INSPIRING ACHIEVEMENT

Port of Townsville Inshore Dolphin Monitoring Program Report

Analysis of the sixth field season (June - July 2024)

(Photo CEBEL, Flinders University ©)

Guido J. Parra[1], Danielle Cagnazzi[2], Caitlin Nicholls[1], Daniella Hanf[1], Lyndon Brooks[2,3], and Robert Rankin[4]

[1] Cetacean Ecology, Behaviour and Evolution Lab, College of Science and Engineering, Flinders University, SA,[2] Marine Ecology Research Centre, Southern Cross University, NSW ,[3] StatPlan Consulting Pty Ltd, NSW, [4] TR Labs, Thomson Reuters, 333 Bay St, Toronto ON M5H 2R2

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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 2024 during boat and land-based surveys were summarised and compared to previous years (2019-2023). The study investigated any changes in coastal dolphin abundance and distribution beyond natural spatial and temporal variations since 2019. Monitoring of Australian snubfin and humpback dolphins spanned the pre-construction (2019), construction (2020–2023), and post-construction (2024) phases of the CU Project. Surveys were conducted annually during June–July, beginning in June 2019.

As in previous years, in 2024 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 (2019-2024). Land-based survey data was analysed using Bayesian p-values and Generalized Additive Models (GAMs) to assess overall differences in dolphin occurrence across all six years (2019-2024) 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 (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) and vessel traffic not associated with CU Project .

Three vessels undertook simultaneous, predetermined line-transect surveys over 18 days between June 1 and July 15, 2024, covering 1596.4 km in Cleveland Bay and 1457.5 km in Halifax Bay. We observed a total of 35 groups of snubfin dolphins (9 in Cleveland Bay and 26 in Halifax Bay), 61 groups of humpback dolphins (28 in Cleveland Bay and 33 in Halifax Bay) and 16 groups of bottlenose dolphins (6 in Cleveland Bay and 10 in Halifax Bay). Twenty-five individual snubfin and 49 humpback dolphins were photo-identified in Cleveland Bay, and 52 snubfin and 84 humpback dolphins were photo-identified in Halifax Bay in 2024. At the same time, we completed a total of 12 days of visual survey scans from the land-based observation point on Berth 11 between 4 and 18 of June. Humpback dolphins were observed on 11 days and snubfins on 5 days of the 12 survey-days. Bottlenose dolphins were not seen on any day.

The total estimated abundance of snubfin dolphins in Cleveland Bay in 2024 was 33 (SE = 10.38, 95% CI = 18–61) and 60 (SE = 3.87, 95% CI = 52–68) in Halifax Bay. The abundance of snubfin dolphins in Cleveland Bay in 2024 marks a recovery to pre-2022 levels (31 in 2019, 42 in 2020, and 34 in 2021) after declines in 2022 (14[*]) and 2023 (27[*]). The number of snubfin dolphins in Halifax Bay have been higher than those in Cleveland Bay over the last three years with 111 in 2022, 73 in 2023, and 60 in 2024. The movement rate from Cleveland Bay to Halifax Bay was 0.41 (i.e. an estimated 41% the dolphins moved from Cleveland Bay to Halifax Bay) between 2023 and 2024, consistent with 2021–2022, indicating continued high emigration from Cleveland Bay to Halifax Bay through 2024. Movement from Halifax Bay to Cleveland Bay between 2023 and 2024 was 0.27 indicating a relatively high rate of exchange (i.e. an estimated 27% of dolphins moved from Halifax Bay to Cleveland Bay), comparable to the levels observed between 2019 and 2021.The number of humpback dolphins present in Cleveland Bay and Halifax Bay in 2024 was 68

[*] The estimates for Cleveland Bay in 2022 and 2023 are considered unreliable and are likely to be too overestimated (see results section of report).

(SE = 7.95, 95% CI = 54–85) and 122 (SE = 11.80, 95% CI = 101–148), respectively. As in previous years, there were more humpback dolphins present in Halifax than in Cleveland Bay in 2024. Humpback dolphin numbers in Cleveland and Halifax Bays have increased over the past three years compared to the first three years of monitoring. In Cleveland Bay, numbers increased from 20 in 2019 to 68 in 2024, while in Halifax Bay they rose from 66 to 122 over the same period. .Between 2019 and 2024, the average annual movement rate between Cleveland and Halifax Bays was approximately equal in both directions, at 0.21, indicating a relatively high level of exchange, with an estimated 21% of dolphins moving between the two bays each year. Species distribution models of the spatial occurrence and relative density of snubfin dolphins reflect the abundance patterns observed across the years in the bays. The 2024 spatial occurrence and relative density of snubfin dolphins show a recovery from the low occupancy and density of 2022–2023 in Cleveland Bay, resembling 2019–2021 patterns with higher concentrations near the southwestern nearshore of Cleveland Bay around the Port of Townsville. The spatial predictions for snubfin dolphins in Halifax Bay are in line with predictions from previous years, showing high-occupancy and density around and north of Toomulla beach and between Toolakea beach and Cape Pallarenda. For humpback dolphins, the spatial occurrence and relative density predictions from the 2024 model 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 Toomula beach and Cape Pallarenda (including both inshore and offshore waters) in Halifax Bay.

Generalised likelihood ratio tests supported the full model that included disturbance effects for both snubfin and humpback dolphins. For humpback dolphins, the relative variable importance analysis indicated maintenance dredging as the most impactful disturbance, with a small decrease in density of species as distance to maintenance dredging increases. For snubfin dolphins, the relative variable importance analysis indicated rock-dumping as key disturbance, with the species density decreasing as distance to rock-dumping increased.

The quantitative assessment of differences in dolphin patterns of attendance to the port area between 2024 and all previous years indicated that the number of encounters of humpback dolphins were in line (or greater) than the expectations of previous years (all Bayesian p-values were close to 1.0). For snubfin dolphins, Bayesian p-values indicated that the number of encounters around the port was higher in the earlier years (2019–2020) compared to 2024. The number of encounters in 2021 was similar to those in 2024, while the 2024 encounters were comparable to—or higher than—those recorded in 2022 and 2023, with all Bayesian p-values close to 1.0. Analysis of land-based observations of dolphin presence with respect to disturbances around the port revealed that humpback dolphin presence was unaffected by capital dredging, maintenance dredging, or piling but decreased during active rock-dumping. Snubfin dolphin occurrence presence was unaffected by maintenance dredging and piling, increased during rock dumping; but decreased when capital dredging was present (dredging vessel is at the site, regardless of whether it is actively operating) and/or active (refers to a period when dredging operations were actively occurring-mechanical removal of sediments).

Overall, monitoring over the past six years reveals a clear increase in humpback dolphin abundance in both Cleveland and Halifax Bays, with consistently higher numbers observed in Halifax Bay. This trend highlights the ecological importance of the region for the Townsville population, and is possibly influenced by factors such as habitat quality, prey availability, and lower anthropogenic disturbance in Halifax Bay. In Cleveland Bay, the increasing trend in humpback dolphin numbers may reflect their capacity to exploit altered environments, including potential prey aggregation around man-made structures, and may also represent a form of competitive release following the decline of sympatric snubfin dolphins.. The potential ability of humpback dolphins to persist under both favourable natural conditions (as in Halifax Bay) and in more modified habitats (as in Cleveland Bay) underscores the species' ecological plasticity and highlights the importance of spatial and species-specific responses to environmental change in shaping local dolphin populations.

In contrast, the occurrence and abundance of snubfin dolphins in Cleveland Bay decreased in 2022 and 2023, coinciding with CU capital dredging and piling activities, but appeared to return to pre-construction levels in 2024 after construction activities ceased. The return of snubfin dolphins to numbers similar to those observed in 2019, the baseline year, suggests that the population declines recorded in 2022 and 2023 may have been temporary rather than indicative of long-term population declines. This recovery could imply that the snubfin population is resilient to certain natural and anthropogenic stressors, provided these pressures are mitigated or removed over time. The observed trends underscore the importance of minimizing anthropogenic disturbances in critical habitats and maintaining connectivity between adjacent areas like Cleveland and Halifax Bays, which provide refuge and support population resilience.

While our findings reveal correlations between dolphin occurrence patterns and the timeline of port construction activities, these associations do not imply direct causation. The observed decline in snubfin dolphin abundance and their reduced presence around the port area in 2022 and 2023 may reflect the influence of various unmeasured factors, including extrinsic drivers such as climatic variability, interspecific interactions, and dispersal limitations, as well as intrinsic factors like prey availability, dietary preferences, and habitat specialization. Furthermore, delayed responses to environmental and anthropogenic pressures are common among marine mammals, suggesting that current patterns could result from cumulative or lagged impacts of earlier disturbances—such as the 2021 completion of the rock wall for the 62-ha port reclamation area. Despite these uncertainties, the timing of capital dredging and piling activities coincided with species-specific changes, particularly in snubfin dolphins, indicating a potential ecological link. In light of these correlations and the inherent uncertainty surrounding their drivers, applying the precautionary approach to species management is essential. This proactive strategy prioritizes the prevention of potential harm to species and their habitats by advocating for protective measures even when causal relationships are not definitively established.

Continued monitoring into the future is essential to assess whether the increased presence and abundance of snubfin dolphins in Cleveland Bay in 2024, relative to the 2022 and 2023 period and in comparison to pre-construction conditions observed in 2019, represents the beginning of a positive trend or simply a short-term fluctuation. Understanding these dynamics is critical for informing conservation planning and policy, particularly as port operations and development/construction will continue into the future.

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 was delivered over a period of six years from 2019 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 'Vulnerable' under the EPBC Act, the International Union for Conservation of Nature (IUCN) (Parra et al. 2017a, Parra et al. 2017b), and the Queensland Nature Conservation Act 1992; and as 'Near Threatened' in the Action Plan for Australian Mammals 2012 (Woinarski et al. 2014). The IDMP was implemented over pre-, during and post-CU Project construction activities. The findings from the IDMP were 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.

Monitoring of Australian snubfin and humpback dolphins spanned pre-, during, and post-construction phases of the CU project. Surveys were conducted annually over June-July, beginning in June 2019. The 2019 inshore dolphin surveys constituted the pre-construction phase as no construction activity occurred during this period. The period between 2020 and 2023 corresponded to the construction phase. The 2020 inshore dolphin surveys corresponded with the initial marine construction activities of the rock wall, which was completed in 2021and 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.Capital dredging activities (using a backhoe dredge) associated with the widening of the shipping channel started in 2022 and continued in 2023 in Cleveland Bay. By the 2024 survey period, all in-water CU Project construction activities had ceased, marking the post-construction monitoring phase. 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 2024 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 2024 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 28th and the 31st of May 2024, 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).

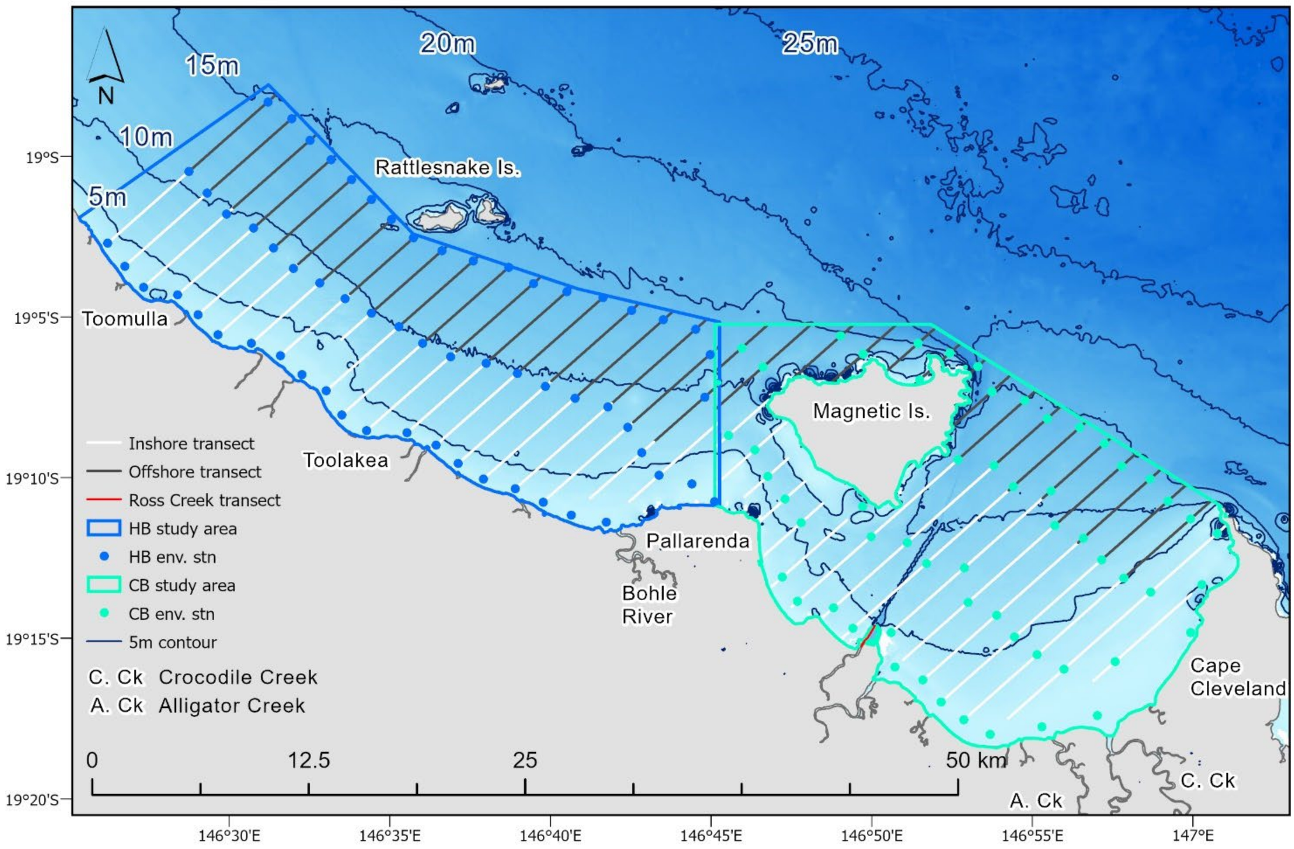
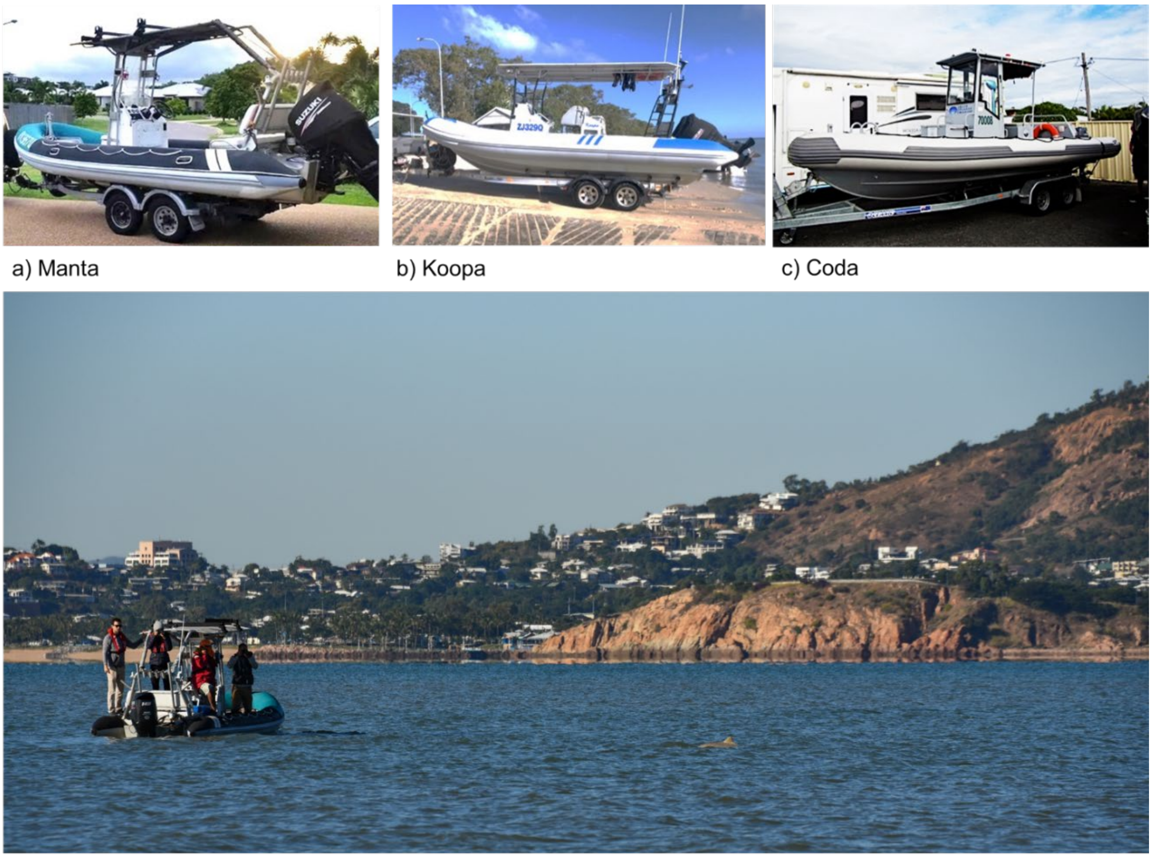


Figure 1. Map of Cleveland and Halifax Bays study areas including inshore and offshore transects, Ross Creek transect, and environmental stations.

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 2024 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/).



a) Manta b) Koopa c) Coda

D) Research team conducting surveys onboard vessel Manta

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 2024. 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 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). In 2024, land-based observations were limited to the month of June (4-18th of June) due to the closure of Berth 11 from June 19 to

August 1 for shipping schedules and required maintenance on the ship loader. 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 enabled 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), covering all visible water within a radius of approximately 1km around the observation point at Berth 11. Observations were conducted by a team of two-three trained observers 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 2023), 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 and 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). the capture-recapture models are updated, along with the corresponding annual population demographic estimates.

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. 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). However extra time was allocated for sampling to allow for days lost due to poor weather and these days were used to complete further secondary samples as the opportunity arose.

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 ($\widehat{M}_p$):

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

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) during (2020-2023) and after (2024) CU project construction activities. 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 associated with 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, 2023 and 2024 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, 2023 and 2024).
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).

As in previous years, we chose to discard the radial basis function (used 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 2024 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 IDMP reports, the presence of such disturbances was 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) across the study area, including Cleveland and Halifax Bays. This allowed us to calculate the distance from each dolphin sighting (and null points’) 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 occurred immediately 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 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 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 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 (2019 and 2024) 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.

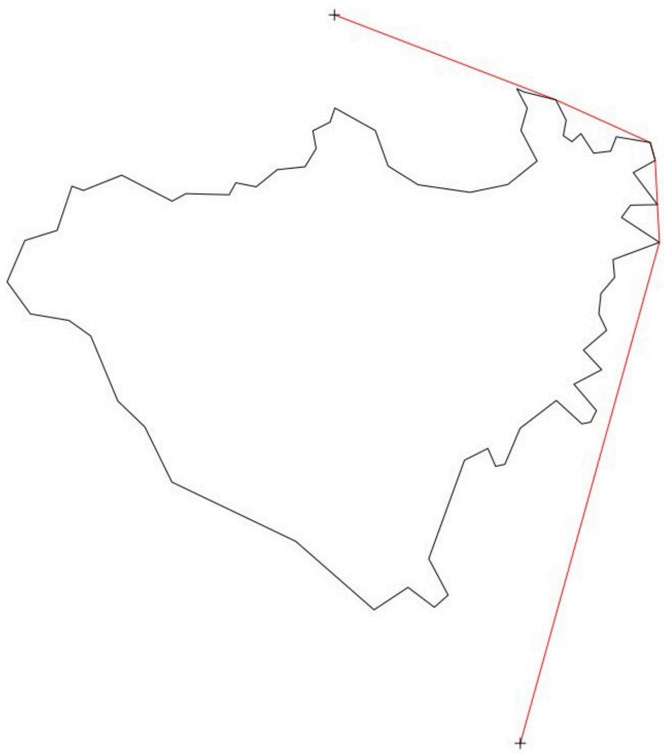


Figure 4. Demonstration of the shortest-distance path between a disturbance point to the south-east of Magnetic Island, and a dolphin point to the north of Magnetic Island, whereby the straight-line is obstructed by the island. These shortest marine paths were used for the distance-to-disturbance covariates.

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 2024 mean-values, and then varying the pair's values uniformly throughout its empirical range (in 2024), 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. This 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 (due to equipment malfunction), 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 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. 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.

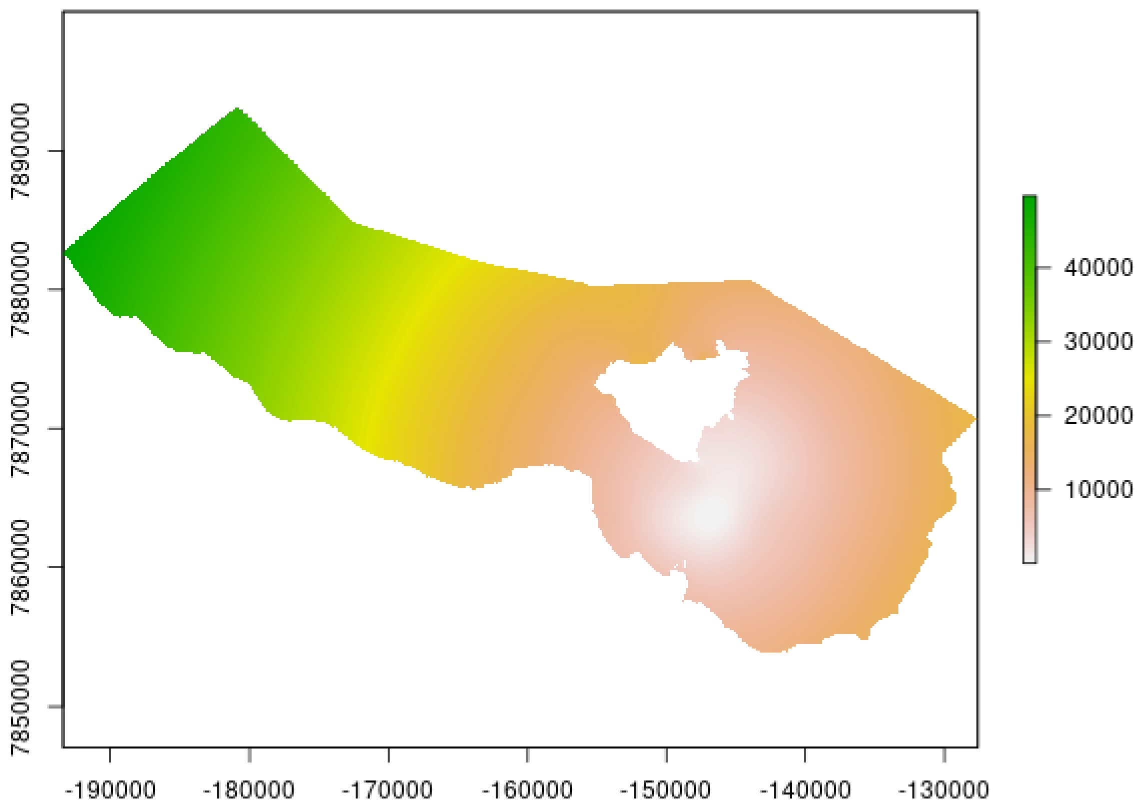


Figure 5. Example of spatial field representation of log-distance to capital dredging in 2022. The X and Y axes represent UTM coordinates (Universal Transverse Mercator projection). The colours represent the distance in meters from the dredging activities. Green areas: Farthest from the dredging activity. 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 capital dredging, presence of maintenance dredging, presence of rock dumping, presence of piling, as well as an overall comparison of the counts of dolphins in 2024 vs 2019, 2024 vs 2020, and 2024 vs 2021, 2024 vs 2022, and 2024 vs 2023. 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, maintenance dredging and CU construction activities (i.e., rock dumping, capital dredging, and piling).

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 2024 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 2024 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, capital dredging, maintenance dredging, rock dumping, and piling. 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, 2023 and 2024.

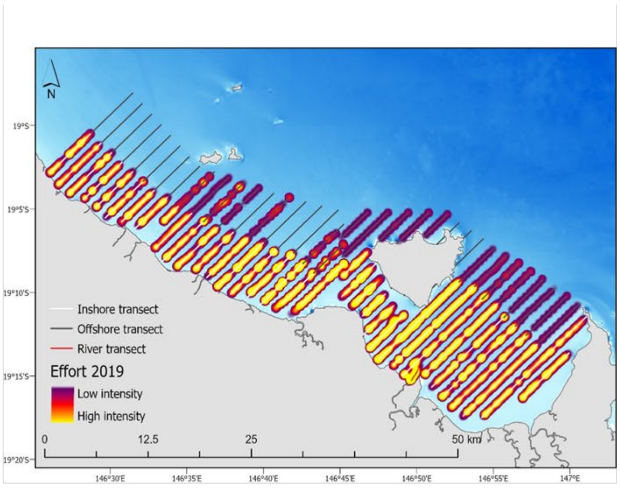
3. Results

3.1 Population demographics

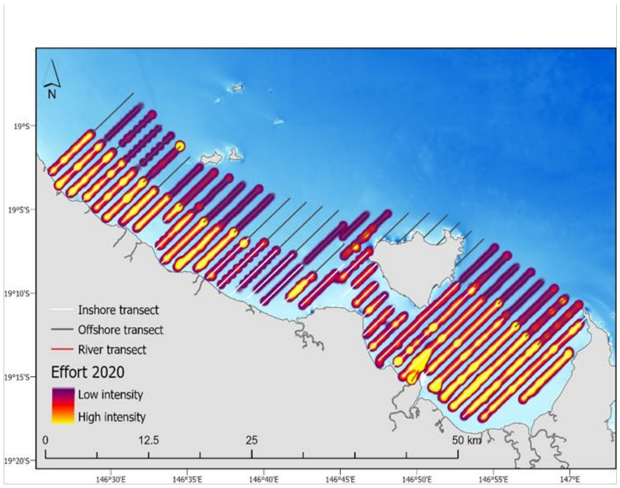
3.1.1 *Vessel based survey effort*

We surveyed a total of 3053.8 km on transect effort over 18 days between June 1 and July 15, 2024, covering 1596.4 km in Cleveland Bay and 1457.5 km in Halifax Bay (Fig. 6, Table 2). Six survey repeats were completed in both bays from 2019 to 2021, seven in 2022 and 2023 and nine in 2024. Like last year, survey effort was higher in inshore areas

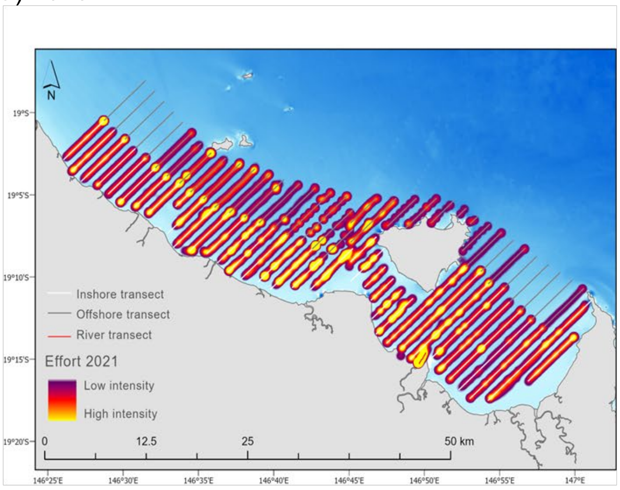
(2369.7 km) than in offshore areas (684.1 km) due to the poor weather conditions encountered often in offshore areas (Beaufort sea state > 4).



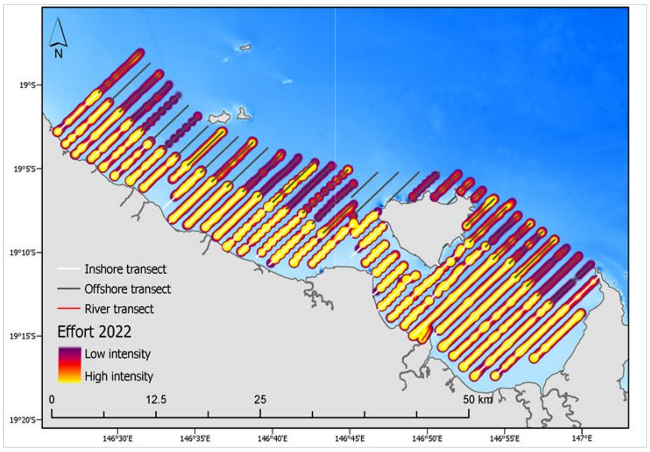
a) 2019



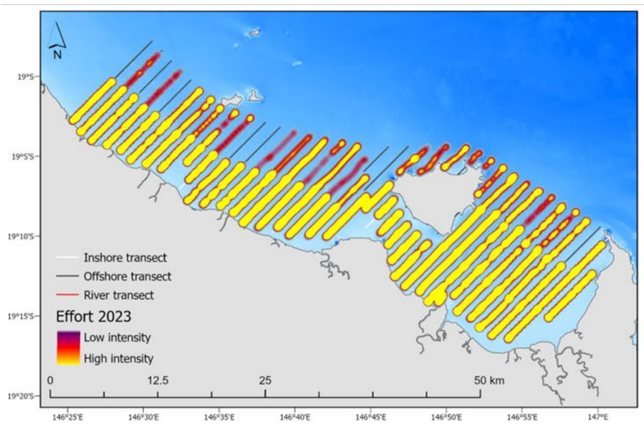
b) 2020



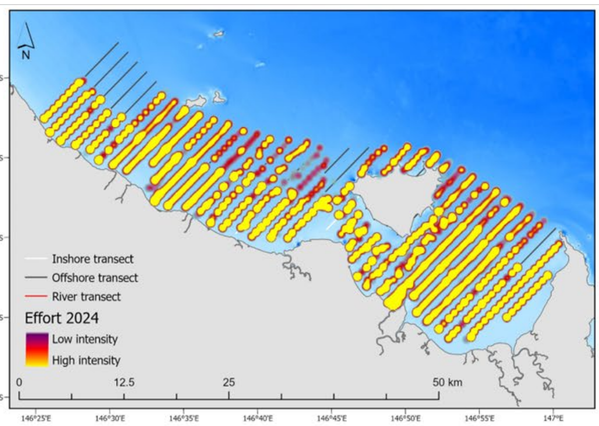
c) 2021



d) 2022



e) 2023` `



f) 2024

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, e) 2023 and f) 2024. 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 2024 primary sample (June-July).

Study area	Sec. period	Dates	Inshore	Offshore	Total	Beaufort Sea State		
			Transect length (km)	Transect length (km)	Transect length (km)	min	max	mode
Cleveland Bay	1	01/06	144.8	50.7	195.5	0	3	1
	2	05/06	133.3	1.4	134.7	0	3	3
	3	11/06	144.8	35.7	180.5	0	3	1
	4	15/06	144.8	54.1	198.9	0	3	1
	5	17/06	139.1	55.5	194.6	0	3	1
	6	19/06	144.8	36.8	181.6	0	3	1
	7	01/07	144.8	43.7	188.5	0	3	2
	8	12/07	144.8	31.1	175.9	0	3	2
	9	14/07	144.8	1.4	146.2	1	3	1
	Total	-	1286.0	310.4	1596.4	-	-	-
Halifax Bay	1	04/06	114.1	27.4	141.5	1	3	2
	2	10/06	121.2	55.4	176.6	0	3	1
	3	12/06	121.2	58.9	180.1	0	3	1
	4	16/06	121.2	46.5	167.7	0	3	1
	5	18/06	121.2	22.7	143.9	1	3	2
	6	20/06	121.2	62.0	183.2	0	3	1
	7	02/07	121.2	47.0	168.2	1	3	2
	8	13/07	121.2	17.5	138.7	0	3	2
	9	15/07	121.2	36.4	157.6	1	3	2
	Total	-	1083.7	373.8	1457.5	-	-	-
	Grand total	-	2369.7	684.1	3053.8	-	-	-

3.1.2 *Dolphin sightings, encounter rates and group sizes*

The vessel surveys in 2024 resulted in a total of 112 dolphin group sightings (including both on and off effort sightings) (Fig. 7f, Table 3). This consisted of 35 groups of snubfin dolphins (Fig. 7f), 61 groups of humpback dolphins (Fig. 7l) and 16 groups of bottlenose dolphins (Fig 7r). Other marine mammals sighted during 2024 surveys included dugongs and humpback whales (Fig 7x). In 2024, we sighted a total of 9 groups of snubfin dolphins in Cleveland Bay (0.0056 dolphin group/km), while 26 were sighted in in Halifax Bay (0.0185 dolphin group/km). A total of 28 groups of humpback dolphins were sighted in Cleveland Bay (0.0175 dolphin group/km) and 33 in Halifax Bay (0.0226 dolphin group/km) (Table 3). Bottlenose dolphin groups were sighted 6 times in Cleveland Bay (0.0038 dolphin group/km) and 10 times (0.0069 dolphin group/km) in Halifax Bay in 2024 (Table 3).

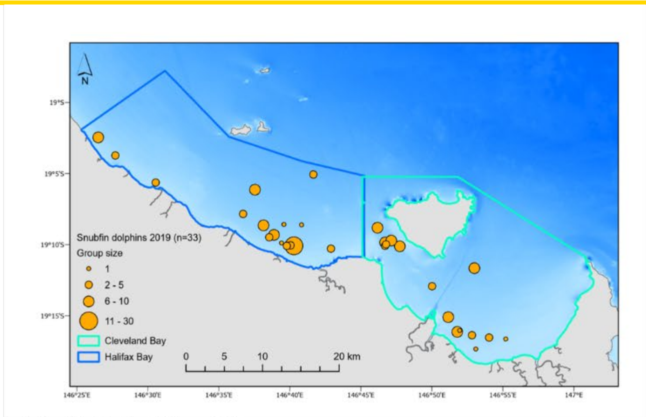
Encounter rates (number of dolphin groups/km) of snubfin dolphin groups in Cleveland Bay showed interannual variability, with the highest encounter rates recorded in 2019 (0.0182 dolphin group/km) and the lowest in 2022 (0.0019 dolphin group/km) and 2023 (0.0016 dolphin group/km), followed by an increase in 2024 (0.0050 dolphin group/km). Encounter rates in Halifax Bay also fluctuated over time, with similar values in 2019 (0.0193 dolphin group/km) and 2020 (0.0191dolphin group/km), a decrease in 2021 (0.0140 dolphin group/km), increases in 2022 (0.0214 dolphin group/km) and 2023 (0.0270 dolphin group/km), and a subsequent drop in 2024 (0.0178 dolphin group/km) (Table 3).

In Cleveland Bay, humpback dolphin encounter rates increased between 2019 (0.0139 dolphin group/km) and 2020 (0.0256 dolphin group/km), but then declined in 2021 (0.0219 dolphin group/km) and 2022 (0.0185 dolphin group/km), increased in 2023 (0.0211 dolphin group/km), followed by a decrease in 2024 (0.0175 dolphin group/km). In Halifax Bay, encounter rates were highest in 2019 (0.0385 dolphin group/km), decreased in 2020 (0.0347 dolphin group/km) and 2021 (0.0162 dolphin group/km), rose again in 2022 (0.0259 dolphin group/km), then decreased in 2023 (0.0223 dolphin group/km) and remained similar in 2024 (0.0226 dolphin group/km) (Table 3).

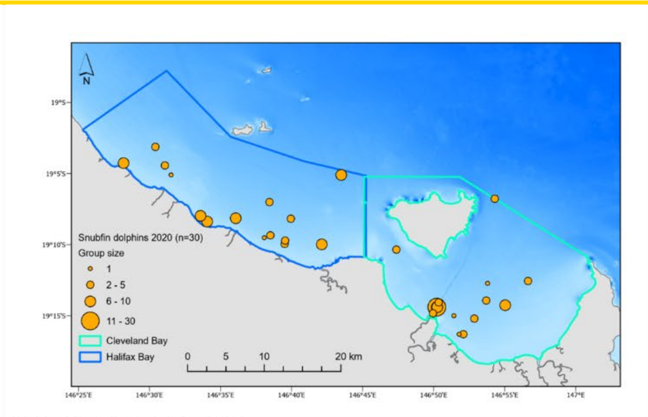
In Cleveland Bay, bottlenose dolphins were rarely recorded: encounter rates fell from 0.0032 dolphin group/km in 2019 to zero in 2020, increased in 2021 (0.0030 dolphin group/km) and again in 2022 (0.0039 dolphin group/km), then dropped in 2023 (0.0016 dolphin group/km), and increased again in 2024 (0.0038 dolphin group/km). In Halifax Bay, encounter rates decreased from 2019 (0.0024 dolphin group/km) to 2020 (0.0012 dolphin group/km), increased in 2021 (0.0100 dolphin group/km), rose slightly in 2022 (0.0101 dolphin group/km), peaked in 2023 (0.0177 dolphin group/km), and decreased in 2024 (0.0069 dolphin group/km) (Table 3).

Groups of humpback dolphins have been sighted in similar numbers in Cleveland Bay (0.01 to 0.026 dolphin group/km) over the years; but have decreased in Halifax Bay from 0.039 dolphin group/km in 2019 to 0.023 dolphin group/km in 2024 (Table 3).

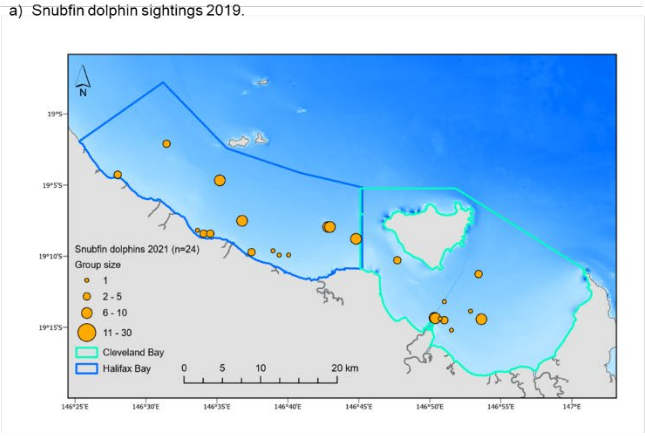
Groups of snubfin dolphins in 2024 varied in size from 1 to 17 individuals, with a mean (± SD) group size of 5.9 ± 4.1 (based on best estimates of group size) (Table 4). The group size of humpback dolphins ranged from 1 to 35 individuals, with a mean (± SD) group size of 5.4 ± 4.5. Bottlenose dolphin groups ranged from 2 to 14 individuals (mean ± SD = 5.7. ± 3.1) (Table 4).



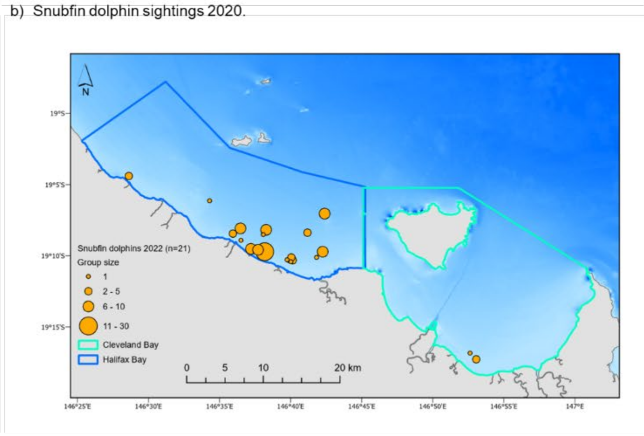
a) Snubfin dolphin sightings 2019.



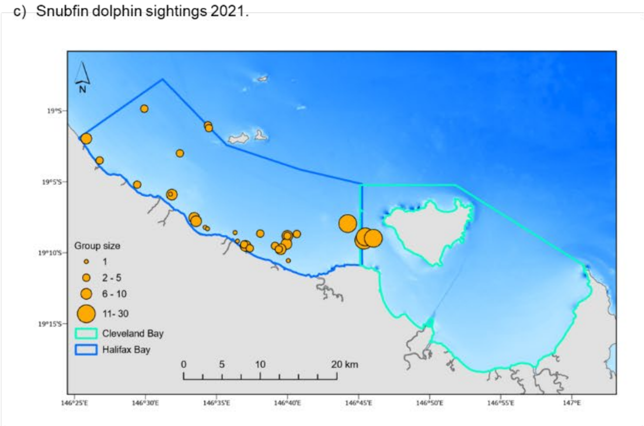
b) Snubfin dolphin sightings 2020.



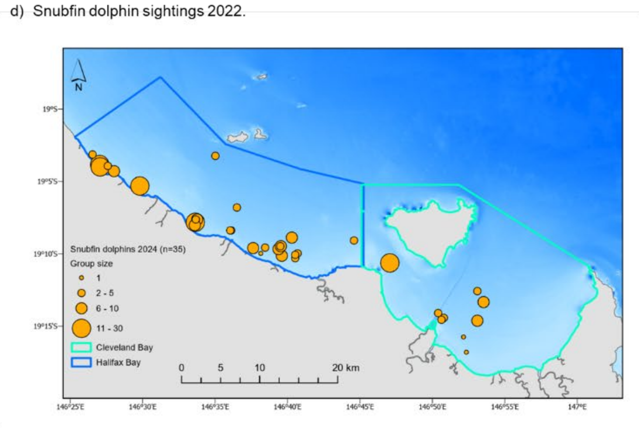
c) Snubfin dolphin sightings 2021.



d) Snubfin dolphin sightings 2022.

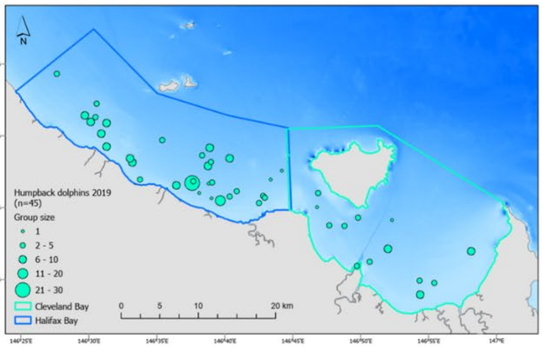


e) Snubfin dolphin sightings 2023.

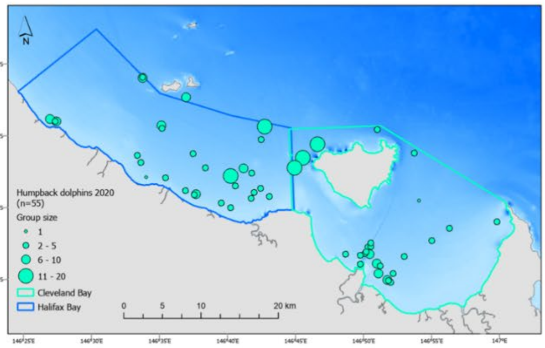


f) Snubfin dolphin sightings 2024.

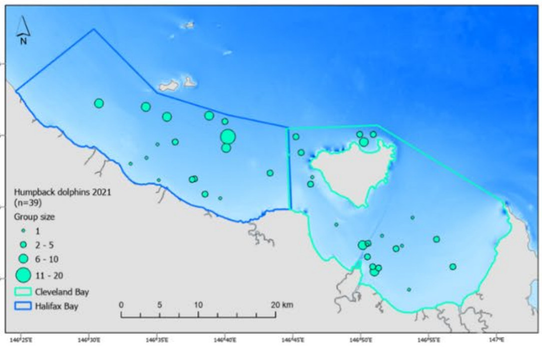
Figure 7. Location and group sizes of Australian snubfin dolphins (a-f), humpback dolphins (g-l), bottlenose dolphins (m-r) and other marine mammals (s-x) sighted in 2019, 2020, 2021, 2022, 2023 and 2024 during boat surveys in Cleveland and Halifax Bays.



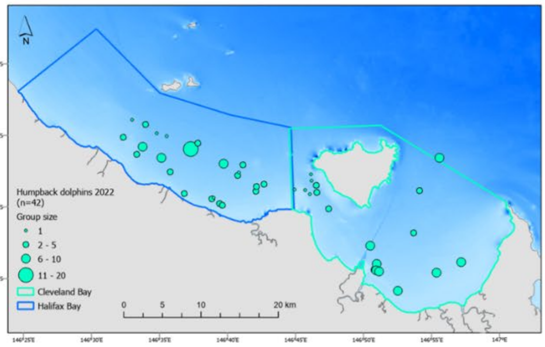
g) Humpback dolphin sightings 2019.



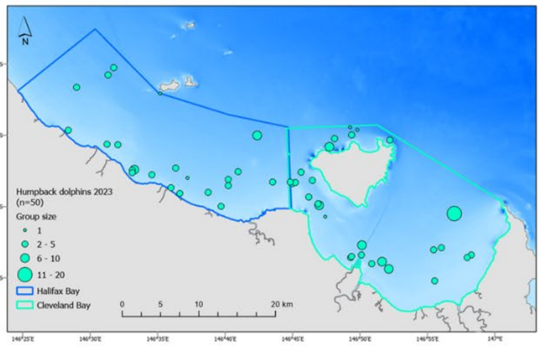
h) Humpback dolphin sightings 2020.



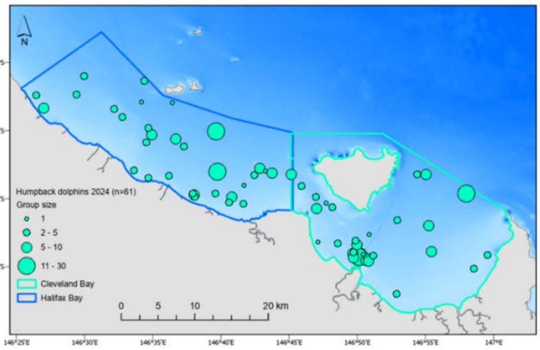
i) Humpback dolphin sightings 2021.



j) Humpback dolphin sightings 2022.

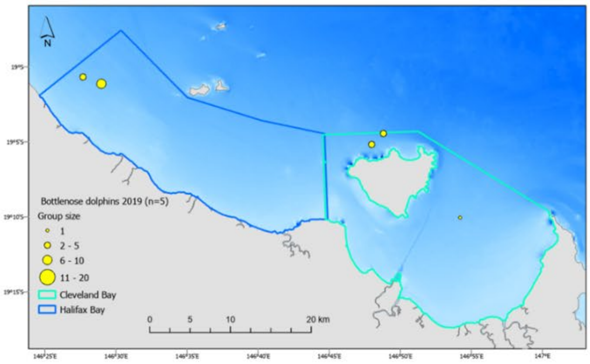


k) Humpback dolphin sightings 2023.

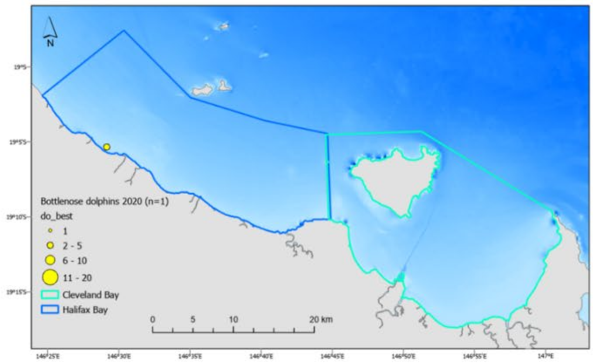


l) Humpback dolphin sightings 2024.

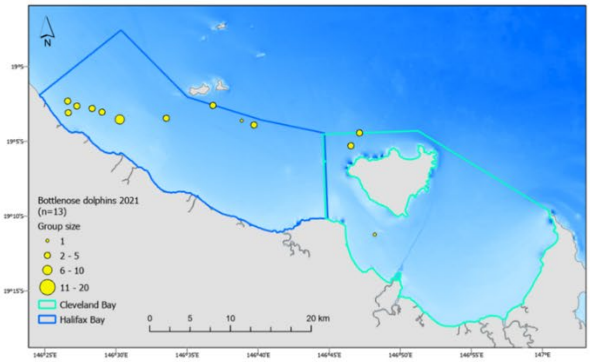
Figure 7 (continued). Location and group sizes of Australian snubfin dolphins (a-f), humpback dolphins (g-l), bottlenose dolphins (m-r) and other marine mammals (s-x) sighted in 2019, 2020, 2021, 2022, 2023 and 2024 during boat surveys in Cleveland and Halifax Bays.



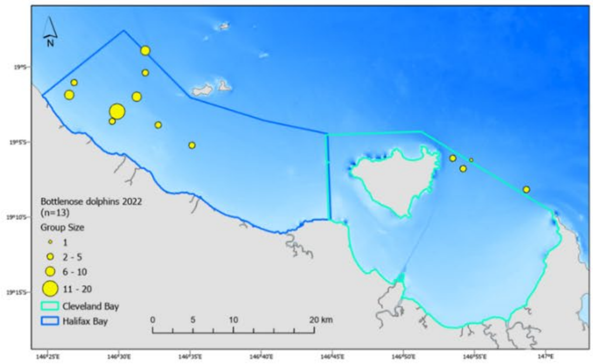
m) Bottlenose dolphin sightings 2019.



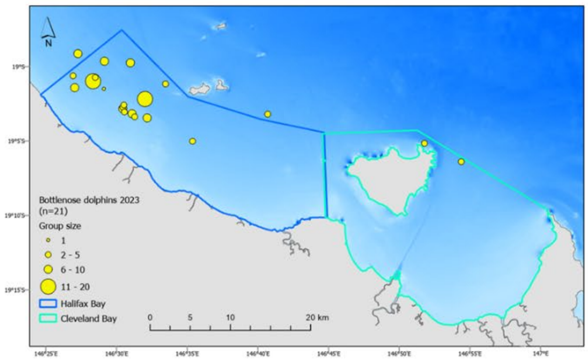
n) Bottlenose dolphin sightings 2020.



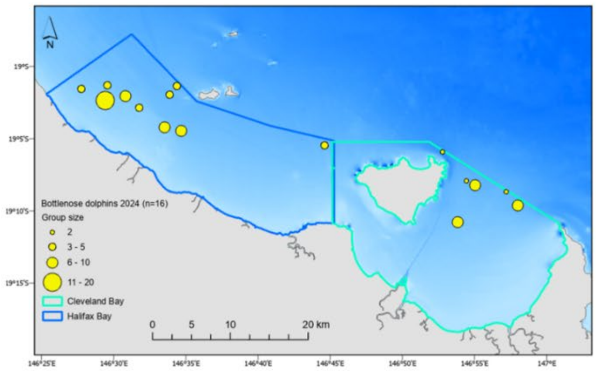
o) Bottlenose dolphin sightings 2021.



p) Bottlenose dolphin sightings 2022.

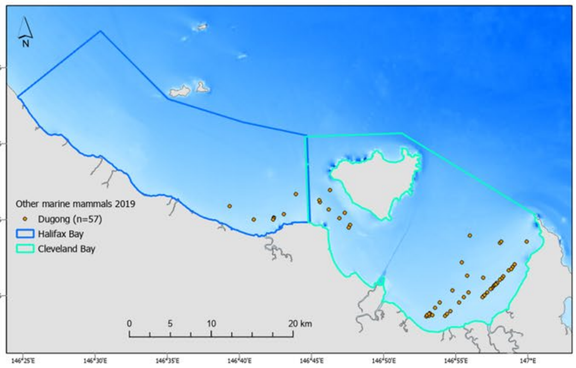


q) Bottlenose dolphin sightings 2023.

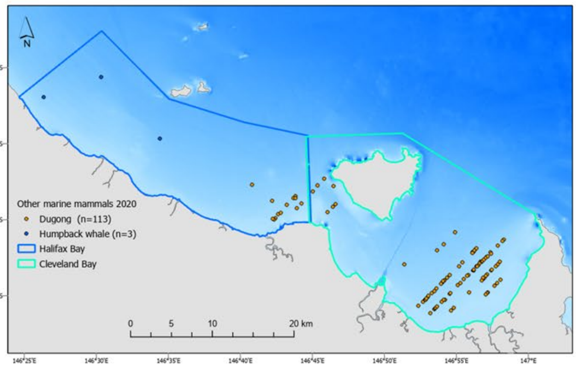


r) Bottlenose dolphin sightings 2024.

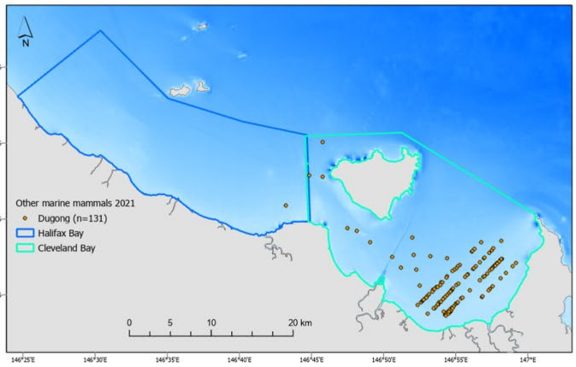
Figure 7 (continued). Location and group sizes of Australian snubfin dolphins (a-f), humpback dolphins (g-l), bottlenose dolphins (m-r) and other marine mammals (s-x) sighted in 2019, 2020, 2021, 2022, 2023 and 2024 during boat surveys in Cleveland and Halifax Bays.



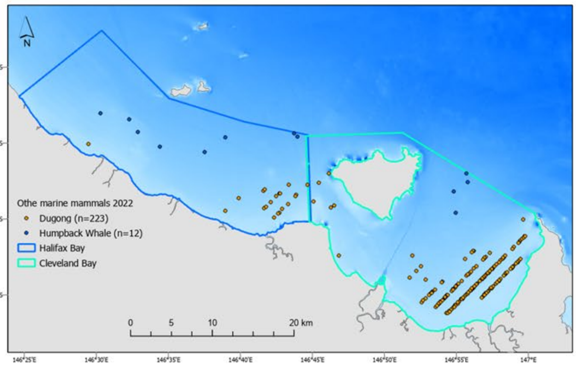
s) Other marine mammal sightings 2019.



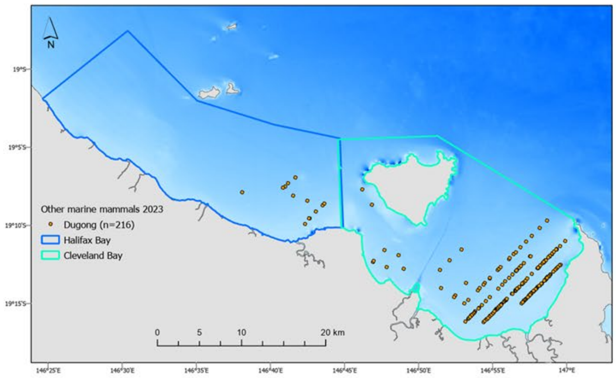
t) Other marine mammal sightings 2020.



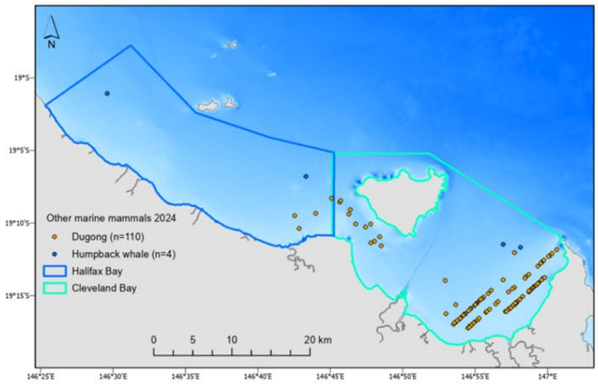
u) Other marine mammal sightings 2021.



v) Other marine mammal sightings 2022.



w) Other marine mammal sightings 2023.



x) Other marine mammal sightings 2024.

Figure 7 (continued). Location and group sizes of Australian snubfin dolphins (a-f), humpback dolphins (g-l), bottlenose dolphins (m-r) and other marine mammals (s-x) sighted in 2019, 2020, 2021, 2022, 2023 and 2024 during boat surveys in Cleveland and Halifax Bays.

Table 3. Number of 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, 2023, and 2024 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
2024	Snubfin	9	0.0056	26	0.0178	35	0.0115
	Humpback	28	0.0175	33	0.0226	61	0.0200
	Bottlenose	6	0.0038	10	0.0069	16	0.0052

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, 2023 and 2024.

Year	Species	Group size			Group age composition			
		Min	Max	Mean (SD)	Mean proportion of adults, juveniles, calves (%)			No. groups with juvenile or calf present
					A	J	C	
2019	Snubfin	1	16	4.7 (3.6)	77	11	10	15 (45%)
	Humpback	1	30	5.18 (4.9)	77	11	10	28 (62%)
	Bottlenose	1	8	4.4 (2.6)	67	10	10	4 (80%)
2020	Snubfin	1	20	4.7 (3.9)	83	6	10	15 (50%)
	Humpback	1	20	4.7 (4.1)	75	13	12	32 (58%)
	Bottlenose	3	3	3 (NA)	NA	NA	NA	1 (100%)
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%)
2024	Snubfin	1	17	5.9 (4.1)	79	9	12	22 (63%)
	Humpback	1	35	5.4 (4.5)	71	16	13	42 (69%)
	Bottlenose	2	14	5.7 (3.1)	72	21	7	12 (75%)

3.1.3 *Photo-identification and capture-recapture data*

One hundred and forty-four individual snubfin and 240 individual humpback dolphins have been identified since sampling began in 2019. 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 2024, 25 individual snubfin and 49 humpback dolphins were photo-identified in Cleveland Bay, and 52 snubfin and 84 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 2024. 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	2024
Snubfin	Cleveland	28/28	26/8	15/5	1/0	10/4	25/9
	Halifax	38/38	26/10	16/2	42/27	53/22	52/20
	Total	57/57	49/14	29/4	43/26	55/17	65/26
Humpback	Cleveland	16/16	25/16	25/9	29/13	51/32	49/22
	Halifax	42/42	39/25	30/9	32/20	40/24	84/58
	Total	54/54	56/30	51/12	58/29	82/46	119/69

Even though many of the dolphins first captured each year may have been present but not captured in previous years, the relatively large numbers of snubfin dolphins first captured in Halifax Bay and humpback dolphins first captured on both sites from 2022 onwards suggest that there may have been immigration to the area in the last three years.

The MSCRD analyses all data on each species captured in both bays in all six 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 six 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.

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). However extra time was allocated for sampling to allow for days lost due to poor weather and these days were used to complete further secondary samples as the opportunity arose. This resulted in seven secondary samples being completed on both sites in 2022 and 2023 and nine in 2024. The data were collapsed to three combined secondary samples (PS_CS) for 2019 to 2021 (1&2=1, 3&4=2, 5&6=3), three combined samples in 2022 and 2023 (5,6&7=3) and four combined samples in 2024 (8&9=4) 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 secondary samples (each composed of two complete transects on a site); PS_CS refers to secondary samples as collapsed from PS_SS (1 & 2 =1; 3 & 4 = 2; 5, 6 & 7 = 3; 8 & 9 =4).

Year	Species	Bay	No. of Individuals identified	Effort	PS_SS									PS_CS			
					s1	s2	s3	s4	s5	s6	s7	s8	s9	S1	S2	S3	S4
2019	Snubfin	Cleveland	27	On only	8	3	9	0	12	6	NA	NA	NA	11	9	13	NA
			28	On + off	8	3	9	11	12	6	NA	NA	NA	11	15	13	NA
		Halifax	36	On only	13	1	11	0	12	10	NA	NA	NA	14	11	20	NA
			38	On + off	13	1	11	2	12	10	NA	NA	NA	14	13	20	NA
	Humpback	Cleveland	12	On only	3	3	9	3	0	0	NA	NA	NA	6	10	0	NA
			16	On + off	3	3	10	5	5	0	NA	NA	NA	6	12	5	NA
		Halifax	42	On only	4	19	1	10	9	17	NA	NA	NA	20	11	25	NA
			42	On + off	4	19	1	10	9	17	NA	NA	NA	20	11	25	NA
2020	Snubfin	Cleveland	26	On only	6	0	2	10	4	7	NA	NA	NA	6	11	11	NA
			26	On + off	6	0	2	10	4	7	NA	NA	NA	6	11	11	NA
		Halifax	26	On only	0	6	7	8	10	8	NA	NA	NA	6	15	18	NA
			26	On + off	0	6	7	8	10	8	NA	NA	NA	6	15	18	NA
	Humpback	Cleveland	25	On only	1	2	8	6	16	8	NA	NA	NA	3	11	20	NA
			25	On + off	1	2	8	6	16	8	NA	NA	NA	3	11	20	NA
		Halifax	39	On only	3	16	5	10	13	5	NA	NA	NA	19	14	18	NA
			39	On + off	3	16	5	10	13	5	NA	NA	NA	19	14	18	NA
2021	Snubfin	Cleveland	15	On only	4	7	1	1	3	0	NA	NA	NA	11	2	3	NA
			15	On + off	4	7	1	1	3	0	NA	NA	NA	11	2	3	NA
		Halifax	16	On only	0	6	4	1	1	6	NA	NA	NA	6	5	7	NA
			16	On + off	0	6	4	1	1	6	NA	NA	NA	6	5	7	NA
	Humpback	Cleveland	23	On only	11	3	0	9	10	2	NA	NA	NA	13	9	11	NA

Year	Species	Bay	No. of Individuals identified	Effort	PS_SS									PS_CS			
					s1	s2	s3	s4	s5	s6	s7	s8	s9	S1	S2	S3	S4
			25	On + off	11	3	0	9	10	7	NA	NA	NA	13	9	14	NA
		Halifax	29	On only	17	1	5	2	0	11	NA	NA	NA	18	7	11	NA
			30	On + off	17	1	5	2	0	12	NA	NA	NA	18	7	12	NA
2022	Snubfin	Cleveland	1	On only	0	0	0	0	0	0	1	NA	NA	0	0	1	NA
			1	On + off	0	0	0	0	1	0	1	NA	NA	0	0	1	NA
		Halifax	40	On only	0	4	12	1	13	13	4	NA	NA	4	13	25	NA
			42	On + off	0	4	12	4	13	13	4	NA	NA	4	16	25	NA
	Humpback	Cleveland	21	On only	0	0	16	6	3	2	3	NA	NA	0	19	6	NA
			29	On + off	6	1	16	6	3	8	3	NA	NA	7	19	11	NA
		Halifax	31	On only	0	2	0	9	4	14	8	NA	NA	2	9	22	NA
			32	On + off	3	2	0	9	4	14	8	NA	NA	4	9	22	NA
2023	Snubfin	Cleveland	10	On only	0	0	0	0	0	10	0	NA	NA	0	0	10	NA
			10	On + off	0	0	0	0	0	10	0	NA	NA	0	0	10	NA
		Halifax	40	On only	1	0	6	4	6	5	22	NA	NA	1	10	33	NA
			53	On + off	1	1	7	18	6	19	22	NA	NA	2	20	41	NA
	Humpback	Cleveland	47	On only	10	2	4	0	23	11	3	NA	NA	10	4	36	NA
			51	On + off	11	2	6	9	23	16	3	NA	NA	11	9	38	NA
		Halifax	30	On only	0	3	6	11	9	0	10	NA	NA	3	15	17	NA
			40	On + off	0	4	8	11	9	7	11	NA	NA	4	17	24	NA
2024	Snubfin	Cleveland	14	On only	0	0	0	2	0	0	0	12	8	0	2	0	13
			25	On + off	0	0	1	2	2	13	0	12	8	0	2	14	13
		Halifax	41	On only	1	12	13	14	5	16	0	6	6	12	25	17	10
			52	On + off	10	15	13	24	5	16	4	6	12	18	33	21	16
	Humpback	Cleveland	40	On only	22	3	1	8	8	1	12	3	1	25	9	16	4
			49	On + off	22	3	9	8	9	14	12	3	19	25	12	22	19

Year	Species	Bay	No. of Individuals identified	Effort	PS_SS									PS_CS			
					s1	s2	s3	s4	s5	s6	s7	s8	s9	S1	S2	S3	S4
		Halifax	72	On only	0	15	4	10	19	0	15	24	9	15	14	34	32
			84	On + off	2	15	4	11	24	4	15	30	11	17	15	41	39

3.1.4 *Goodness of fit*

The goodness of fit test statistics from U-Care were, for the snubfin data $\chi^2 = 8.562$, $df = 18.00$, $p = 0.969$ and, for the humpback data $\chi^2 = 19.297, df = 22$, $p = 0.627$ 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_CS) 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_CS) 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, …, 2023 to 2024). 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, and no captures were made in the first combined sample in 2024. The capture probability for the years 2022 and 2023 were modelled as having been constant over combined samples and constant over the first two combined samples in 2024 to allow the models to run and estimates to be produced. 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 13 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 and was not observed to do so). Movement between 2023 and 2024 was fitted separately, as equal to the movement between 2019 and 2021 in another model and equal to the movement between 2021 and 2022 in a third. 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. Movement between 2023 and 2024 was fitted separately in one model and equal to the movements between 2019 and 2021 in another. The best-fitting model had the movement between Cleveland and Halifax Bay between 2023 and 2024 equal to the movement between 2021 and 2022 and the movement between Halifax Bay and Cleveland Bay equal to the movements between 2019 and 2021.All attempts to model temporary emigration from either Bay for snubfin dolphins produced estimates that were either very small with a large standard error or very large with a standard error of zero indicating improper estimation. Consequently, temporary emigration from both Bays was fixed at zero and not estimated in any model reported here. 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 fitted as constant over all years and both sites and separately as constant over years within but different between sites. The final set for averaging included six models.

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 2019-2024*

Five 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 = 0.010. 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 2024 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 estimated total abundance of snubfin dolphins in Cleveland Bay in 2024 was 33, representing a return to an approximately pre 2022 number after the low numbers in 2022 and 2023. In terms of the numbers of captures, there was a very large decline in numbers in 2022 and a slight recovery in 2023, but as previously discussed, the resulting abundance estimates for these two years (as shown in Table 7) are considered unreliable (with wide confidence intervals) and are likely to be overestimated. 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 13 for 2023. The estimated total abundance of snubfin dolphins in Halifax Bay decreased from 56 in 2019 to 35 in 2020 and 31 in 2021 before increasing greatly to 111 in 2022 before falling to 73 in 2023 and 60 in 2024 (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 2024 were very similar for the two bays at an average of 0.80 (95% CI = 0.72 – 0.86). With an estimated rate of biological survival of snubfin dolphins of 0.95 p.a. (Taylor et al. 2007), the estimated rate of permanent emigration is 16% p.a., i.e., 16% have left each Bay, have not moved to the other, and our modelling suggests they may not return.

The rate of movement (estimated probability of movement) between Cleveland Bay and Halifax Bay between 2019 and 2020, and 2020 and 2021 was 0.14 (i.e. an estimated 14% of the dolphins moved from Cleveland Bay to Halifax Bay). This increased to 0.42 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 Cleveland to Halifax Bay between 2023 and 2024 was similar to the rate between 2021 and 2022 at 0.41 indicating that the relatively high rate of movement out of Cleveland Bay has continued through to 2024. The rate of movement from Halifax Bay to Cleveland Bay between 2019 and 2020, and 2020 and 2021 was greater than the rate of movement in the other direction at 0.24.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, and the rate between 2022 and 2023 was very small, could not be reliably estimated and was also fixed at zero. Movement between 2023 and 2024 returned to the rate seen previously between 2019 and 2021 or slightly greater at 0.27. Although data limitations have posed difficulties for estimation, these estimates provide 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 has returned to approximately the rate seen previously between 2019 and 2021. The estimated probability of movement from Cleveland Bay to Halifax Bay was 0.41 between 2023 and 2024, consistent with the 2021–2022 estimate, indicating continued high emigration from Cleveland Bay through 2024. In contrast, the probability of movement from Halifax Bay to Cleveland Bay was 0.27 during the same period, returning to levels observed between 2019 and 2021.

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 very small and fixed at zero to facilitate reliable estimation of other parameters.

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 per individual of relevant species, except population sizes.

Parameter*	Bay	Year	Estimate	SE	LCI	UCI
Apparent survival (φ)	CB	2019-2024	0.80	0.04	0.72	0.86
Apparent survival (φ)	HB	2019-2024	0.79	0.03	0.72	0.85
Movement between sites (ψMS)	CB to HB	2019-2020	0.14	0.06	0.05	0.31
		2020-2021	0.14	0.06	0.05	0.31
		2021-2022	0.42	0.11	0.23	0.63
		2022-2023	0.00	0.00	0.00	0.00
		2023-2024	0.41	0.12	0.21	0.64
Movement between sites (ψMS)	HB to CB	2019-2020	0.24	0.07	0.13	0.40
		2020-2021	0.24	0.07	0.13	0.40
		2021-2022	NIL (fixed)	NA	NA	NA
		2022-2023	NIL (fixed)	NA	NA	NA
		2023-2024	0.27	0.09	0.12	0.49
Temporary emigration from (ψTE)	CB	2019-2024	NIL (fixed)	NA	NA	NA
	HB	2019-2024	NIL (fixed)	NA	NA	NA
Marked population size (N_{marked})	CB	2019	28	3.42	22	35
		2020	37	7.44	23	52
		2021	31	9.08	13	49
		2022	13 * (See text)	18.34	-23	49
		2023	24 * (See text)	11.75	1	47
		2024	30	9.34	12	48
Marked population size (N_{marked})	HB	2019	50	9.53	32	69
		2020	32	3.72	24	39
		2021	28	7.83	13	43
		2022	100	21.40	58	142
		2023	65	8.14	50	81
		2024	54	3.43	47	60
Total population size (N_{total})	CB	2019	31	3.81	25	40
		2020	41	8.28	28	61
		2021	34	10.10	20	60
		2022	14 * (See text)	20.38	2	113
		2023	27 * (See text)	13.06	11	66
		2024	33	10.38	18	61
	HB	2019	56	10.61	39	81

Parameter*	Bay	Year	Estimate	SE	LCI	UCI
		2020	35	4.15	28	44
		2021	31	8.71	18	53
		2022	111	23.81	73	168
		2023	73	9.08	57	93
		2024	60	3.87	52	68

*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.

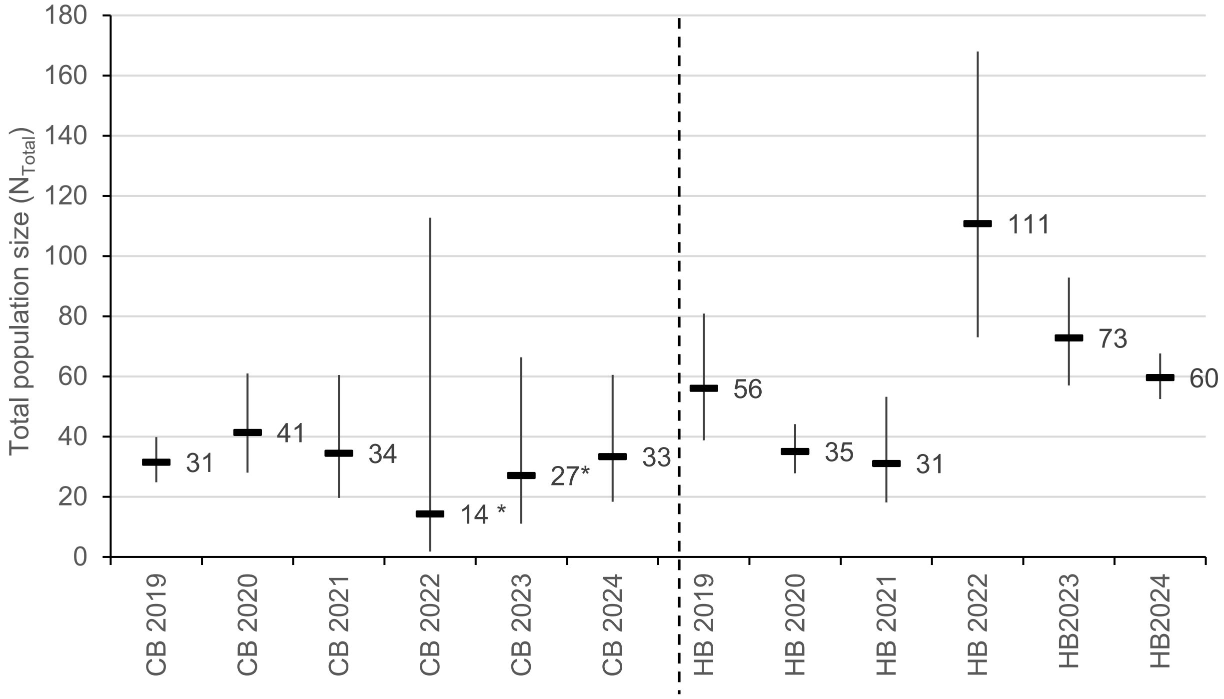


Figure 8. Estimates of the total population size of Australian snubfin dolphins with 95% confidence intervals in Cleveland (CB) and Halifax Bays (HB) for the years 2019 to 2024. The estimates for Cleveland Bay in 2022 and 2023 are considered unreliable (*) and are likely overestimated (see text).

3.1.7 *Australian humpback dolphin: population parameters 2019-2024.*

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 = 0.009. 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 2024 in Figure 9. The number of humpback dolphins present in Cleveland Bay increased from 20 in 2019 to 32 in 2020 and 2021 and increased again to 48 in 2022 and 81 in 2023 but declined slightly to 68 in 2024 (Fig. 9).

There were more humpback dolphins present in Halifax Bay than Cleveland Bay in all years, with 66 in 2019, 53 in 2020, 45 in 2021, 80 in 2022, 87 in 2023 and 122 in 2024 (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 three years (Table 5) that there may have been immigration into both bays in these years and to Halifax Bay between 2023 and 2024 in particular.

Estimates for the average rate of apparent survival (alive and remaining in the bay) in the intervals between consecutive years between 2019 and 2024 were the same for both bays at 0.80 p.a. (Table 8). With an estimated rate of biological survival of humpback dolphins of 0.97 p.a., the estimated rate of permanent emigration was 17.5% p.a. from both bays. This is a quite high rate of permanent emigration but one that has been more than balanced by immigration in recent years indicating substantial connectivity between the Townsville humpback dolphin populations and populations elsewhere.

The average rates of movement between the Bays in the intervals between consecutive years between 2019 and 2024 were approximately equal in both directions at an average of 0.21 p.a. (Table 8). That is a substantial proportion (21%) in the context of ecological and demographic processes of small populations, 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 p.a. 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 0.53 p.a. for Halifax Bay. These rates of temporary emigration from and return to Halifax Bay may be part of a flow of humpback dolphins between Halifax Bay and another population nearby.

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 per individual of relevant species, except population sizes.

Parameter*	**Bay**	**Year**	**Estimate**	**SE**	**LCI**	**UCI**
Apparent survival (φ)	CB	2019-2024	0.80	0.04	0.72	0.87
Apparent survival	HB	2019-2024	0.80	0.04	0.72	0.87
Movement between sites (ψ_{MS})	CB to HB	2019-2024	0.22	0.04	0.15	0.30
	HB to CB	2019-2024	0.20	0.03	0.14	0.27
Temporary emigration from (ψ_{TE})	CB	2019-2024	0.00	0.00	0.00	0.00
	HB	2019-2024	0.27	0.07	0.15	0.43
Return of previously emigrated dolphins to (ψ_{TE})	CB	2019-2024	0.00	0.00	0.00	0.00
	HB	2019-2024	0.53	0.24	0.15	0.88
Marked population size (N_{marked})	CB	2019	17	2.07	13.43	21.56
	CB	2020	17	2.07	13	22
	CB	2021	28	4.04	20	36
	CB	2022	28	3.38	21	34
	CB	2023	41	6.69	28	54
	CB	2024	70	9.87	50	89
	HB	2019	57	9.60	38	76
	HB	2020	46	6.62	33	59
	HB	2021	39	6.07	27	51
	HB	2022	69	18.35	33	105
	HB	2023	75	17.60	40	109
	HB	2024	105	10.09	86	125
Total population size (N_{total})	CB	2019	20	2.42	16	26
	CB	2020	32	4.71	24	43
	CB	2021	32	3.94	26	41
	CB	2022	48	7.80	35	66
	CB	2023	81	11.51	62	107
	CB	2024	68	7.95	54	85
	HB	2019	66	11.19	47	92
	HB	2020	53	7.72	40	71
	HB	2021	45	7.07	33	61
	HB	2022	80	21.36	48	134
	HB	2023	87	20.49	55	137
	HB	2024	122	11.80	101	148

*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.

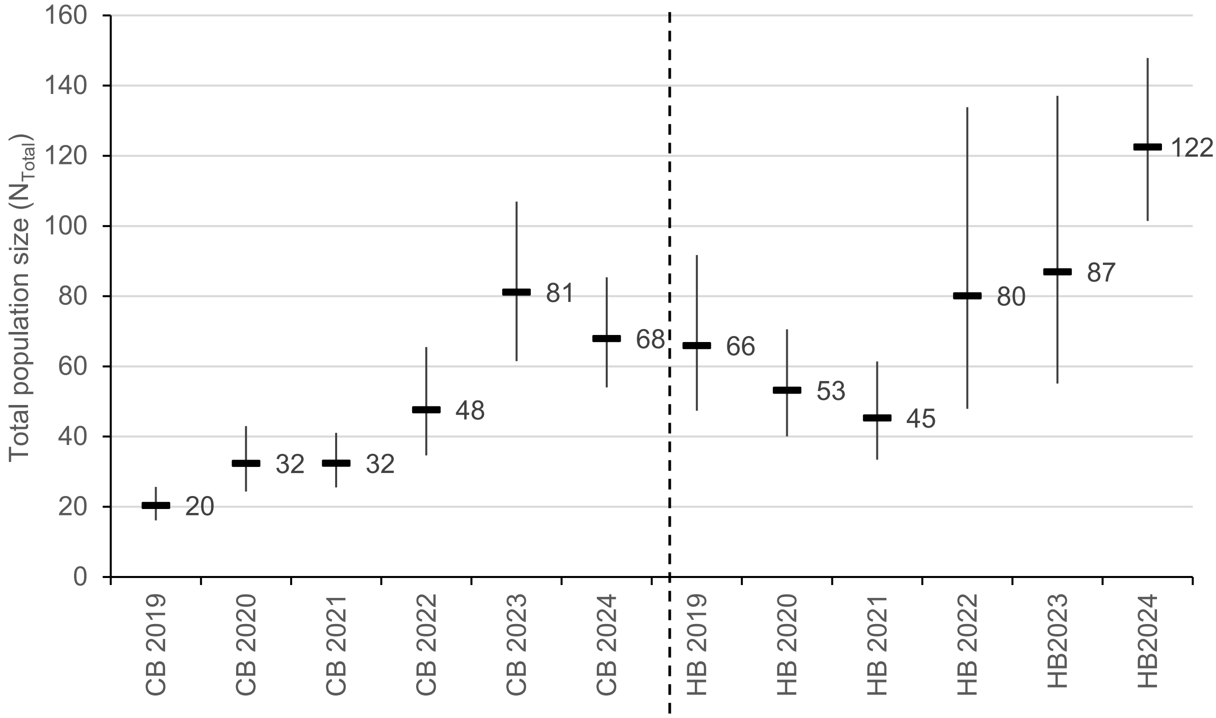


Figure 9. Estimates of total population size with 95% confidence intervals of Australian humpback dolphins in Cleveland (CB) and Halifax Bays (HB) for the years 2019 to 2024.

3.2 Spatial distribution modelling

3.2.1 *Model performance and spatial predictions*

In 2024, 35 encounters with groups of snubfin dolphins and 61 encounters with groups of humpback dolphins were recorded. The number of points representing the pseudo-zeros for the snubfin dolphins SDM was 1003 and 977 for the SDM of humpback dolphins.

Overall, the final ensemble models for generating species distribution plots for 2024 had good predictive performance. Humpback dolphin’s model had slightly lower performance in comparison to 2023, whereas the snubfin model had better performance. The ensemble model for humpback dolphins obtained a global cv-ROC-AUC of 0.820 (lower than the 2023 value of 0.833 and the 2022 value of 0.840) and a cv-precision-recall-AUC of 0.342 (lower than the previous two-years values of 0.38 and 0.462, respectively). For snubfin dolphins, the global cv-ROC-AUC was 0.860 (higher slightly than the previous two years’ values of 0.853 and 0.833); the cv-precision-recall-AUC was 0.278 (compared to the previous two years’ values of 0.300 and 0.217).

The per-year predictive performance (cv-ROC-AUC) for humpback dolphins, using the 2023 ensemble model, were 0.884, 0.929, 0.805, 0.785, 0.733, and 0.784, for survey-years 2019 through to 2024, respectively. This suggests that earlier years (2019-2021, especially 2020) had better predictive performance than latter years (2022-2024). The per-year predictive performance for snubfin dolphins, using the 2023 ensemble model, were 0.898, 0.919, 0.779, 0.821, 0.829, 0.879, for survey-years 2019 through to 2024, respectively. Similar to the humpback model, the 2020 survey year had the strongest predictive performance, but 2021 had the lowest predictability.

3.2.2 *Relative Variable Importance*

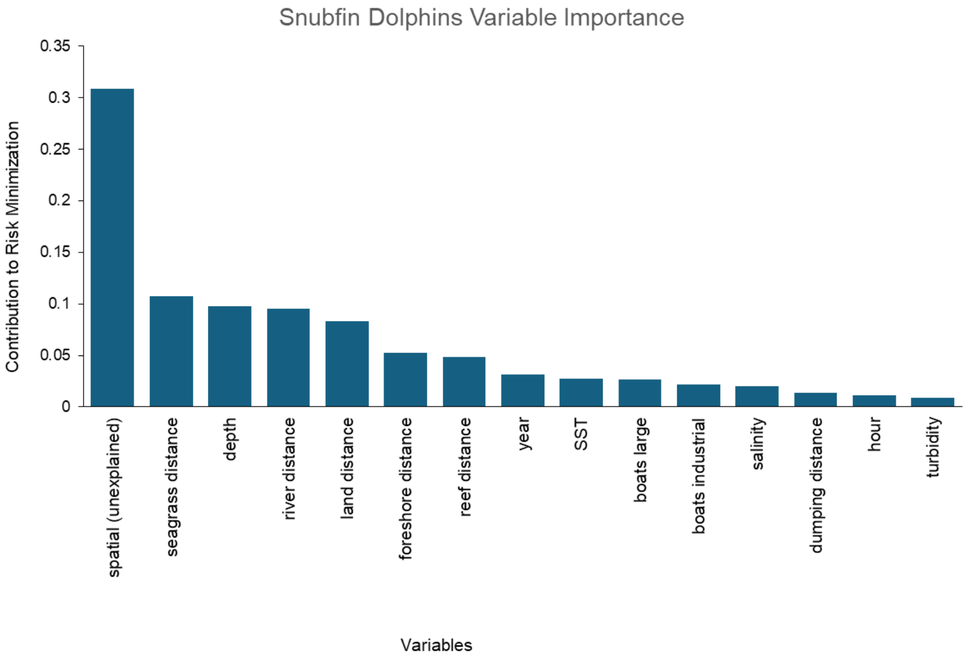
For snubfin dolphins, the order of RVIs was: an unexplained spatial process (30.9%), log-distance to seagrass meadows (10.7%), depth (9.8%), log-distance to river (9.5%), log-distance to land (8.4%), log-distance to the foreshore (5.3%), log-distance to reefs (4.9%), year as a categorical variable (3.1%), SST (2.7%), counts of large boats (2.6%), counts of industrial boats (2.2%), salinity (2.0%), log-distance to rock-dumping (1.34%), time-of-day (1.14%), and turbidity (0.9%) (Fig. 10a) .

For humpback dolphins, the most important explanatory variable was the flexible spatial base-learners, representing unexplained spatial variation, and accounted for 29% of risk-minimisation (Fig. 10b). Thereafter, the most important variables were log-log-distance to land (22%), then log-distance to rivers (16%), depth (9.0%), SST (8.4%), year as a categorical variable (2.9%), counts of large boats (1.58%), counts of all boats (1.24%), time-of-day (1.03%), log-distance to seagrass meadows (0.77%), counts of small boats (0.75%), swell (0.68%), log-distance to maintenance dredging (0.58%). All covariates thereafter had RVIs of less than 0.5%. Compared to the 2023 humpback RVIs, most of the top covariates had similar percentages and ordering. However, the 2023 model attributed a 0.8% RVI to distance to maintenance dredging.

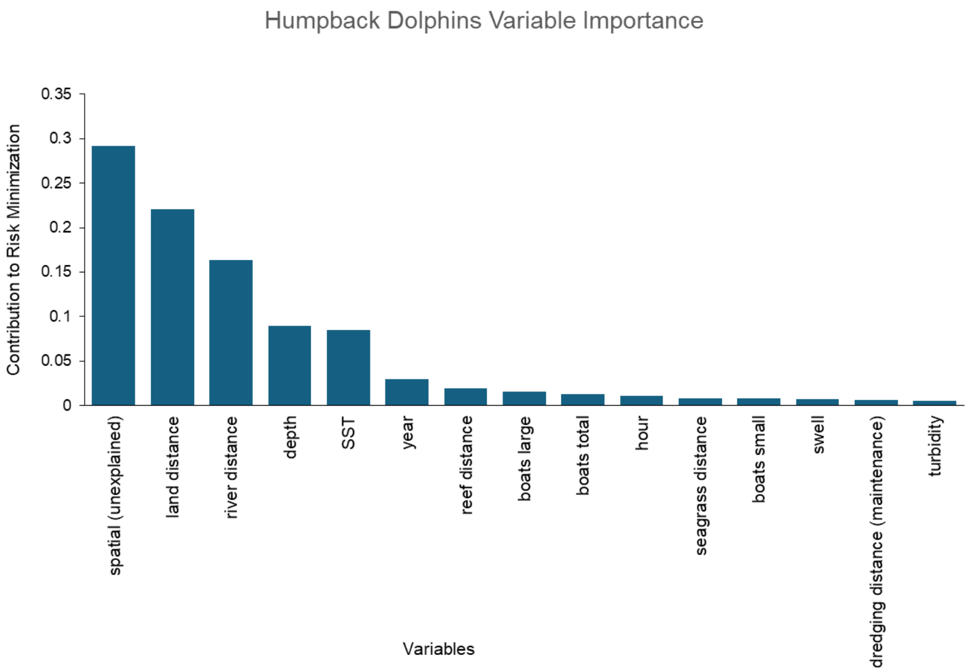
Unlike the humpback models, the ordering and percentages of snubfin RVIs in 2024 were somewhat different as compared to the 2023 RVIs. For instance, the top 5 covariates in 2023 were: unexplained spatial process (45%), distance to rivers (12%), depth (9.9%), distance to land (6.6%), distance to foreshore (5.3%). It is noteworthy that the 2024 snubfin model had more variation explained by named environmental predictors and temporal variables, rather than an unexplained spatial processes. This corresponds to a much better predictive performance for the 2024 model (cv-ROC of 0.860 vs 0.833 in 2023), suggesting that the inferences from the 2024 RVIs may be more trustworthy than previous models. It is also noteworthy that whereas the 2023 snubfin model allocated a relatively high RVI to the covariate representing distance to maintenance dredging (2.5%), this covariate was not important in the 2024 model, but was replaced by a higher importance of rock-dumping (1.34%).

For both species, the human-related covariates, such as counts of boats, seemed to have systematic and measurable effects, but whose contributions are relatively small (<<5%) compared to other environmental predictors. Furthermore, the distribution-related covariates (like maintenance dredging) received lower RVIs in 2024 despite having modest RVIs in 2023. It could be that, for past-years' analyses, the effect of disturbance is more pronounced given its proportionally higher-share of the data, whereas the addition of post-disturbance data from 2024, swamps their weak by natural variation.

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 2024.

3.2.3 *Likelihood Ratio Tests Disturbance Covariates*

We performed a 5-fold cross-validation to compare the CV-likelihood of the base-model versus a reduced model that dropped the five disturbance covariates (distance to pilings, distance to dumping, distance to capital dredging, distance to maintenance dredging, and minimum distance to any disturbance covariate). 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.

For snubfin dolphins, the CV-likelihood ratio was $1.6 \times 10^{-24} << 1$, supporting the full model that included disturbance variables. The relative variable importance (RVI) analysis suggests that distance to rock-dumping was most strongly associated with model fit, with distance to maintenance dredging also contributing (RVI = 0.8%), both showing positive associations with snubfin dolphin distribution.

For humpback dolphins, the CV-likelihood ratio was $1.0 \times 10^{-35} << 1$, also supporting the full model that included disturbance variables. The analysis suggest that maintenance dredging was the disturbance variable most strongly associated with the model outcomes, indicating a positive relationship with humpback dolphin occurrence.

3.2.4 *Covariate Two-Way Interaction Partial Plots*

We made partial plots of two-way interactions between pairs of covariates and the marginal predicted density, after marginalizing-out the contributions of the flexible spatial base-learners (i.e., as visualised in the SDM maps) (Fig. 11). Such partial plots help to visualise the complex influence of covariates on species' abundance. We used two-way interaction plots because of inherent interactive nature of the underlying machine-learning method, in which the relationship between predictors and response variables may change as a function of other variables, and so cannot be perceived independently.

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 (2024)

- Distance to seagrass meadows: large increase (i.e., species density increased further away from seagrass meadows).
- Depth: large decrease (i.e., species density decreased in deeper waters), however, it depended on other covariates, and in many cases showed a non-linear concave-up pattern.
- Distance to river: large decrease (i.e., species density decreased at further distances from rivers), non-monotonic, with a slight concave-down peak at small distances, and whose effect was especially pronounced in the presence of boats.
- Distance to land: moderately concave-down effect (i.e., inverted u-shape), with a pronounced peak occurring a mid-distances.
- Distance to the foreshore: small decrease (i.e., species density decreased as distance increased) with a slight concave-down peak at moderate distances, and declining further away.
- SST: moderately-small decrease (i.e., higher temperatures had lower species density), but also often with a pronounced concave-down profile, whereby species density peaked at middle temperatures, and declined rapidly at cooler temperatures, and a shallower decline at higher temperatures.

- Distance to reefs: small increase (i.e., as the distance from reefs increased, the species density increased).
- Counts of industrial boats: small increase (i.e., the species density increased as the counts of boats increased).
- Distance to rock-dumping: small decrease, non-linear (i.e, the species density decreased further away from the rock-dumping).
- Counts of large boats: small increase.
- Salinity: small decrease.
- Time-of-day/hour: small concave-up shape, such that there were higher species densities during earlier hours, followed by a decrease, and then a large rise in the late survey hours.

<u>Humpback Dolphins Functional Relationships with Covariates (2024):</u>

- Distance to land: strong increase (i.e., species density increased as the distance from land increased), non-linear, whereby most of the increase happened at the furthest distances from land.
- Distance to rivers: strong decrease (i.e., species density declined with increasing distance from rivers), non-linear with a sigmoidal shape.
- Depth: moderate decrease (i.e. species density decreased in deeper waters), highly non-linear, with a flat response in mid-to-shallow waters followed by large decreases in deep waters.
- SST: moderate increase.
- Counts of large boats: moderate increase.
- Counts of all boats: moderately small increase.

- Time-of-day/hour: moderately small concave-up non-linear effect (i.e., high species density occurred during the early and late survey hours, with lower density in between).
- Distance to seagrass meadows: small increase, but varied according to other covariates (e.g., there was a declining-relationship when paired with dredging, but a positive-relationship when paired with swell).
- Counts of small boats: small decrease.
- Swell: small increase
- Distance to maintenance dredging (Year 3) small decrease.

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

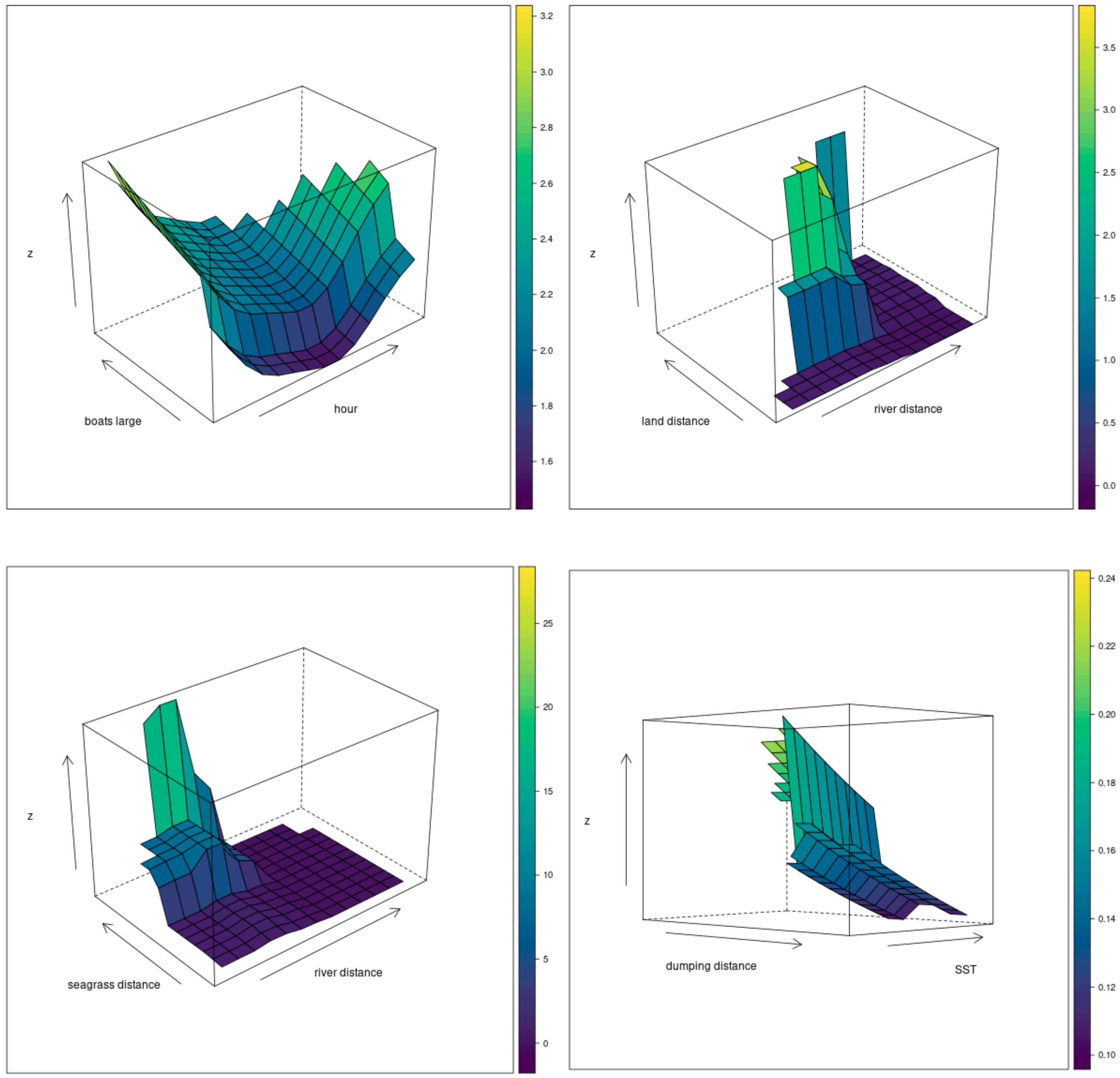


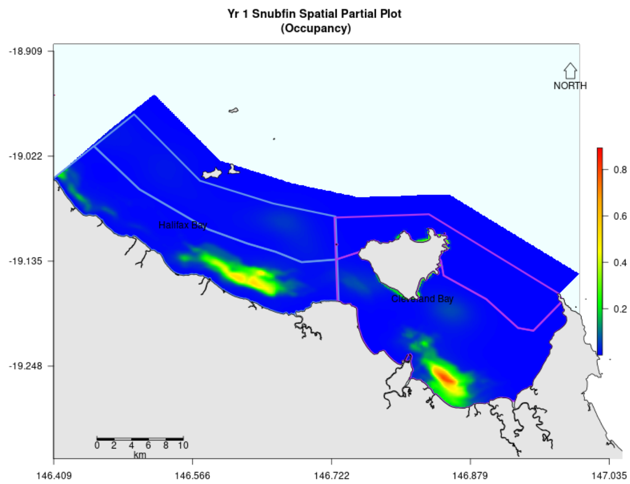
Figure 11. Examples of two-way partial plots for humpbacks (top) and snubfin (bottom) predicted marginal density, where the x-axes are two interacting covariates, and the y-axis is marginal density. Notice the different colour-coded scales of the y-axis, per plot. The x-axis have been mean-centred and re-scaled to unit variance.

3.2.5 *Plots and Summaries of Spatially Varying SDM Components*

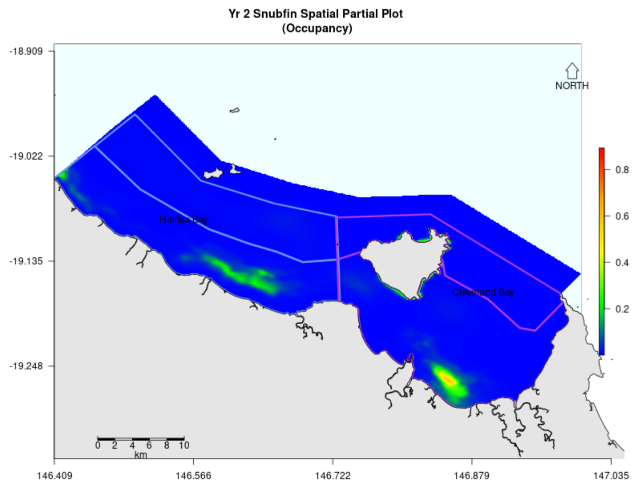
The spatial partial plots of snubfin and humpback dolphins across the survey area are shown in Figures 12 and 13 respectively. These plots show three series: the probability of occurrence per year (Figs. 12a-f and 13a-f), the conditional group size (i.e., the size of an encounter, if a group is present) per year (Figs. 12g-l and 13g-l), and relative density per year (Figs. 12m-r and 13m-r). The first two components (occupancy and conditional counts), constitute the zero-inflated Poisson bivariate distribution. The third series, the relative density, is the probability of occupancy multiplied by the conditional counts per year. 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-TSHD or distance-to-rock dumping), the SDM the model is conditioned on the disturbance being present.

Snubfin dolphin occurrence and relative density showed significant yearly variation, with a sharp decline in Cleveland Bay occupancy in 2022 and no dolphins estimated there in 2023.The 2024 predictions of spatial occurrence of snubfin dolphins (Fig 12f) and their relative density (Fig 12r) were more similar to the 2019 pattern, in which there was a higher relative concentration of snubfins along the south-western nearshore of Cleveland Bay around the Port of Townsville, and the south-eastern nearshore of Halifax Bay, and almost no presence and densities in offshore waters.

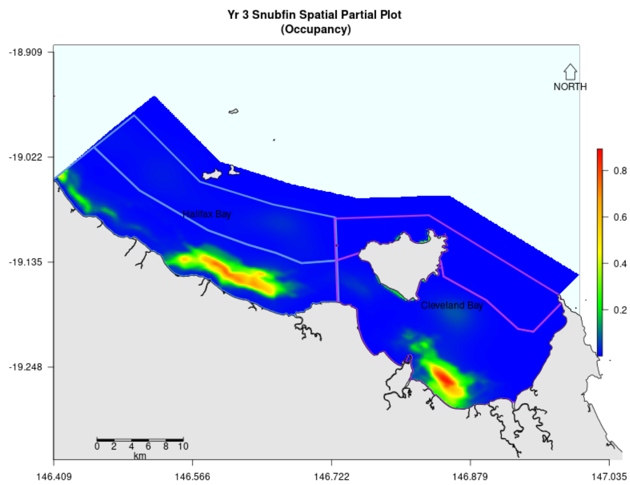
The predictions of humpback dolphin occurrence and relative density across all years are very similar in overall pattern, except for some differences in some areas of punctuated densities. Across all years, there was high occupancy (Fig. 13a-f) and density (Fig 13m-r) to the north and to the east of Port of Townsville, along the shore of Cleveland Bay, as well as a large expanse of high-occupancy and density between Toolakea beach and Cape Pallarenda along the shore of Halifax Bay. 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 13a-f). In 2024 the spatial patterns of density in Cleveland and Halifax Bays exhibit a similar pattern t to 2023, but with a higher overall density (Fig. 13m-r). For instance, whereas a diffuse cloud of relatively high density enveloping the nearshore of Port of Townsville in 2023, for 2024 this is also predicted to have a singular point of very high densities to the east of Port of Townsville. Also, in the eastern nearshore region of Cleveland Bay, the 2024 SDM suggests there is also a singular point of very high density in 2024 (and in 2021), whereas in 2023 this was a more diffused region of moderately high density. This could be due to an increased confidence as more data is accumulated over the years, resulting in less "shrinkage" towards zero (i.e., models without a lot of data).



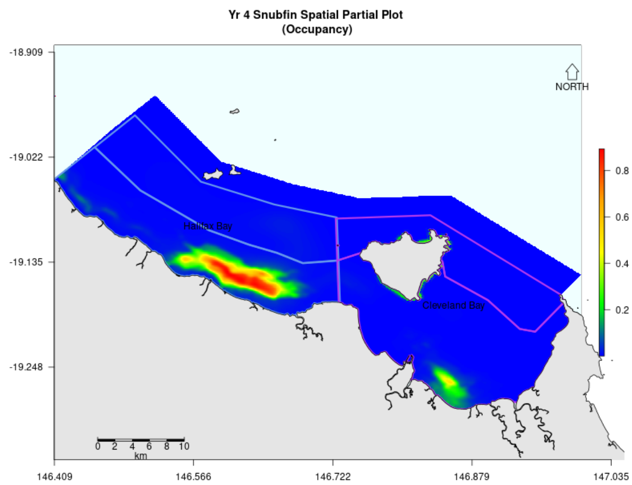
a) 2019



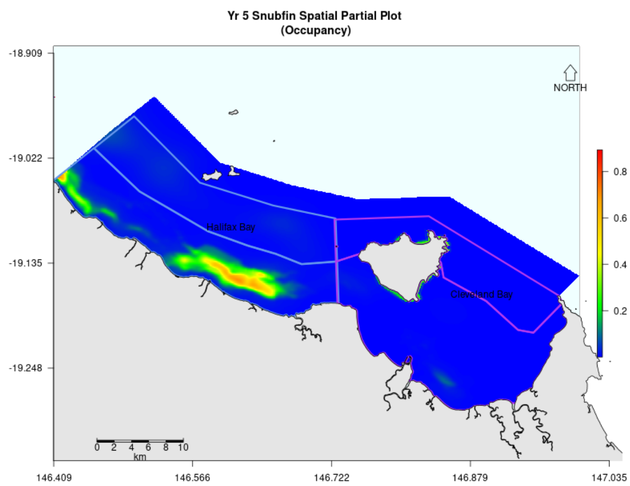
b) 2020



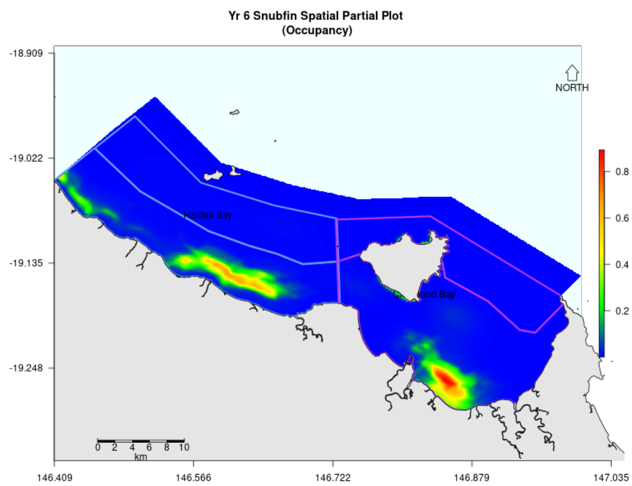
c) 2021



d) 2022

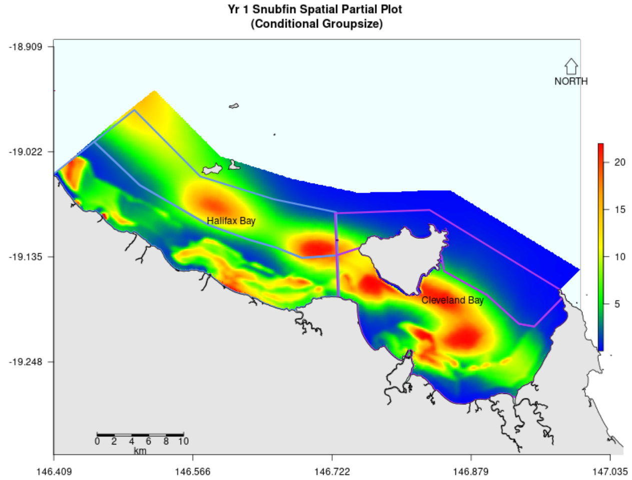


e) 2023

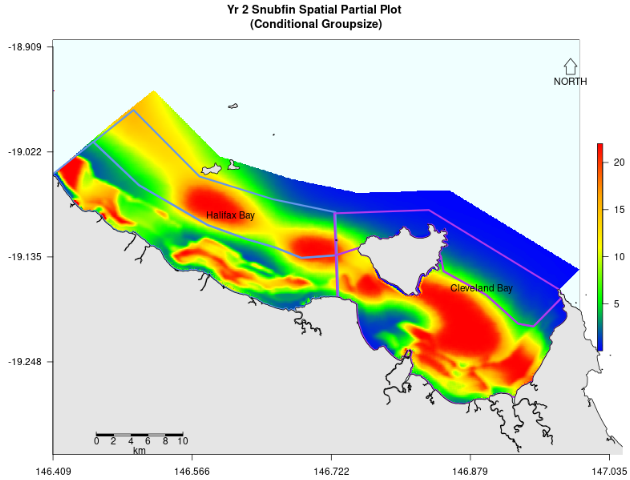


f) 2024

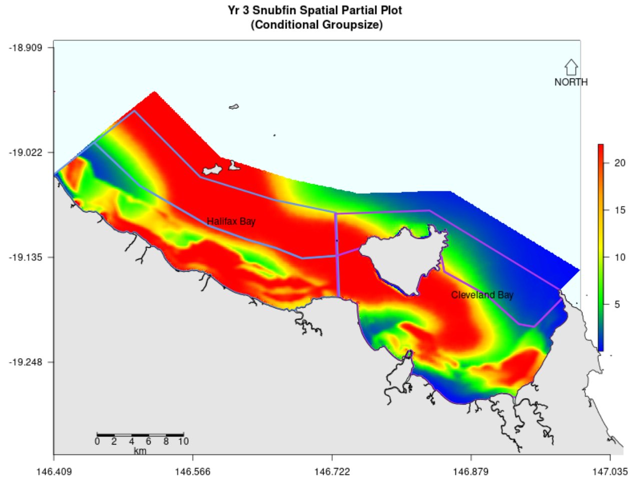
Figure 12. Spatial partial plots of Australia snubfin dolphins from ensemble-modelling of species distribution across the survey area based on data collected in 2019, 2020, 2021, 2022, 2023 and 2024: (a-f) shows how the probability of dolphins' presence/absence varies spatially over the study area, (g-l) shows how expected group size varies spatially (conditional on being present), and (m-r) shows the relative density function of dolphins across the bays.



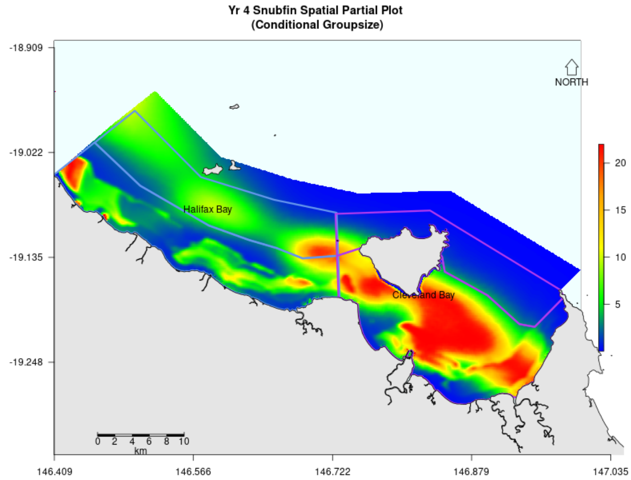
g) 2019



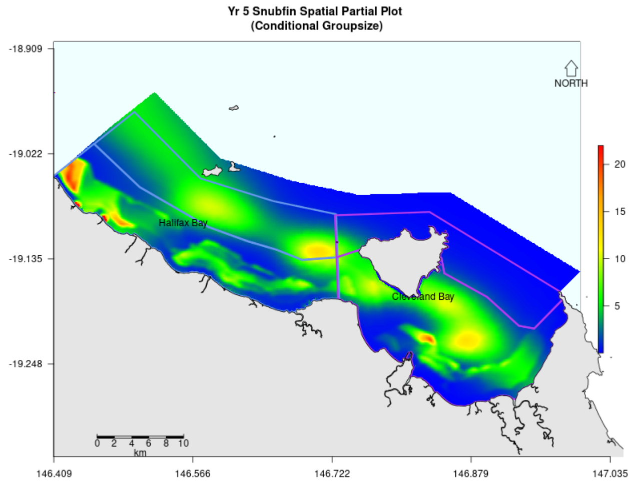
h) 2020



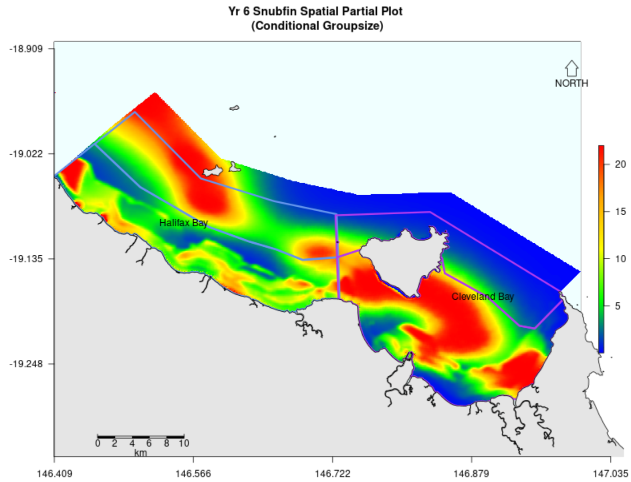
i) 2021



j) 2022

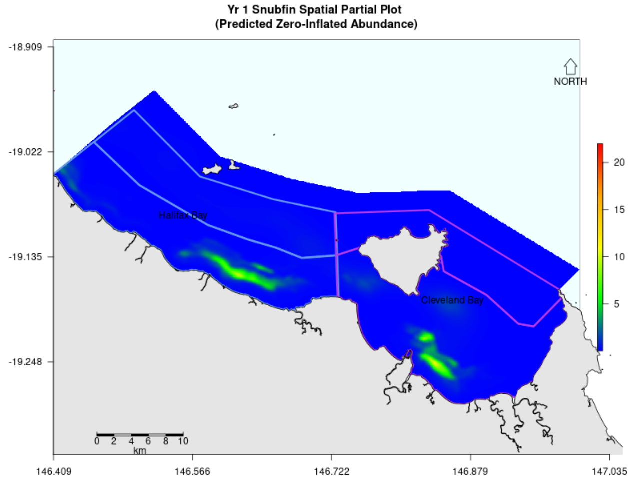


k) 2023

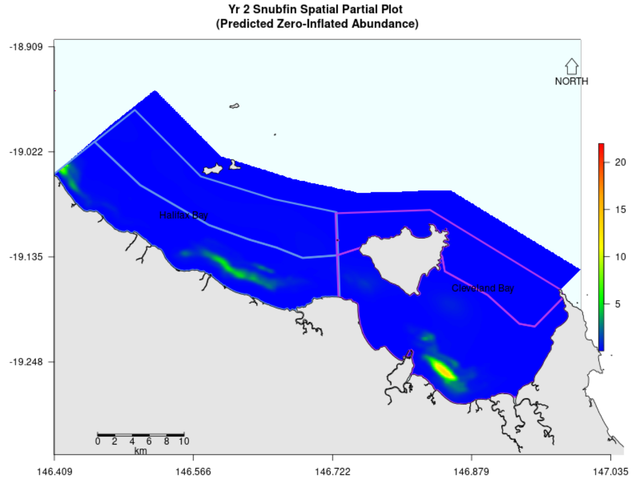


l) 2024

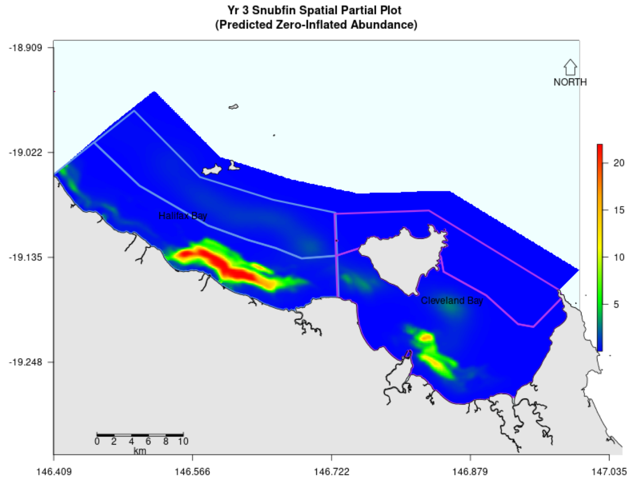
Figure 12 (continued). Spatial partial plots of Australia snubfin dolphins from ensemble-modelling of species distribution across the survey area based on data collected in 2019, 2020, 2021, 2022, 2023 and 2024: (a-f) shows how the probability of dolphins' presence/absence varies spatially over the study area, (g-l) shows how expected group size varies spatially (conditional on being present), and (m-r) shows the relative density function of dolphins across the bays.



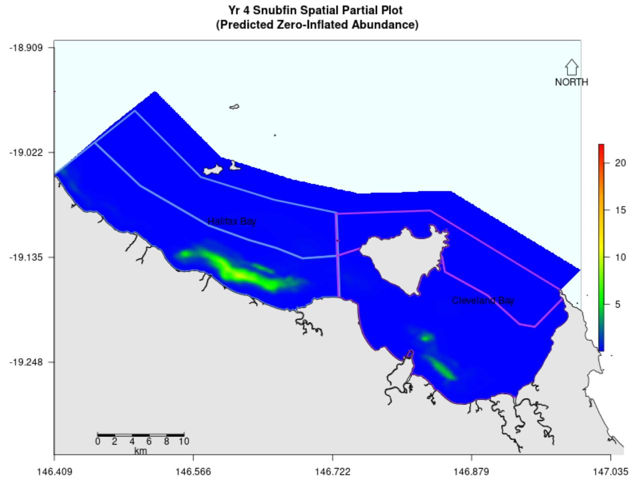
m) 2019



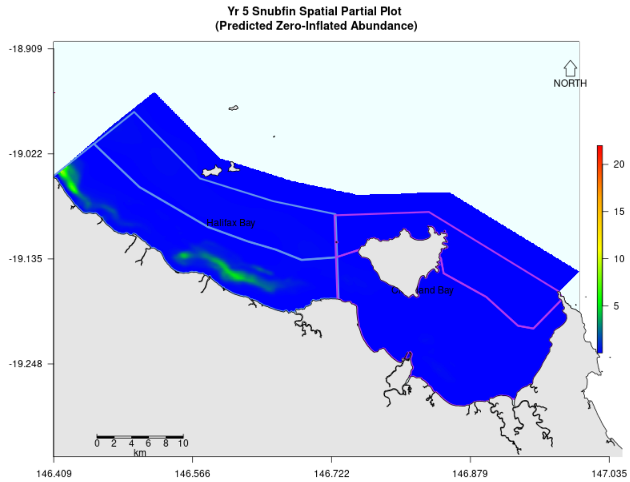
n) 2020



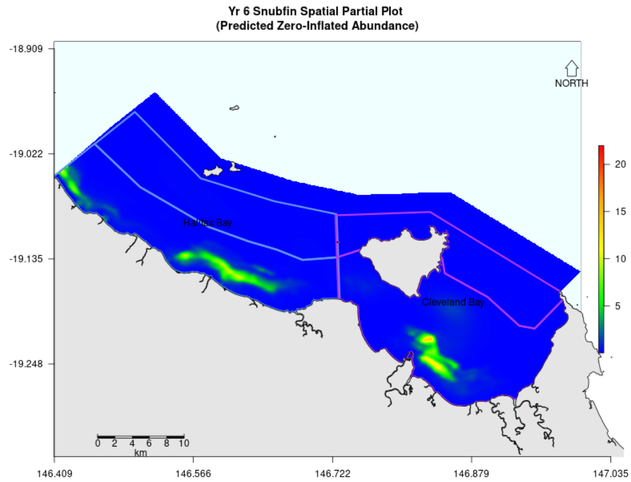
o) 2021



p) 2022

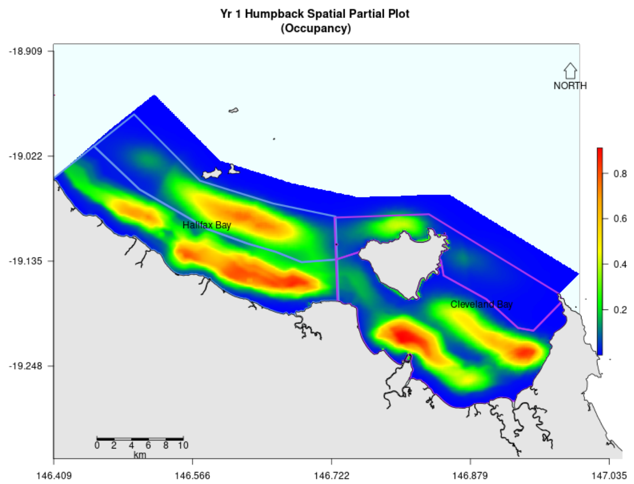


q) 2023

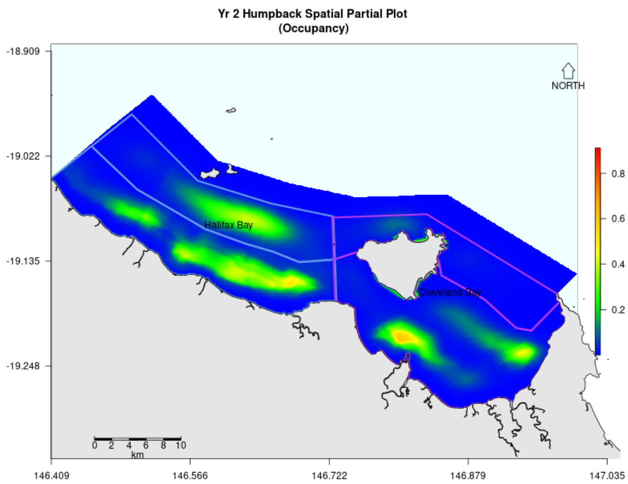


r) 2024

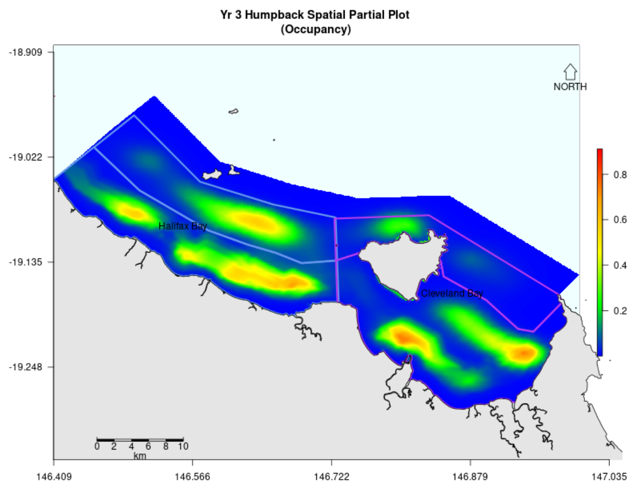
Figure 12 (continued). Spatial partial plots of Australia snubfin dolphins from ensemble-modelling of species distribution across the survey area based on data collected in 2019, 2020, 2021, 2022, 2023 and 2024: (a-f) shows how the probability of dolphins' presence/absence varies spatially over the study area, (g-l) shows how expected group size varies spatially (conditional on being present), and (m-r) shows the relative density function of dolphins across the bays.



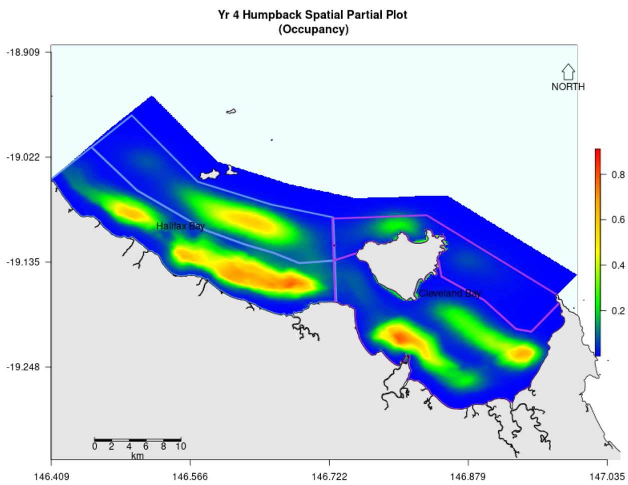
a) 2019



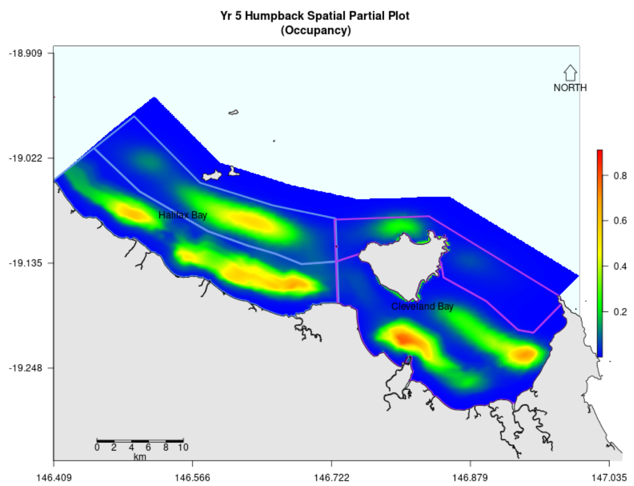
b) 2020



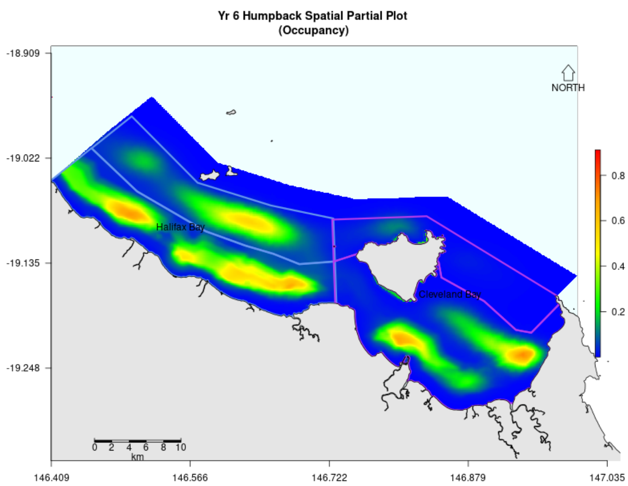
c) 2021



d) 2022

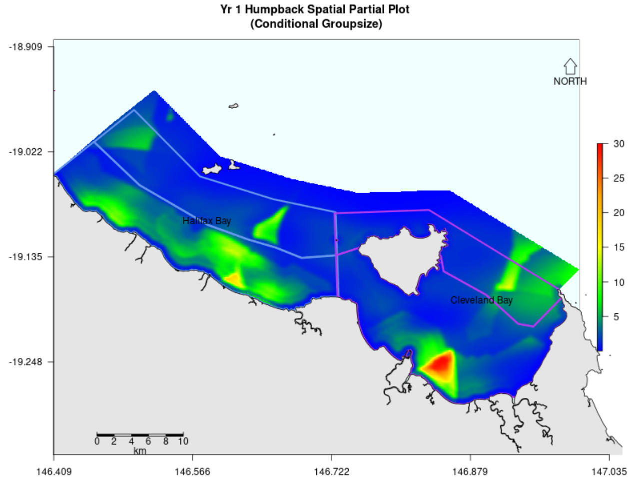


e) 2023

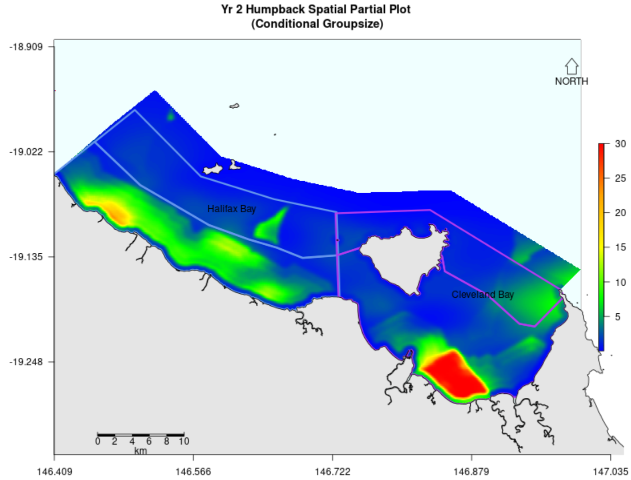


f) 2024

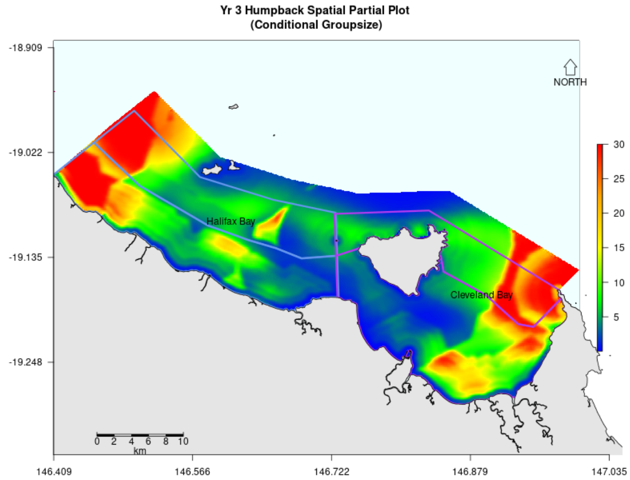
Figure 13. Spatial partial plots of Australia humpback dolphins from ensemble-modelling of species distribution across the survey area based on data collected in 2019, 2020, 2021, 2022, 2023 and 2024: (a-f) shows how the probability of dolphins' presence/absence varies spatially over the study area, (g-l) shows how expected group size varies spatially (conditional on being present), and (m-r) shows the relative density function of dolphins across the bays.



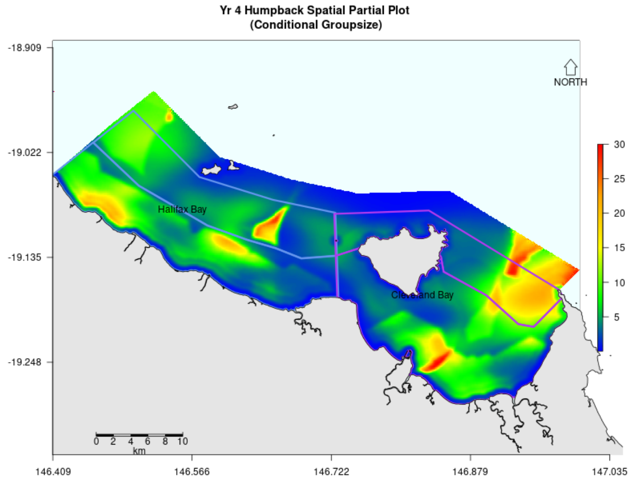
g) 2019



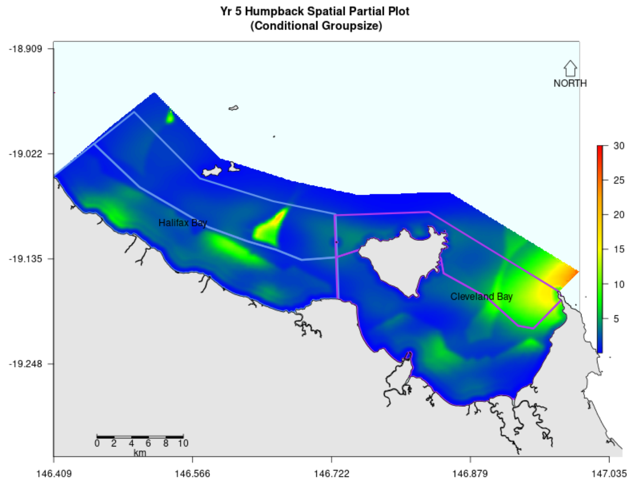
h) 2020



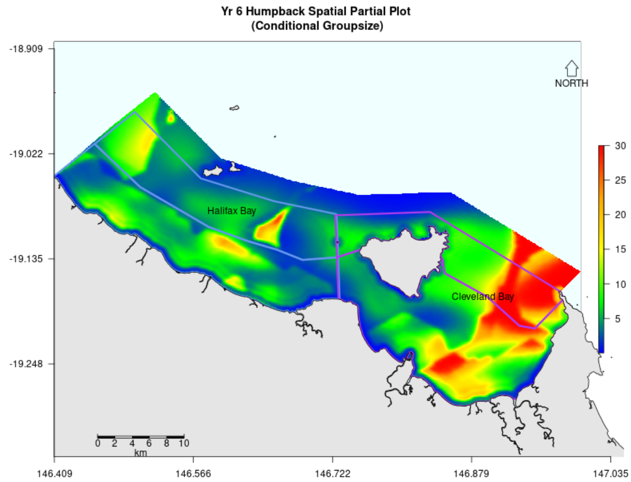
i) 2021



j) 2022

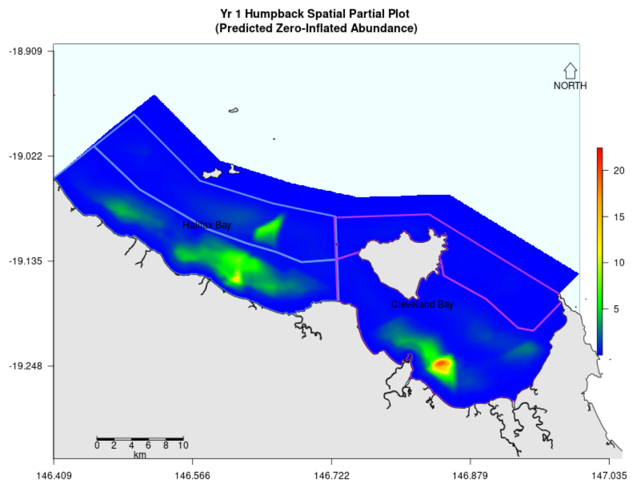


k) 2023

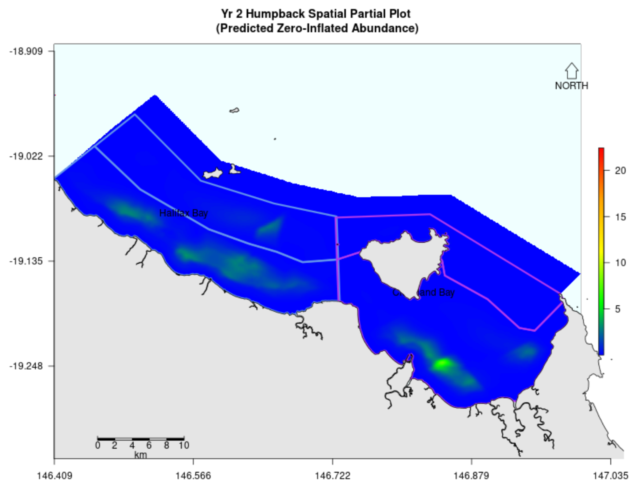


l) 2024

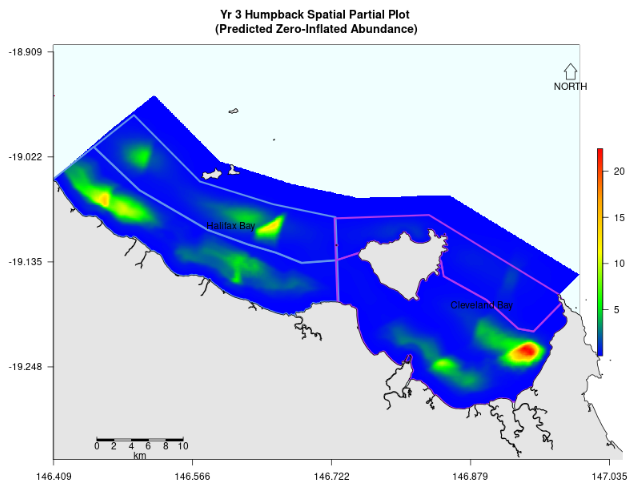
Figure 13 (continued). Spatial partial plots of Australia humpback dolphins from ensemble-modelling of species distribution across the survey area based on data collected in 2019, 2020, 2021, 2022, 2023 and 2024: (a-f) shows how the probability of dolphins' presence/absence varies spatially over the study area, (g-l) shows how expected group size varies spatially (conditional on being present), and (m-r) shows the relative density function of dolphins across the bays.



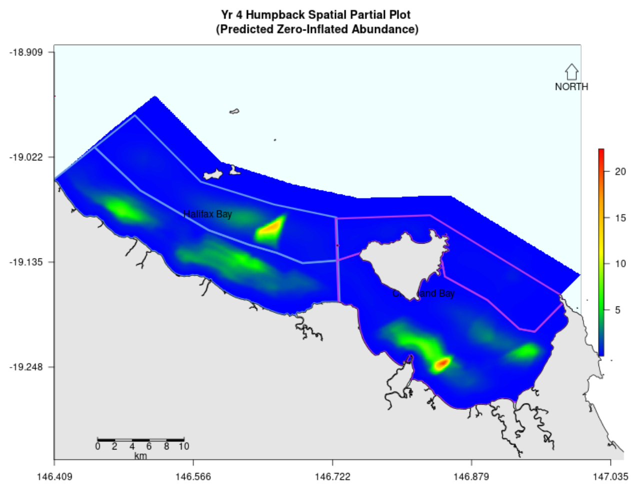
m) 2019



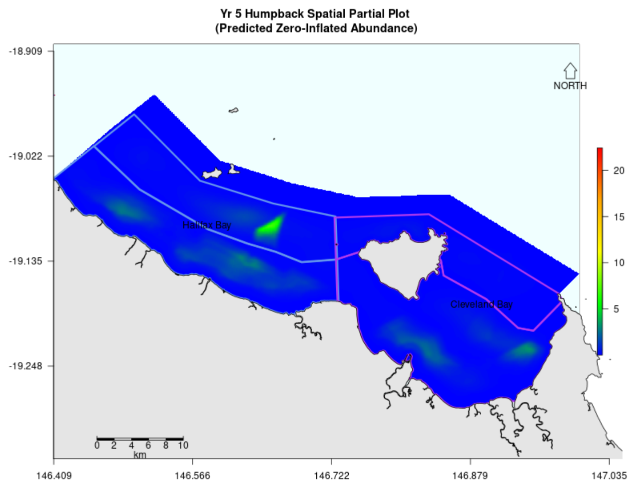
n) 2020



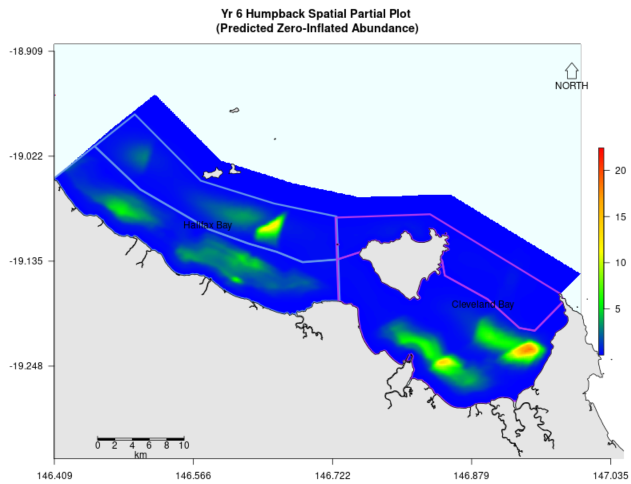
o) 2021



p) 2022



q) 2023



r) 2024

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, 2023 and 2024: (a-f) shows how the probability of dolphins' presence/absence varies spatially over the study area, (g-l) shows how expected group size varies spatially (conditional on being present), and (m-r) shows the relative density function of dolphins across the bays.

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 (Fig. 13g-l). Group-sizes in 2022 were high around the Port of Townsville (northeast and southeast of port, Fig. 13j), and small between Port of Townsville and Magnetic Island, both locations being in the vicinity where capital 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 (shown in red) conditional group-size were: i) to the west of Magnetic Island on the nearshore boundary between Cleveland and Halifax Bays; 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 snubfins, Table 9a shows the average predicted values (for predicted occupancy and expected) across years, strata (Cleveland Bay vs. Halifax Bay), and inshore waters vs. offshore waters. Table 9b shows the same for humpback dolphins. For snubfin dolphins, the 2024 values showed a pattern of being high in the inshore waters, and low in the offshore waters. For instance, whereas the relative density of snubfins in Halifax Bay’s and Cleveland Bay’s inshore waters were higher than the respective values in 2019, 2020, 2022, and 2023, the offshore values were the lowest in the time series.

For humpbacks, the 2024 fields obtained values for occupancy and relative density that were in-line with past years’ values for most strata, and for some waters, were much higher. For instance, in the inshore waters of Cleveland Bay, the mean relative densities were predicted to be the highest areas all years, attaining a 64% premium over the 2019 pre-construction baseline. In contrast, the offshore waters of Halifax Bay had the highest mean relative densities across all years. The fact that such high-rankings for 2024 were not also shown in the expected occupancies (which were close to median values over the time-series), suggest that it was the group-size which drove the overall higher relative densities.

Table 9. Summaries of a) snubfin dolphins and b) humpback dolphins predicted occupancy and relative density, by strata and year.

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	0.051	0.012	0.050	0.013	0.475	0.108	0.396	0.015
2020	0.021	0.004	0.026	0.013	0.324	0.051	0.347	0.014
2021	0.087	0.011	0.056	0.007	2.457	0.487	0.723	0.012
2022	0.109	0.005	0.021	0.013	0.629	0.031	0.130	0.013
2023	0.084	0.016	0.010	0.010	0.444	0.072	0.021	0.013
2024	0.074	0.003	0.057	0.006	0.727	0.029	0.531	0.007

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	0.29	0.23	0.23	0.08	1.41	0.53	0.89	0.09
2020	0.1	0.08	0.07	0.03	0.6	0.17	0.37	0.02
2021	0.16	0.12	0.13	0.05	1.59	1.2	1.28	0.3
2022	0.2	0.13	0.13	0.05	1.22	0.88	1.01	0.12
2023	0.17	0.13	0.13	0.05	0.51	0.39	0.34	0.1
2024	0.19	0.13	0.11	0.02	1.1	0.94	1.46	0.13

3.3 Patterns of attendance to the port area

3.3.1 *Land based survey effort*

During the 2024 field season, there were 12 days of land-based surveys, conducted between June 4th and June 18th. There was a total of 766 scans (compared to 870 scans in 2019, 948 in 2020, 1533 in 2021, 1490 scans in 2022, and 1164 scans in 2023 Table 10). The lower number of scans in 2024 was due to land-based observations being restricted to a short window from June 4 to 18, as Berth 11 was closed from June 19 to August 1 for scheduled shipping activities and essential maintenance on the ship loader. Despite the fewer number of scans, there were many more humpbacks and snubfins observed from the land-based station as compared to previous years: humpbacks were observed on 11 of the 12 survey-days; snubfins were observed on 5 days (compared to 0 in 2023 and 1 in 2022). As in previous years, no bottlenose dolphins were seen in 2024.

Table 10. Survey effort and dolphins observed from Berth 11 at the Port of Townsville during June 2024. 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 Mode	BSS Max
4/06/2024	64	0	0	0	0	2	3
5/06/2024	64	1	0	0	1	1	1
6/06/2024	64	2	0	0	1	1	2
7/06/2024	64	4	0	0	0	1	3
8/06/2024	64	11	0	0	1	1	4
10/06/2024	64	16	2	0	1	1	4
11/06/2024	66	3	0	0	0	1	4
12/06/2024	64	4	1	0	0	1	3
14/06/2024	62	3	0	0	0	1	3
15/06/2024	62	2	6	0	0	1	3
17/06/2024	64	7	1	0	1	1	3
18/06/2024	64	7	2	0	1	1	4
Total	**766**	**60**	**12**	**0**			

3.3.2 *Overall difference in dolphin occurrence between years*

For humpbacks dolphins, all the Bayesian p-values that compared the 2024 scans versus survey-years 2019 through to 2023 were close to 1.0 (Table 11), i.e., the number of encounters of humpback dolphins were in line (or greater) than the expectations of previous years. This was driven by a large number of scans with humpbacks and fewer overall scans than in previous survey years (i.e., large numerator and smaller denominator).

For snubfin dolphins, the 2024 survey year yielded a relatively high number of snubfin observations as compared to the previous two survey years, in which there were one or no snubfins. However, the Bayesian p-values for 2019 (baseline) and 2020 were close to zero, and the 2021 p-value was intermediate (Table 11). This suggests that encounters of snubfin dolphins were higher around the port in earlier years (2019-2020), declined into 2022 and 2023, and then returned in 2024 to values similar to the 2021 year.

Table 11. Comparison of dolphin occurrences between 2024 and all other years and corresponding Bayesian P-values.

a) 2019-2024

Species	Year	Number of Scans	N occurrences of dolphins	Bayesian P-value
Snubfin	2019	867	49	0
	2024	766	12	
Humpback	2019	867	19	1
	2024	766	60	

b) 2020-2024

Species	Year	Number of Scans	N occurrences of dolphins	Bayesian P-value
Snubfin	2020	948	34	0.004
	2024	766	12	
Humpback	2020	948	7	1
	2024	766	60	

c) 2021-2024

Species	Year	Number of Scans	N occurrences of dolphins	Bayesian P-value
Snubfin	2021	1533	27	0.36
	2024	766	12	
Humpback	2021	1533	32	1
	2024	766	60	

d) 2022-2024

Species	Year	Number of Scans	N occurrences of dolphins	Bayesian P-value
Snubfin	2022	1490	1	1
	2024	766	12	
Humpback	2022	1490	65	1
	2024	766	60	

e) 2023-2024

Species	Year	N Scans	N Occurrences of Dolphins	Bayesian P-value
Snubfins	2023	1164	0	1
	2024	766	12	1
Humpbacks	2023	1164	53	1
	2024	766	60	1

3.3.3 *Diel and behavioural patterns observed*

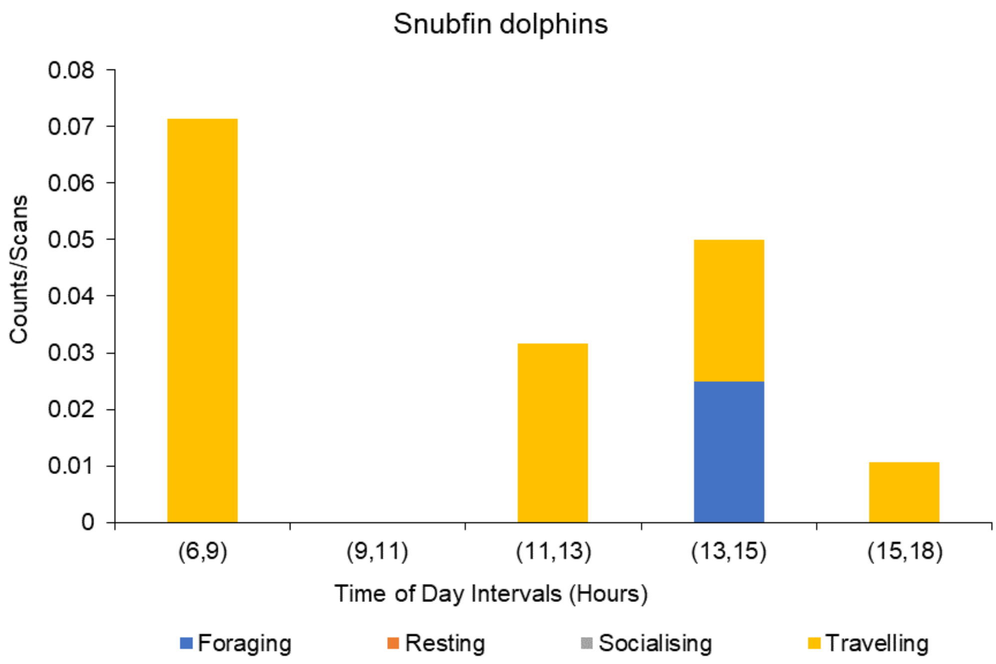
Among the behaviours observed for snubfin dolphins in 2024, travelling was the most common (67%), followed by foraging (17%), with no other behaviours observed (Table 12). This is not surprising given the low number (n =6) of snubfin dolphin groups observed in 2024. Foraging was observed only in the late afternoon, and all other time-periods consisted of travelling (Fig. 14a). Across all survey years, the composition of snubfin behaviours was more erratic than for humpbacks, e.g., in the early survey years (2019-2021) foraging was the dominant behaviour, followed by travelling and/or socialising, which contrasts with 2024. The all-year pooled behavioural composition showed more regularity in behaviours across time-intervals, such that foraging was the dominant behaviour across all time intervals, followed by travelling, then socialising, and resting occurring more rarely (Fig. 15a) The majority of snubfin dolphin groups across years were sighted during the morning and early afternoon (06:00–13:00) (Fig 15a).

In 2024, humpback dolphins were mainly observed foraging (39%; Table 12), followed by travelling (32%), then socialising (25%). These behaviours were especially dominant in the morning between 9:00 am to 11:00 am (Fig. 14b). While the proportion of foraging in 2024 is low, it still remains the most common activity observed, both in that year and across the full dataset. The composition of behaviours was relatively stable across the latter survey years, with more erratic ordering of behaviours in the early years, e.g., in years 2020 and 2021, socialising was the second-most common behaviour after foraging. Figure 15b shows the all-year pooled summaries of behaviours, which shows more consistency in behaviours across time-intervals (i.e., each time-interval showed a consistent ordering of behaviours whereby foraging was the most common, followed by travelling, and then socialising. The majority of humpback dolphin groups across years were sighted during the morning and early afternoon (06:00–13:00) (Fig 15a).

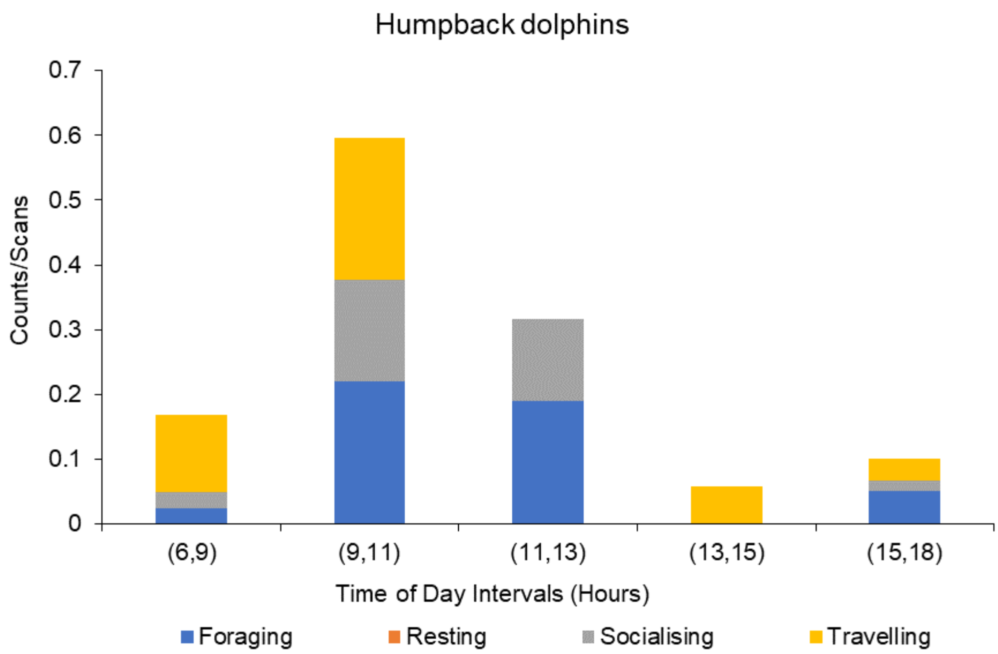
Table 12. The total number of scans where either species was present (and behaviour could be determined) during land-station surveys from 2019 to 2024, and the proportion of times they were observed engaged in foraging, resting, socializing, and travelling behavior. The aggregated numbers for all survey 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	0	0	0	0
	2024	6	0.17	0	0	0.67
	Pooled	107	0.66	0.02	0.08	0.23
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	0.4
	2024	44	0.39	0	0.25	0.32
	Pooled	209	0.46	0.01	0.17	0.34

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

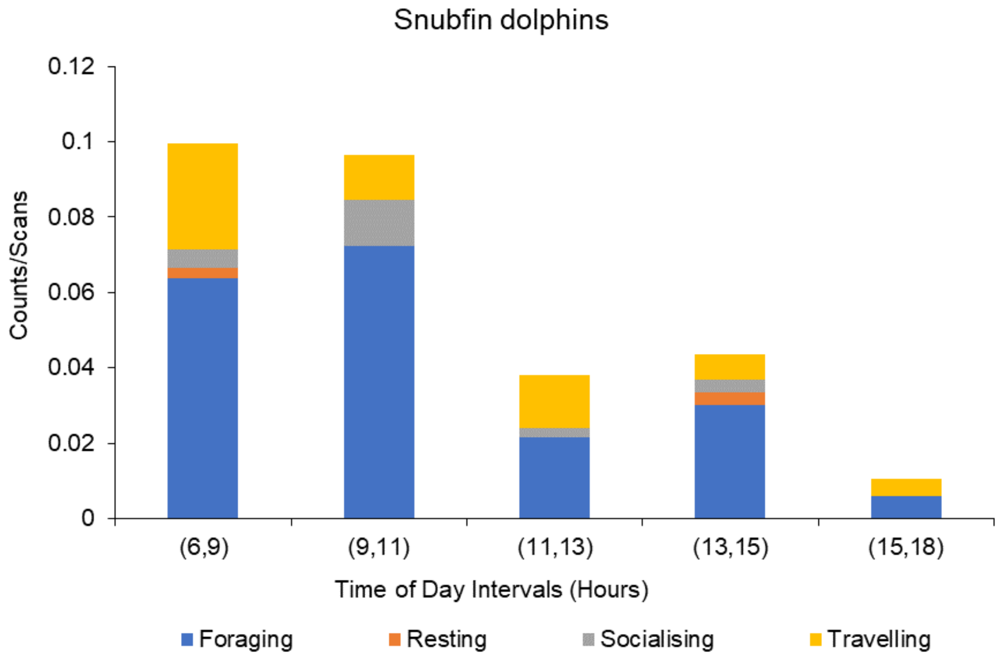


a)



b)

Figure 14. a) Australian snubfin and b) humpback dolphin observations by time of day (2-3 hourly bins) in 2024. Bar height represents densities of counts (number of dolphin's groups seen divided by number of scans); bar compositions represent proportion time observed in various behaviours.



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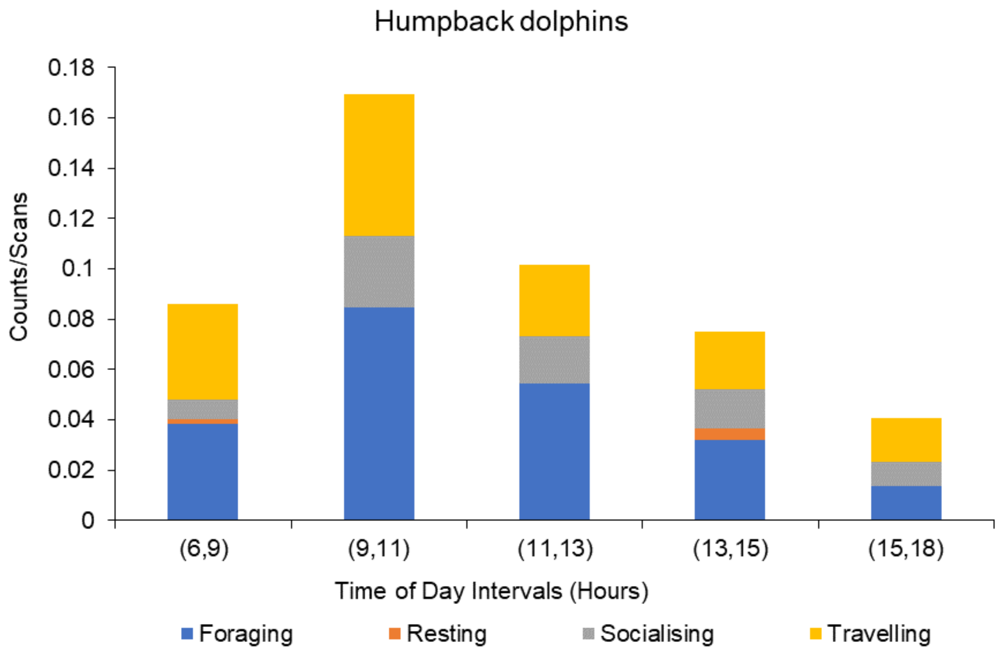


b)

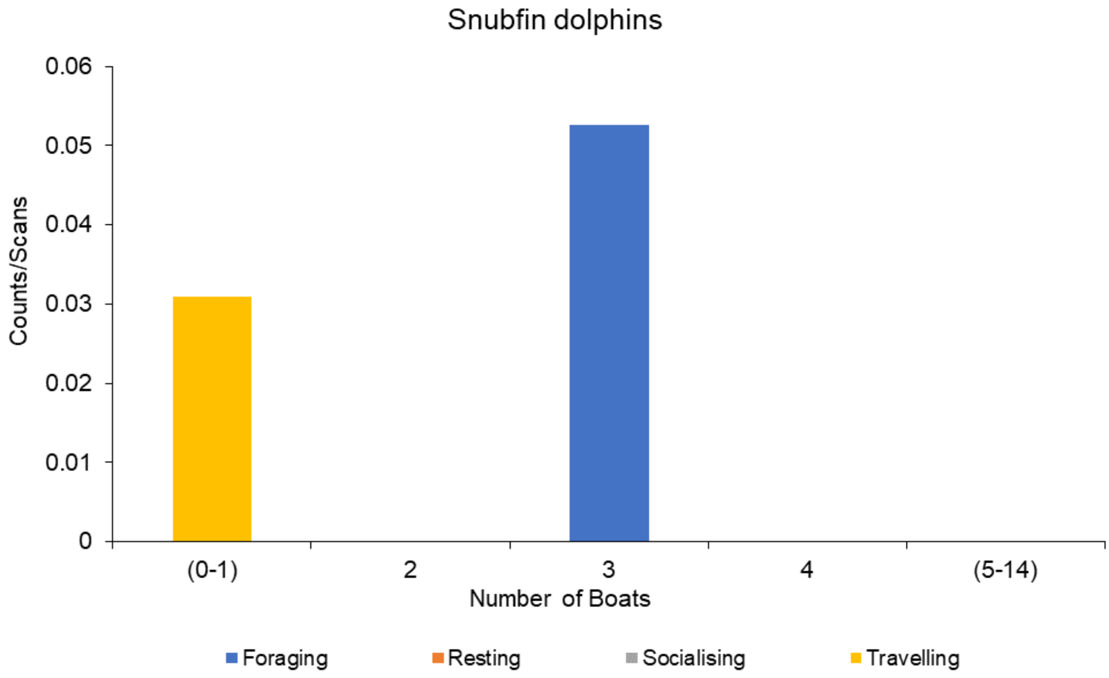
Figure 15. Pooled observations (2019 to 2024 inclusive) of a) snubfin and b) humpback dolphins by time of day (2-3 hourly bins). Bar height represents densities of counts (number of dolphin groups seen divided by number of scans); bar compositions represent proportion time observed in various behaviours.

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

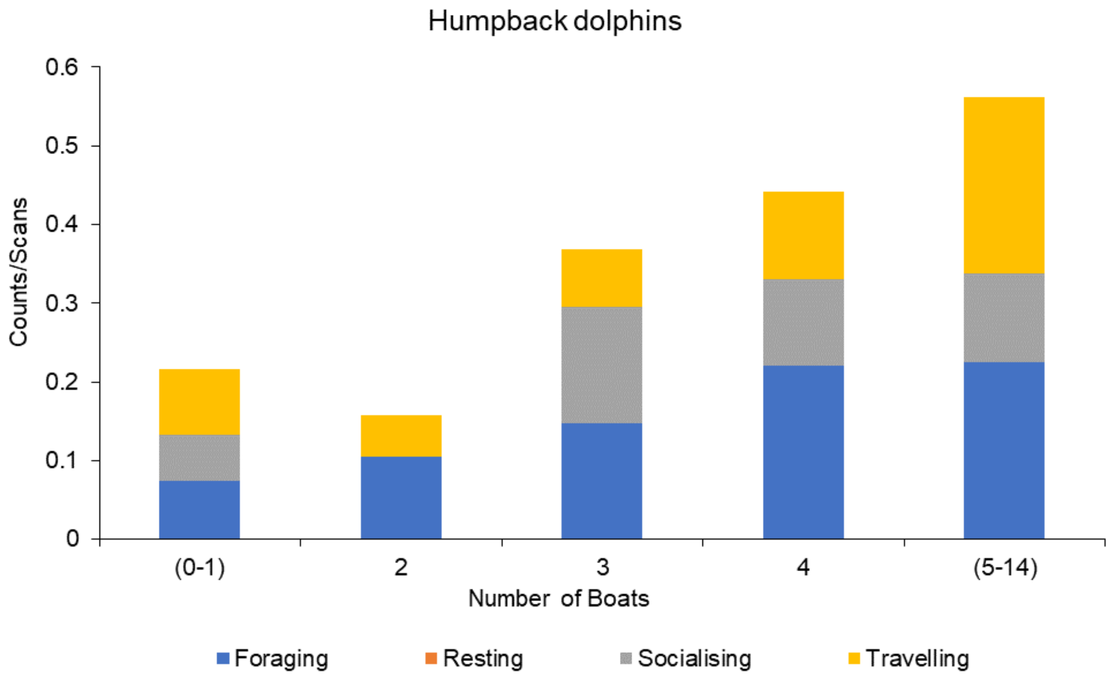
Boats

Among snubfin dolphins, there were too sparse observations in 2024 to discern a pattern: with less than 3boats all snubfins were observed travelling, at 3 boats they were observed foraging (Fig. 16a). When pooling all snubfin observations across all survey years, no consistent pattern emerges (Fig. 17a). Overall, there may have been a slight decrease in the number of snubfin dolphins with increasing number of boats, and a decreasing tendency to forage.

The presence and behavioural activity of humpback dolphins observed from Berth 11 changed as the number of boats increased (Fig 16b). In 2024, humpback dolphin counts tended to increase with increasing number of boats, and they tended to increase their proportion of time travelling (although all behaviours recorded in 2024 were observed across all counts of boats). However, in 2023, an opposite trend was observed, whereby fewer humpbacks were observed with more boats present, and foraging decreased concomitantly. When considering all years of data pooled together (Fig.17b), no consistent pattern emerges in behavioural composition nor total counts. It is possible that foraging behavior diminished in response to increased boat activity, while traveling behavior became more prevalent.

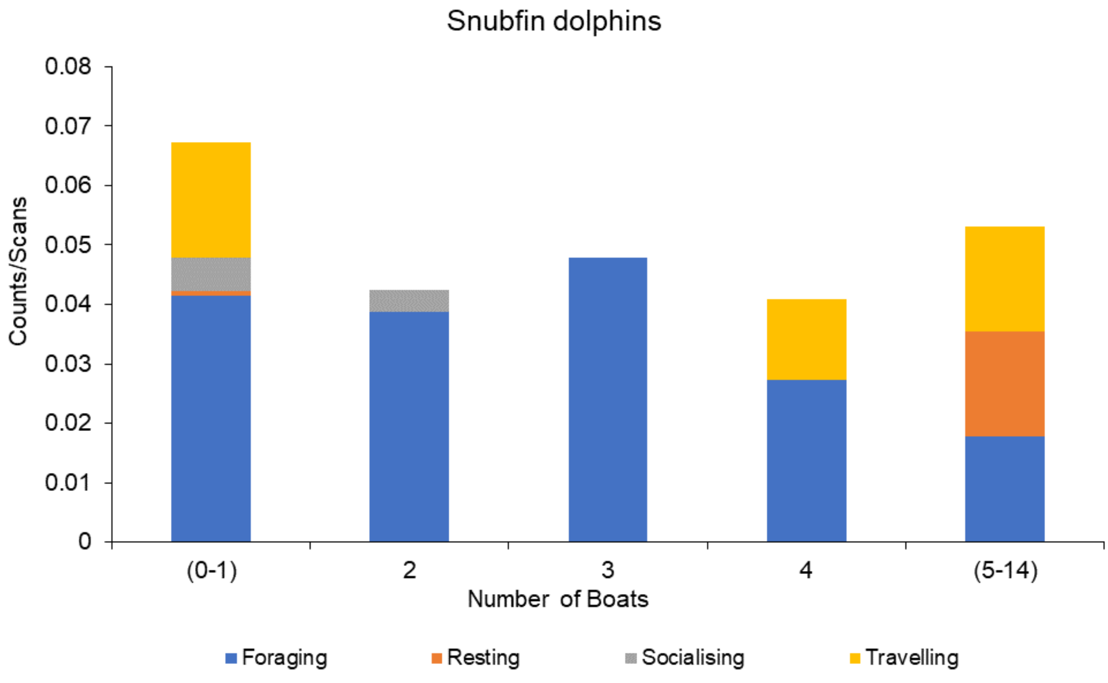


a)

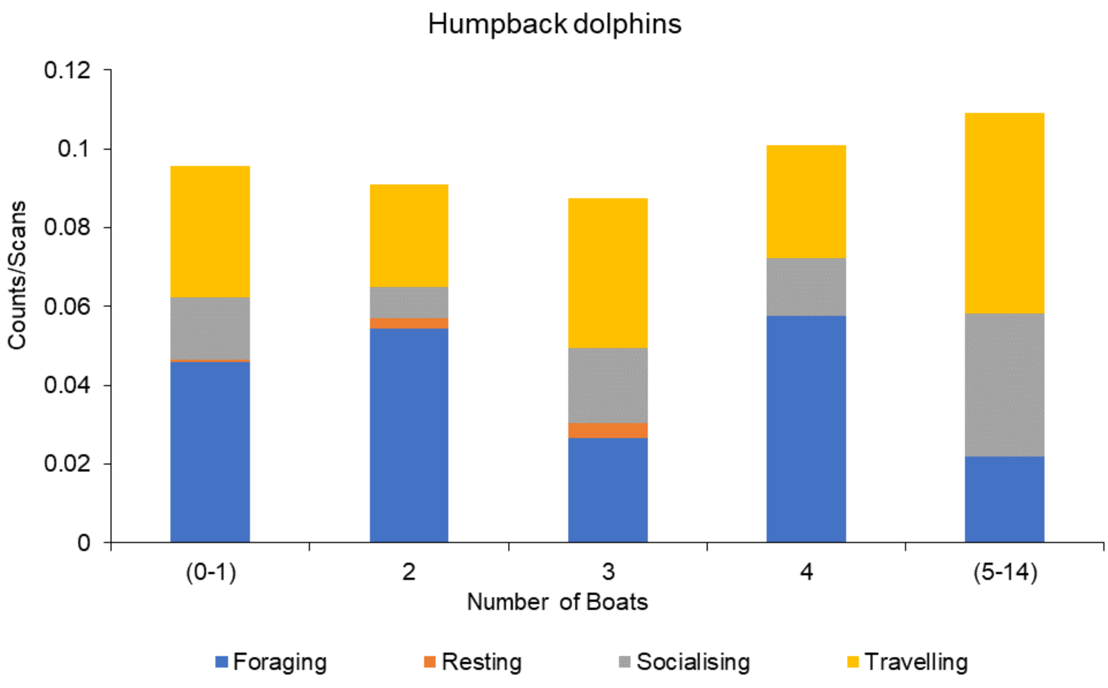


b)

Figure 16. Counts of a) snubfin and b) humpback dolphins groups observed and their behaviours, stratified by the number of boats present, for the 2024 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 2024 inclusive) of counts of a) snubfin and b) humpback dolphins groups observed and their behaviours, stratified by the number of boats present. Bar height represents densities of counts (number of dolphin groups seen divided by number of scans).

Dredging

As in the 2023 analysis, we pooled all years and used the absence of dredging (of all types) as the null-model to calculate Bayesian p-values. 2024 was a post-construction survey-year, in which there were no additional observations of dredging. Therefore, all land-based observations of snubfin and humpbacks in 2024 merely add to the presumed null-distribution of occupancy (i.e., no capital or maintenance dredging present or active).

For capital dredging, we further analysed the data based on whether the dredging was active (when dredging operations were ongoing) vs. inactive(when dredging vessel was present but not in operation), as well as present (dredging vessel is in the area regardless of active or inactive) vs. not present (no dredging vessel was in the area) (Table 13).

Over 6 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 it may even suggest 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), indicating that capital dredging resulted in snubfin counts that were very out-of-line with the no-dredging null-model. Therefore, maintenance dredging was not associated with noticeable changes in the presence or absence of snubfin dolphins around the port area, whereas capital dredging coincided with variations in their occurrence.

Table 13. Land-based observations of Australian snubfin and humpback dolphins during a) maintenance dredging with trailing suction hopper dredger (TSHD); 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	5444	120	0.99
	yes	21	2	
Humpback	no	5444	136	0.9
	yes	21	1	

b)

Species	Capital dredging (BHD)	Number of Scans*	Number of Scans with Dolphins Present	Bayesian P-value
Snubfin	no	5465	122	0
	yes	1327	1	
Humpback	no	5465	137	1
	yes	1327	101	

c)

Species	Capital dredging (BHD)	Number of Scans*	Number of Scans with Dolphins Present	Bayesian P-value
Snubfin	not present/inactive	5934	122	0
	active	858	1	
Humpback	not present/inactive	5934	178	1
	active	858	60	

* For the two types of dredging, the number of scans does not add up to the total number of scans, because of the treatments/sets. For presence and absence counts for capital dredging, we excluded from the "no

dredging" treatment both types of dredging (both maintenance and capital dredging), and likewise for the maintenance dredging. We excluded from the "no dredging" treatment both types of dredging (both maintenance and capital dredging). This was done to remove any confounding effect in the "no dredging" treatment where another type of dredging occurred.

Rock-Dumping

There were no additional incidences of rock dumping in 2024. 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 dumping (Table 14). Therefore, the presence or absence of snubfin dolphins around the port area did not show a clear association with rock dumping, whereas patterns in humpback dolphin occurrence appeared to coincide with this activity.

Piling Activities

There was no additional piling activity in 2024. The additional non-piling scans add to the null-distribution. All 9 scans in which piling occurred were from 2022. There were no observed snubfin or humpback 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 (0.72 – 0.844) (Table 15). It is important to recognize that with only 9 piling events, the statistical power to detect small to moderate effects is low. However, that does not invalidate the finding—rather, it emphasizes that the absence of dolphins during piling is not inconsistent with the null expectation. It does not prove there is no effect, but suggests the data do not provide evidence of an effect, given current sample size.

Table 14. Land-based observations of snubfin and humpback dolphins during rock dumping and non-rock dumping construction activities across all survey-years (2019-2024).

Species	Rock-Dumping Present	Number of Scans	Number of Scans with Dolphins Present	Bayesian P-value
Snubfin	no	6390	103	1
	yes	401	20	
Humpback	no	6390	238	0
	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	6783	123	0.84
	yes	9	0	
Humpback	no	6783	238	0.72
	yes	9	0	

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, the same as in the 2023 report. For snubfin and humpback 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 snubfin dolphins, the top model had 1.7% of the AIC-weights, and included covariates:

- glare
- activity of capital dredging (BHD) (dredging vessel was present and active)
- year as a categorical variable
- spline (time-of-day x year)
- spline (julian-day-of-year x year)

Of the linear covariates of the best model, only glare was deemed statistically significant according to naive p-values. The non-model-averaged coefficients glare was positive, suggesting that increased glare was positively associated with occupancy by snubfin dolphins.

For humpbacks, the top model had 24.0% of the AIC-weights. It included covariates:

- BSS
- counts of all boats (total boats)

- presence of capital dredging (BHD) (regardless if was active or not)
- year as a categorical variable
- spline (time-of-day x year)
- spline (julian-day-of-year x year)

All the linear covariates of the best model were deemed statistically significant according to naive p-values (i.e., non-model-averaged p-values). The non-model-averaged coefficients of boats and capital dredging were positive, suggesting that increased presence of boats and increased presence of capital dredging were positively associated with increased occupancy by humpbacks.

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 the temporal covariates had inclusion probabilities greater than 0.99 The environmental covariate with the largest inclusion probability was glare with 0.88, activity of capital dredging with an inclusion probability of just 0.15, then counts of small boats with an inclusion probability of 0.145, then counts of fishing boats with an inclusion probability of 0.12, then recreational boats and medium-sized boats with an inclusion probability of 0.11, each. All other covariates had inclusion probabilities below 0.1.

For humpback dolphins, the highest posterior probabilities (greater than 0.99, or 99% inclusion) were obtained by four covariates, including: all the temporal covariates (hour-of-day, Julian day-of-year, year-as-a-categorical variable), and the presence of capital dredging. The next largest component was BSS with an inclusion probability of 0.64, then counts of all boats (total boats) with an inclusion probability of 0.365, then recreational boats with an inclusion probability of 0.25, then small boats with an inclusion probability of 0.22. All other 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	0.04	0.05
BSS	**0.64**	0.04
swell	0.06	0.09
visibility	0.07	0.09
glare	0.05	**0.88**
time-of-day/hour	**1**	**1**
julian-day-of-year	**1**	**1**
year as categorical variable	**1**	**1**
boats small	0.22	0.15
boats medium	0.05	0.11
boats large	0.09	0.06
boats fishing	0.05	0.12
boats recreational	0.25	0.11
boats total	0.37	0.12
boats industrial	0.04	0.06
capital dredging (BHD) presence	**1**	0.06
capital dredging (BHD) active	0	0.15
maintenance dredging (TSHD)	0	0.04
rock dumping	0	0.06
piling	0	0.04
aggregate disturbance	0	0.05

Table 17 shows the estimate of standardised regression coefficients (mean-centred and scaled to unit-variance, i.e., 1 unit change in logit-probability of dolphin presence per unit of the coefficient). The coefficients were model-averaged over top models with highest posterior weights.

For snubfin dolphins, many of the models 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. As remedy, we truncation the individual models' coefficients to have an absolute logit-value of at most 50, thereby stabilising the model-averaging process (because a single low-probability model can explode the model-averaged estimates if its coefficient is extreme). The only statistically significant model-averaged effect was due to glare, such that more glare was associated with higher odds of detecting snubfins.

For humpback dolphins, there was only one (non-temporal) covariate that had a statistically significant model-averaged coefficient: capital dredging (BHD) presence. It had a high positive covariate, suggesting a positive association between the presence of capital dredging and occurrence of humpback dolphins. The next most-significant covariate was BSS with a p-value of 0.238, with a negative coefficient. All the other disturbance covariates had coefficients estimated to be exactly 0 because their posterior inclusion probabilities were approximately zero.

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

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	0.03	0	0	0.96	0	0.03	-0.04	0	0.91
BSS	-0.19	0.17	-0.47	0	0.24	-0.01	0.04	-0.06	0	0.89
swell	-0.01	0.05	-0.2	0	0.83	0.01	0.04	0	0.12	0.89
visibility	690.84	Inf	-Inf	Inf	1	-0.01	0.03	-0.1	0	0.87
glare	0.01	0.04	0	0.14	0.84	**0.25**	**0.11**	**0**	**0.44**	**0.02**
boats small	0.03	0.07	0	0.24	0.65	0.02	0.05	0	0.19	0.76
boats medium	0	0.02	0	0.05	0.9	0.01	0.04	0	0.13	0.84
boats large	0.01	0.05	0	0.19	0.81	0	0.03	-0.02	0	0.97
boats fishing	0	0.02	-0.06	0	0.89	0.01	0.05	0	0.17	0.79
boats recreational	0.04	0.08	0	0.24	0.61	0.01	0.04	0	0.14	0.83
boats total	0.07	0.1	0	0.3	0.5	0.01	0.05	0	0.19	0.8
boats industrial	0	0.03	0	0	0.99	0.01	0.05	0	0.1	0.92
capital dredging presence	**0.76**	**0.12**	**0.54**	**1**	**0**	0.08	9.25	-25	28.06	0.99
capital dredging active*	0	0	0	0	-	-0.08	14.41	-40.99	40.97	1
maintenance dredging*	0	0	0	0	-	0	0.01	-0.01	0	0.94
rock dumping	0	0	0	0	-	0.01	0.05	0	0.18	0.82
piling*	0	0	0	0	-	-0.08	6.73	0	0	0.99
aggregate disturbance	0	0	0	0	-	0.01	0.05	0	0.2	0.85

* truncated effects on logit scale to a maximum absolute logit of -50 or 50.

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, do not include the positive and negative contributions of covariates that may systematically vary by year (such as certain disturbances), meaning that the presence or absence of such affects can adjust the per-year aggregate effects. For snubfin dolphins, the only years with reliable model-averaged per-year effects were 2019 (-3.16, SE: 0.48; 95%CI:-4.09 - -2.21), 2021 (-4.34, SE: 0.26; 95%CI: -4.85 - -3.83), and 2024 (-2.24; SE: 0.75; 95%CI: -3.73 - -0.79), whereas other years, like 2023, had little or no observations of snubfins. 2024 had a much higher estimate per-year effect, with strongly non-overlapping 95%CI from 2021. This suggests that the snubfins occupancy was as great or greater than in previous years, including the baseline year.

For humpback dolphins, the model-averaged point-wise estimates showed a lot of interannual variability, such that high-years were followed by low-years, etc. The point-wise estimates were highest for 2024 (-1.246), followed by 2021 (-3.88), then the pre-construction baseline of 2019 (-3.94), then 2020 (-5.02), then 2023 (-5.521); finally, 2022 had the lowest point-wise coefficient for humpbacks, with a value of -5.693. However, almost all of the model-averaged 95%CIs were overlapping, with the exception of 2023 (-6.498, -4.652) versus 2019 (-4.448, -3.435) and 2021 (-4.27, -3.496), suggesting that 2023 was systematically lower than others. Notice the very large 95%CI for 2024 (-1.246, SE: 7.244; 95%CI:-15.88 – 12.959), suggesting its ranking to be less confident; it was also the year with least number of scans.

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

	Snubfin				Humpback			
Year	**Mean**	**S.E.**	**Lower 95%CI**	**Upper 95%CI**	**Mean**	**S.E.**	**Lower 95%CI**	**Upper 95%CI**
2019	-3.16	0.48	-4.09	-2.21	-3.94	0.26	-4.45	-3.44
2020	-17.31	12.44	-41.09	6.18	-5.02	0.41	-5.77	-4.2
2021	-4.34	0.26	-4.85	-3.83	-3.88	0.2	-4.27	-3.5
2022	-7.05	17.69	-41.54	44.83	-5.69	0.88	-7.46	-3.96
2023	-Inf	Inf	NA	NA	-5.52	0.48	-6.5	-4.65
2024	-2.24	0.75	-3.73	-0.79	-1.25	7.24	-15.88	12.96

4. Discussion and conclusions

It is important to emphasize that the observed correlations between dolphin occurrence and port construction activities do not necessarily indicate direct causation. The abundance and distribution of dolphins in Cleveland and Halifax Bays, as well as their presence near the port area, may also be influenced by various extrinsic factors, such as climatic variability, competition with other species, or dispersal limitations, as well as intrinsic factors like dietary preferences and habitat specialization. These variables, which were not directly assessed in this study, could independently or interactively affect the presence of snubfin and humpback dolphins in the monitored regions. Nonetheless, the marked interspecific differences observed in population dynamics, spatial distribution, and occurrence patterns over the monitoring period raises the possibility of a link between anthropogenic disturbances and shifts in snubfin dolphin abundance, behaviour, and habitat use. For snubfin dolphins, these changes—including a decline in abundance and reduced use of Cleveland Bay in 2022 and 2023, followed by a rebound in 2024—closely align with the timing of CU construction activities and its subsequent cessation.

4.1 Survey effort

The 2024 (post-construction) vessel surveys of inshore dolphins for the Port of Townsville proceeded well. We were able to carry out nine full surveys of Cleveland and Halifax Bay between June-July.

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 estimates for snubfin dolphins in Cleveland Bay for 2022 and 2023 should be interpreted with caution, as they are likely overestimated due to the limited number of captures available in both years (see results). The abundance estimates of snubfin dolphins in Cleveland Bay during the first three survey years (2019–2021) indicated a relatively stable population of 30–40 individuals. This was followed by a substantial decline in 2022 and 2023, and a recovery to pre-2022 numbers in 2024. Despite data limitations in 2022 and 2023, our results suggest that the sharp decline in snubfin dolphins in Cleveland Bay was primarily due to an increase in their movement to Halifax Bay before 2022. In 2024, the return rate from Halifax to Cleveland Bay has since rebounded to levels observed in 2019–2021. The high estimated biological survival rate (0.95) of snubfin dolphins further supports the conclusion that the observed decline was not due to mortality.

The return of snubfin dolphins to numbers similar to those observed in 2019, the baseline year, suggests that the population changes recorded in 2022 and 2023 may have been temporary changes rather than indicative of long-term population declines. This recovery could imply that the snubfin population is resilient to certain stressors, such as habitat disturbances or resource availability shifts, provided these pressures are mitigated or removed over time. The observed trends underscore the importance of minimizing environmental and anthropogenic stressors in important habitats and maintaining connectivity between adjacent areas like Cleveland and Halifax Bays, which may provide refuge and support population resilience.

The temporary nature of the observed changes may reflect short-term behavioral responses, such as displacement to alternative habitats, rather than lasting demographic impacts like reduced reproduction or survival rates. For instance, snubfins may have shifted to Halifax

Bay during periods that coincided with peak construction activities or other environmental changes in Cleveland Bay, with their subsequent return aligning with reduced disturbance levels or improved habitat conditions. While the data do not allow for direct attribution, this pattern aligns with a potential behavioral response to changing local conditions. Comparable temporal associations have been documented in Australian humpback dolphins in Port Curtis-Gladstone, within the southern Great Barrier Reef region, where a decline in female abundance coincided with the onset of port development, followed by a return to previous levels after construction concluded (Cagnazzi et al. 2020). While these patterns may seem encouraging, they should not dismiss the potential cumulative impacts of repeated or prolonged disturbances, which could exceed the population's adaptive capacity. Long-term monitoring is critical to understanding whether this recovery represents a full return to ecological stability or if the population remains vulnerable to recurring or intensifying pressures.

As indicated in previous report, 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, Brooks and Pollock 2015, Pirotta et al. 2013, Cagnazzi et al. 2020). 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, snubfin dolphin numbers increased significantly in Halifax Bay during 2022, 2023 and 2024 due to movements from Cleveland Bay and immigration from outside the study area. Many snubfin dolphins identified in Halifax Bay from 2022 onwards were likely new immigrants, as indicated by the relatively large number of individuals first captured in the bay during this period. This suggests that, in addition to the movement of animals from Cleveland Bay to Halifax Bay, there may have been immigration into the area over the past three years, reflecting connectivity between local populations in Cleveland Bay, Halifax Bay, and adjacent regions. Halifax Bay may have offered comparable or improved habitat quality relative to Cleveland Bay during the period of observed change, which 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. We acknowledge that this temporal alignment does not demonstrate that the CU Project caused the increase, but given the overlap in timing, it is appropriate to note the coincidence as part of the discussion of potential contributing factors.

If prey availability, water quality, or acoustic conditions were more favourable, dolphins may have been attracted to Halifax Bay, not only from Cleveland Bay but also from adjacent coastal regions (e.g., further north), particularly if those areas experienced environmental disturbances such as cyclones, habitat degradation, or shifts in prey distribution that triggered broader redistribution. It is also possible that the observed movements of snubfin dolphins from Cleveland Bay to Halifax Bay facilitated additional immigration from outside the study area. Social attraction, conspecific cues, and perceived habitat suitability may have drawn individuals from neighbouring regions, contributing to the significant increase in dolphin abundance in Halifax Bay between 2022 and 2024. This connectivity suggests demographic and genetic links between subpopulations in the region, consistent with similar immigration events observed in Bynoe Harbor, Northern Territory (Brooks et al. 2017).

Humpback dolphins

Abundance estimates over the past six years indicate an increasing trend in humpback dolphin numbers in both Cleveland and Halifax Bays during the last three years (2022–2024), with higher abundance consistently observed in Halifax Bay compared to Cleveland Bay since monitoring began in 2019. The increasing abundance of humpback dolphins in Cleveland and Halifax Bays, particularly the consistently higher numbers in Halifax Bay, reflects the ecological significance of this region for the Townsville population. Halifax Bay's larger fraction of the population could be attributed to its ecological characteristics, such as prey availability, habitat quality, or lower levels of anthropogenic disturbance compared to Cleveland Bay. Such differences in habitat suitability underscore the critical role of spatial heterogeneity in supporting local dolphin populations (Parra 2006).

Several ecological and behavioural mechanisms may explain the increasing trend in abundance of humpback dolphins in Cleveland Bay in contrast to snubfin dolphins. First, humpback dolphins may possess behavioural flexibility that allows them to exploit anthropogenically altered environments more effectively than other species. For instance, construction activities and modified coastal features may lead to localized prey aggregation, such as schooling fish or invertebrates attracted to increased turbidity or nutrient runoff, enhancing foraging opportunities for these opportunistic predators. Second, built structures like seawalls, jetties, and pilings can serve as artificial reefs, attracting prey species and creating foraging hotspots. Humpback dolphins have been observed using such structures to herd fish or concentrate prey, effectively enhancing their feeding efficiency in areas where natural features may have been diminished. These modified habitats may inadvertently benefit dolphins by concentrating prey in accessible zones. Third, the observed increase may also reflect a competitive release following the decline of sympatric snubfin dolphins. As snubfin dolphins vacate or reduce their use of key habitats in Cleveland Bay, resources such as prey and space may become more readily available to humpback dolphins, allowing them to expand their range and increase their residency or site fidelity in the area. In addition, humpback dolphins may exhibit stronger tolerance or habituation to anthropogenic noise and activity compared to snubfin dolphins, which are known to be more sensitive to disturbance. This differential tolerance could facilitate the displacement of snubfins and the subsequent occupation of disturbed areas by humpbacks.

The high biological survival rate estimated for Cleveland and Halifax Bays (0.97 p.a.) aligns with values reported for other healthy dolphin populations (Cenci et al. 2011, McDonald et al. 2017, Jaakkola and Willis 2019), suggesting that humpback dolphins in the study area are not experiencing severe mortality pressures from environmental variability or anthropogenic impacts. Together with the increasing abundance, this demographic robustness suggests that despite facing potential threats—such as port development, increased human activities, or environmental changes—the dolphins are adapting well, showing no immediate signs of population-level declines or elevated mortality. However, this does not preclude the need for continued monitoring to ensure the population remains resilient in the face of ongoing or increasing pressures.

The observed movement rates between Cleveland and Halifax Bays (0.21 p.a.) and the substantial permanent emigration rate (0.17 p.a.) highlight the dynamic nature of humpback dolphin distribution in this region. The high connectivity between these bays and with populations beyond the study area supports genetic assessments indicating that humpback dolphins in the Townsville region form part of a broader metapopulation structure (Parra et al. 2018). Such connectivity facilitates genetic exchange, enhances population viability, and allows dolphins to exploit resources across a mosaic of habitats.

Halifax Bay's higher temporary emigration and return rates compared to Cleveland Bay provide further evidence of its role as a hub within this interconnected network. The frequent movement of individuals in and out of Halifax Bay suggests linkages with nearby populations, possibly driven by seasonal shifts in prey distribution or habitat conditions. This level of connectivity underscores the importance of Halifax Bay in sustaining regional population dynamics.

4.3 Spatial distribution

The spatial distribution patterns of humpback dolphins in Cleveland Bay and Halifax Bay have exhibited consistency during the past six years of monitoring. The spatial distribution of snubfin dolphins showed consistent use of similar areas with some significant changes in 2022-2023, and a return to pre-2022 space use patterns in 2024.

Overall, both humpback and snubfin dolphins 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.

The consistency in the spatial distribution patterns of humpback dolphins in Cleveland Bay and Halifax Bay over six years reflects their strong fidelity to specific habitats, a well-documented trait for this species (Parra 2006, Parra et al. 2006a, Meager et al. 2018). Such spatial consistency suggests that these bays provide essential ecological resources within their home range, including foraging opportunities, shelter, and suitable conditions for social interactions and reproduction.

The spatial distribution patterns of snubfin dolphins, characterized by consistent use of similar areas but with significant shifts in 2022–2023 and a return to pre-2022 patterns in 2024, provide key insights into their ecological flexibility and responses to environmental and anthropogenic changes. The observed shifts in 2022–2023 coincide with changes in abundance and movement patterns, as indicated by capture-recapture modelling. The increased abundance of snubfin dolphins in Halifax Bay and higher movement rates from Cleveland Bay to Halifax Bay before 2022 suggest a redistribution of individuals within the region. Marine dredging activities can result in both temporary and long-term alterations of habitats, impacting the overall ecological dynamics of marine ecosystems (see reviews in Erftemeijer et al. 2012, Wenger et al. 2017, Borland et al. 2022, Eke et al. 2023). These impacts stem from various mechanisms, including physical alterations of the seabed, introduction of noise pollution, and changes in species composition. Pile driving, a common component of marine construction, generates significant underwater noise that has the potential to produce physiological and/or behavioural effects on fish (Popper et al. 2013, Casper et al. 2016) and marine mammals (David 2006, Brandt et al. 2011, Kastelein et al. 2013, Dahl et al. 2014). Such disturbance can elicit both short-term responses, such as temporary avoidance, altered vocal behaviour, or changes in dive patterns, and longer-term effects when exposure is repeated, prolonged, or intense enough to influence habitat use, movement patterns, or energetic budgets (Brandt et al. 2012, Kastelein et al. 2013, Graham et al. 2017, Clement et al. 2025). Both dredging and pile driving can lead to behavioral changes in marine mammals, including avoidance of affected areas (Pirotta et al. 2013, Graham et al. 2017, Leunissen et al. 2019, Fang et al. 2023).The decrease in the occurrence and abundance of snubfin dolphins in Cleveland Bay in 2022 and 2023 could have been driven by changes in habitat conditions, prey availability, or disturbance levels in Cleveland Bay, possibly linked to construction activities for the CU project, including dredging and piling.

The return of snubfin dolphins to pre-2022 space use patterns in 2024, along with movement rates comparable to those observed in 2019–2021, suggest that the stressor(s) that may have contributed to their earlier decline and displacement in Cleveland Bay are no longer present and/or ecological conditions (e.g., prey availability, habitat quality) may have improved. This temporal pattern coincided with the post-construction phase of the CU project, and suggests that reduced disturbance levels and/or potential habitat improvements may have supported the reoccupation of previously used areas.

Interestingly, the overall condition of seagrass meadows in Cleveland Bay, used as a proxy for habitat quality and a feature associated with snubfin dolphin habitat preferences (Parra 2006), was reported as satisfactory in 2019, good in 2020, 2021, and 2022, satisfactory in 2023, and poor in 2024 (McKenna et al. 2020, 2021, 2022, 2023, 2024, 2025). The observed decline in most seagrass meadows in Cleveland Bay in recent years (2023-2024) has been attributed to a combination of simultaneous and successive system-wide meteorological influences (i.e. flooding, above average rainfall and extreme temperatures) (McKenna et al. 2024, 2025). The decline in snubfin dolphins during 2022–2023, when seagrass condition was good to satisfactory, and their return in 2024, when seagrass was poor, highlight an opposing trend between seagrass habitat quality and dolphin abundance/presence, suggesting that these shifts are unlikely to be explained by seagrass condition alone. Instead, it seems more plausible that their decline in 2022–2023 and subsequent return in 2024 were related to the presence and later cessation of stressors and disturbances potentially associated with CU construction activities (e.g., capital dredging and piling). While causation cannot be confirmed, these findings are consistent with the hypothesis that snubfin dolphins are capable of responding to changes in local environmental conditions and may re-establish use of preferred habitats when pressures diminish and/or ecological conditions improve.

Regarding their spatial distribution across both Cleveland and Halifax bays in relation to known disturbances (boats, dredging, rock-dumping, piling), 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, providing evidence that the disturbances had some effect. Based on RVI values and covariate interaction plots, maintenance dredging seems to have a small effect on humpback dolphin spatial distribution (i.e. density of species decreases as distance to maintenance dredging increases). The temporary release of organic nutrients during dredging, as documented in previous studies (see review in Todd et al. 2015), has the potential to enhance local prey abundance. Enhanced benthic diversity and biomass near dredged channels could provide a temporary boost in foraging opportunities for humpback dolphins, and thus explain their affinity for dredge channels and proximity to maintenance dredging.

For snubfin dolphins, RVI values and covariate interaction plots of their spatial distribution over the whole study area (including Cleveland and Halifax Bays) indicated a small effect of distance to rock-dumping, with snubfin dolphin density decreasing slightly with increasing distance from rock-dumping locations. Snubfin dolphins in Cleveland Bay have been shown to exhibit high levels of site fidelity, with individuals frequently returning to the same locations across multiple years including areas around the Port of Townville associated with anthropogenic structures such as pier pilings, channels and rock walls. (Parra et al. 2006a). This pattern was consistent with vessel- and land-based observations in the present study, except in 2022 and 2023, when snubfin dolphins were virtually absent from Cleveland Bay and the waters around the Port. This is likely a result of their need for predictable access to resources such as food, and their reliance on specific habitat features (e.g., shallow coastal waters with seagrass and mangroves) for foraging and social activities. Additionally, coastal structures such as seawalls, jetties, and pier pilings can support diverse marine life and provide valuable habitat for fish (Bulleri 2005, Dugan et al. 2011, Brandl et al. 2017). These features may also aid dolphins in herding prey or benefit from prey aggregations (Moreno and Mathews 2018, Methion and Díaz López 2019, Mills et al. 2024, Haughey et al. 2025). Port areas and shipping channels have been linked to dolphin distribution, likely due to high prey availability from nutrient mixing and proximity to productive habitats and fishing grounds (Maricato et al. 2022, Ledwidge et al. 2024, Mills et al. 2024) Given these habitat features the strong site fidelity of snubfin dolphins , it is plausible thatthey may not be highly disturbed by rock dumping activities, especially if these activities do not drastically alter the core features of their foraging habitats.

4.4 Patterns of attendance to the port area

Land-based observations from Berth 11 within the Port of Townsville were feasible throughout the day in 2024, given good weather conditions. However, our sampling was limited to 12 days in June due to the closure of Berth 11 for maintenance work for the rest of our sampling season. Despite this limitation, humpback dolphins were frequently observed from the land-based station, and snubfin dolphins were seen on five days in 2024.

The frequent observations of humpback dolphins from the land-based station reflect the ongoing use of the area by this species, which has been consistently observed in years of monitoring and aligns with patterns of abundance and space use identified through vessel surveys in Cleveland Bay. The sighting of snubfin dolphins on five separate days in 2024 is notable, especially considering the absence of sightings in 2023 and the minimal presence in 2022, when they were observed only once. This suggests a potential return to the area, which may be indicative of a recovery in the species' use of the bay. The return of snubfin dolphins in 2024 could also signal that disturbances or changes in the environment that caused their displacement in 2022 and 2023 were temporary in nature.

The quantitative assessment of differences in dolphin occurrence between 2024 and all previous years indicated that the patterns of occurrence of humpback dolphins around the port area in 2024 met or exceeded expectations based on prior years. For snubfin dolphins, the 2024 land-based surveys showed that snubfin dolphins patterns of occurrence around the port were higher in 2019-2020, declined in 2022-2023, and returned to 2021-levels in 2024. These patterns agree with sighting patterns reported during vessel-based surveys, abundance estimates and spatial distribution patterns.

Analysis of dolphin presence revealed interspecific differences in association with construction activities. Snubfin dolphin sightings decreased during capital dredging, while humpback dolphin presence showed a similar decline during rock dumping. In contrast, humpback dolphins displayed a positive association with capital and maintenance dredging, and snubfin dolphins with rock dumping. The observed interspecific differences highlights that the response to these pressures differ between species and may depend on differences in behavioral plasticity and resilience (Brakes and Dall 2016).

The decline in snubfin dolphin sightings around the port during capital dredging activities suggests that this species may be more sensitive to disturbances associated with sediment suspension, noise, or habitat disruption. While the observed pattern does not confirm a causal relationship, it points to a potential link between these construction-related activities and changes in dolphin occurrence. In contrast, humpback dolphins were more frequently observed during construction and maintenance dredging, potentially indicating an ability to exploit the altered environment, perhaps through increased foraging opportunities associated with prey aggregation near disturbed areas.

Even when causation cannot be firmly established, applying the precautionary principle is appropriate when dealing with vulnerable species like snubfin dolphins. This principle supports the implementation of proactive mitigation measures, such as noise abatement, temporal-spatial restrictions on capital dredging to avoid time and areas of core dolphin activity, and habitat-sensitive planning, which may help reduce potential impacts even when scientific certainty about the specific drivers of observed changes is lacking.

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