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College of Science & Engineering

INSPIRING ACHIEVEMENT

Port of Townsville Inshore Dolphin Monitoring Program Report

Analysis of the first field season (June - July 2019)

(Photo Kaja Wierucka, CEBEL, Flinders University ©)

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Executive Summary

Background

The Port of Townsville Limited (POTL) Inshore Dolphin Monitoring Program (IDMP) was introduced as part of their environmental approval under the Commonwealth *Environment Protection and Biodiversity Conservation Act 1999* (EPBC Act) for the Townsville Port Channel Upgrade Project (CU Project). The aims of the IDMP are to establish baseline information and monitor and report on changes beyond natural spatial and temporal variation in the distribution, abundance, habitat use and behaviour of Australian snubfin dolphins (*Orcaella heinsohni*) and Australian humpback dolphins (*Sousa sahulensis*) in association with the CU Project construction activities. The IDMP will be implemented over pre-, during and post-CU Project construction activities. Pre-construction monitoring began in June 2019 following the approved study design and methods outlined in the IDMP scope of work developed for the CU-Project (Parra et al. 2019). In this report, we summarise data collected during boat and land-based surveys in 2019. The data collected, and analyses presented here, are intended to help inform the development of future model-based analyses, as well as provide a baseline on dolphin abundance and spatial distribution in the study area and patterns of occurrence (presence/absence) around the Townsville port area under pre-construction conditions.

Methods

The IDMP methodology involved an integrated approach including boat and land-based surveys. The boat-based surveys required a total of 12 people (4 per research vessel), and the land-based surveys required a team of three people. We made efforts to source local university students to work with us while providing training, jobs and skilling of professional workers. Half of our research team was made up of local graduate students, and the other half were professionals from interstate.

Sampling began on the 1st of June and ended on the 14th of July 2019. Vessel and land-based surveys were conducted during daylight hours (i.e. between 07:00 and 17:00), in suitable weather conditions. The vessel survey was designed to sample three similarly sized areas in Cleveland Bay, Halifax Bay and Bowling Green Bay. Access to Bowling Green Bay was not feasible, however, due to the February-March 2019 storm damage to Australian Institute of Marine Science's (AIMS) boat ramp at Cape Ferguson. The closest other available boat ramps required considerable travel time by road (over an hour) and rivers (over 30mins) and were highly tide dependant, thus making it impractical to conduct vessel-based surveys in this bay under the planned allotted time. Therefore, vessel surveys were only conducted in Cleveland Bay and Halifax Bay. We used three vessels simultaneously to cover inshore and offshore areas of both bays to collect data on inshore dolphin occurrence, undertake photo-identification, and record environmental parameters (i.e. water depth, sea surface temperature, turbidity, and salinity) associated with dolphin's sightings and study area. Capture-recapture histories of distinctive individuals from photo-identification data were used to estimate abundance of snubfin and humpback dolphin in Cleveland Bay and Halifax Bay using capture-recapture population models. Species distribution modelling methods were used to model the distribution of snubfin and humpback dolphin occurrence (presence/absence) and group size across the study area as a function of spatial-temporal covariates. The predicted probability of occurrence and group sizes were multiplied to give a prediction of relative density of snubfin and humpback dolphins in Cleveland Bay and Halifax Bay.

We conducted visual land-based observations from Berth 11 within the Port of Townsville, covering a radius ≤ 1 km around the observation point. Visual scans every 15 min were used to record presence or absence of dolphins, their group size, age composition, behaviour, the number and types of boats traversing the area, and the presence or absence of maintenance dredging not associated with CU Project (i.e. routine dredging carried out every year to remove material that has drifted into the channel over time and limits the access of ships). Land-based survey data was analysed using descriptive statistics (e.g. total dolphin counts by species, and their behavioural composition) and further summarised by a range of covariates (i.e. hours of day, presence of boats, and presence of maintenance dredging).

Results

<u>Abundance</u>

A total of 1767.1 kms were travelled on transect effort over 15 days between 1st June and 14th July 2019, completing six survey repeats of Cleveland Bay and Halifax Bay. Survey effort was higher in inshore areas (1577.1 km) than in offshore areas (190 km) due to the poor weather conditions encountered often in offshore areas (Beaufort sea state > 4). We recorded a total of 83 dolphin groups (including both on and off effort sightings), consisting of 33 snubfin dolphin sightings and 45 humpback dolphin sightings, and five bottlenose dolphin sightings. Snubfin and bottlenose dolphins were sighted at the same rate in Cleveland Bay and Halifax Bay, whereas humpback dolphins were more frequently sighted in Halifax Bay. Sixty-one individual snubfin dolphins, 60 individual humpback dolphins and seven bottlenose dolphins were photo-identified on and off effort during sampling in 2019. Three snubfin and four humpback dolphin individuals were photo-identified at both sites, whereas no bottlenose dolphin was identified at both sites.

Using closed population models, we estimated the total number of snubfin dolphins using Cleveland Bay at 54 (95% CI = 33-106) individuals and at 89 (52-181) individuals for Halifax Bay. The total population size of humpback dolphins was estimated at 30 (95% CI = 19-59) individuals for Cleveland Bay and at 71 (95% CI = 57-112) individuals for Halifax Bay. Given the small numbers of bottlenose dolphins photo-identified we were not able to generate estimates of abundance for this species.

Spatial distribution

Preliminary species distribution models indicated that humpback dolphin occurrence and relative density tended to be higher in Cleveland Bay for inshore waters between the Port of Townsville and Magnetic Island, and for inshore and offshore waters around the centre of Halifax Bay. For snubfin dolphins, areas of high dolphin occurrence were predicted along the central and northern inshore and offshore areas of Halifax Bay, between Cape Pallarenda and Magnetic Island, and to the east along the inshore waters between the Port of Townsville and Cape Cleveland. A higher density of snubfin dolphins was predicted to occur mainly towards the centre of Cleveland Bay between the port of Townsville, Magnetic Island and Cape Cleveland to the east. For both species, most of the variation regarding the predicted number of dolphins across the study area was allotted to unknown spatial processes rather than environmental parameters. Model performance statistics indicated that the predicted ability of the models was limited, with only slightly-better-than random predictive ability. These models will be fine-tuned as more dolphin data become available, and we refine both the parameters included in the models, and our new methods to handle group size uncertainty.

Patterns of attendance to the port area

We conducted 870 visual scans from the land-based platform at Berth 11. Snubfin dolphins were seen on 9 days and present in 50 scans, humpback dolphins were observed on 10 days and present in 20 scans, and bottlenose dolphins were seen on one day in a single scan. Snubfin and humpback dolphins were observed throughout different times of the day, engaged mainly in foraging and travelling behaviours. Snubfin dolphin sightings peaked between 07:00 and 09:00 in the morning, and between 13:00 and 15:00 in the afternoon. Humpback dolphin sightings peaked between 09:00 and 11:00 in the morning, and between 15:00 and 17:00 in the afternoon. Snubfin and humpback dolphin occurrence and behaviour showed no distinct patterns in relation to the presence of boats or maintenance dredging.

Discussion and conclusions

Despite some weather and logistical constraints, the 2019 pre-construction monitoring of inshore dolphins proceeded well, and we were able to gather important baseline data on the distribution and abundance of snubfin and humpback dolphins in Cleveland and Halifax Bay under pre-construction conditions of CU Project.

The abundance estimates for snubfin and humpback dolphins in Cleveland Bay and Halifax Bay, their predominant inshore spatial distribution, and frequent occurrence around the port area resembles historical patterns and suggests the populations have remained relatively stable over time. The analysis used and estimates of abundance and spatial distribution obtained fairly represent the state of the local inshore dolphin populations at the baseline stage of the study in June-July 2019. The data collected offer a sound platform on which to inform future model-based analyses, improve the precision of estimates, and refine the analytical framework to optimise the capacity of the study to detect substantial changes in population demographics and spatial habitat use in the study area.

1. Introduction

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

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

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

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

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

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

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

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

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

The IDMP of snubfin and humpback dolphins for the CU project commenced in July 2019. The 2019 inshore dolphin surveys constituted the pre-construction phase as no construction activity occurred during this period. Therefore, and in line with the scope of work, the objective of this report is to 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. Although snubfin and humpback dolphins are the primary focus of the IDMP, information is also presented on bottlenose dolphins (*Tursiops* spp.).

2. Methods

2.1 Data collection

2.1.1 Scientific permits and animal ethics

The 2019 inshore dolphin monitoring was conducted under Scientific Permit G19/42001.1 issued by the Great Barrier Reef Marine Parks Authority, permit SPP19-001808 from the Queensland Department of Environment and Science, and Animal ethics approval E477/18 from the Animal Ethics Committee of Flinders University.

2.1.2 Training

All IDMP personnel received boat and land safety induction and were trained in survey techniques and protocols between 28th-31st of May 2019. During these days we tested all boat and land-based equipment and data collection procedures.

2.1.3 Vessel-based survey methods

As described in detail in the Inshore Dolphin Monitoring Program developed for the CU-Project, the vessel sampling design for the IDMP is 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 each of three similarly sized areas: Cleveland Bay, Halifax Bay and Bowling Green Bay (Fig. 1). Due to the rain and floods in the Townsville region during February-March 2019, boat ramp access to Bowling Green Bay at Cape Ferguson within the Australian Institute of Marine Science (about 50 km from

Townsville's CBD) was inaccessible. Therefore, surveys were only conducted in Cleveland Bay and Halifax Bay.

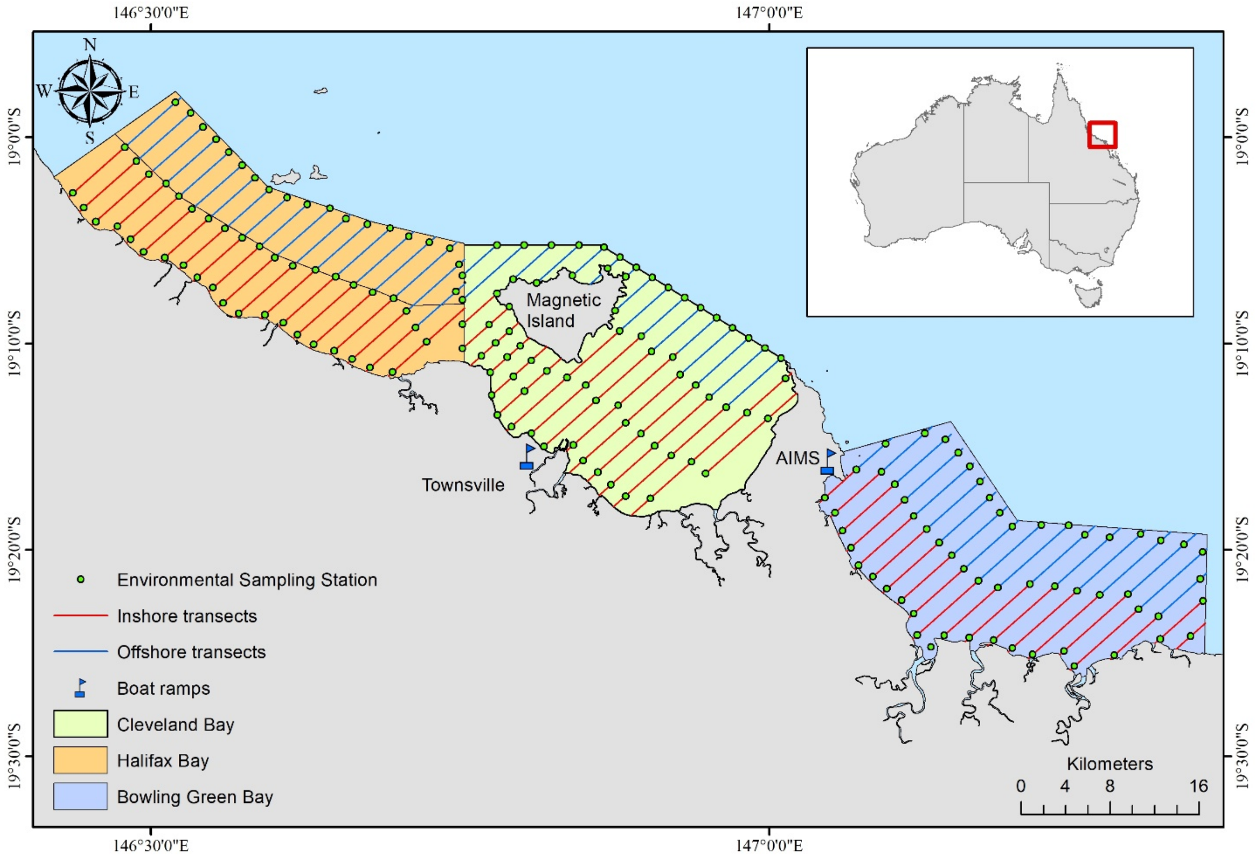


Figure 1. Map showing the proposed survey design (including inshore/offshore transects and environmental sampling stations) to cover areas of similar size in Cleveland Bay, Halifax Bay and Bowling Green Bay.

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

We used three Rigid Hull Inflatable Vessels (RHIB Coda, Koopa and Manta, Fig. 2) simultaneously to cover different areas of each bay during June-July 2019, aiming to do a complete survey of a single bay within one day. Surveys across each study site were conducted mostly in 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.

a) Manta

b) Koopa

c) Coda

D) Research team conducting surveys onboard vessel Manta

Figure 2. Rigid hull inflatable vessels a) Manta, b) Koopa and c) Coda used for boat-based surveys of inshore dolphins in the Townsville region during June and July 2019. Research team conducting surveys of inshore dolphins in Cleveland Bay onboard vessel Manta (d).

2.1.4 Land-based survey methods

As part of the monitoring program we also conducted visual land-based observations of dolphin presence/absence in June /July 2019 from Berth 11, an elevated platform 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). Conducted over time, this method will enable us to determine the dolphins' occurrence (presence/absence) in this area and assess their response to CU project dredging and pile driving operations that occur within approximately 1km of this location (Pirotta et al. 2013).

Visual scan sampling every 15 min was used to record the presence of dolphins (Altmann 1974, Mann 1999b), and covered a radius of approximately 1km around the observation point on Berth 11. Observations were conducted by a team of two trained observers doing one or two three-hour shifts per day between 07:00 and 17:00. Visual observations were mostly undertaken during good weather conditions (i.e. Beaufort sea state ≤ 3 and no rain) and whenever the berth was not operational. Each observer scanned to the left (i.e. West) or the right-hand (i.e. East) side of the observation point with the aid of 7 x 50 binoculars and the naked eye. During each visual scan we recorded, within approximately 1km of observation point on Berth 11, the presence or absence of dolphins, their group size, age composition, behaviour, the number and types of boats traversing the area, and the presence or absence of CU construction activities including dredging and rock dumping.

a) Berth 11

b) Researchers conducting observations

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

2.2 Data analysis: Population demographics

We used photo-identification data collected during boat surveys to estimate the abundance of Australian snubfin and humpback dolphins in the study area using capture-recapture population models. Details of the analysis involved are explained in the following sections (2.21-2.2.4).

2.2.1 Photo-identification

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

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

2.2.2 Capture-recapture models

Capture-recapture methods (Williams et al. 2002, Amstrup et al. 2005) can be used to estimate population sizes and rates of apparent survival (alive and in the area), temporary emigration and movement between sites. The Multistate Closed Robust Design model

(MSCRD, Brownie et al. 1993, Nichols and Coffman 1999, Kendall and Nichols 2002, Kendall 2013) will be fitted to estimate these parameters. The MSCRD will require, however, data from a minimum of three yearly samples and simpler models will need to suffice until such data are available.

The MSCRD is an extension of the Closed Robust Design model (CRD, Pollock et al. 1990, Kendall and Nichols 1995, Kendall et al. 1997) to the case of multiple states or, in this case, multiple sites, that incorporates ideas from the multistate model for recapture data (Arnason 1972, 1973, Brownie et al. 1993, Schwarz et al. 1993). While this model will be fully described when it is first used, it is sufficient at present to describe the models that will be used in this and the next report and their relationship with the MSCRD.

Capture-recapture methods can be broadly classified into those for populations that are demographically and geographically closed during sampling (no births, no deaths, no immigration, no emigration) – closed population models – and models for populations that are changing in size during sampling due to births, deaths, immigration and emigration – open population models (Williams et al. 2002, Amstrup et al. 2005). The population closure assumption – that the population under study does not change in size or composition during sampling – affords closed population models the capacity to model various complex effects that may be present in the data that cannot be accommodated by models for open populations. These effects include, in particular, variation in the probabilities of capture between the first and subsequent captures of individuals (indicating behavioural response to first capture – e.g., dolphins may become attracted to boats or avoidant of them), or between individuals due to their age, sex, parental status, previous experience with the capture method or other factors (individual heterogeneity of capture probabilities). Failure to model these effects should they be present in the data results in biased estimation of population size (Borchers et al. 2002, Williams et al. 2002, Amstrup et al. 2005).

Robust Design models nest a series of closed population models within an open population model and thereby attain the capacity to deal with potentially complex behavioural response and heterogeneity effects in estimating population sizes over a series of sampling events and also to yield estimates of the probability of apparent survival (the probability of remaining alive and present in the sampling area). Sampling for robust design models is hierarchical with primary samples separated by periods of time over which births, deaths, immigration and emigration are expected to occur with a set of secondary samples nested within each primary sample that are separated by relatively short periods of time over which the population closure assumption is reasonable. The probability that an animal was absent from the sampling area for the duration of a primary sample – temporary emigration – can also be estimated by using the differences between capture probabilities from the closed parts of the model and the open part (Kendall and Nichols 1995).

Until there are sufficient data to build an open population model or fit a Robust Design model, closed population models may be fitted to the data from each year. The estimates provided by these models will be replicated when a Robust Design model is fitted to the data from the first three or more years' samples but fitting them in the meantime allows judgements to be made about whether the sampling design is generating data that will be suitable for modelling with the MSCRD.

Objective three of the IDMP for the CU Project is to monitor and report on changes, beyond natural spatial and temporal variation, to the population and behaviour of the snubfin dolphin and humpback dolphin species in the local area throughout and for a period following the CU Project. Such changes could include movement of substantial portions of the populations between the bays or out of the area entirely either permanently or temporarily in response to construction activities in Cleveland Bay. The MSCRD is ideally suited to the task of estimating such movements by modelling data collected simultaneously (ideally) and separately in the three bays. In order that the analysis performed on the present data is as relevant to generating expectations for the performance of the MSCRD as possible, the data analysed here are those taken on the individual bays.

2.2.3 Goodness of fit of closed population models

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

It is unlikely that satisfactory estimates could be obtained for MSCRD models involving either behavioural response or individual heterogeneity with the relatively small populations studied here and the likely relatively small numbers of captures in the data. CAPTURE uses the results of its GOF tests to identify a preferred model for a set of data. Should a CAPTURE-preferred model not involve behavioural response or heterogeneity effects, it will be assumed that it is not necessary to attempt to model them in the MSCRD.

2.2.4 Model selection – AIC

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

2.2.5 Estimating the total population size

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

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

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

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

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

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

2.3 Data analysis: Spatial distribution

2.3.1 Modelling framework

Species distribution modelling (SDM) can provide a useful analytical framework to investigate the environmental and anthropogenic factors affecting species distribution. The SDM analysis involved statistical modelling of occurrence and counts (i.e. numbers of dolphins as indicated by estimates of group size) of humpbacks and snubfin dolphins as a function of spatial-temporal covariates (Table 1). Our goal was to obtain baseline information on dolphin's spatial distribution in the study area before CU project construction activities begin. At a mature stage of the project, with more data, the goal of the analysis will be inference about the spatial distribution of dolphins, especially in relation to human disturbances. As part of the development of a robust modelling process, the analyses reported in this this initial report had the following objectives:

- experiment with feature-engineering and spatial-interpolation of spatial covariates;
- develop the modelling approach;
- trial a method to use uncertainty-in-counts (i.e., min/best/max estimates of group size);
- estimate covariates importance (i.e., relative variable importance);
- initial assessment of predictive performance (e.g., ROC-AUC and PR-AUC scores);

The modelling framework was an ensemble method known as component-wise gradient-boosting (Bühlmann and Yu 2003, Schmid and Hothorn 2008), specifically emulating the works of Kneib et al. (2009) and Hothorn et al. (2010). We selected this method due to its robustness to certain 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).

Our model incorporated 5 sub-components, representing different groupings of covariates and wrapped in different sub-models (Table 1) (in parentheses):

1: Weather conditions affecting detectability of dolphins by observers (wrapped in a decision-tree);

2: Ecological parameters and human activities (decision-tree);

3: Temporal trends (splines);

4: Geographical trends (bivariate spline) and

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

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

Sub-model	Model type	Covariate	Covariate description	Source at training	Source at prediction
1	Decision tree	Wind	Windspeed from anemometer	In-situ measurement	Constant, average conditions
		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
2	Decision tree	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 water-ways/estuaries	GIS, derived (Dyall et al. 2004)	Same as training
		Reef Distance	Log-distance to reefs	GIS, derived (Beaman 2012)	Same as training
		Seagrass Distance	Log-distance to seagrass meadows	GIS, derived (McKenzie et al. 2014)	Same as training

Sub-model	Model type	Covariate	Covariate description	Source at training	Source at prediction
		Foreshore Distance	Log-distance to foreshore ecotypes	GIS, derived (Beaman 2012)	Same as training
		Land Distance	Log-distance to land	GIS, derived (Beaman 2012)	Same as training
		Bathymetry	Average depth	GIS, bathymetric DEM (Whiteway 2009, Beaman 2010)	Same as training
		Chl-a	Climatology of chlorophyll-a based on ocean colour	GIS, remote sensing (CSIRO Oceans and Atmosphere, Australia)	Same as training
		Boats Total	Counts of all boats in vicinity	In-situ counts	Interpolated spatial surface
		Boats Small	Counts of all boats in vicinity, small size	In-situ counts	Interpolated spatial surface
		Boats Medium	Counts of all boats, medium size	In-situ counts	Interpolated spatial surface
		Boats Large	Counts of all boats, large and industrial and ferries	In-situ counts	Interpolated spatial surface
		Boats Fishing	Counts of all fishing boats and trawlers	In-situ counts	Interpolated spatial surface
		Boats Recreational	Counts of all recreational and sailing boats	In-situ counts	Interpolated spatial surface
		Boats Industrial	Counts of all barges, trawlers, tugs and other industrial	In-situ counts	Interpolated spatial surface
3	Univariate spline	Time-of-day	Metric time at observations	In-situ measurement	Constant, average conditions
		Day-of-Year	Julian-day	In-situ measurement	Constant, average conditions
4	Bivariate spline	Space X & Y	UTMs used in spatial spline	GIS	Same as training
5	Radial basis function	Space X & Y	UTMs used in spatial covariance function	GIS	Same as training

In the boosting framework, the five sub-models compete to minimise an empirical "risk" function (the negative log-likelihood of the zero-inflated Poisson distribution). Although the total model is theoretically very complex, the overall model complexity is strongly penalised by "tuning" regularisation hyper-parameters via leave-one-out cross-validation. The focal hyper-parameters were: the number of boosting iterations; depth of decision-trees, and the degrees-of-freedom of spatial learners.

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

Model performance was assessed by statistics including the area under the receiver-operator curve (cv-ROCAUC) and the area under the precision-recall curve (cv-PRAUC) (Fielding and Bell 1997, Harrell Jr 2015). The cv-ROCAUC measures how good the models are in discriminating between true and false presences and absences. The cv-PRAUC measures how correct (precise) the model is in predicting true positives and how sensitive the models are in identifying true positives (Sofaer et al. 2019). For the AUC statistics, values above 0.5 to 1 are considered improvement over random classification (but see below about the use of min/best/max counts and their possible effect on depressing these statistics).

2.3.2 Uncertainty in group size estimates

One innovation in the SDM was the development of a method to accommodate uncertainty in estimates of group size. This was motivated by our attempt to best utilise the dolphin-encounter data, which consisted of estimates of minimum, maximum, and best group size. These observations will be referred to as "min/best/max counts."

The min/best/max counts were incorporated into the model by “data-augmentation”. Specifically, we assumed the counts followed a Truncated Poisson (TP) distribution, whereby each min/best/max observation parameterised a local TP: the estimated “best” count served as the Poisson rate parameter (a.k.a *lambda*), and the min and max estimates served as lower and upper truncation bounds. Assuming this distribution, we then calculated probabilities for each intermediate count between the minimum and maximum group-sizes. Call these probabilities “weights”. The range of counts then served as multiple pseudo-observations for the component-wise boosting algorithm (the data-augmentation), and the weights controlled how much each pseudo-count contributed to the models’ log-likelihood-function. Importantly, each group-encounter only contributed a total weight of “1” to the log-likelihood across all pseudo-counts, ensuring informational-equality between observations with only a single high-certainty estimate, and group-encounters with min/best/max estimates.

For example, if a dolphin encounter yielded min/best/max counts of [4, 9,10], the resulting TP distribution would have the follow pseudo-counts and weights: [(count: weight): (4: 0.04), (5: 0.077), (6: 0.121), (7: 0.165), (8: 0.195), (9: 0.206), (10: 0.196)]. In other words, the model sees an observation with a count of “4” with probability 0.04, and a count of “10” with probability 0.196, and so on.

An advantage of this method versus just using the “best estimate” is that it is a form of regularisation: the realistic portrayal of count-uncertainty keeps the model from over-learning a single “best estimate” value with artificially high precision (i.e., a “best” estimate does not include the actual uncertainty). Also, larger counts have more uncertainty. A disadvantage of the min/best/max data is that assessment statistics like the ROC-AUC and PR-AUC are slightly more difficult to interpret. This is because the model makes a single best prediction for all pseudo-counts. This means that diagnostic statistics (which expect one prediction vs. one single observation) can have many more ways of being “wrong” and this depresses the assessment statistic (i.e. the prediction will, by design, never perfectly match the range of min/best/max observations). This means that the theoretically maximum values of the AUC statistic (max value of 1) cannot be achieved; instead the theoretical maximum of the AUC is much lower when using the min/best/max counts. See the discussion for more thoughts on this phenomenon.

2.3.3 Spatial predictions

The main output of the SDMs are the model themselves, with their associated ability to evaluate patterns such as the relationship between dolphin distribution and environmental variables. The best fitting model can then be used to make spatial predictions (i.e. spatial partial plots) of dolphins’ distribution over an area of interest. The spatial partial plots produced described, firstly, the probability of occurrence (presence/absence) of snubfin and humpback dolphins and, secondly, group size across the study area as predicted by the best fitting SDM. The predicted probability of occurrence and group sizes were then multiplied to give a prediction of relative density of snubfin and humpback dolphins in Cleveland Bay and Halifax Bay.

Inference about a model’s spatial component involves some extra non-trivial steps and complications. This is due to the nature of the spatial data used to train the models. For some covariates, the data may not be readily available as a spatial layer for spatial prediction. For instance, *in-situ* measurements like temperature, turbidity and salinity were not available as spatial climatologies. To make spatial partial plots, we used spatial-temporal modelling techniques to interpolate values of the *in-situ* measurements (temperature, turbidity, salinity, boats) across the study area, at a resolution of 100m by 100m (in UTM coordinates). We used an ensemble of two methods:

- GAMs: model-averaged GAMs with soap-films spatial smooths, bi-variate temporal splines, and univariate splines on covariates, using the R-package mgcv (Wood 2003).
- Component-wise boosting: including spatial splines, bi-variate temporal splines, and decision-tree sub-model for spatial covariates, using the R-packages gamboostLSS and mboost (Hofner et al. 2012).

The former method (mgcv) benefits from a spatial smooth that respects maritime boundaries and islands (unlike generic kriging methods) and includes advantageous features like AIC model-averaging and shrinkage on spurious effects. The latter method (mboost) allows automatic learning of higher-order features (such as 3-way interactions) and is itself a prediction-optimised ensemble method. We pooled their outputs for a final ensemble-based spatial interpolation.

Both techniques allow decomposition of variation into spatial component and temporal components. Only the spatial components were subsequently used as an input-features for the SDM spatial partial plots: these can be interpreted as medium-term spatial means that persist over many months.

Finally, it should be noted that while the SDMs included weather covariates, like wind speed, swell, BSS, visibility and glare, we assumed that these covariates primarily affected the observers' ability to detect dolphins. Therefore, these covariates were not used for spatial predictions. Instead, their marginal contributions were removed. This means that the SDM plots primarily represent the expected dolphins' occurrence and abundance at "average" weather conditions (i.e. wind speed, swell, BSS, visibility and glare).

2.4 Data analysis: Patterns of attendance to the port area

2.4.1 Land-based survey preliminary analyses

During the early-phase of this study, we have analysed the land-based survey data using a combination of qualitative and descriptive statistics. These preliminary exploratory analyses are intended to help inform the development of future model-based analyses, as well as provide early impressions about how dolphins may be behaving under normal pre-construction conditions.

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, and presence of maintenance dredging (i.e. routine dredging not associated with CU project that is carried out every year to remove material that has drifted into the channel over time and limits the access of ships).

In addition to summaries, we also provide two preliminary statistical tests of the presence of dolphins under maintenance dredging. These are not anticipated to have a strong association but serve as a useful benchmark versus latter construction dredging. We used a method called the “Bayesian p-value” (Gelman 2005), which has a similar interpretation as classical Fisherian p-values. We used the distribution of dolphins during non-dredging periods as the “null model” (characterising normal conditions of the dolphins), and calculated the probability of seeing dolphin counts as low as that observed during dredging operations. Low Bayesian p-values suggest that the counts of dolphins were lower during dredging activities (i.e., a low-probability events according to the null-models), while high Bayesian p-values suggest that the counts during dredging were no different than under normal background conditions.

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

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

where:

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

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.

3. Results

3.1 Population demographics

3.1.1 Vessel based survey effort

We travelled a total of 1767.1 km on transect effort over 15 days, between 1st June and 14th July, covering 936.3 km in Cleveland Bay and 830.8 km in Halifax Bay (Fig. 4, Table 2). As planned, we completed six survey repeats of each bay, each representing a secondary period. Survey effort was higher in inshore areas than in offshore areas due to the poor weather conditions encountered often in offshore area (Beaufort sea state > 4).

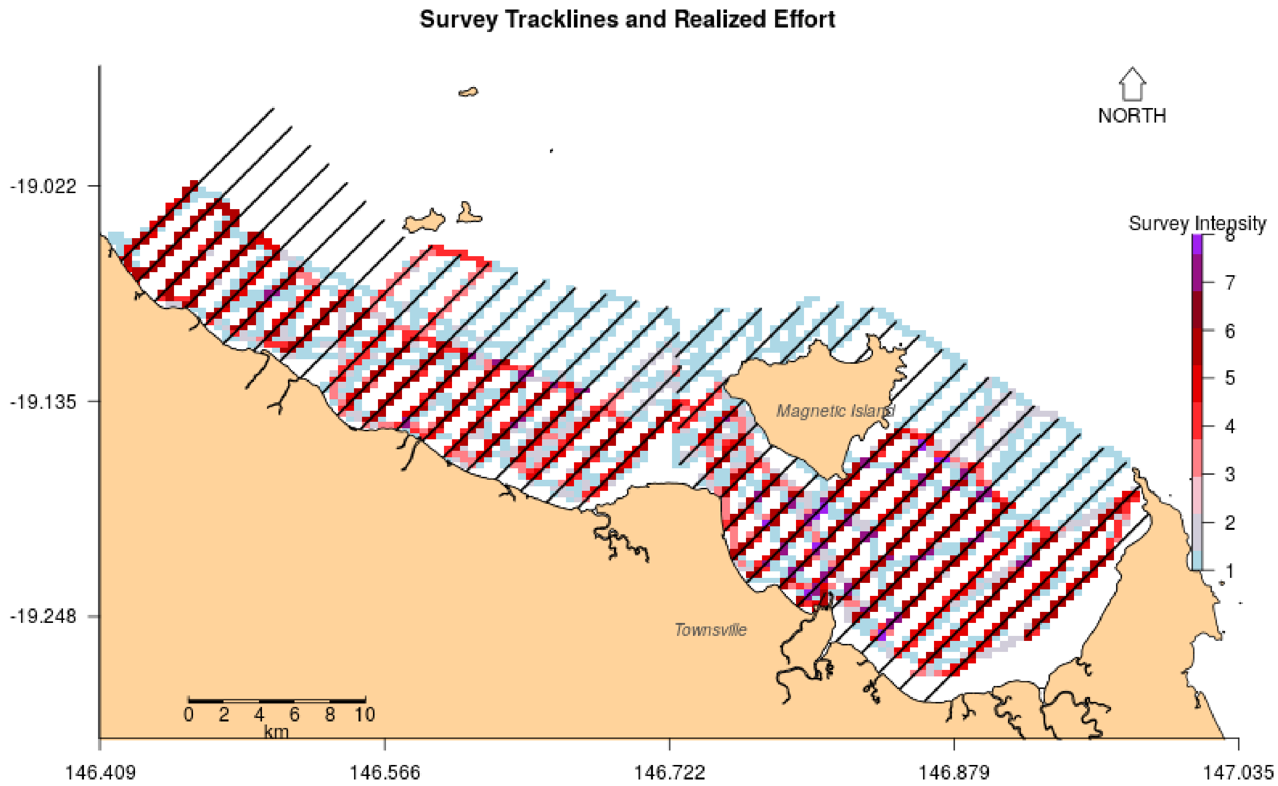


Figure 4. Map of survey area showing survey transects (solid black lines) and realized survey effort (light blue to dark red) in Cleveland and Halifax Bay in June-July 2019. Survey intensity scale represents the amount of times a grid cell was visited, as an approximate visual indicator of observational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

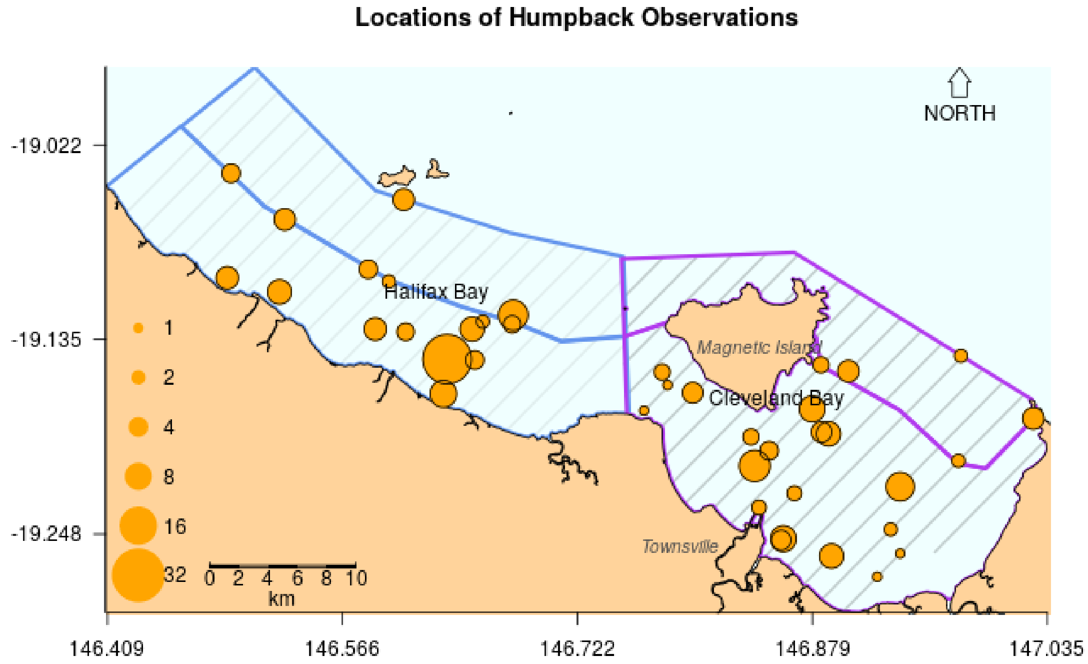
Table 2: Summary of boat-based survey effort (total length of transects completed on effort) and sea state conditions encountered in Cleveland Bay (CB) and Halifax Bay (HB) during each complete survey (secondary period) in the 2019 primary sample (June-July).

Bay	Sec. period	Date/s	Inshore	Offshore	Sea State		
			Length (km)	Length (km)	min	max	mode
CB	1	11-13/06	140.8	10.7	0	4	3
CB	2	14-15/06	144.8	0	0	4	2
HB	1	15-16/06	121.2	63.3	0	4	2
HB	2	17/06	121.2	11.9	0	3	1
CB	3	18/06	140.8	29.2	0	3	1
CB	4	19/06	133.4	30.1	0	3	2
HB	3	20/06	121.2	11.2	0	3	3
HB	4	2/07	121.2	4.8	0	3	1
CB	5	3/07	144.8	0	0	4	1
CB	6	11/07	144.8	16.9	0	4	3
HB	5	12/07	121.2	0	1	3	2
HB	6	13/07	121.2	11.9	1	4	3
CB	Total	-	849.4	86.9	-	-	-
HB	Total	-	727.7	103.1	-	-	-

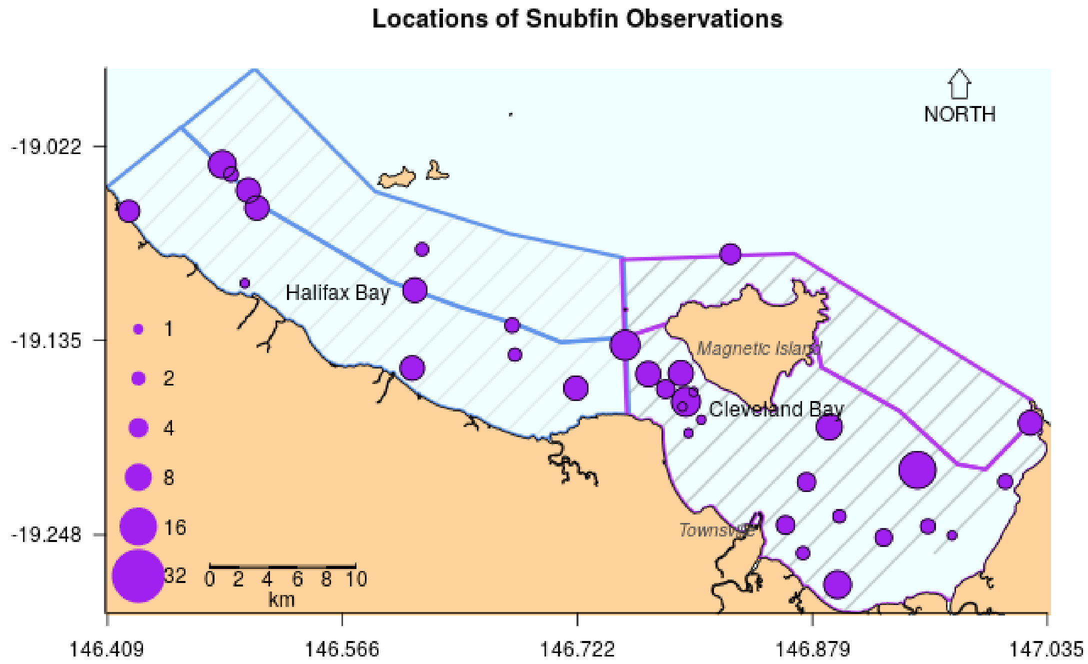
3.1.2 Dolphin sightings, encounter rates and group sizes

The vessel surveys in 2019 resulted in a total of 83 dolphin group sightings (including both on and off effort sightings). This consisted of 33 sightings of snubfin dolphins, 45 sightings of humpback dolphins, and five sightings of bottlenose dolphins, and included five mixed species groups of snubfin and humpback dolphins (Fig. 5, Table 3). The total number of dolphin groups sighted on effort per km of transect surveyed varied by species and by survey site. Snubfin dolphin encounters were even between Cleveland and Halifax bays, whereas humpback dolphins were encountered more often in Halifax Bay (Table 3).

Groups of snubfin dolphins varied in size from 1 to 16 individuals, with a mean (± SD) group size of 4.7 ± 3.65 (based on best estimates of group size). The group size of humpback dolphins ranged from 1 to 30 animals, with a mean (± SD) group size of 5.18 ± 4.9. Bottlenose dolphins were found in groups ranging from 1 to 8 (Mean ± SD = 4.4 ± 2.6). Groups of all dolphin species were composed mainly of adult animals and contained similar numbers of juveniles and calves (Table 4).



a)



b)

Figure 5. Location and group sizes of a) Australian humpback and b) snubfin dolphins sighted on and off effort during 2019 boat surveys. Note that the snubfin dolphin sighting off the northern coast of magnetic island (b) is tentative as there was uncertainty associated with species identification.

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

Species	Cleveland Bay		Halifax Bay	
	n	Number of dolphin groups/km	n	Number of dolphin groups/km
Snubfin	17	0.07	16	0.07
Humpback	13	0.05	32	0.15
Bottlenose	3	0.01	2	0.01

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

	Group size			Group age composition	
Species	**Min**	**Max**	**Mean (SD)**	**Mean as a ratio (adults:juveniles:calves) and proportions**	**No. groups with juvenile or calf present**
Snubfin	1	16	4.7 (3.6)	8:1:1 A:76.9%; J:11%; C:10%	15 (45%)
Humpback	1	30	5.18 (4.9)	8:1:1 A:77%; J:10.71%; C:10.22%	28 (62%)
Bottlenose	1	8	4.4 (2.6)	7:1:1 A: 66.67%; J:9.9%; C10.28%	4 (80%)

3.1.3 Photo-identification and capture-recapture data

Sixty individual snubfin and 55 individual humpback dolphins were captured (i.e., photo-identified) on-effort during sampling in 2019 (Table 5). When off-effort captures were included, these numbers increased to 61 snubfin and 60 humpback dolphins. A total of seven bottlenose dolphins were captured, five on-effort and two off-effort. Given the small number of bottlenose dolphins encountered and photo-identified during 2019, no capture-recapture analysis was possible on this species.

Twenty-seven snubfin dolphins were captured on-effort in Cleveland Bay and 36 in Halifax Bay. When off-effort captures were included, the number captured in Halifax Bay increased by one to 37. Three individuals were captured on-effort and none off-effort on both sites. Thirteen humpback dolphins were captured on-effort in Cleveland Bay and 46 in Halifax Bay. When off-effort captures were included, the number captured in Cleveland Bay increased by six to 19. Four individuals were captured on-effort and five on- plus off-effort on both sites. Five bottlenose dolphins were captured on-effort in Cleveland Bay and two were captured off-effort in Halifax Bay.

The present objective is to assess, for snubfin and humpback dolphins, whether the (re)capture data on the originally-planned six secondary samples (PS_SS) are suitable or whether they would be better collapsed to three secondary samples (PS_SS3) for analysis, and whether using the off-effort together with the on-effort data would provide better data for analysis. Too few bottlenose dolphins were captured too few times for analysis with a capture-recapture model and they are not further considered here.

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

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

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

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

There were no zero or very small (≤ 3) numbers of captures in the on-effort only data in the three new secondary samples (PS_SS3) except for humpback dolphins in Cleveland Bay (Table 5). Inclusion of the off-effort captures removed all instances of zero or very small (≤ 3) numbers of captures in the three secondary sample data.

The three secondary sample data constituted adequate numbers of captures for analysis, especially if the off-effort captures were included. If the spatial distribution of off-effort captures were correlated with the spatial habitat use of sub-groups of dolphins, inclusion of the off-effort data might have introduced heterogeneity of capture probabilities into the data. This question is addressed in the section on goodness of fit.

3.1.4 Goodness of fit

The CAPTURE preferred models (Table 6) indicate that sufficient evidence was not found to require models which accommodate either behavioural response to first capture or individual heterogeneity of capture probabilities for either the on-effort only or on-plus off-effort data. Indeed, the same models were preferred for both the on-effort only and on-plus off-effort data indicating that inclusion of the off-effort data had not introduced heterogeneity effects.

Table 6. Program CAPTURE-preferred models for the capture-recapture data on each species in each bay and for the on-effort only and on-plus off-effort captures. No preferred model had behavioural or heterogeneity effects. Model M0 has a constant capture probability while model Mt has capture probability varying by secondary sample (PS_SS3).

Species	Bay	On + Off Effort	On Effort Only
Snubfin	Cleveland	M0	M0
	Halifax	M0	M0
Humpback	Cleveland	Mt	NA*
	Halifax	Mt	Mt

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

3.1.5 Models

Closed population models were run in Program Mark (V8.1, White and Burnham 1999) on the three-secondary sample (PS_SS3) on- plus off-effort capture-recapture data on snubfin and humpback dolphins in Cleveland and Halifax Bays. No model with either behavioural response to first capture or individual heterogeneity of capture probabilities was attempted. All the best-fitting (lowest AIC_c) models had time-varying capture probabilities (model Mt) except for snubfin dolphins in Cleveland Bay for which a single, constant capture probability was adequate. (model M0). The model with the lower AICc was chosen for interpretation. The parameter estimates, their standard errors and 95% confidence intervals are shown in Table 7.

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

Species	Bay	Parameter	Estimate	SE	L95%CI	U95%CI
Snubfin	Cleveland	p_1	0.20	0.069	0.10	0.37
		p_2	0.20	0.069	0.10	0.37
		p_3	0.20	0.069	0.10	0.37
		N_m	54	16.36	36	108
	Halifax	p_1	0.13	0.056	0.06	0.29
		p_2	0.11	0.049	0.05	0.25
		p_3	0.23	0.088	0.11	0.45
		N_m	89	28.69	56	180
Humpback	Cleveland	p_1	0.20	0.093	0.07	0.44
		p_2	0.43	0.154	0.18	0.72
		p_3	0.17	0.083	0.06	0.39
		N_m	30	8.68	22	62
	Halifax	p_1	0.29	0.073	0.17	0.45
		p_2	0.14	0.047	0.07	0.26
		p_3	0.41	0.090	0.25	0.59
		N_m	71	12.00	57	107

3.1.6 Total population sizes

The estimated proportions of marked dolphins were 0.914 (SE=0.025) for the snubfin population and 0.890 (SE=0.031) for the humpback population. These estimates were used to estimate the total population sizes from the estimated sizes of the populations of marked dolphins shown in Table 8. The total number of snubfin dolphins using Cleveland Bay and Halifax Ba was estimated at 54 (95% CI = 33-106) and 89 (95% CI = 52-181) individuals, respectively. (Table 8). The total population size of humpback dolphins was estimated at 30 (95% CI = 19-59) individuals for Cleveland Bay and at 71 (95% CI = 57-112) individuals for Halifax Bay.

Table 8. Estimated sizes of the total populations of snubfin and humpback dolphins in Cleveland Bay and Halifax Bay with their associated standard errors (SE), coefficients of variance (CV) and lognormal 95% confidence intervals (lower and upper limits).

Species	Bay	Parameter	Estimate	SE	CV	L95%CI	U95%CI
Snubfin	Cleveland	N_{total}	54	17.97	0.33	33	106
	Halifax	N_{total}	89	31.50	0.35	52	181
Humpback	Cleveland	N_{total}	30	9.82	0.33	19	59
	Halifax	N_{total}	71	13.77	0.19	57	112

3.2 Spatial distribution

The species distribution models provided preliminary exploratory analyses intended to help inform the development of future model-based analyses, as well as provide early impressions about how dolphins may be distributed under normal pre-construction conditions. These models will be fine-tuned as more data become available and we refine the relevant covariates to include in the models.

There were 34 encounters of snubfin and 40 of humpbacks dolphins with associated estimates of group size and measurement of environmental conditions that were used for the SDM modelling. The positive-counts were modelled together with “pseudo-zeros”, i.e., locations where environmental samples were collected but there were no dolphin observations. For each species, there were 592 pseudo-zeros for snubfins and 584 pseudo-zeros for humpbacks. The large number of pseudo-zeros vs. positive observations motivated the use of a zero-inflated count distribution.

The final model for humpbacks had tuned hyper-parameters: 1309 boosting iterations, a learning rate of 0.018, a decision-tree maximum depth of 3, and spatial degrees-of-freedom of 10 (long-distance effects) and 12 (spatial-auto-correlation). The final model for snubfins was similar but ran for 1919 iterations, and a learning-rate of 0.022.

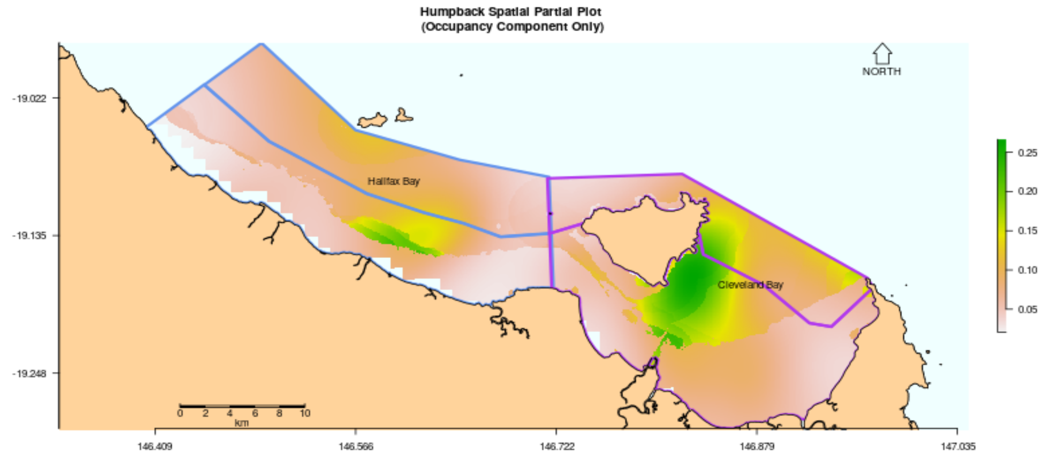
The spatial partial plots of humpback and snubfin dolphin across the survey area are shown in Figures 6 and 7 respectively. The plots show the probability of occupancy and group size, which are the two components of the zero-inflated Poisson model. The plots also show the integration of the two processes, the relative density, which is the probability of occupancy multiplied by the conditional abundance. Note that the influence of temporal covariates (time-of-day, day-of-year) and environmental conditions (swell, wind, BSS, glare, visibility) have been set to their global averages.

Excluding the effects of temporal variation, the spatial partial plots indicate that humpback dolphin occupancy (Fig. 6a), group size (Fig. 6b) and relative density (Fig. 6c) tended to be higher in Cleveland Bay for inshore waters between the Port of Townsville and Magnetic Island, and for inshore and offshore waters around the centre of Halifax Bay. There is a low-level of occupancy (less than 0.25, Fig. 6a) across the entire study area, reflecting the mobile nature of the species and that, for any given point in time, even areas of high-relative occupancy will not have consistent presence of dolphins. The spatial partial plots of group size indicate that large groups (>10 animals) were more likely to be seen in inshore waters around the mouth of Ross River, the port and east towards Alligator Creek in Cleveland Bay. The spatial partial plot of density (probability of occupancy times group size) across the study area shows small number of animals (less than 2) across most of the study area, except for inshore waters between the Port of Townsville and Magnetic Island (Fig. 6c). For snubfin dolphins, areas of high probability of occurrence were predicted to occur mainly towards the centre of Cleveland Bay between the Port of Townsville and Cape

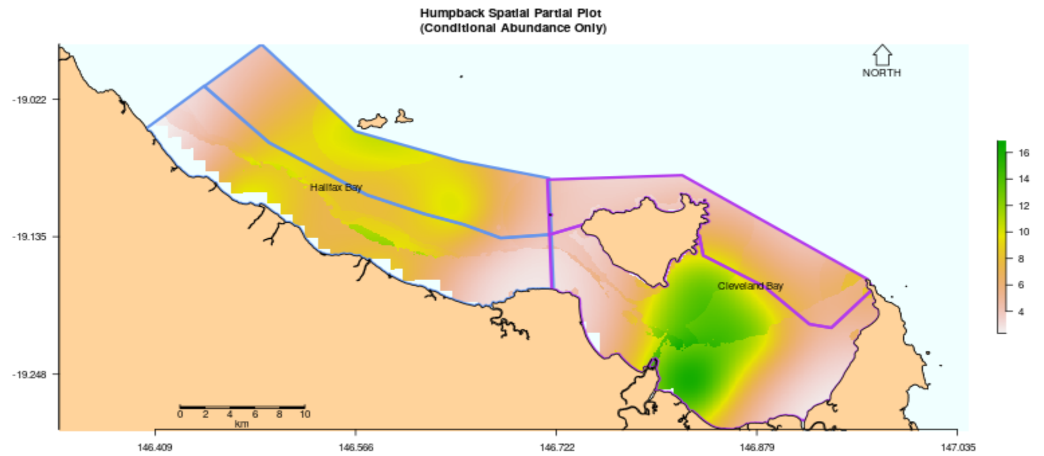
Cleveland to the east, between Magnetic Island and Cape Pallarenda, and the central and northern inshore and offshore areas of Halifax Bay (Fig. 7). The occupancy plot shows several large regions of relative higher occupancy, suggesting more spatial homogeneity than the humpbacks; however, the spatial partial plots of group size is much more punctuated in certain locations (i.e. large groups of > than 6 animals), such as in the middle of Cleveland Bay and to the east of Magnetic island and the upper-north-east quadrant of Halifax Bay, such that, overall, the relative density of snubfin dolphins is high in a few smaller regions within Cleveland Bay and Halifax Bays.

Some spatial artefacts and odd-patterns in the partial-plots deserve some attention. For example, the apparent “jagged-teeth”-like pattern for dolphins along the coast of Halifax Bay is a reflection of the poor-spatial resolution of the Chl-a data. In this case, the Chl-a values along the coast are contributing to missing data that was excluded from modelling. Future efforts will try to rectify this missingness.

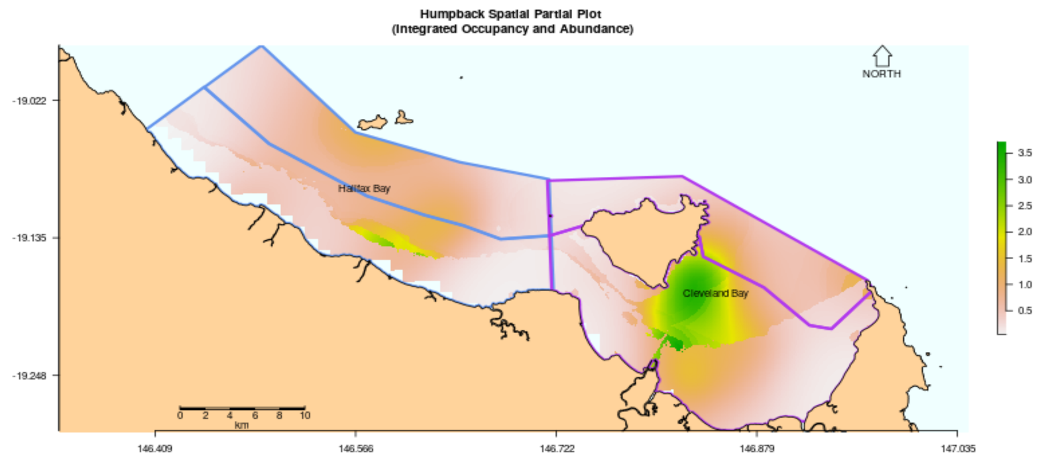
Counts may vary due to non-spatial effects, like time-of-day (especially for snubfin, as indicated by the RVIs statistics). Although these models provide an indication of the mean spatial distribution of snubfin and humpback dolphins across the whole study area, the final models had poor predictive ability according to model performance statistics. The area under the receiver-operator curve (cv-ROCAUC) score for snubfins was 0.61, while the area under the precision-recall curve (cv-PRAUC) was 0.25. For humpbacks, the cv-ROC-AUC score was 0.57, while the cv-PR-AUC score was 0.23. The cv-ROCAUC scores suggest that the models had slightly-better-than random predictive ability, while the cv-PRAUC scores suggest that the models were inadequately learning the positive-cases, and over-fixated on the negative cases. Inspections of plots of the prediction-vs-observation suggest that the models had difficulty distinguishing zeros from encounters of just one dolphin.



a)

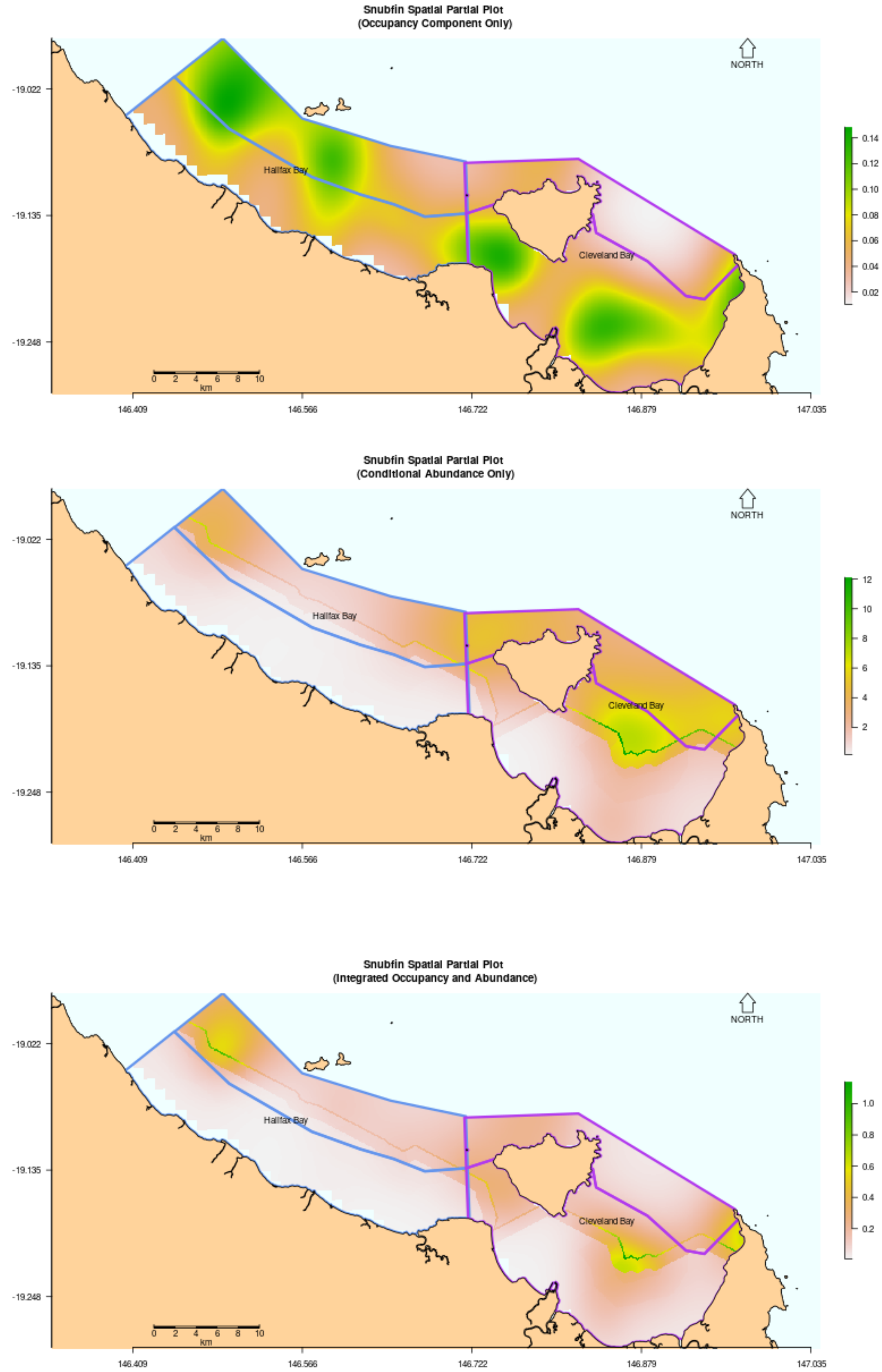


b)



c)

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



a)

b)

c)

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

The relative variable importance (RVI) are shown in Figure 8. Variable importance scores measure how much each covariate contributes to reduction in the model risk-function (negative log-likelihood). For both species, the majority of RVI was allotted to spatial-processes (spatial spline and Matern radial-basis-function), rather than known spatial covariates. For humpbacks, the second most import covariate was the presence of fishing boats (half the RVI as the 1st-ranking covariate), then water depth/bathymetry. For snubfin, the unexplained spatial processes had an RVI that was greater than 60% of the total risk-reduction, followed by time-of-day(hours) which constituted 1/5 of the total risk-reduction. One should keep-in-mind that ensemble-modelling plus multi-collinearity among environmental predictors means that individual RVIs could be artificially depressed.

As explained by Bühlmann et al (2013), model-averaging methods and ensemble methods with correlated variables mean that the ensemble is pooling information from across multiple variables, rather than uniquely attributing high-variable importance (RVI) to any single variable (e.g., as compared to a model with a single uncorrelated variable). However, for prediction (rather than attribution), it is better to include covariates that are somewhat correlated (<0.7) rather than exclude them. In the discussion, we talk more about exploring alternative inference frameworks (e.g., AIC model averaging) for better isolating which covariates may be influential.

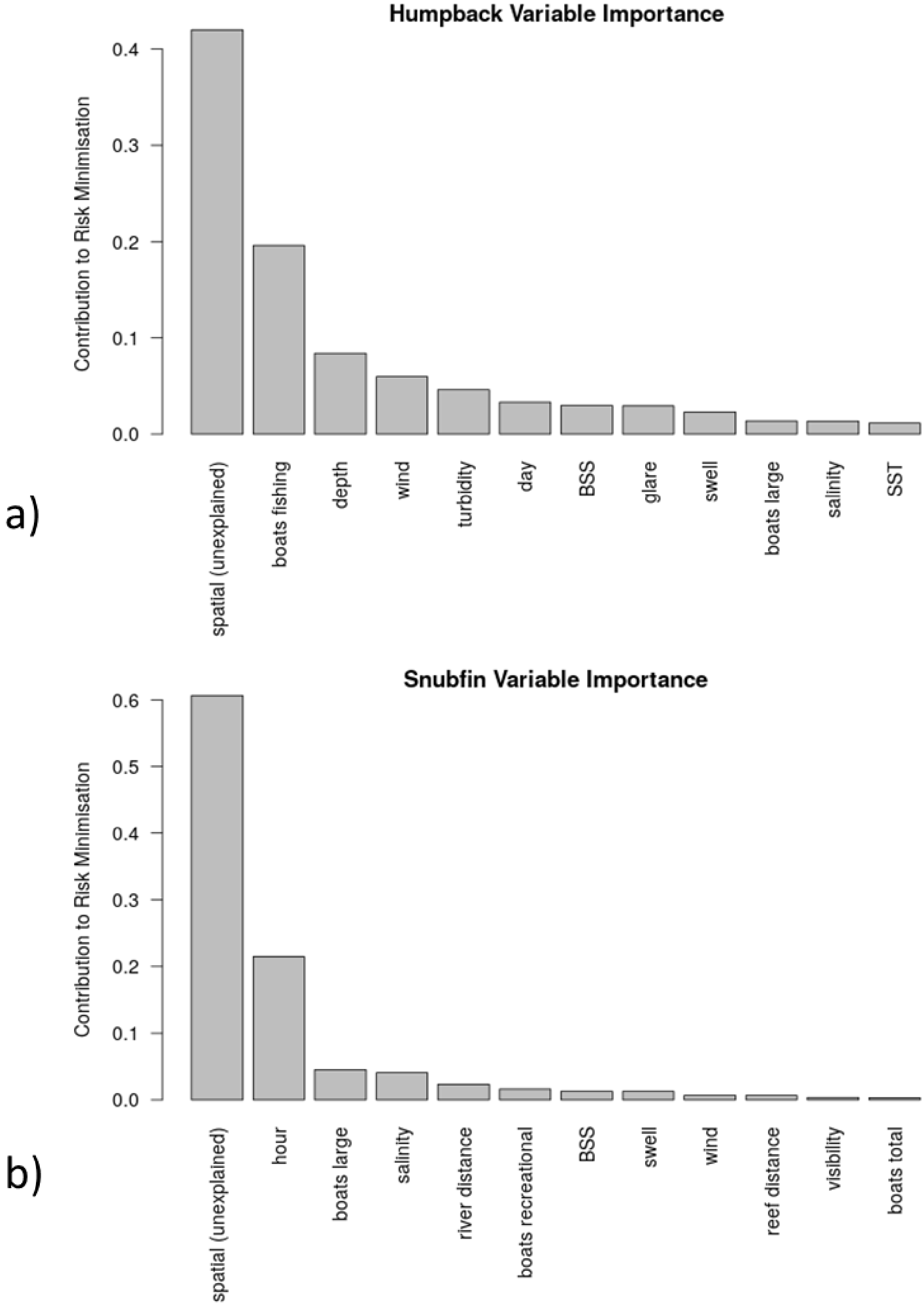


Figure 8. The relative variable importance (contribution to risk-minimisation) of each covariate considered in ensemble species distribution modelling of Australian humpback (a) and snubfin dolphins (b) in the Townsville region based on data collected in 2019.

3.3 Patterns of attendance to the port area

3.3.1 Land based survey effort

We were able to conduct land-based observations on 17 days between the 1st of June and the 14th of July, completing a total of 870 scans of the coastal waters (within approximately 1 km) adjacent to Berth 11 (Table 9). Out of the 17 days surveyed snubfins were seen on 9 days, humpback on 10 days, and bottlenose on 1 day. There were more observations of snubfins than humpbacks (present in 50 vs 20 scans, Table 9).

Table 9. Survey effort and dolphins observed from Berth 11 at the Port of Townsville during June-July 2019

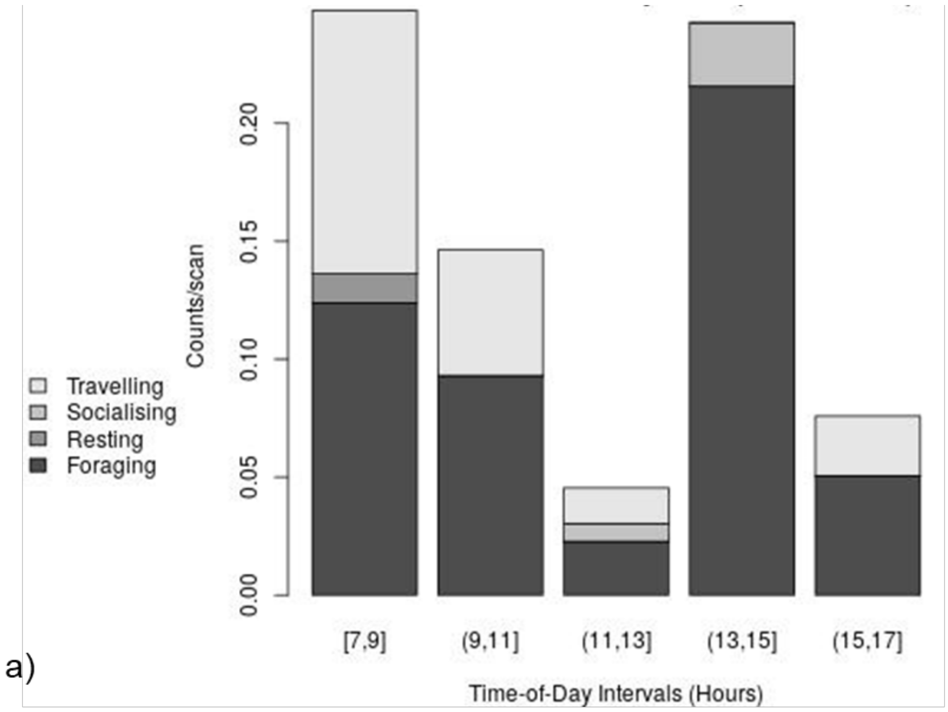
Date	Number of scans	Number of scans with humpback dolphins present	Number of scans with snubfin dolphins present	Number of scans with bottlenose dolphins present
3/06/2019	46	0	8	0
4/06/2019	46	1	3	0
5/06/2019	46	0	13	0
6/06/2019	68	4	5	0
12/06/2019	46	3	0	0
13/06/2019	58	1	0	0
14/06/2019	47	0	0	0
15/06/2019	61	4	0	1
17/06/2019	47	0	6	0
18/06/2019	60	1	3	0
26/06/2019	60	0	4	0
27/06/2019	48	2	1	0
30/06/2019	60	0	0	0
1/07/2019	31	0	0	0
2/07/2019	52	3	6	0
3/07/2019	43	0	0	0
6/07/2019	51	1	1	0
TOTAL	870	20	50	1

3.3.2 Diel and behavioural patterns observed

Both snubfin and humpback dolphins were observed mainly foraging, followed by travelling (Table 10) throughout the day (Fig. 9). Snubfins dolphin sightings peaked at 07:00-9:00 in the morning and at 13:00-15:00 in the afternoon. Humpback dolphin sightings peaked at 09:00-11:00 in the morning and 15:00-17:00 in the afternoon (Fig.9). Snubfin dolphins seemed to exhibit a slight bar-bell distribution in their propensity for foraging, whereby they foraged more during the early morning and late-afternoon (Fig. 9). Humpback dolphins had a more even distribution, with animals seen foraging in similar proportions throughout the day, with peaks in travelling during the morning (09:00-11:00) and towards the end of the day (15:00-17:00) (Fig. 9).

Table 10. The total number of scans where either species was present (out of 870 scans) and the proportion of times they were observed engaged in foraging, resting, socializing and travelling behavior.

Species	Number of Scans with Species Present	Foraging	Resting	Socialising	Travelling
Snubfin	50	0.61	0.02	0.04	0.33
Humpback	20	0.52	0	0	0.48



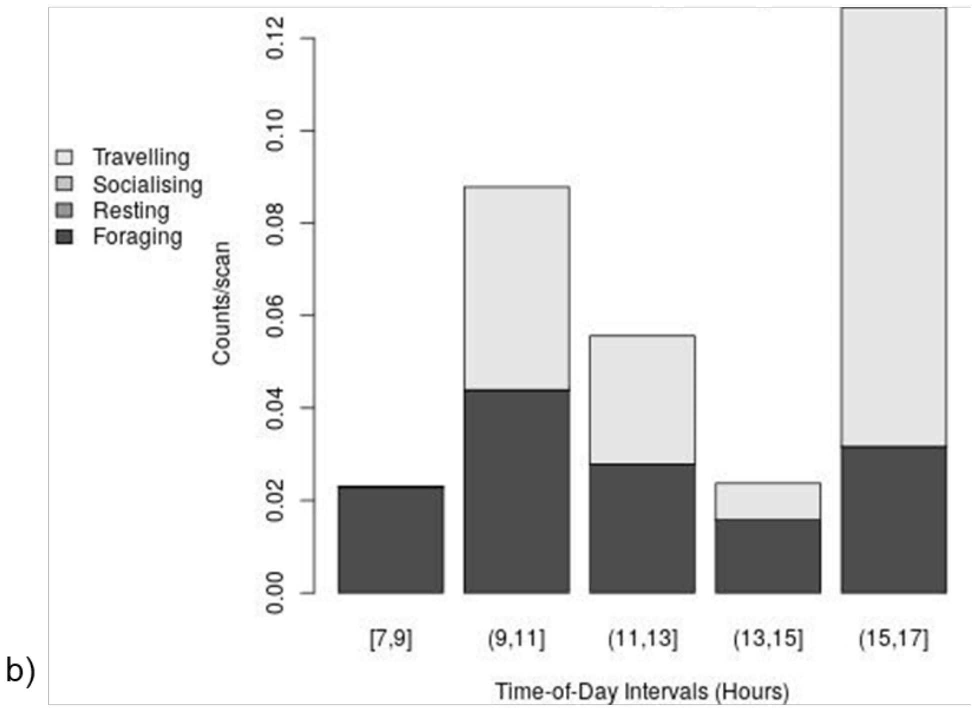


Figure 9. Snubfin (a) and humpback dolphin (b) observations by time of day (2 hourly bins). Bar height represents densities of counts (number of dolphins seen divided by number of scans); bar compositions represent proportion time observed in various behaviours.

3.3.3 Dolphins patterns of occurrence in relation to boats and maintenance dredging

As observations took place during pre-construction period of the CU project, no construction activities (dredging and rock dumping) associated with the CU project were recorded. Snubfin and humpback dolphin occurrence and behaviour showed no distinct patterns in relation to the presence of boats recorded within approximately 1km of observation platform (Fig. 10). Both species were seen mainly travelling and foraging while different number of boats were in the area. The majority of vessels observed from Berth 11 during dolphin scans were recreational vessels (52%), passenger vessels (19%), tugs/barges (12%), sailboats (11%), and fishing vessels (5%).

Out of the 870 scans carried out from Berth 11, maintenance dredging activities (located within 1km of observation platform on Berth 11) were recorded during nine scans. While there were no observations of dolphins, of either species, during the maintenance dredging activities (Table 11), the P-Bayes statistics (>0.05) suggest that the probability of observing no-dolphins was consistent with the background/null distribution of dolphin-occupancy during normal non-dredging scans. In other words, the absence of dolphins during maintenance dredging cannot be considered unusual.

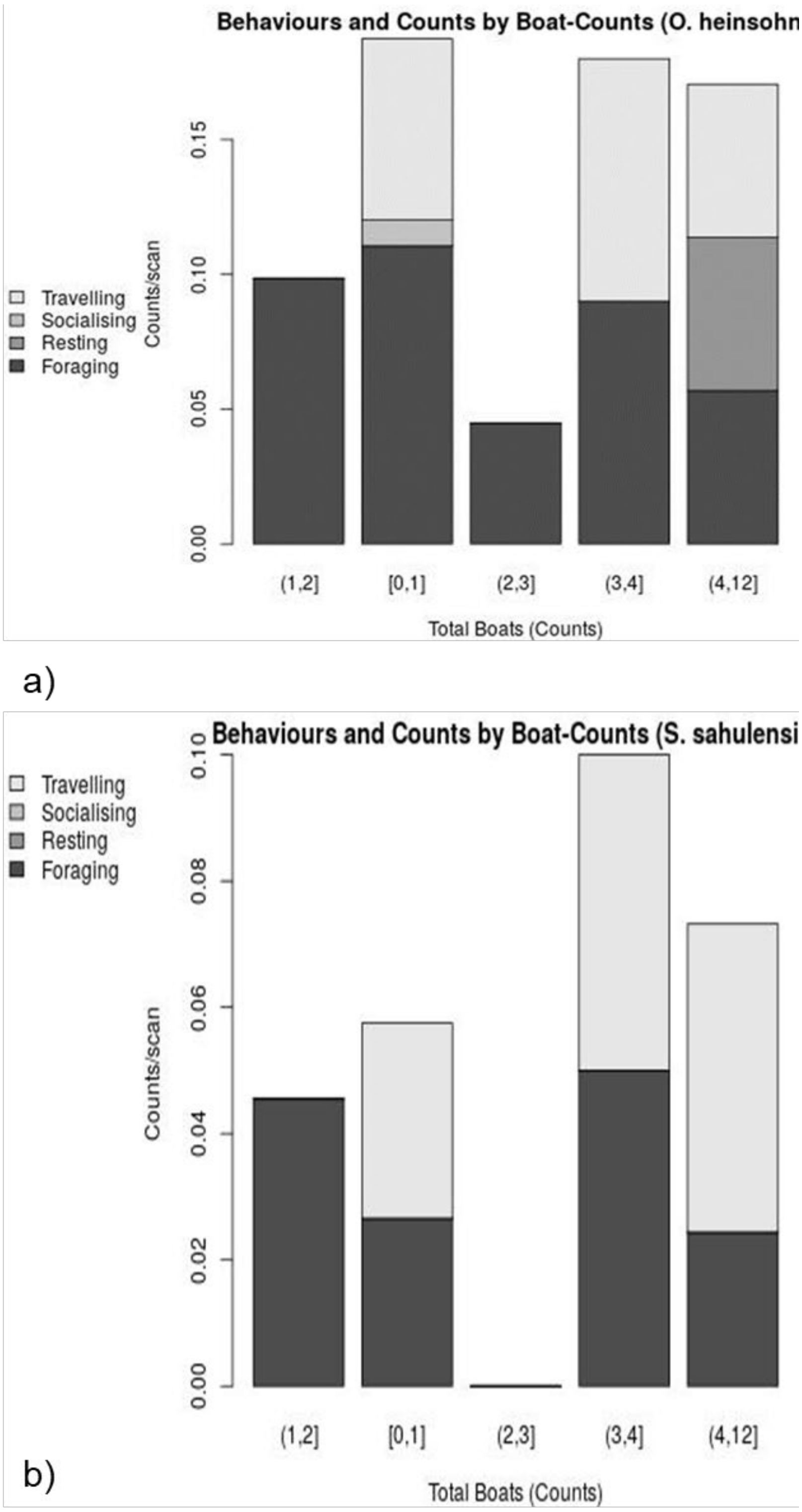


Figure 10. Number of observations of (a) snubfin and (b) humpback dolphins per scan and their respective behaviour versus the total number of boats (of all kinds) present in the area while doing observation from Bert 11 at the Port of Townsville in June-July 2019.

Table 11. Land-based occurrences of snubfin and humpback dolphins from Berth 11 during maintenance dredging and non-dredging operations in June-July 2019.

Species	Maintenance Dredging Presence	N-scans	N Occurrences of Dolphins	P-Bayes
Snubfin	no	861	50	NA
	yes	9	0	0.55
Humpback	no	861	20	NA
	yes	9	0	0.77

4. Discussion and conclusions

4.1 Survey effort

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

We were not able to survey Bowling Green Bay due to boat-ramp inaccessibility at Cape Fergusson due to floods and rain earlier in the year. Thus, we were not able to generate estimates of abundance or gain insights into the spatial distribution of snubfin and humpback dolphins in this area pre-construction activities. Given the allotted time for conducting the vessel surveys (40 days) and needed survey repeats (six), future surveys in Bowling Green Bay will depend highly on boat ramp access at Cape Fergusson. The only other available boat ramps providing safe access to Bowling Green Bay (Morrisey's Creek and Haughton River boat ramps) with our boats are more than an hour away by car from Townsville, require significant travel through rivers (more than 30 mins) to make it out to coastal waters, and are highly tide dependant. Thus, making it impractical given the planned allotted time to conduct the surveys. Collecting dolphin data in Bowling Green Bay would be beneficial in understanding the local dolphin populations, but If the boat ramp at Cape Ferguson is not operational in the future, we recommend continuing to focus survey effort on Cleveland Bay and Halifax Bay.

4.2 Estimates of Abundance

As previous studies have shown, Australian humpback and snubfin dolphins are the most common dolphin species found in coastal waters of the Townsville region. Adequate data were available to obtain estimates of abundance for snubfin and humpback dolphins in Cleveland Bay and Halifax Bay using closed capture-recapture population models. In the future, similar data collected over three years will support the use of Multistate Closed Robust Design models (MSCRD) to estimate rates of apparent survival (alive and in the area), temporary emigration and movement between sites in addition to population sizes.

Both snubfin and humpback dolphins were more abundant in Halifax Bay than in Cleveland Bay. Although not directly comparable due to differences in study design (i.e. the transect layout and the areas covered by previous studies are different from present study), estimates of abundance from 2019 fall within the ranges of historical estimates in the region. This indicates that the coastal waters off Cleveland Bay and Halifax Bay continue to support important populations of Australian snubfin and humpback dolphins. The estimates from present survey indicated 54 (95% CI = 33-106) and 89 (95% CI =52-181) snubfin dolphins used Cleveland Bay and Halifax Bay, respectively, and about 30 (95% CI = 19-59) humpback dolphins used Cleveland Bay and 71 (95% CI = 57-112) Halifax Bay. Surveys from 1999-2002 covering the coastal area of Cleveland Bay and southern Halifax Bay (i.e. from Cape Pallarenda to Black River Mouth) indicated the total population size of snubfin dolphins for this whole area ranged from 64 (95% CI=51–80) individuals in 2001 to 76 (95% CI=65–88) in 2000, and from 34 (95% CI=24–49) humpback dolphins in 2001 to 54 (95% CI=38–77) in 2002 (Parra et al. 2006a). The most recent surveys conducted between May and September 2016 in Cleveland Bay and southern Halifax Bay (i.e. from Cape Pallarenda to Bluewater Creek/Saunders Beach) estimated 133 (95% CI=90-196) snubfin dolphins and 86 (5% CI = 70-106) humpback dolphins (Beasley et al. 2016). It is important to note that the2016 estimates were plagued by the presence of heterogeneity in capture probabilities for which there were too few data to deal with adequately. Heterogeneity in capture probabilities can lead to large biases in abundance estimates when using models assuming no heterogeneity (Amstrup et al. 2005). Thus, it is difficult to assess if the apparent increase in dolphins in 2016 represents a true increase in the number of dolphins using this area or is simply a result of biases in abundance estimation.

The estimated capture probabilities (mostly $p \geq 0.20$) were adequate to support reliable population size estimates with a relatively good precision (CVs ranging from 0.19 to 0.35). The estimated population sizes for snubfin and humpback dolphins were however, associated with wide 95% confidence intervals. We expect the confidence intervals on future population size estimates from an MSCRD model to be narrower than those obtained from closed population model estimates due to parameter sharing and a higher data to parameters ratio. The use of the planned MSCRD model in the future and the estimation of movements between sites, and temporary emigration in addition to abundance will depend highly on obtaining as good or better capture probabilities as those obtained here.

4.3 Spatial distribution

Preliminary species distribution models of occupancy, group size and relative density of dolphins across the study area indicated that both species were mainly using the coastal inshore waters of Cleveland Bay and the central and northern inshore and offshore waters of Halifax Bay. As indicated in previous studies, the area around the port of Townsville, mouth of Ross River, and east towards Alligator Creek continues to be an area of high probability of occurrence for both species within Cleveland Bay. The high use of inshore waters by both species in Cleveland Bay and Halifax Bay have been observed in previous studies (Parra 2006, Nagombi 2018), indicating the importance of coastal habitats for these species.

With just a few dozen observations of either snubfin and humpback dolphins, the species distribution modelling exercise was effectively an exploration of the data and modelling approach. The exercise served to probe the data and models for challenges. In particular, the current analyses highlighted some key-points that require attention to strengthen future analysis, when more data is available:

1. ***Inference Framework****.* The current modelling framework, ensemble modelling via component-wise boosting, is a high-performance prediction method whose primary use is spatial prediction and derivation of Relative Variable Importance indices (Elith et al. 2008). The current analysis demonstrated the kinds of inferences and outputs that are possible with the technique, but also highlighted how they do not readily lend themselves to rigorous hypothesis-testing that will be important in later stages of the project. The boosting/RVI framework should be complimented with other statistics that have better-known properties and interpretations. Within the same framework, there is the possibility of using machine-learning techniques like “stability selection” (Shah and Samworth 2013) to derive p-values and/or inclusion probabilities that can be used for hypothesis testing. Additionally, we should complement such analyses with more-familiar semi-parametric methods that have tractable AIC-statistics, such as spatial GAMS (e.g., mgcv package). Such GAMs can provide both high-performance prediction and allow calculation of familiar AIC-based statistics, such as AIC model-weights and evidence ratios (Taper and Ponciano 2016). Although not discussed in this report, these have been presently explored and should be available in future reports.
2. ***Zero-inflation and data-sparsity***. In the future, and with more years of data, the imbalance between zero-encounter and positive encounters will likely remain highly skewed towards the zeros. The current analysis attempted to handle this imbalance with a zero-inflated count distribution. With more data, it would be prudent to test several candidate distributions, such as Tweedie or Negative Binomial distributions, or explore re-weighting the model-likelihood to favour learning about the positive

counts, rather than over-learn the zero-counts (which are not really “zeros” in the sense that dolphins were never at such locations).

3. ***Min/max/best counts***. The current analysis used a novel data-augmentation technique to leverage the uncertainty in the group size data (i.e., group encounters had minimum, maximum, and best estimates of group size). This technique, however, meant that the traditional model-diagnostic statistics were artificially depressed (such as the ROC-AUC). Future analyses should use simulations to re-scale these statistics and present a better picture of the overall adequacy of the SDM models.
4. ***Covariates spatial and temporal resolution.*** The performance of species distribution models is influenced by deficiencies and biases in the covariates used to build the models. Ideally, species observations and environmental variables are measured at the same spatial and temporal resolution, however this is hardly the case due to the time and resources needed to do so. We attempted to make use of most of the relevant and up-to-date spatial data available on environmental variables known or suspected to affect dolphins’ spatial distribution. Some of these datasets unfortunately offered poor-spatial resolution for inshore areas (e.g. Chl-a) or are outdated (e.g. seagrass cover). Thus, some of the spatial relationships and predictions show here may be biased and thus could have affected model’s performance. In the future, we will use more up to date spatial data if available, or filter covariates identified here as providing poor spatial and temporal resolution.

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 on good weather conditions and yielded unprecedented data on the patterns of occurrence of snubfin and humpback dolphins in inshore waters adjacent to the Port. Land-based observations from Berth 11 corroborated the frequent use by both dolphin species of the coastal waters close to the Port of Townsville, mainly for foraging and travelling activities as has been shown in the past (Parra 2006, Nagombi 2018). Furthermore, we show that both species are using this area throughout different times of the day, with particular peaks in the morning and afternoon. Land based observations also indicated that present levels of maintenance dredging and vessel traffic do not seem to influence the patterns of attendance and behaviour of dolphins around the port area. These observations will serve as a strong baseline on which to compare future patterns of attendance and behaviour of snubfin and humpback dolphins during construction and post construction activities.

5. References

Altmann, J. 1974. Observational study of behavior: sampling methods. Behaviour **49**:227-266.

Amstrup, S. C., T. L. McDonald, and B. F. J. Manly, editors. 2005. Handbook of Capture-Recapture Analysis. Princeton University Press, Princeton, New Jersey.

Arnason, A. N. 1972. Parameter estimates from mark-recapture experiments on two populations subject to migration and death. Researches on population ecology **13**:97-113.

Arnason, A. N. 1973. The estimation of population size, migration rates and survival in a stratified population. Researches on population ecology **15**:1-8.

Beaman, R. 2012. Project 3DGBR: Great Barrier Reef and Coral Sea Geomorphic Features (JCU) [Dataset]. eAtlas Repository. http://eatlas.org.au/data/uuid/25685ba5-6583-494f-974d-cce2f3429b78.

Beaman, R. J. 2010. Project 3DGBR: A high-resolution depth model for the Great Barrier Reef and Coral Sea. Marine and Tropical Sciences Research Facility (MTSRF) Cairns, Australia.

Beasley, I., L. Brooks, G. J. Parra, and H. Marsh. 2016. Evaluating Inshore Dolphin Conservation Status in Cleveland and Halifax Bays, North Queensland-Unpublished report. James Cook University.

Borchers, D. L., S. T. Buckland, W. Stephens, and W. Zucchini. 2002. Estimating animal abundance: closed populations. Springer Science & Business Media.

Brooks, L., C. Palmer, A. D. Griffiths, and K. H. Pollock. 2017. Monitoring Variation in Small Coastal Dolphin Populations: An Example from Darwin, Northern Territory, Australia. Frontiers in Marine Science **4**.

Brownie, C., J. Hines, J. Nichols, K. Pollock, and J. Hestbeck. 1993. Capture-recapture studies for multiple strata including non-Markovian transitions. Biometrics:1173-1187.

Buckland, S. T., K. P. Burnham, and N. H. Augustin. 1997. Model selection: an integral part of inference. Biometrics:603-618.

Bühlmann, P., P. Rütimann, S. van de Geer, and C.-H. Zhang. 2013. Correlated variables in regression: Clustering and sparse estimation. Journal of Statistical Planning and Inference **143**:1835-1858.

Bühlmann, P., and B. Yu. 2003. Boosting with the L2 loss: regression and classification. Journal of the American Statistical Association **98**:324–339.

Burnham, K., and D. Anderson. 2002. Model selection and multi-model inference: a practical information-theoretic approach (2nd edition). Springer-Verlag, New York.

Burnham, K. P., D. R. Anderson, G. C. White, C. Brownie, and K. H. Pollock. 1987. Design and analysis methods for fish survival experiments based on release-capture. American Fisheries Society Monograph 5. **American Fisheries Society, Maryland, U.S.A. No. of pages: 437. ISBN (hard) 0-913235-41-5**.

Cagnazzi, D. B. D., P. L. Harrison, G. J. B. Ross, and L. P. 2011. Abundance and site fidelity of Indo-Pacific humpback dolphins in the Great Sandy Strait, Queensland, Australia. Marine Mammal Science **27**:167-180.

Chen, T., and C. Guestrin. 2016. XGBoost: A Scalable Tree Boosting System. Pages 785–794. ACM.

Du Fresne, S., D. Fletcher, and S. Dawson. 2006. The effect of line-transect placement in a coastal distance sampling survey Journal of Cetacean Research and Management **8**:79-85.

Dyall, A., G. Tobin, J. Creasey, J. Gallagher, D. A. Ryan, A. Heap, and E. Murray. 2004. Queensland coastal waterways geomorphic habitat mapping (1:100 000 scale

digital data). Geoscience Australia. http://www.ozestuaries.org, Canberra: Commonwealth of Australia.
Elith, J., J. R. Leathwick, and T. Hastie. 2008. A working guide to boosted regression trees. The Journal of Animal Ecology **77**:802–813.
Fielding, A. H., and J. F. Bell. 1997. A review of methods for the assessment of prediction errors in conservation presence/absence models. Environmental Conservation **24**:38-49.
Gailey, G., and L. Karczmarski. 2012. Discovery: Photo-identification data-management system for individually recognizable animals. The Swire Institute of Marine Science, The University of Hong Kong and Mammal Research Institute , University of Pretoria.
Gelman, A. 2005. Comment: Fuzzy and Bayesian p -Values and u -Values. Statist. Sci. **20**:380-381.
Harrell Jr, F. E. 2015. Regression modeling strategies: with applications to linear models, logistic and ordinal regression, and survival analysis. Springer.
Hofner, B., A. Mayr, N. Robinzonov, and M. Schmid. 2012. Model-based Boosting in R: A Hands-on Tutorial Using the R Package mboost. Technical Report 120, Department of Statistics, Ludwig-Maximilians-Universität, Munich.
Hothorn, T., J. Müller, B. Schröder, T. Kneib, and R. Brandl. 2010. Decomposing environmental, spatial, and spatiotemporal components of species distributions. Ecological Monographs **81**:329-347.
Hunt, T. N., L. Bejder, S. J. Allen, R. W. Rankin, D. Hanf, and G. J. Parra. 2017. Demographic characteristics of Australian humpback dolphins reveal important habitat toward the southwestern limit of their range. Endangered Species Research **32**:71-88.
Kendall, W. L. 2013. The robust design. In Cooch, E.G. and White, G.C. “Program Mark – a gentle introduction (Edition 13), Chapter 15. http://www.phidot.org/software/mark/docs/book/.
Kendall, W. L., and J. D. Nichols. 1995. On the use of secondary capture-recapture samples to estimate temporary emigration and breeding proportions. Journal of Applied Statistics **22**:751-762.
Kendall, W. L., and J. D. Nichols. 2002. Estimating state-transition probabilities for unobservable states using capture–recapture/resighting data. Ecology **83**:3276-3284.
Kendall, W. L., J. D. Nichols, and J. E. Hines. 1997. Estimating temporary emigration using capture-recapture data with Pollock's robust design. Ecology **78**:2248.
Kneib, T., T. Hothorn, and G. Tutz. 2009. Variable selection and model choice in geoadditive regression models. Biometrics **65**:626–634.
Mann, J. 1999a. Behavioral sampling methods for cetaceans: a review and critique. Marine Mammal Science **15**:102-122.
Mann, J. 1999b. Behavioural sampling methods for cetaceans: A review and critique. Marine Mammal Science **15**:102-122.
Mayr, A., H. Binder, O. Gefeller, and M. Schmid. 2014. The evolution of boosting algorithms: from machine learning to statistical modelling. Methods of Information in Medicine **53**:419-427.
McKenzie, L. J., R. L. Yoshida, A. Grech, and R. Coles. 2014. Composite of coastal seagrass meadows in Queensland, Australia - November 1984 to June 2010., PANGAEA, https://doi.org/10.1594/PANGAEA.826368.
Meir, R., and G. Rätsch. 2003. An introduction to boosting and leveraging. Lecture Notes in Computer Science **2600**:118-183.

Nagombi, E. 2018. Using GIS and home range analysis to provide spatial and temporal information about two inshore dolphin populations in Cleveland and Halifax Bay, Queensland. SC5912_5913 Minor Project Report. James Cook University.
Nichols, J. D., and C. J. Coffman. 1999. Demographic parameter estimation for experimental landscape studies on small mammal populations. Pages 287-309 Landscape ecology of small mammals. Springer.
Oppel, S., C. Strobl, and F. Huettmann. 2009. Alternative methods to quantify variable importance in ecology. Technical Report 65, Department of Statistics, Ludwig-Maximilians-Universität, Munich.
Otis, D. L., K. P. Burnham, G. C. White, and D. R. Anderson. 1978. Statistical inference from capture data on closed animal populations. Wildlife Monographs **62**:135.
Parra, G., D. Cagnazzi, and I. Beasley. 2017a. *Orcaella heinsohni*. The IUCN Red List of Threatened Species 2017: e.T136315A50385982. http://dx.doi.org/10.2305/IUCN.UK.2017-3.RLTS.T136315A50385982.en. Downloaded on 06 March 2018.
Parra, G., D. Cagnazzi, W. Perrin, and G. T. Braulik. 2017b. *Sousa sahulensis*. The IUCN Red List of Threatened Species 2017: e.T82031667A82031671. Downloaded on 07 December 2017.
Parra, G. J. 2006. Resource partitioning in sympatric delphinids: Space use and habitat preferences of Australian snubfin and Indo-Pacific humpback dolphins. Journal of Animal Ecology **75**:862-874.
Parra, G. J., D. Cagnazzi De Biasi, L. Brooks, and R. W. Rankin. 2019. Inshore Dolphin Monitoring Program for The Channel Capacity Upgrade Project of Port of Townsville. Report produced for the Port of Townsville Limited., Flinders University.
Parra, G. J., and P. J. Corkeron. 2001. Feasibility of using photo-identification techniques to study the Irrawaddy dolphin, *Orcaella brevirostris* (Owen in Gray 1866). Aquatic Mammals **27**:45-49.
Parra, G. J., P. J. Corkeron, and H. Marsh. 2006a. Population sizes, site fidelity and residence patterns of Australian snubfin and Indo-Pacific humpback dolphins: Implications for conservation. Biological Conservation **129**:167-180.
Parra, G. J., P. J. Corkeron, and H. Marsh. 2006b. Population sizes, site fidelity and residence patterns of Australian snubfin and Indo-Pacific humpback dolphins: Implications for conservation. Biological Conservation **129**:167-180.
Pirotta, E., B. E. Laesser, A. Hardaker, N. Riddoch, M. Marcoux, and D. Lusseau. 2013. Dredging displaces bottlenose dolphins from an urbanised foraging patch. Marine Pollution Bulletin **74**:396-402.
Pollock, K. H., J. D. Nichols, C. Brownie, and J. E. Hines. 1990. Statistical Inference for capture-recapture experiments. Wildlife Monographs **107**:1-98.
Schmid, M., and T. Hothorn. 2008. Flexible boosting of accelerated failure time models. BMC Bioinformatics **9**:269.
Schmid, M., S. Potapov, A. Pfahlberg, and T. Hothorn. 2010. Estimation and regularization techniques for regression models with multidimensional prediction functions. Statistics and Computing **20**:139–150.
Schwarz, C. J., J. F. Schweigert, and A. N. Arnason. 1993. Estimating migration rates using tag-recovery data. Biometrics:177-193.
Shah, R. D., and R. J. Samworth. 2013. Variable selection with error control: another look at stability selection: *Another Look at Stability Selection*. Journal of the Royal Statistical Society: Series B (Statistical Methodology) **75**:55-80.
Sofaer, H. R., J. A. Hoeting, and C. S. Jarnevich. 2019. The area under the precision-recall curve as a performance metric for rare binary events. **10**:565-577.
Strindberg, S., and S. T. Buckland. 2004. Design of distance sampling surveys and Geographic Information Systems. Pages 190-228 *in* S. T. Buckland, D. R.

Anderson, K. P. Burnham, J. L. Laake, D. L. Borchers, and L. Thomas, editors. Advanced Distance Sampling: Estimating Abundance of Biological Populations. . Oxford University Press, New York.
Taper, M. L., and J. M. Ponciano. 2016. Evidential statistics as a statistical modern synthesis to support 21st century science. Population Ecology **58**:9-29.
Thomas, L., J. L. Laake, E. Rexstad, S. Strindberg, F. F. C. Marques, S. T. Buckland, D. L. Borchers, D. R. Anderson, K. P. Burnham, M. L. Burt, S. L. Hedley, J. H. Pollard, J. R. B. Bishop, and T. A. Marques. 2009. Distance 6.0. Release 2. . Research Unit for Wildlife Population Assessment, University of St. Andrews, UK. http://www.ruwpa.st-and.ac.uk/distance/.
Thomas, L., R. Williams, and D. Sandilands. 2007. Designing line transect surveys for complex survey regions. Journal of Cetacean Research and Management **9**:1-13.
White, G. C., and K. P. Burnham. 1999. Program MARK: Survival estimation from populations of marked animals. Bird Study **46**:S120-S139.
Whiteway, T. G. 2009. Australian Bathymetry and Topography Grid, June 2009. Geoscience Australia, Canberra.
Williams, B. K., J. D. Nichols, and M. J. Conroy. 2002. Analysis and Management of Animal Populations: Modeling, Estimation, and Decision Making. Academic Press, San Diego, California.
Woinarski, J., A. Burbidge, and P. Harrison. 2014. Action Plan for Australian Mammals 2012. CSIRO Publishing, Collingwood, Victoria, Australia.
Wood, S. N. 2003. Thin plate regression splines. Journal of the Royal Statistical Society: Series B (Statistical Methodology) **65**:95-114.

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