# Chapter 1

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

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# Abstract

* 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. For marine mammals these methods traditionally 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 because …. 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 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 72% of baleen whale populations, 90% of beaked whale populations, and 78% of dolphin and porpoise populations (Taylor et al. 2007). In that study, 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.

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 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 Blainville’s beaked whales (*Mesoplodon densirostris;* [Marques et al.](#_bookmark25), [2009)](#_bookmark25) and sperm whales (*Physeter macrocephalus;* [Ward et al.](#_bookmark29), [2012)](#_bookmark29) in the Bahamas, Baltic Sea harbor porpoise (*Phocoena phocoena*) and North Pacific right whale (*Eubalaena japonica;* [Marques et al.](#_bookmark24), [2011](#_bookmark24)), and to document the decline of the critically endangered vaquita (*Phocoena sinus;* [Jaramillo-Legorreta](#_bookmark23), [2016)](#_bookmark23) 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 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 km2 and consists of approximately 3,700 individuals ([Forney et al.](#_bookmark16),[2014](#_bookmark16)). This population is distinct from other harbor porpoise populations along the U.S. West Coast ([Calambokidis and Barlow](#_bookmark11),[1991;](#_bookmark11)Chi[vers et al.,](#_bookmark13)2002[).](#_bookmark13) While fishery mortality is currently insignificant for this population ([Carretta et al.](#_bookmark12),[2015)](#_bookmark12) the population is likely still recovering from bycatch in a set gillnet fisheries for halibut that operated in the mid-20th century ([Jefferson et al.](#_bookmark22),[1994;](#_bookmark22)F[orney](#_bookmark16) [et al.](#_bookmark16),[2014](#_bookmark16)) and earlier gillnet fisheries for white seabass (Barlow and Hanan 1995). There have also been some harbor porpoise deaths over the past decade due to bottlenose dolphin *(Tursiops truncatus)* attacks on harbor porpoise in this region ([Cotter et al.](#_bookmark14),[2012;](#_bookmark14) [Jacobson et al.](#_bookmark21),[2014;](#_bookmark21)W[ilkin et al.,](#_bookmark30)2012[).](#_bookmark30) The Monterey Bay population of harbor porpoise has been studied using line-transect aerial surveys since the late 1980s ([Forney et al.](#_bookmark15),[1991](#_bookmark15)). Additionally, since 2000, line-transect aerial surveys targeting 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 alternative fixed passive acoustic survey designs for detecting trends in the abundance of the Monterey Bay population of harbor porpoise.

# Methods

* + 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.](#_bookmark15),[1991](#_bookmark15)). 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,](#_bookmark3) left panel; Table1.1[).](#_bookmark4) 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,](#_bookmark3) 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 km2. 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](#_bookmark3), right panel). Further details of passive acoustic instrument deployments can be found in [Jacobson et al.](#_bookmark20)([2016)](#_bookmark20) and [Jacobson et al.(](#_bookmark19)2017[).](#_bookmark19)

# Data analysis

**Aerial survey data processing**

Aerial survey line-transect 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)](#_bookmark10) and [Jacobson et al.(2017),](#_bookmark19) 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)](#_bookmark26) 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),](#_bookmark19) 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 ([Hastie and Tibshirani](#_bookmark18),[1990,](#_bookmark18) GAM;) im- plemented in the package mgcv (v. 1.8-12;W[ood and Wood,](#_bookmark31)2017[)](#_bookmark31) 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](#_bookmark32),[2003)](#_bookmark32) 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;T[regenza,2012)](#_bookmark28) to detect harbor porpoise 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).

Follo[wing Jacobson et al.(2017),](#_bookmark19) 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 for each of the 91 days between September 1st and December 1st.

# Relating passive acoustic and aerial survey data

We used a generalized linear model (GLM; Eq.[1.1)](#_bookmark0) 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 (*D*ˆ*n*) as estimated by the spatial smooth of aerial survey observations (described above). A covariate for year, *Y*, was included to account for potential changes in passive acoustic detection rates

over the 3-yr monitoring period (e.g., due to continuing population recovery from past impacts).

*log*(*PPSn,y*) *∼* α0 + β1*log*(*D*ˆ*n*) + β2*Yy* + ε (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)](#_bookmark0) 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 population change, 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 population change, 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,](#_bookmark1) 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,](#_bookmark1) 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.For this third design, 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

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Y (km)

−40

−60 −30 0 30 60 −60 −30 0 30 60 −60 −30 0 30 60

X (km)

**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 change rates, *ry,* over *y*

= 10 years such that the product of the *ry* 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 *ry* value was calculated so that *R* = *y ry*. Finally, the values of *ry* 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).

∏*i*=1

For each simulation run, a single intercept term *a* was drawn from a normal distribu- tion with a mean and standard error (SE) from the GLM model estimate α0. For each of *n* simulated sensors, a spatial location was drawn randomly according to the survey design and a simulated underlying density *dn* was drawn from a lognormal distribution with mean and SE of the estimated *D*ˆ 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 β1. As described above, a cumulative rate of change *y* (1 *− ry*) 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](#_bookmark0)), we added an error term *En,y* drawn from a normal distribution with a mean of 0 and a SD equal to the residual SD of the GLM.

∏*i*=1

*y*

*ppsn,y* = *e*(*a*0+*b*1*,nlog*(*dn*)+*En,y*) ∏(1 *− ry*) (1.2)

*i*=1

Once data were generated for *n* moorings and *y* years, each simulated dataset was evaluated using a mixed effects model [(Eq.1.3)](#_bookmark2) with *log*(*ppsn,y*) modeled as a function of year (fixed effect) and sensor (random effect).

*log*(*ppsn,y*) *∼* λ*y* + γ*n* + ε (1.3) This model differs from the GLM in Eq.1.1in that the underlying mean density

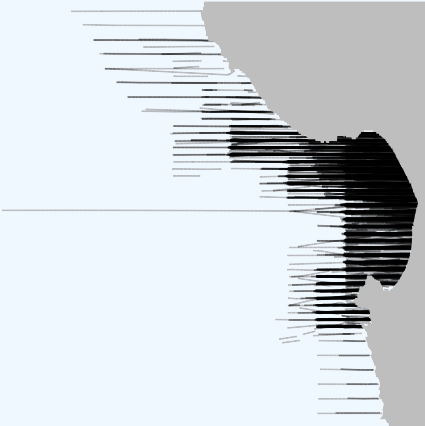
is assumed to be unknown, so a random effect was used to account for sensor-specific differences in detection rates. For each simulated dataset, if the year term in this mixed effects model was significant and the sign of the covariate λ matched the sign of the simulated change in the population, that 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 (in the correct direction) was statistically significant (α = 0.05). This was repeated for each combination of survey design, response to disturbance, number of sensors, and change in the population.

# Results

* + 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

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*Monterey Bay*

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CPOD1 CPOD2 CPOD3

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CPOD4 CPOD5

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CPOD6

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CPOD7 CPOD8 CPOD9

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CPOD10 CPOD11

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15

0

Y (km)

Y (km)

10

−25

−50

−50 −25 0 25 50

X (km)

5

0

30 40 50

X (km)

**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 (sea states 0-3) was conducted in the Monterey Bay region [(Fig.1.2,](#_bookmark3) left panel), resulting in 2,715 sightings of harbor porpoise groups (Table[1.1](#_bookmark4)). The quantity of aerial survey effort varied among years (Table[1.1)](#_bookmark4) and months (Fig.1.3[),](#_bookmark5) with most effort occurring in August, September, and October. Most aerial survey effort occurred within Monterey Bay itself (Fig.[1.2,](#_bookmark3) left panel).

# 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;](#_bookmark6) Fig.1.2[).](#_bookmark3)

# 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 km2. The GAM explained 24.7% of deviance in the aerial survey data, which is comparable to other cetacean-habitat models [(e.g.,Gilles](#_bookmark17) [et al.](#_bookmark17),[2016](#_bookmark17)). The smooth term on X and Y from the centroid of the study region was

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| --- | --- | --- | --- |
| 2000 |  | ● |  |
| 2001 |  | ● ● ● ● |  |
| 2002 | ● | ● ● ● |  |
| 2003 |  | ● ● ● ● |  |
| 2004 |  | ● ● ● ● ● ● |  |
| 2005 |  | ● ● |  |
| 2006 |  | ● |  |
| 2007 |  | ● ● |  |
| 2008 |  | ● |  |
| 2009 |  | ● |  |
| 2010 |  | ● |  |
| 2011 |  | ● ● |  |
| 2012 | Survey Type | ● |  |
| 2013 | * Aerial | ● ● |  |
| 2014  2015 | Acoustic |  |  |

1 2 3 4 5 6 7 8 9 10 11 12

Month

**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.

# PPS

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Instrument** |  | | | |
|  | 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 |  |

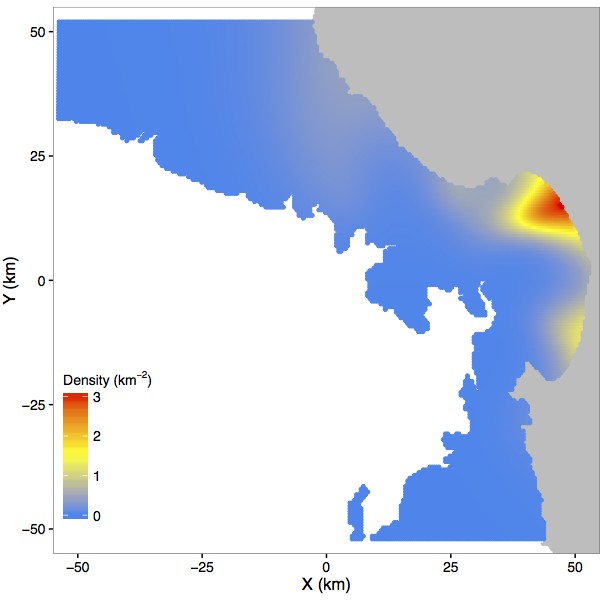
significant (p *<* 0.001). The GAM predicted highest densities of harbor porpoise in the northern part of Monterey Bay with moderate densities predicted in nearshore southern Monterey Bay [(Fig.1.4](#_bookmark7)).

# Relating passive acoustic and aerial survey data

Underlying mean density as calculated using aerial survey observations was a sig- nificant 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](#_bookmark9)). With 100 sensors, a -20% change in the population over 10 years 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](#_bookmark8)). 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).

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Log Mean PPS Observed by C−PODs

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0.5 1.0 1.5 2.0 2.5

Mean Porpoise Density Estimated by Spline

**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

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0.75

No. Moorings

10

25

Power

0.50 50

75

100

0.25

0.00

−50% −25% 0% 25% 50%

Percent Change in Population

**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

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