Chapter 1

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

Abstract

Designing passive acoustic surveys for long-term monitoring of cetacean populations is now feasible; however, there is no framework for optimizing passive acoustic surveys to maximize their precision and the resulting statistical power to detect trends in abundance. In this study, we used simulation to explore alternative fixed passive acoustic survey design for detecting trends in the abundance of harbor porpoise in Monterey Bay, CA. Using aerial survey and passive acoustic data collected in Monterey Bay, we simulated datasets for hypothetical passive acoustic monitoring network designs and changes in harbor porpoise abundance. We considered the number and placement of sensors and scenarios of overall population decline as well as range contraction to a core habitat area. When the population declined uniformly over its geographic range, the placement of sensors did not impact power to detect a trend in abundance. However, scenarios where animals contracted to core, high-quality habitat resulted in lower power to detect trends in abundance. Our simulation study demonstrated that the effectiveness of PAM varies greatly depending on both survey design (number and placement of sensors) and manifestation of the change in the population (extent and spatial pattern of increase or decrease). When planning passive acoustic surveys, it will be important to consider different possible population responses so that power can be accurately assessed and an appropriate number and design of sensors employed. While this simulation study was specific to the Monterey Bay population of harbor porpoise and employed a specific type of passive acoustic sensor, our results are generalizable to other regions, species, and types of passive acoustic surveys.

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 removal or incidental harm 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. For marine mammals, these methods have traditionally relied on visual observations of the species of interest. For cryptic or visually inaccessible taxa, like many cetaceans, visual surveys often produce imprecise estimates of animal abundance. However, these hard-to-see species produce sounds that are comparatively easy to hear and therefore can be used as proxies for the animals themselves (Zimmer, 2009). 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 of cetaceans (Marques et al., 2013). For many cetacean 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 changes in populations over time.

Here, we focus on cetaceans, which are particularly difficult to monitor using visual methods because they spend much of their time below the surface of the water, where they are not observable. High natural variability in cetacean distributions combined with the high sampling variance associated with typical visual surveys (due to low effort, inclement conditions, missed groups, and group size estimation error) lead to low precision in visual abundance estimates and, therefore, low statistical power to detect changes in abundance. In the U.S., given the current frequency and extent of cetacean surveys, 50% declines over a 15-year period would be undetectable in 90% of beaked whale populations and 78% of dolphin and porpoise populations (Taylor et al., 2007). 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 odontocete cetaceans which frequently produce echolocation clicks, whistles, and other vocalizations that can be detected at distances that are similar to or greater than visual detection distances. Fixed PAM networks in particular are a relatively inexpensive monitoring technology and can be deployed for months at a time. Compared to visual 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;* Ward et al., 2012) in the Bahamas, Baltic Sea harbor porpoise *Phocoena phocoena* and North Pacific right whale (*Eubalaena japonica;* Marques et al., 2011), and to document the decline of the critically endangered vaquita (*Phocoena sinus;* Jaramillo-Legorreta et al., 2017) 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 (Zimmer, 2009). 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 (e.g., Harris et al., 2013) or relied on general design principles from the visual survey literature to guide data collection (e.g., Jaramillo-Legorreta et al., 2017). 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 to evaluate the statistical power of potential passive acoustic network designs to detect trends in abundance. This population occupies a nearshore area of 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 bycatch in set gillnet fisheries for halibut that operated in the mid-20th century (Jefferson et al., 1994; Forney et al., 2014) and earlier gillnet fisheries for white seabass (Barlow and Hanan, 1995). There have also been some deaths over the past decade due to bottlenose dolphin *(Tursiops truncatus)* attacks on harbor porpoise in this region (Cotter et al., 2012; Wilkin et al., 2012; Jacobson et al., 2014). 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 2000, line-transect aerial surveys targeting leatherback sea turtles have been conducted in the region using the same survey methodology, thereby also collecting data on cetaceans including harbor porpoises.

In the present study, we used aerial survey data collected in Monterey Bay to estimate the mean density of harbor porpoise across the region. Then, we related these underlying mean porpoise densities to passive acoustic detection rates observed over a three-year period. Using this paired dataset, we simulated hypothetical changes in harbor porpoise abundance and corresponding changes in passive acoustic detection rates. Through these simulations we explored alternative 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 Aerial survey data collection and analysis

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 leatherback sea turtles between 2000 and 2013 (Fig. 1.2, left panel; Table 1.2). 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 that was directly connected to a hand-held Global Positioning System.

Aerial survey line-transect data were read from tab-delimited files into R (v. 3.2.2, **?**) for processing. All data were converted from geographic coordinates (latitude and longitude) into a custom two-dimensional projection (X and Y km from the centroid of the study area) using the spherical law of cosines to ensure uniformity of calculated distances (Miller et al., 2013). 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 R 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 missing 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 (GAM; Hastie and Tibshirani, 1990) 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).

1.2.2 Passive acoustic data collection and analysis

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).

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. Dall's porpoise *Phocoenoides dalli* are also found along the U.S. West Coast and produce similar NBHF echolocation signals; however, Dall's porpoise are typically found in deep water (100s to 1000s of m deep; Forney, 2000) and no Dall's porpoise were seen in our study area during aerial surveys conducted in 2011 or 2013. 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, PPS was calculated as the total number of porpoise positive seconds between September 1st and December 1st of each year (a 91 day period).

1.2.3 Relating passive acoustic and aerial survey data

To simulate changes in passive acoustic detection rates resulting from changes in harbor porpoise abundance, we first needed to describe the relationship between the density of harbor porpoise (as estimated using aerial survey data) to observed passive acoustic detection rates. 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. The intercept α_0 and covariate β_1 describe the relationship between the density of harbor porpoise and the passive acoustic detection rate.

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

We included a covariate for year (β_2) to account for potential differences in the actual passive acoustic detection rates between years (e.g., due to continuing population recovery from past impacts). By explicitly describing between-year variance in the model formulation, we were able to more precisely estimate the relationship between the density of harbor porpoise and the passive acoustic detection rate. This allowed us to simulate only the hypothetical changes in density that we wanted to investigate. The error term ε describes unexplained variance in the relationship between harbor porpoise density and passive acoustic detection rate.

1.2.4 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-yr periods. Our simulation explored three possible survey designs and two possible behavioral responses to population change, resulting in six hypothetical scenarios. The base case (random survey design and uniform change in the population) was simulated 1,000 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 1,000 simulations in which a change in the population was detected with the correct sign (i.e, positive or negative). All combinations of survey design, response to disturbance, change in abundance, and number of passive acoustic sensors (see Table 1.1) were repeated 1,000 times.

Three possible survey design strategies were investigated. In the *random* sampling scenario, sensors were placed randomly throughout the study area in water 0 to 150 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 allocated to shallow (0-40 m deep) and deep (40-150 m deep) strata in proportion to harbor porpoise density in the two strata (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 refer to as a *scaled* sampling design. For this third design, we rescaled 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, but the distribution of densities was not altered. Then, we iteratively selected points at random and conducted a binomial trial where the probability of success was equal to the rescaled 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

Table 1.1: Description of variables used in the simulation.

Variable	**Description**	**Values**
Design	Controls simulated placement of sensors	Random, Stratified, or Scaled
Response	Controls how animals respond to change	Uniform or Range Contraction
Change	Change in the population over a 10-yr period	-50% to +50%
No. Sensors	Number of sensors deployed each year	5 to 100

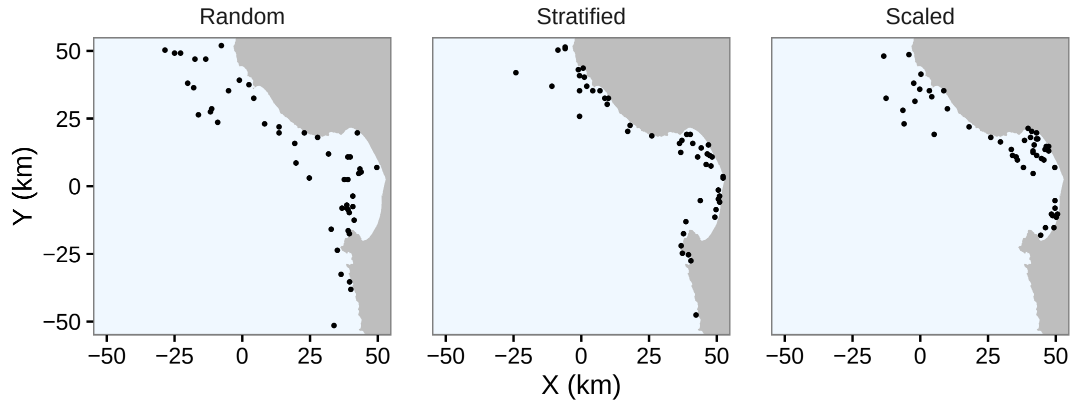

Figure 1.1: Example simulated placement of 75 sensors in the Monterey Bay study area using random (left panel), stratified (center panel), and scaled (right panel) sampling design strategies in water 0-150 m deep.

distribution of harbor porpoise, with more sensors in high-density areas and fewer sensors in low-density areas. For each of the three possible survey designs, we simulated designs with 5-100 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 hypothesized that animals may contract their distribution to the highest-quality habitat as the population declined (Lomolino and Channell, 1995). 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 severe decline than low-density, low-quality habitat areas.

The simulated rate of change was divided into linear, incremental change rates r_y over y = 10 yr 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 of 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 normal distribution with mean and SE of the estimated $\hat{D}$ at that spatial location. Coefficients for the effect of density on detection rate 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). 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.

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

This process was repeated for each of the 1,000 simulated datasets and statistical power was calculated as the proportion of those 1,000 datasets in which a change (in the correct direction, positive or negative) was statistically significant ($\alpha < 0.05$). We repeated the simulation methods for each possible combination of survey design, response to change, number of sensors, and change in the population.

1.3 Results

1.3.1 Aerial survey data collected

Between 2000 and 2013, 31,722 km of aerial survey effort in good weather conditions (Beaufort sea states 0-3) was conducted in the Monterey Bay region (Fig. 1.2, left panel), resulting in 2,715 sightings of harbor porpoise groups (Table 1.2). More sightings occurred

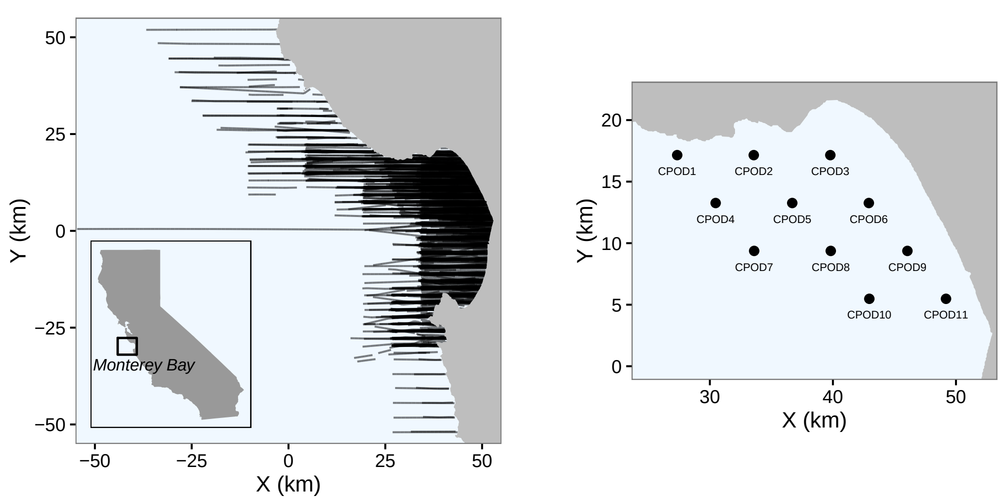

Figure 1.2: Map of completed aerial survey tracklines (left panel, black lines) and passive acoustic instrument deployments (right panel, black circles) in Monterey Bay, CA.

Table 1.2: 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

in shallow (0-40 m) water depths than in deep (40-150 m) depths (Fig. 1.4, lower panel). Less than 2% of sightings occurred in water 150-1000 m deep. The quantity of aerial survey effort varied among years (Table 1.2) 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). 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 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. 1.5).

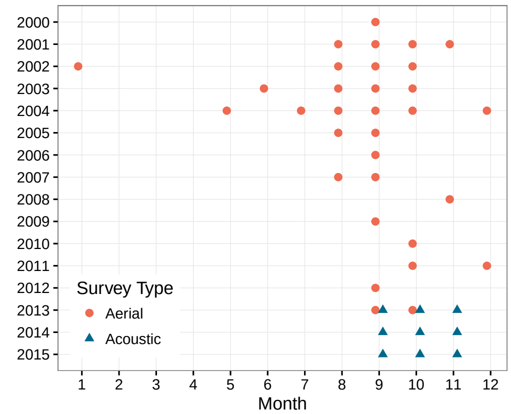

Figure 1.3: Visual representation of aerial survey and passive acoustic data collection in the Monterey Bay region in different months (x-axis) between 2000 and 2015 (y-axis). Circles indicate month/year combinations during which aerial surveys were conducted, while triangles indicated month/year combinations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

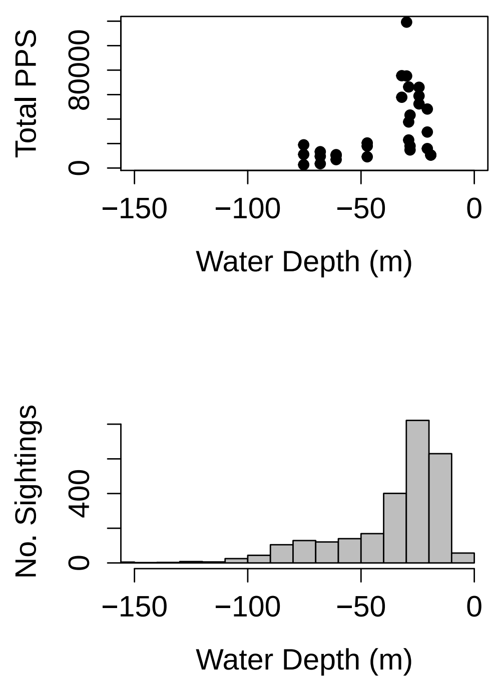

Figure 1.4: Water depth (0-150 m, x-axis) in Monterey Bay vs. total PPS observed by C-PODs (top panel) and number of visual harbor porpoise sightings (bottom panel).

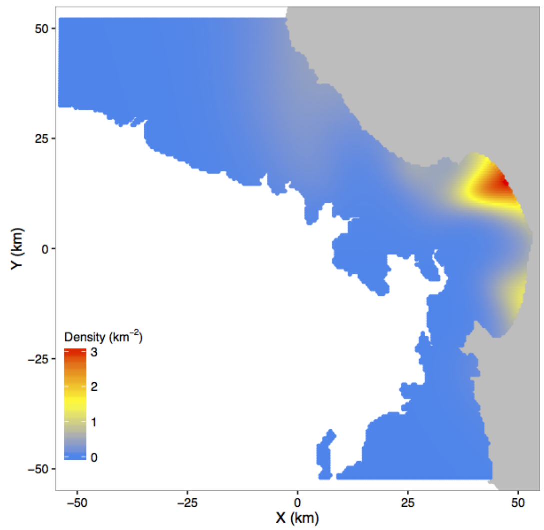

Figure 1.5: Harbor porpoise density (km^{-}2) in water 0-1000 m deep estimated using a two-dimensional spline on harbor porpoise density calculated using aerial survey observations. Note that densities are not corrected for $g(0)$.

1.3.2 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 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 data loss rate of 9% over the three-year study. Passive acoustic detection rates varied by two orders of magnitude among instruments, with recorded values as low as 30 PPS per day and as high as 1,320 PPS per day, and total PPS over the course of the season as low as 2,707 and as high as 119,209 (Table 1.3). 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; Table 1.3; Fig. 1.2; Fig. 1.4).

Table 1.3: Passive acoustic detection rates (total PPS over 91 days) 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	18,057	14,771	43,280
C-POD 2	10,601	NA	10,610
C-POD 3	15,879	48,206	29,426
C-POD 4	20,481	9,201	17,919
C-POD 5	NA	75,473	57,840
C-POD 6	65,991	58,923	52,403
C-POD 7	9,585	3,528	13,331
C-POD 8	6,872	10,923	10,228
C-POD 9	22,925	66,293	37,639
C-POD 10	2,707	11,143	18,959
C-POD 11	NA	119,209	75,229

1.3.3 Relationship between 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 ($p < 0.001$; Fig. 1.6). A GLM with a year term included performed better (AIC = 71) than a GLM with only harbor porpoise density as a predictor (AIC = 74). The pseudo-R^2 of this model was 0.44. The year term was also significant ($p < 0.05$) with a positive covariate indicating a possible increase in the population or movement of animals into the study area over the three-year passive acoustic monitoring period.

1.3.4 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. 1.7). With 100 sensors, a -20% change in the population would be detectable 80% of the time, and a -30% change would be detectable 100% of the time.

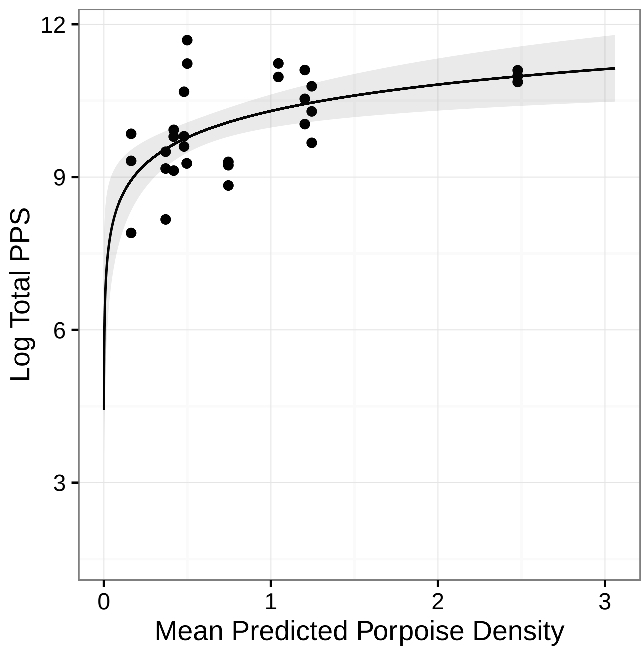

Figure 1.6: Black dots indicate estimated mean harbor porpoise density at the location of each C-POD (km^{-2}; x-axis) and mean observed acoustic detection rate in each year (PPS; y-axis). The black line is the modeled relationship between mean density and mean acoustic detection rate (pooled across all years) and the gray shading indicates the 95% confidence interval of the model fit.

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. However, scenarios where animals contracted to core, high-quality habitat resulted in lower power to detect trends in abundance. For example, when 75 sensors were used and the population declined by 25% over the 10-yr period (Table 1.4), random placement of sensors resulted in the lowest power when animals responded with range contraction (power = 0.72); using a stratified design improved power (power = 0.79), 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 = 0.83).

When few (<25) sensors were used in a simulation where the population decreased

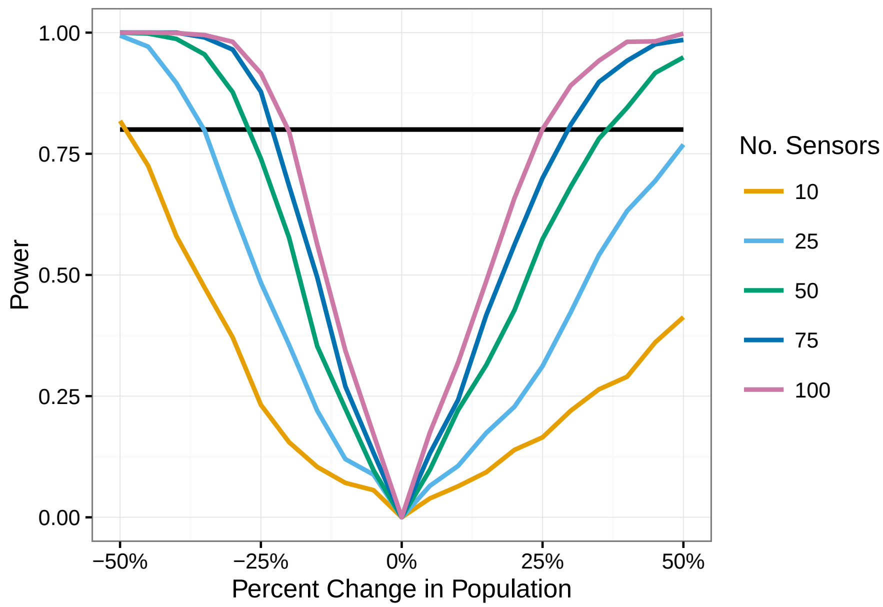

Figure 1.7: Statistical power (y-axis) to detect simulated changes in the Monterey Bay population of harbor porpoise (x-axis) using 10-100 sensors (colored lines) placed randomly in water 0-150 m deep. The black line indicates conventionally accepted power of 0.8, which represents an 80% probability of detecting a change in the population when a change does occur.

Table 1.4: Power to detect a -25% decline over a 10-yr period with 75 passive acoustic sensors using three different sampling designs (random, stratified, and scaled) under two different decline scenarios (uniform decline across the entire range and range contraction to preferred habitat).

Design	**Power**	
	Uniform	Range Contraction
Random	0.87	0.72
Stratified	0.87	0.79
Scaled	0.87	0.83

by 25% and animals contracted to core habitat, design impacted power very little (Fig. 1.8). However, with many (> 75) sensors, the stratified and scaled designs performed much better (power > 0.8 with 75+ sensors) than the random design, which achieved power = 0.75 with 100 sensors. Similarly, when the simulated change in the population was relatively small ($<$ 15%; Fig. 1.9) and 75 sensors were used, the three designs produced similarly low power (< 0.5). When the simulated change in the population was greater than 15%, the scaled and stratified designs clearly outperformed the random design; however, with catastrophic changes in the population (>50%) it appears that with 75 sensors all designs would have power approaching 1.

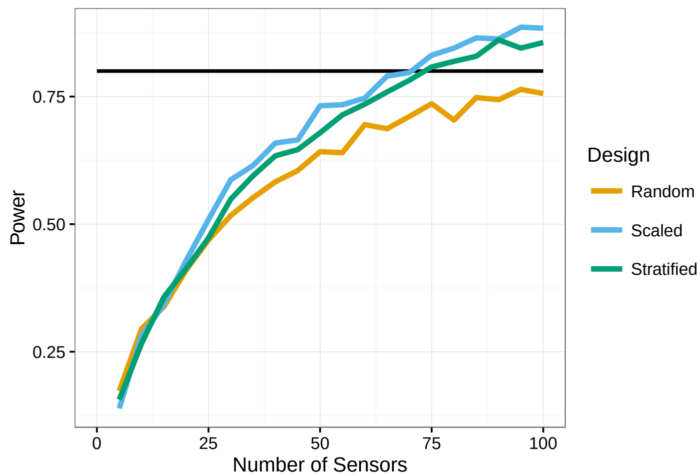

Figure 1.8: Power (y-axis) when the population decreased by 25% and animals contracted to core habitat with varying number of sensors (x-axis) and placement of sensors (Design, colored lines). The black line indicates conventionally acceptable power of 0.8.

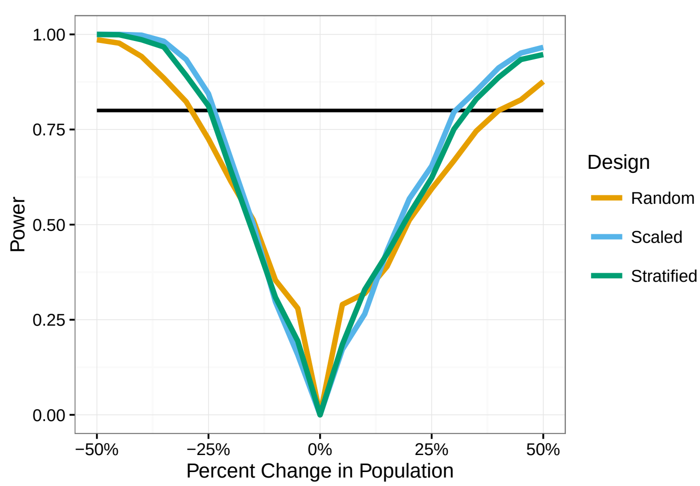

Figure 1.9: Power (y-axis) to detect changes in the harbor porpoise population varying from -50% to +50% (x-axis) using 75 sensors when the simulated population contracted its range to core habitat with three different designs (colored lines). The black line indicates conventionally acceptable power of 0.8.

1.4 Discussion

Our simulation study demonstrated that the effectiveness of PAM varies greatly depending on both survey design (number and placement of sensors) and manifestation of the change in the population (extent and spatial pattern of increase or decrease). When planning passive acoustic surveys, it will be important to consider different possible population responses so that power can be accurately assessed and an appropriate number and design of sensors employed. While this simulation study was specific to the Monterey Bay population of harbor porpoise and employed a specific type of passive acoustic sensor, our results are generalizable to other regions, species, and types of passive acoustic surveys.

In our study, when changes in the population were assumed to occur uniformly over its range, the design of the passive acoustic survey did not affect power (Table 1.4). This is because in Monterey Bay, within water 0-150 m deep, mean harbor porpoise density is never estimated to be zero. Therefore, simulated passive acoustic detection rates were rarely zero, and changes in the population were more easily detected. When animal density is very low, or when range extent is unknown, we would expect to see many more sensors with zero detections in the lowest density areas, and therefore could achieve higher statistical power using stratified or scaled designs rather than random placement of sensors. For computational efficiency, spacing between sensors was not considered in any of our three sampling designs. In practice, a uniform grid with a random starting point would minimize the correlation between sensors and effectively increase sample size (CITE).

To achieve statistical power > 0.8 to detect a 25% decline in the Monterey Bay harbor porpoise population would require at least 75 passive acoustic sensors to be deployed annually over the 10-yr period (Table 1.4; Fig. 1.7). Based on reported precision of aerial surveys (Forney et al., 2014), to detect the same change in the population using aerial surveys would require approximately 20 replicate surveys per year. To put that in perspective, current aerial survey effort is at the level of one replicate every four years. Considerably more resources would be required to implement this level of monitoring for the Monterey Bay harbor porpoise population, which may not be warranted given the current lack of threats to the population. In cases where impacts from anthropogenic activities are expected, PAM and aerial surveys are both capable of achieving acceptable power to detect trends in abundance at similar cost; however, PAM may be preferable due to safety concerns about aerial surveys.

The Monterey Bay population of harbor porpoise is unusually well-studied; we would not typically expect to have such detailed spatial information on the distribution and density of a cetacean population. The scaled design of passive acoustic surveys for cetaceans is not likely to be widely practicable. However, based on our results, the stratified design performed similarly to the scaled design and required less information about distribution and density to implement (Fig. 1.8, 1.9). Our simulation of range contraction to core habitat also relied on detailed information on distribution and abundance of harbor porpoise in the study area; however, literature suggests that this pattern of range collapse as a population declines is persistent across mammalian species (Lomolino and Channell, 1995) and therefore could potentially be simulated in a more generic sense when detailed information about a population of interest is not available. In fact, the R package DSsim (Marshall, 2016), which simulates distance sampling surveys, allows for the user to create density ”hotspots” in the study area; this method could be used in simulations of passive acoustic surveys where the spatial distribution of animals is less well-known.

Our methods evaluated simulated data using traditional null hypothesis significance testing (NHST) and associated decision rules (Gerrodette, 1987). This framework minimizes the probability of incorrectly detecting a change when the population is stable at the expense of increasing the probability of failing to recognize a true change, and the appropriateness of this framework for conservation and management has been questioned (Taylor and Gerrodette, 2017). In future, a Bayesian approach may be more appropriate for quantifying trends in animal populations over time. Several recent studies have used a Bayesian approach to trend analysis for cetacean populations (Moore and Barlow, 2013, 2014). Bayesian trend analysis provides the range and likelihood of trend parameters consistent with the data, which are more practical and intuitive results than the rejection of the null hypothesis in NHST methods (Wade, 2000). For example, this approach can determine the probability that a population is declining. Additionally, a Bayesian approach can be used to compare and optimize the statistical power of different survey designs, where power is defined as the probability of achieving the goal of the study (Kruschke, 2013).

Several ancillary pieces of information are required to estimate animal abundance from passive acoustic data, including the rate at which the species of interest vocalizes and the distances at which those vocalizations can be detected by a passive acoustic sensor (Marques et al., 2013). The certainty with which these parameters are known affects the precision of the resulting abundance estimate, and therefore the power of PAM to detect trends in abundance. Future simulations could explore how expected power can be gained by reducing, e.g., uncertainty in the relationship between animal density and passive acoustic detection rates.

Finally, the scenarios of population change explored in this study were extremely generic. In future, it would be worthwhile to work with managers to investigate more plausible scenarios of population impacts, and to consider different possible goals and practical decision criteria relevant to management needs.

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