance of snubfin dolphins in Cleveland Bay over the first three years of survey (2019-2021) indicated a relatively stable population of about 30-40 snubfin dolphins; and a substantial decrease in the number of snubfin dolphins using the bay in 2022 and 2023. The substantial decrease in sightings of animals suggest that there has been either a decrease in their apparent survival (due to deaths or permanent emigration from the bay), an increase in their rate of movement from Cleveland to Halifax Bay, a decrease in their rate of movement from Halifax Bay to Cleveland Bay, or an increase in their temporary emigration from the Townsville area (absent from both Cleveland and Halifax Bays). Although data limitations in 2022 and 2023 posed difficulties for estimation of demographic parameters, our results indicate that an increase in permanent emigration (i.e.

10% have left each Bay, have not moved to the other, and are not expected to return), an increase in movement of snubfins out of Cleveland Bay into Halifax Bay, and a decrease in movement of animals from Halifax Bay to Cleveland bay likely account for the large reduction in the number of snubfin dolphins in Cleveland Bay in 2022 and 2023. As more data are collected next year, we should be able to assess if this decrease in abundance in Cleveland bay continues or dolphins return to the bay.

The decrease in the abundance of snubfin dolphins in Cleveland Bay in 2022 and 2023 could be the result of a variety of extrinsic (e.g., climate, competitive exclusion, or dispersal limitation) and intrinsic factors (e.g., spatial, and temporal variation in abundance of prey species, habitat specialization) which are not accounted for in this study. Moreover, temporal delays in marine mammals' response to pressures are often expected, and changes in population abundance, distribution and behavior often lag several years behind habitat loss or degradation caused by environmental and anthropogenic disturbances (Heithaus et al. 2008, Hawkins et al. 2017). Although we cannot account for the influence of these factors, it is important to note that: 1) the estimates of the abundance of snubfin dolphins in Cleveland Bay across the first three years of monitoring (2019-2021) were relatively stable (30-40 snubfin dolphins used Cleveland Bay regularly), and that 2) the decrease in abundance in 2022 and 2023 coincided with capital dredging and piling activities associated with CU project; and followed the completion of the rock wall construction for the 62 ha port reclamation area at the eastern end of the Port in 2021.

Although our research does not prove what caused the decrease in snubfin dolphin abundance in Cleveland Bay in 2022-2023 in comparison to previous years, it suggests disturbance from port construction activities as a potential explanation. The decline in snubfin dolphin abundance in Cleveland Bay during 2022 and 2023 may result from various extrinsic (e.g., climate, competition, dispersal) and intrinsic factors (e.g., prey abundance, habitat specialization) not accounted for in this study and for which there is no data availabe. However, the decrease in abundance in 2022 and 2023 and increased movement of snubfins from Cleveland to Halifax Bay coincided with capital dredging and piling activities associated with CU project; and followed the completion of the rock wall construction for the 62-ha port reclamation area at the eastern end of the Port in 2021. Such activities have been associated with declines in dolphin abundance in other areas (Jefferson et al. 2009, Dungan et al. 2011). For example, significant declines in Australian humpback dolphins were observed in Port Curtis-Gladstone after extensive dredging and land reclamation (Cagnazzi et al. 2020). The number of humpback dolphins present in Darwin Harbour showed a steady decline during periods coinciding with pile driving associated with the Ichthys LNG Project (Brooks and Pollock 2015). Dredging caused common bottlenose dolphins (*Tursiops truncatus*), to spend less time in Aberdeen harbour (Scotland), despite high baseline levels of disturbance and the importance of the area as a foraging patch (Pirotta et al. 2013)

In contrast to Cleveland Bay, the number of snubfin dolphins in Halifax Bay in 2022 and in 2023 have increased greatly relative to previous years. Part of this increase can be attributed to increase in movements of snubfin dolphins from Cleveland Bay to Halifax Bay, the decrease in movement of animals from Halifax Bay to Cleveland Bay in the last two years, and immigration of new snubfin dolphins to Halifax Bay from outside the Townsville area. As suggested in section 1.1.1, the number of snubfin dolphins first identified in Halifax Bay in 2022 (Table 5) suggests that there may have been immigration into Halifax Bay between 2021 and 2022. Similarly, there were a substantial number of snubfin dolphins first identified in Halifax Bay in 2023 suggesting further immigration. However, the decline in the estimated total number between 2022 (117, Figure 8) and 2023 (76, Figure 8) suggests that many of the dolphins first identified in 2023 had arrived prior to 2022 but were not captured until 2023. If these new individuals were all true immigrants, the population estimate would have increased rather than decreased between 2022 and 2023 (Figure 8). Therefore, the apparent surge of first captures in 2023 reflects both some immigration and a lag in detection.

Such movements and immigration events provide evidence of connectivity between local populations of snubfin dolphins in Halifax Bay, Cleveland Bay, and adjacent areas outside the sampling study area. This indicates that snubfin dolphins in Halifax Bay are demographically and genetically connected to other coastal subpopulations around the coastal waters of the study area. Similar, immigration events, including the entry of apparently large numbers of new snubfin dolphins from outside the sample area have been detected in Bynoe Harbor, Northern Territory (Brooks et al. 2017).

Various factors likely contributed to the decline of snubfin dolphins in Cleveland Bay and their redistribution to Halifax Bay in 2022–2023:

- Changes in Prey Availability: Shifts in the distribution, abundance, or quality of prey species could drive dolphins to adjust their home ranges. A decline in prey availability in Cleveland Bay—whether due to seasonal cycles, environmental change, or construction activities associated with the CU project—may have prompted dolphins to move to Halifax Bay in search of better foraging opportunities.
- Habitat Quality and Environmental Conditions: Changes in water quality (e.g., turbidity, salinity, pollutants), habitat structure (e.g., seagrass coverage, mangrove health), or oceanographic variables (e.g., temperature, freshwater runoff) can influence habitat suitability. Such changes—driven by natural variability, environmental change, or construction-related impacts—may have degraded conditions in Cleveland Bay while enhancing them in Halifax Bay, affecting prey dynamics and consequently dolphin distribution.

- Social Dynamics: Snubfin dolphins exhibit fission–fusion social structures and may adjust group composition or movement patterns in response to social cues. If key individuals or groups moved to Halifax Bay—whether due to natural cycles, habitat changes, or construction-related disturbance—others may have followed, particularly if those individuals were socially influential (e.g., females with calves or members of social alliances).
- Disturbance Sensitivity and Risk Avoidance: Increasing levels of anthropogenic disturbance—such as vessel traffic, underwater noise, and recreational activities—in Cleveland Bay, in addition to construction activity associated with the CU project, may have created a more energetically costly or risky environment, encouraging dolphins to shift to the relatively less disturbed Halifax Bay.

These factors likely interact with one another and with anthropogenic pressures, collectively contributing to the decline of snubfin dolphins in Cleveland Bay and their redistribution to Halifax Bay.

Humpback dolphins

Overall, estimates of abundance, apparent survival, movements and temporary emigration across the last five years for humpback dolphins indicated that: 1) there has been an increase in their abundance in both Cleveland and Halifax Bays over last two years (2022-2023); 2) their apparent survival has remained relatively high in both bays; 3) that humpback dolphins are more abundant in Halifax Bay than in Cleveland Bay, 4) that there is steady movement of humpback dolphins in both directions between Cleveland and Halifax Bays, and 5) that temporary emigration is higher in Halifax Bay than in Cleveland Bay. The larger abundance of humpback dolphins in Halifax Bay over the years indicates this bay holds a larger fraction of the population in the study area.

Our results showed opposing population trends in Cleveland Bay over the last two years (2022-2023) between humpback dolphins, which increased, and snubfin dolphins, which declined over this study period. Both trajectories were observed over a period characterized by dredging and piling construction activities associated with the CU project in Cleveland Bay. At this point, the abundance of snubfin dolphins started to decline significantly in Cleveland Bay, while humpback dolphins abundance increased. At the same time movements of snubfin between Cleveland Bay and Halifax Bay increased and so did their abundance in Halifax Bay.

Natural environments are dynamic systems with conditions and environmental and anthropogenic disturbances varying across years. Higher trophic level consumers such as dolphins may respond to changes in their habitat (due to habitat loss and degradation); distribution and quality of their available prey, and interspecific competitor by moving to new areas to more suitable habitats to locate new resources and/or avoid competition.

In order to persist, sympatric species with similar ecological niches may show contrasting responses to changes in environmental conditions. Sympatric species, sharing the same geographic range and often possessing similar ecological requirements, may exhibit contrasting population responses to disturbances due to a combination of ecological, behavioral, and evolutionary factors. Several key mechanisms may contribute to this variability including:

- Resource Partitioning: Sympatric species may evolve to utilize resources in slightly different ways, allowing them to coexist in the same habitat. When disturbances alter resource availability, species with effective resource partitioning strategies may be better equipped to adapt and maintain stable populations.

- Adaptation and Evolution: Over time, sympatric species may evolve different adaptations in response to ecological challenges. If a disturbance affects a specific aspect of the environment, the species with relevant adaptations will have a selective advantage, leading to varying population dynamics.
- Competitive Interactions: Even with similar ecological requirements, sympatric species may engage in competitive interactions for resources. Disturbances can alter the competitive landscape, favouring certain species over others. Some species may thrive under new conditions, while others may struggle.
- Life History Strategies: Differences in life history strategies, such as reproductive rates, age at maturity, and parental care, can influence how species respond to disturbances. Species with flexible life history strategies may adapt more effectively to changing conditions.
- Behavioral Responses: Species may exhibit different behaviours in response to disturbances. Some may have more flexible behaviours, allowing them to exploit new opportunities or avoid threats, while others may be more specialized and less adaptable.
- Spatial Heterogeneity: Disturbances often lead to spatial heterogeneity in environmental conditions. Species with the ability to disperse, colonize new areas, or shift their distribution may fare better than those with limited mobility, contributing to divergent population responses.
- Genetic Diversity: The genetic diversity within populations influences their ability to adapt to changing conditions. Species with higher genetic diversity may be more resilient and able to cope with disturbances, whereas those with limited genetic variability may face greater challenges.
- Prior Adaptations: Species may have evolved specific adaptations to historical disturbance regimes. If a disturbance aligns with a species' historical adaptations, it may thrive, while species without such adaptations may experience population declines.

In summary, the contrasting population responses of sympatric species with similar ecological requirements to the same disturbances arise from a complex interplay of ecological, behavioral, and evolutionary factors. Understanding these dynamics is crucial for predicting and managing biodiversity in the face of environmental changes.

4.3 Spatial distribution

The spatial distribution patterns of humpback dolphins in Cleveland Bay and Halifax Bay have exhibited consistency during the past five years of monitoring. The spatial distribution of snubfin dolphins showed consistent use of similar areas with some significant changes over the last two years (2022-2023). The continuous use of similar core areas in Cleveland Bay and Halifax Bay by snubfin and humpback dolphins throughout the years highlights their strong site fidelity to these areas and importance of this region to their conservation, as has been indicated by previous research (Parra 2006, Parra et al. 2006a).

Overall, both humpback and snubfin dolphins are mainly found along inshore areas of Cleveland Bay and Halifax Bay. Both species seem to favour approximately three core areas: i) to the west, around and to the east of the Port of Townsville in Cleveland Bay; and ii) the central coastal waters between Cape Pallarenda/Bohle River and Toolakea, and iii) the northern inshore areas off and west of Toomulla in Halifax Bay. Humpback dolphins also seem to inhabit some offshore areas in Halifax Bay, and occasionally occupy nearshore areas in the northeast of Magnetic Island.

Humpback dolphins' spatial occupancy and density in Cleveland Bay and Halifax Bay has remained relatively stable over the years, showing only a slight decline in 2020, particularly in the inshore area of Cleveland Bay. In contrast, snubfin dolphin spatial occupancy and density has shown a decrease in Cleveland Bay, and an increase in Halifax Bay over the last two years (2022-2023). These shifts in distribution and density are in line with abundance and movement estimates from capture-recapture modelling, with snubfin dolphins showing an increase in abundance in Halifax Bay and movement rates from Cleveland Bay to Halifax Bay in 2022 and 2023.

Regarding their spatial distribution in relation to known disturbances (boats, capital dredging, maintenance dredging, rock dumping), neither species seems to have a convincing statistic relationship to such covariates. Like previous years' analyses, the high allocation of RVI to the unexplained spatial processes (i.e., spatial splines) for both species suggests that a lot of the spatial variation was not captured by known environmental or human related covariates, whether linear or not linear.

The CV likelihood ratio tests however, provided substantial support for the full model including disturbance covariates for both species, but the cross-validation p-value suggests that a "no effect" null-model cannot be ruled out completely. Based on RVI values both capital and maintenance dredging appear to have a small influence on snubfin dolphins spatial distribution, and counts of large boats, fishing boats and maintenance dredging on humpback dolphins spatial distribution. Covariate interaction plots suggested that snubfin dolphin density increased with proximity to maintenance dredging but also increased with greater distance from capital dredging. For humpback dolphins, covariate interaction plots indicated that their density increased with a higher number of large boats, decreased with more fishing boats, and increased with greater distance from maintenance dredging.

4.4 Patterns of attendance to the port area

Land-based observations from Berth 11 within the Port of Townsville in 2023 were feasible throughout the day with good weather conditions. However, like 2022, 2023 was an unusual year compared to the three previous years. In 2023 there were no sightings of snubfin dolphins from Berth 11 observation station, while the number of scans with observations of humpback dolphins, as in 2022, exceeded all previous years by at least a multiple of 2 (and often more) (Parra et al. 2019, 2020, 2021).

The quantitative assessment of differences in snubfin dolphin occurrence between 2023 and all previous pairs suggest that 2023 was similar to the 2022 field season (Table 11), but quite different from 2019, 2020 and 2021. Thus, there is strong evidence that there has been a substantial decrease in the number of sightings of snubfin dolphins in Cleveland Bay from Berth 11 land station since 2022. The decline in sightings of snubfin dolphins is in line with the low number of sightings reported during vessel-based surveys, decline in abundance estimates and shifts in spatial distribution patterns. In contrast, the number of encounters of humpback dolphins were in line (or greater) than the expectations of previous years (able 11). The 2023 and pooled behavioural summaries (from 2019 to 2023) of dolphin observations from Berth 11 indicate that humpback dolphins feed regularly in the area, while snubfin dolphins did so up until 2021.

Bayesian hypothesis testing of dolphin presence with respect to maintenance dredging, capital dredging, rock dumping and piling indicated some interspecific differences. Capital dredging appears to be related with the presence/absence patterns of snubfin dolphins around the Port, with snubfin dolphin sightings decreasing when capital dredging is present and/or active. For humpback dolphins, rock dumping shows a similar relationship. In contrast, the presence or absence of humpback dolphins around the port appears to have a positive affinity with both construction and maintenance dredging, and snubfin dolphins with rock dumping.

The GAM model-averaging exercise, which estimates the marginal effect of various covariates while adjusting for the impact of other covariates, did not lend strong credence to the conclusion that either dolphin species was impacted by disturbances (maintenance dredging, capital dredging, rock dumping and piling). Model-averaged effects indicate that two covariates had statistical significance: BSS and the presence of capital dredging, with BSS negatively associated and capital dredging positively associated with humpback dolphins presence. For snubfins, only glare had a statistically significant contribution (aside from the temporal covariates). Taken together, the GAM and Bayesian hypothesis testing results, suggest that while capital dredging and rock dumping activities may be associated with reduced snubfin and humpback dolphin sightings around the port, respectively, other co-occurring factors likely contribute, and further investigation is warranted to isolate the causal mechanisms.

Here again, it is important to reiterate that these correlations do not imply causation as these patterns of attendance to port area may also be contingent on a variety of extrinsic (e.g., climate, competitive exclusion, or dispersal limitation) and intrinsic factors (e.g., diet, habitat specialization) that could influence a species' occurrence and that are not accounted for in this study. Despite this, the stark difference in the abundance and occurrence patterns of snubfin dolphins in Cleveland Bay and around the port in 2022 and 2023 in comparison to previous years, and in comparison, to humpback dolphins, raises concerns about the potential impact of extrinsic/intrinsic factors and CU construction activities on this species. It also highlights that the response to these pressures may differ between species and may depend on differences in behavioral plasticity and resilience (Brakes and Dall 2016). These changes may not necessarily reflect long-term population impacts but short-term effects; emphasising the need for monitoring programs to operate long enough (before, during and after construction activities) to ensure that species-specific population responses can be detected.

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