Chapter 1

PAMPower: Investigating the statistical power of passive acoustic monitoring networks to detect trends in cetacean abundance

Abstract

1.1 Introduction

Knowledge of population abundance and trend is crucial for effective management and conservation. Animal abundance is monitored to identify species of concern, to evaluate the success of conservation actions, and to calculate allowable capture of individuals. Because it is rarely possible to count all of the individuals within a population, statistical methods for estimating population size have been developed. Traditionally, these methods rely on visual observations of the species of interest. For cryptic or visually inaccessible taxa, visual surveys often produce imprecise estimates of animal abundance. However, many hard-to-see species produce sounds that are comparatively easy to hear. These sounds can be used as proxies for the animals themselves. Recent advances in recording technology, detection and classification algorithms, and statistical methods have led to the development and rapid growth of passive acoustic monitoring (PAM) and, in particular, passive acoustic density and abundance estimation. For many species, there is enormous potential to use passive acoustic methods to increase the precision of abundance estimates, thereby improving our ability to monitor and detect change in populations over time.

Here, we focus on cetaceans, which are particularly difficult to monitor using visual methods. Given current budgets, it is not possible to detect biologically significant declines for most cetacean populations using traditional visual survey methods and associated statistical techniques. High natural variability in cetacean distributions combined with the high variability in visual surveys (due to cost, conditions, and observer error) lead to low precision in visual abundance estimates. In the U.S., given the current frequency and extent of cetacean surveys, 50% declines over a 15-year period would be undetectable in 72% of baleen whale populations, 90% of beaked whale populations, and 78% of dolphin and porpoise populations. Even when all available visual survey data are pooled across regions and species groups, declines less severe than 50% over a 15 year period are only detectable in about half of cetacean families in the Atlantic and Pacific Oceans (Taylor et al., 2006).

Without the ability to detect changes in the abundance of these populations, it is nearly impossible to implement effective management actions.

PAM is an excellent alternative to visual surveys for these species, as cetaceans produce echolocation clicks, whistles, and other vocalizations that can propagate long distances underwater. Fixed PAM networks in particular are a relatively inexpensive monitoring technology and can be deployed for months at a time. Compared to aerial surveys, the long deployments of PAM sensors provide data with lower variance, which increases the precision of the resulting abundance estimates and therefore statistical power to detect trends. PAM networks have been used to estimate the abundance of Blainvilles beaked whales (*Mesoplodon densirostris;* Marques et al., 2009) and sperm whales (*Physeter macrocephalus;* W ard et al., 2012) in the Bahamas, and to estimate the abundance of the critically endangered Baltic Sea harbor porpoise and North Pacific right whale (*Eubalaena japonica;* Marques et al., 2011), and to document the decline of the critically endangered vaquita (*Phocoena sinus;* Legorreta, 2016) in the Gulf of California.

Designing PAM schemes for long-term monitoring of cetacean populations is now feasible through advances in affordable underwater instrumentation, improvements in cetacean vocalization detection algorithms, and development of statistical methods for estimating animal abundance using passive acoustic data. However, there is no framework for optimizing PAM surveys to maximize precision. To date, most studies attempting to estimate cetacean abundance using passive acoustic data have either used existing acoustic datasets or relied on general design principles from the visual survey literature to guide data collection. There is a growing need in science, management, and industry for quantitative design criteria to optimize the implementation of passive acoustic monitoring networks for cetaceans.

We use the Monterey Bay population of harbor porpoise as a case study for evaluating the statistical power of potential passive acoustic network designs to detect trends in abundance. This population occupies a nearshore area approximately 2,500 km^2 and consists of approximately 3,700 individuals (Forney et al., 2014). This population is distinct from other harbor porpoise populations along the U.S. West Coast (Calambokidis and Barlow, 1991; Chivers et al., 2002). While fishery mortality is currently insignificant for this population (Carretta et al., 2015) the population is likely still recovering from take in a set gillnet fishery for halibut that operated in the mid-20th century (Jefferson et al., 1994; Forney et al., 2014). There has also been some mortality over the past decade due to bottlenose dolphin *(Tursiops truncatus)* attacks on harbor porpoise in this region (Cotter et al., 2012; Jacobson et al., 2014; Wilkin et al., 2012). The Monterey Bay population of harbor porpoise has been studied using line-transect aerial surveys since the late 1980s (Forney et al., 1991). Additionally, since XXXX, line-transect aerial surveys for leatherback sea turtles have been conducted in the region using the same survey methodology. We used aerial survey and passive acoustic data collected in Monterey Bay to simulate datasets for hypothetical passive acoustic monitoring network designs and changes in harbor porpoise abundance. Through these simulations we explored optimal fixed passive acoustic survey design for detecting trends in the abundance of the Monterey Bay population of harbor porpoise.

1.2 Methods

1.2.1 Data collection

Aerial survey methods

Aerial surveys have been conducted in the Monterey Bay region using a consistent survey methodology since the late 1980s (Forney et al., 1991). In the present study, we used aerial survey data collected during surveys for harbor porpoise and for leatherback sea turtles between 2000 and 2013 (Fig. 1.2, left panel; Table 1.1). All surveys were conducted from a Partenavia P-68 high-wing two-engine aircraft. During aerial surveys, two observers searched from bubble windows on either side of the aircraft while a third observer searched from a belly window in the rear of the aircraft. A data recorder transcribed verbal sighting information for cetaceans and turtles (including declination angle, species, and number of animals) and environmental (visibility conditions) information from the observers into a custom-written software program on a laptop computer (Toshiba T-1000, Japan) that was directly connected to a hand-held Global Positioning System (Garmin 12XL, USA).

Passive acoustic methods

In 2013, 2014, and 2015 we installed a grid of PAM sensors (C-PODs; Chelonia Ltd., United Kingdom, www.chelonia.co.uk) in northern Monterey Bay (Fig. 1.2, right panel). C-PODs detect harbor porpoise echolocation clicks in real time and store summary information about detected clicks. Instruments were deployed between late July and late August and retrieved between early December and early February each year. In all years, instruments were consistently deployed for the months of September, October, and November, with exact deployment and retrieval dates dependent on suitable weather conditions and availability of a research vessel and required personnel. These seasonal deployments were designed to be consistent with historical aerial survey effort in the region, most of which has occurred in August, September, and October. The passive acoustic study area included waters from 10 to 100 m depth, north of 36.8° N and east of 122.1° W, with a total area of 370 km^2. The study design was a systematic, randomly positioned offset grid of 11 C-PODs spaced 0.035° latitude and 0.07° longitude apart and oriented to follow the shape of the coastline (see Fig. 1.2, right panel). Further details of passive acoustic instrument deployments can be found in Jacobson et al. (2016) and Jacobson et al. (2017).

1.2.2 Data analysis

Aerial survey data processing

Data were read from tab-delimited files into R (v. 3.2.2; R Core Team, 2016) for processing. All data were converted from geographic coordinates (latitude and longitude) into a two-dimensional projection (X and Y km from the centroid of the study area) to ensure uniformity of calculated distances. Aerial survey line transect effort was divided first into segments with continuous effort in constant sighting conditions (Beaufort sea state) and then divided again into 1-km effort subsegments. Following Becker et al. (2010) and Jacobson et al. (2017), when it was not possible to divide effort segments exactly into 1-km subsegments, if the remainder of the effort segment was less than 500m it was added randomly to one of the subsegments, while if the remainder was greater than 500m a new subsegment was created and positioned randomly into the effort segment. Due to the low probability of observing harbor porpoise in high sea states, only data from the aerial survey effort obtained in Beaufort sea states 0–3 were included.

We used the package Distance (v. 0.9.4; Miller, 2016) to fit a detection function to the aerial survey data using a halfnormal key function with cosine adjustments. We considered models with and without Beaufort sea state as a covariate and used Akaike's Information Criterion (AIC) to select the best model. Following Jacobson et al. (2017), we calculated the point density of harbor porpoise at the midpoint of each subsegment of aerial survey effort. This calculation did not include a correction for the probability of seeing animals directly on the trackline; i.e., $g(0) < 1$.

To generate an average, decadal-scale harbor porpoise density surface in our study region, we used a generalized additive model (Hastie and Tibshirani, 1990, GAM;) implemented in the package mgcv (v. 1.8-12; Wood and Wood, 2017) with a log link to model harbor porpoise density at the midpoint of each effort subsegment as a function of a two-dimensional thin-plate regression spline (Wood, 2003) on projected coordinates X and Y from the centroid of the study area. We used a Tweedie distribution to account for overdispersion in the response variable. The smoothing spline was optimized using the outer Newton method and penalized for overparameterization with restricted maximum likelihood (REML).

C-POD data processing

C-POD data were processed using the KERNO algorithm in the program CPOD.exe (v. 2.044; Tregenza, 2012) to detect click trains. All narrowband, high-frequency (NBHF) click trains were classified as belonging to harbor porpoise, and we chose to include only high-quality click trains (as defined by the KERNO algorithm) in our analysis in order to minimize false positives in the dataset. Data were exported from CPOD.exe and all further analyses were performed in R (v. 3.2.2; R Core Team, 2016).

Following Jacobson et al. (2017), we chose to use the number of porpoise positive seconds (PPS) per day as our passive acoustic metric. This metric is less likely to become saturated when multiple animals are present and it reduces the impact of animal orientation on detectability by effectively averaging over 1-s periods. This metric assumes that only one porpoise can be detected within any 1-s period. For each instrument and year, mean PPS was calculated as the mean number of porpoise positive seconds per day between September 1st and December 1st of each year (91 days).

Relating passive acoustic and aerial survey data

We used a generalized linear model (GLM; Eq. 1.1) to relate the log-transformed passive acoustic detection rate (PPS) at each instrument n and year y to the log-transformed average underlying harbor porpoise density at the location of each instrument ($\hat{D}_n$) as estimated by the spatial smooth of aerial survey observations (described above). A covariate for year was included to account for a potential changes in passive acoustic detection rates over the 3-yr monitoring period (e.g., due to continuing population recovery from past impacts).

$$log(PPS_{n,y}) \sim \alpha_0 + \beta_1 log(\hat{D_n}) + \beta_2 Y_y + \varepsilon \tag{1.1}$$

Simulation methods

We used the observed relationship between passive acoustic detection rates and the density of harbor porpoise (as described by Eq. 1.1) to create simulated datasets for hypothetical passive acoustic monitoring networks over 10 year periods. Our simulation explored three possible survey designs and two possible behavioral responses to disturbance, resulting in six hypothetical scenarios. The base case (random survey design and uniform change in the population) was simulated 10,000 times each with changes in abundance from -50% to +50% and 5 to 100 passive acoustic sensors. Power was defined as the proportion of the 10,000 simulations in which a change in the population was detected. All combinations of survey design, response to disturbance, change in abundance, and number of passive acoustic sensors were repeated 10,000 times with 75 simulated sensors and a -25% change in harbor porpoise abundance.

Three possible survey design strategies were investigated. In the random sampling scenario, sensors were placed randomly throughout the study area in water depths 0 to 1000 m deep (Fig. 1.1, left panel). Harbor porpoise densities are highest near shore, so we also generated a stratified sampling strategy where sensors were only placed in water 0 to 100 m deep (Fig. 1.1, right panel). Finally, we developed a sampling strategy proportional to the mean density of harbor porpoise in our study area, which we referred to as a scaled sampling design. First, we normalized the density values calculated using the aerial survey data to be between 0 and 1; i.e., locations with highest densities were assigned a value of 1. Then, we iteratively selected points at random and conducted a binomial trial where the

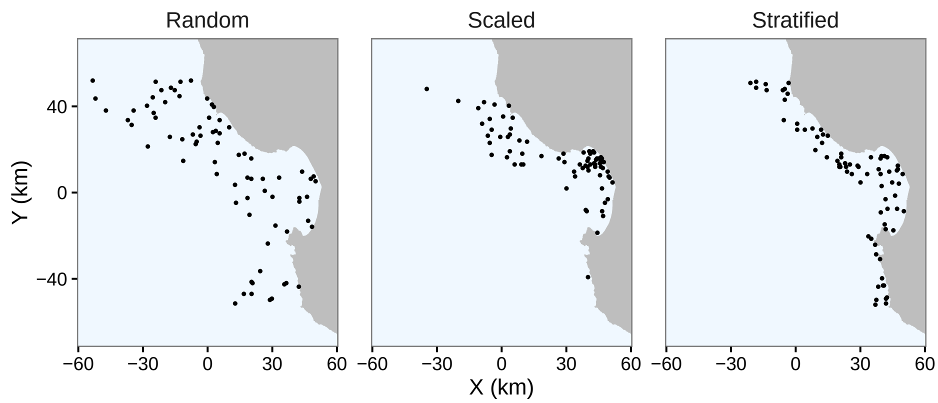

Figure 1.1: Example simulated placement of 75 sensors in the Monterey Bay study area using random (left panel), scaled (center panel), and stratified (right panel) sampling design strategies.

probability of success was equal to the normalized harbor porpoise density at that point. If the trial was successful, that point was included as a location for sensor deployment; we repeated this process until we achieved the desired number of sensors. This method resulted in a distribution of sensors that mirrored the distribution of harbor porpoise. For each of the three possible survey designs, we simulated designs with 75 sensors.

We simulated two possible scenarios of harbor porpoise population response to disturbance. In the base scenario, the population was assumed to change uniformly over the study area. In the range contraction scenario, we simulated a possible basin-type response (sensu Gilpin?) where animals were hypothesized to contract their distribution to the highest-quality habitat as the population declined. To implement this, we again used the underlying mean density of harbor porpoise as calculated from the aerial survey data to inform a habitat quality score for each point in the study area. We assumed that harbor porpoise density was positively and linearly related to habitat quality. We used this relationship to scale the simulated impact, so that high-density, high-quality habitat areas experienced less decline than low-density, low-quality habitat areas.

The simulated rate of change was divided into linear, incremental changes r_y over y = 10 years such that the product of the r_y was equal to the total desired change R. Because a population is unlikely to change in identical stepwise increments each year, we chose to add variability to the rate of change over time. We drew $y-1$ values from a normal distribution with mean = $(1+R)^{(1/(y-1))}$ and standard deviation (SD) = 0.05. The choice of SD was arbitrary. The final r_y value was calculated so that $R = \prod_{i=1}^{y} r_y$. Finally, the values of r_y were randomly reordered. We simulated rates of change ranging from -50% (i.e., the population decreased by half) to +50% (i.e., the population increased by half).

For each simulation run, a single intercept term a was drawn from a normal distribution with a mean and standard error (SE) from the GLM model estimate α_0. For each of n simulated sensors, a spatial location was drawn randomly according to the survey design and a simulated underlying density d_n was drawn from a lognormal distribution with mean and SE of the estimated $\hat{D}$ at that spatial location. Coefficients for density at the location of each sensor $b_{1,n}$ were drawn from a normal distribution with mean and SE from the model estimate of β_1. As described above, a cumulative rate of change $\prod_{i=1}^{y}(1-r_y)$ was applied in each time step. Because there was unexplained variance in the modeled relationship between harbor porpoise density and passive acoustic detection rate (see Eq. 1.1), we added an error term $E_{n,y}$ drawn from a normal distribution with a mean of 0 and a SD equal to the residual SD of the GLM.

$$pps_{n,y} = e^{(a_0+b_{1,n}log(d_n)+E_{n,y})}\prod_{i=1}^{y}(1-r_y) \tag{1.2}$$

Once data were generated for n moorings and y years, each simulated dataset was evaluated using a mixed effects model (Eq. 1.3) with $log(pps_{n,y})$ modeled as a function of year (fixed effect) and sensor (random effect).

$$log(pps_{n,y}) \sim \lambda y + \gamma_n + \varepsilon \tag{1.3}$$

This model differs from the GLM in Eq. 1.1 in that the underlying mean density is assumed to be unknown, so a random effect was used to account for sensor-specific differences in detection rates. For each simulated dataset, if the year term in this mixed effects model was significant and the sign of the covariate λ matched the sign of the simulated change in the population, that particular iteration was marked as a success. This process was repeated for each of the 10,000 simulated datasets and statistical power was calculated as the proportion of those 10,000 datasets in which a change was detected. This was repeated for each combination of survey design, response to disturbance, number of sensors, and change in the population.

1.3 Results

1.3.1 Results of data collection

Passive acoustic data collected

We deployed 11 C-PODs in north Monterey Bay in the late summer or early fall of 2013, 2014, and 2015. Instruments were retrieved between early December and early

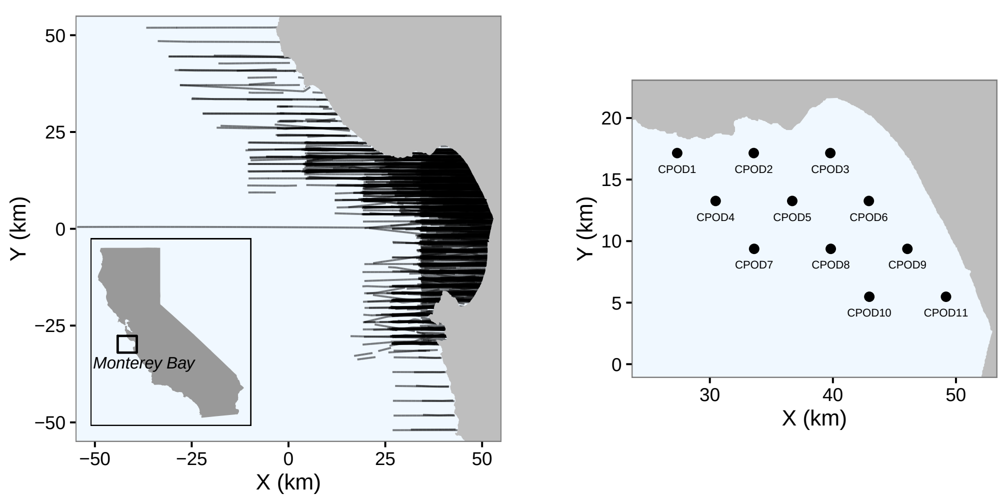

Figure 1.2: Map of completed aerial survey tracklines (left panel, black lines) and passive acoustic instrument deployments (right panel, black circles) in Monterey Bay, CA.

Table 1.1: Aerial survey effort (km) and number of harbor porpoise sightings (groups) per year between 2000 and 2013.

Year	**Survey Effort (km)**	**Porpoise Sightings**
2000	342	11
2001	2972	200
2002	4017	252
2003	3837	300
2004	6840	528
2005	2124	202
2006	1178	76
2007	1271	91
2008	137	9
2009	1500	176
2010	951	161
2011	2566	202
2012	1014	94
2013	2973	383
Total	31722	2715

February each year, so that instruments were deployed for approximately four months per year. Data were recovered from nine instruments in the 2013 season, 10 instruments in the 2014 season, and 11 instruments in the 2015 season, for a total loss rate of 9%.

Aerial survey data collected

Between 2000 and 2013, 31,722 km of aerial survey effort in good weather conditions was conducted in the Monterey Bay region (Fig. 1.2, left panel), resulting in 2,715 sightings of harbor porpoise groups (Table 1.1). The quantity of aerial survey effort varied among years (Table 1.1) and months (Fig. 1.3), with most effort occurring in August, September, and October. Most aerial survey effort occurred within Monterey Bay itself (Fig. 1.2, left panel).

1.3.2 Results of data analysis

C-POD data analysis

Passive acoustic detection rates varied widely among instruments, with recorded values as low as 30 PPS per day and as high as 1,320 PPS per day over the course of the season. Nearshore instruments (C-POD 3, C-POD 6, and C-POD 9) recorded higher detection rates than offshore instruments (C-POD 4, C-POD 5, C-POD 7, C-POD 8, C-POD 10; Tab. 1.2; Fig. 1.2).

Aerial survey data analysis

Calculated harbor porpoise densities at the midpoint of each aerial survey subsegment ranged from 0 to 78.5 harbor porpoise per km^2. The GAM explained 24.7% of deviance in the aerial survey data, which is comparable to other cetacean-habitat models (e.g., Gilles et al., 2016). The smooth term on X and Y from the centroid of the study region was

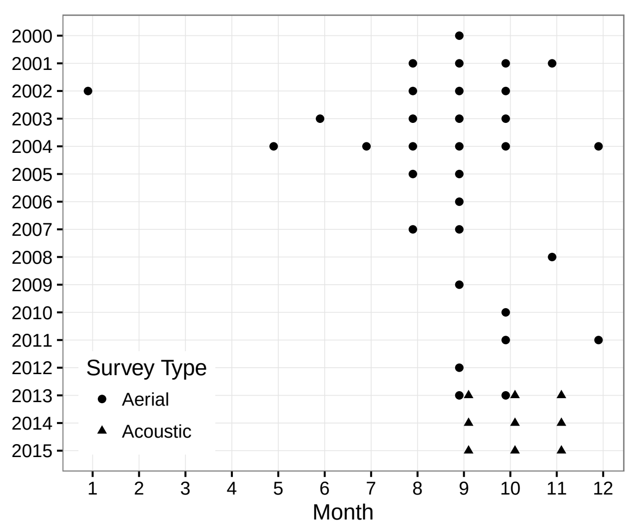

Figure 1.3: Visual representation of aerial survey and passive acoustic data collection in the Monterey Bay region in different months (x-axis) between 2000 and 2015 (y-axis). Circles indicate month/year combinations during which aerial surveys were conducted, while triangles indicated month/year combinations during which passive acoustic data were collected.

Table 1.2: Passive acoustic detection rates (PPS per day) recorded on each of 11 C-PODs (rows) during three years of data collection (columns). NA values indicate that the instrument was lost or that no data were recovered from the instrument.

Instrument	PPS		
	2013	2014	2015
C-POD 1	198	162	476
C-POD 2	116	NA	117
C-POD 3	530	174	323
C-POD 4	101	197	225
C-POD 5	NA	829	636
C-POD 6	648	725	576
C-POD 7	39	146	105
C-POD 8	76	120	112
C-POD 9	252	728	414
C-POD 10	30	122	208
C-POD 11	NA	1320	827

significant ($p < 0.001$). The GAM predicted highest densities of harbor porpoise in the northern part of Monterey Bay with moderate densities predicted in nearshore southern Monterey Bay (Fig. 1.4).

Relating passive acoustic and aerial survey data

Underlying mean density as calculated using aerial survey observations was a significant predictor of harbor porpoise click detection rate ($p < 0.001$). The year term was also significant ($p < 0.05$) with a positive covariate indicating a probable increase in the population over the three year passive acoustic monitoring period.

Simulation results

With random placement of sensors and geographically uniform changes in the population, a 50% decrease in the population over a 10-yr period could be detected 80% of the time with as few as 10 sensors (Fig. 1.6). With 100 sensors, a -20% change in the population would be detectable 80% of the time, and a -30% change would be detectable

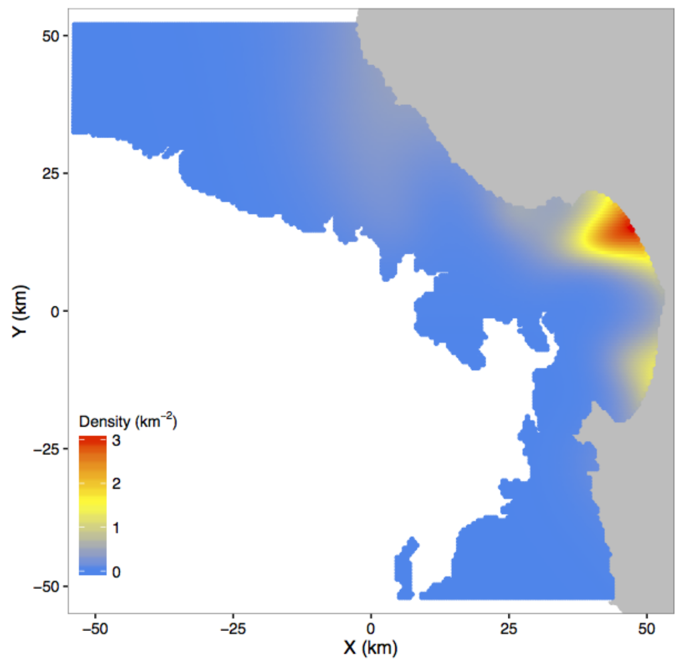

Figure 1.4: Harbor porpoise density (km^{-}2) in water 0-1000 m deep estimated using a two-dimensional spline on harbor porpoise density calculated using aerial survey observations. Note that densities are not corrected for $g(0)$.

100% of the time.

When the population declined uniformly over its geographic range, the placement of sensors (random, stratified, or scaled) did not impact power to detect a trend in abundance (Table 1.3). However, scenarios where animals contracted to core, high-quality habitat resulted in lower power to detect trends in abundance. Random placement of sensors resulted in the lowest power when animals responded with range contraction (power = 0.67); using a stratified design improved power slightly (power = 0.71), and a survey design with sensors placed in proportion to the underlying harbor porpoise density (scaled design) resulted in the highest power to detect trends in abundance under the range contraction scenario (power = 0.82).

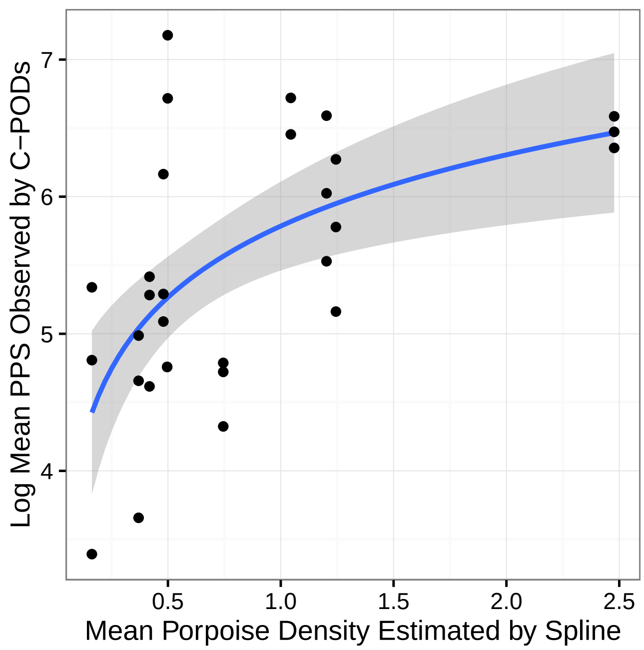

Figure 1.5: Estimated mean harbor porpoise density at the location of each C-POD (km^{-}2; x-axis) and mean observed acoustic detection rate in each year (PPS; y-axis). The blue line is the modeled relationship between mean density and mean acoustic detection rate and the gray shading indicates the 95% confidence interval of the model fit.

Table 1.3: Power to detect a -25% decline over a 10 yr period with 75 passive acoustic sensors using three different sampling designs (random sampling, stratified sampling limited to water depths 0-100 m deep, and sampling proportional to porpoise density) under two different decline scenarios (uniform decline across the entire range and range contraction to preferred habitat).

Design	**Power**	
	Uniform	Range Contraction
Random	0.86	0.67
Stratified	0.87	0.71
Scaled	0.87	0.82

1.4 Discussion

- Issues with statistical power

-

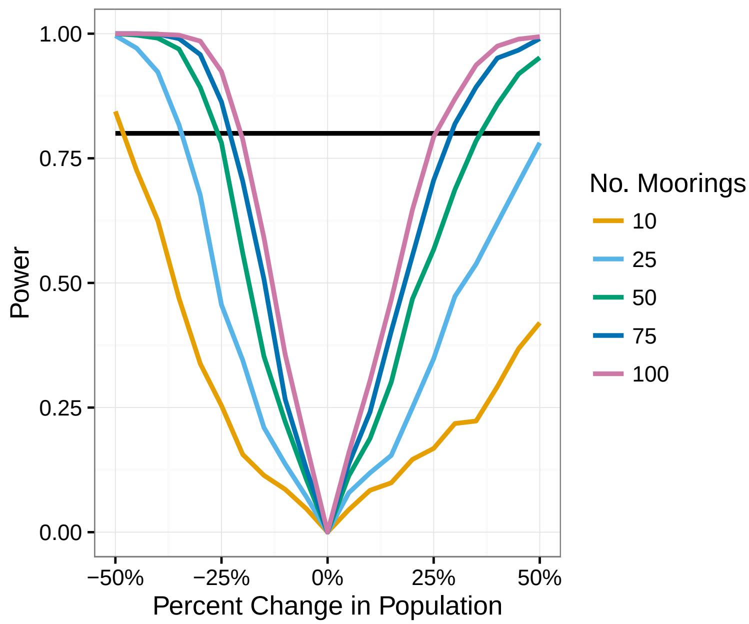

Figure 1.6: Statistical power (y-axis) to detect simulated changes in the Monterey Bay population of harbor porpoise (x-axis) using 10-100 moorings (colored lines). The black line indicates typically accepted power of 0.8, which represents an 80% probability of detecting a change in the population when a change does occur.

Acknowledgements

References

Becker, E., Forney, K., Ferguson, M., Foley, D., Smith, R., Barlow, J., and Redfern, J. (2010). Comparing California Current cetacean–habitat models developed using in situ and remotely sensed sea surface temperature data. *Marine Ecology Progress Series*, 413:163–183.

Calambokidis, J. and Barlow, J. (1991). Chlorinated hydrocarbon concentrations and their use for describing population discreteness in harbor porpoises from Washington, Oregon, and California. In *Marine mammal strandings in the United States: proceedings of the Second Marine Mammal Stranding Workshop, Miami, Florida, December 3-5, 1987*, page 101. US Dept. of Commerce, National Oceanic and Atmoospheric Administration, National Marine Fisheries Service.

Carretta, J., Oleson, E. M., Weller, D. W., Lang, A. R., Forney, K., Baker, J., Muto, M. M., Hanson, B., Orr, A. J., Huber, H., Lowry, M. S., Barlow, J., Moore, J. E., Lynch, D., Carswell, L., and Brownell Jr, R. L. (2015). U.S. Pacific Marine Mammal Stock Assessments: 2014. Technical Report NOAA-TM-NMFS-SWFSC-549.

Chivers, S. J., Dizon, A. E., Gearin, P. J., and Robertson, K. M. (2002). Small-scale population structure of eastern North Pacific harbour porpoises *(Phocoena phocoena)* indicated by molecular genetic analyses. *Journal of Cetacean Research and Management*, 4(2):111–122.

Cotter, M. P., Maldini, D., and Jefferson, T. A. (2012). "Porpicide" in California: Killing of harbor porpoises *(Phocoena phocoena)* by coastal bottlenose dolphins *(Tursiops truncatus)*. *Marine Mammal Science*, 28(1):E1–E15.

Forney, K., Hanan, D. A., and Barlow, J. (1991). Detecting Trends in Harbor Porpoise

Abundance from Aerial Surveys Using Analysis of Covariance. *Fishery Bulletin*, 89(3):1–11.

Forney, K. A., Carretta, J. V., and Benson, S. R. (2014). Preliminary estimates of harbor porpoise abundance in Pacific Coast waters of California, Oregon, and Washington, 2007-2012. Technical Report NOAA -TM-NMFS-SWFSC-537.

Gilles, A., Viquerat, S., Becker, E. A., and Forney, K. (2016). Seasonal habitat-based density models for a marine top predator, the harbor porpoise, in a dynamic environment. *Ecosphere*, 7(6):1–22.

Hastie, T. J. and Tibshirani, R. J. (1990). Generalized additive models.

Jacobson, E. K., Forney, K., and Barlow, J. (2017). Using paired visual and passive acoustic surveys to estimate passive acoustic detection parameters for harbor porpoise abundance estimates. *The Journal of the Acoustical . . . .*

Jacobson, E. K., Forney, K., and Harvey, J. T. (2016). EVALUATION OF A PASSIVE ACOUSTIC MONITORING NETWORK FOR HARBOR PORPOISE TO ASSESS MARINE RENEWABLE PROJECTS IN CALIFORNIA. pages 1–33.

Jacobson, E. K., Forney, K. A., and Harvey, J. T. (2014). Acoustic evidence that harbor porpoises (Phocoena phocoena) avoid bottlenose dolphins (Tursiops truncatus). *Marine Mammal Science*, 31(1):386–397.

Jefferson, T., Curry, B., and Black, N. (1994). Harbor porpoise mortality in the Monterey Bay halibut gillnet fishery, 1989. *Rep. Int. Whaling Comm. Spec*, (15):445–448.

Legorreta, A. J. (2016). Passive acoustic monitoring of the decline of Mexico’s critically endangered vaquita. *Conservation Biology*, 31(1):183–191.

Marques, T. A., Munger, L., Thomas, L., Wiggins, S., and Hildebrand, J. A. (2011). Estimating North Pacific right whale Eubalaena japonica density using passive acoustic cue counting. *Endangered Species Research*, 13(3):163–172.

Marques, T. A., Thomas, L., Ward, J., DiMarzio, N., and Tyack, P. L. (2009). Estimating cetacean population density using fixed passive acoustic sensors: An example with Blainville?s beaked whales. *The Journal of the Acoustical Society of America*, 125(4):1982–1994.

Miller, D. L. (2016). *Distance: Distance Sampling Detection Function and Abundance Estimation*, 0.9.6 edition.

Taylor, B. L., Martinez, M., Gerrodette, T., Barlow, J., and Hrovat, Y. N. (2006). Lessons from monitoring trends in abundance of marine mammals. *Marine Mammal Science*, 23(1):157–175.

Tregenza, N. (2012). *CPOD.exe: a guide for users*.

W ard, J. A., Thomas, L., Jarvis, S., DiMarzio, N., Moretti, D., Marques, T. A., Dunn, C., C laridge, D., Hartvig, E., and Tyack, P. (2012). Passive acoustic density estimation of sperm whales in the Tongue of the Ocean, Bahamas. *Marine Mammal Science*, 28(4):E444–E455.

Wilkin, S. M., Cordaro, J., and Gulland, F. (2012). An Unusual Mortality Event of Harbor Porpoises (Phocoena phocoena) Off Central California: Increase in Blunt Trauma Rather Than an Epizootic. *Aquatic Mammals*, 38(3):301–310.

Wood, S. and Wood, M. S. (2017). Package 'mgcv'. *R package version*.

Wood, S. N. (2003). Thin plate regression splines. *Journal of the Royal Statistical Society: Series B (Statistical Methodology)*, 65(1):95–114.