SC/66b/WW/09

# A Comparison of Cetacean Abundance Estimates and Trends Derived from Opportunistic and Systematic Survey Methods

Jens J. Currie, Stephanie H. Stack, Gregory D. Kaufman

INTERNATIONAL WHALING COMMISSION

# A Comparison of Cetacean Abundance Estimates and Trends Derived from Opportunistic and Systematic Survey Methods

Jens J. Currie, Stephanie H. Stack, Gregory D. Kaufman
*Pacific Whale Foundation, 300 Ma`alaea Road, Suite 211, Wailuku, HI, USA 96793*
*Contact email: research@pacificwhale.org*

## Abstract

Spatial density surface models were used to estimate and compare humpback whale abundance and density estimates collected using systematic and opportunistic survey designs within the four-island region of Maui, Hawai'i. Data were collected simultaneously on two separate platforms utilizing opportunistic and systematic sampling methods over two years. These estimates were then compared to each other as well as previous estimates of Hawai'i's four island region humpback whale population, to determine the efficacy of using platforms of opportunity for estimating annual humpback whale abundance and trends. Monthly abundance estimates using spatial density surface models showed similar results for data collected opportunistically and systematically. To our knowledge, this is the first use of spatial density surface modelling, which bases abundance estimates on the observed relationship between animals and spatial covariates, to estimate abundance of humpback whales of the four-island region of Maui.

## Introduction

The North Pacific humpback whale population spends the boreal summer months along the Pacific Rim from the Western United States to Russia and in the winter months migrates to three main geographical isolated areas: Mexico, Hawai'i, and Japan (Calambokidis *et al*., 2001). The most recent estimate of the North Pacific humpback whale population is 21,808 individuals with an annual growth rate of 5.5-6.0%. Of these 21,808 individuals approximately 57% migrate annually to Hawai'i's breeding and birthing grounds (Calambokidis *et al*. 2008).

To effectively determine abundance estimates, analyses must incorporate both the probability that an individual produces a cue during the survey time (availability bias) and that the individual will be detected (perception bias). Comparison of humpback populations across space or time requires estimates of abundance. To reduce uncertainty in abundance estimates, standardized survey protocols should estimate perception and availability bias corrections to adjust final estimates (Buckland *et al*., 2004). However availability bias is often an overlooked component of detectability (McCallum, 2005). Distance sampling estimates for cetacean species, such as humpback whales which are known to dive for up to 30 minutes, are the product of density and the proportion of individuals within the area producing a cue (e.g. blow) during a survey period.

Systematic surveys utilizing a distance sampling approach have long been a standard technique for estimating abundance of wild populations, but must follow a strict set of assumptions (Buckland *et al*., 2004). These assumptions can be problematic, particularly for diving marine mammal species. As a result, some research has focused on models that relax assumptions (*e.g.* Laake, 1997; Borchers *et al*., 1998) to obtain abundance estimate from both aerial (Alpizar-Jara and Pollock, 1996) and boat-based (Evans *et al*., 2002) surveys. Alternatively, data can also be collected from platforms of opportunity (PoPs) (Moore *et al*., 2000), which are non-systematic surveys taking place primarily on oceanographic, fisheries, and/or whalewatch vessels (Buckland *et al*., 2004). PoPs do not follow a systematic survey design and therefore cannot achieve equal coverage of the sampling area. However, PoP's offer some advantages such as the ability to operate in heavier seas than smaller research vessels and are not constrained by funding and limited research personnel.

The analysis undertaken to estimate abundance for systematic and opportunistic survey designs has varied over time (*e.g.* Hedley *et al*., 1999; Buckland *et al*., 2004; Hedley and Buckland, 2004; Cañadas and Hammond, 2006; Miller *et al*., 2013) The advancement of statistical tools, however, has led to the development of new methods for analyzing, modeling, and predicting species distribution and abundance, such asgeneralized additive models (GAMs) and spatial density surface models (DSMs) (Hedley *et al*., 2004). Model based methods of abundance estimates, including DSMs, generally do not require transect surveys that achieve equal coverage of the study area and therefore are appropriate for PoPs as well as systematic survey designs (Buckland *et al*., 2004; de Segura *et al*., 2007; Miller *et al*., 2013; Buckland *et al*., 2015).

In the current study, DSMs were used to estimate and compare humpback whale abundance and density estimates collected using systematic and PoP survey designs within the four-island region of Maui, Hawai'i. An alternative approach to previous estimates of Hawai'i's breeding humpback population, which used mark-capture methods (Mobley *et al*. 2001). These estimates were then used to determine the efficacy of using PoPs as an alternative to systematic surveys for estimating humpback whale abundance and trends.

## Materials and Methods

### *Study area*

This study was undertaken in the four-island region of Maui, Hawai′i, incorporating waters between the islands of Maui, Moloka′i, Lana′i, and Kaho′olawe. The majority of the study area was within the Hawaiian Islands Humpback Whale National Marine Sanctuary (HIHWNMS) boundaries (**Fig. 1**) and was composed of shallow depths, ranging from 60-300 m, with outer edges sloping to a maximum depth of approximately 900 m.

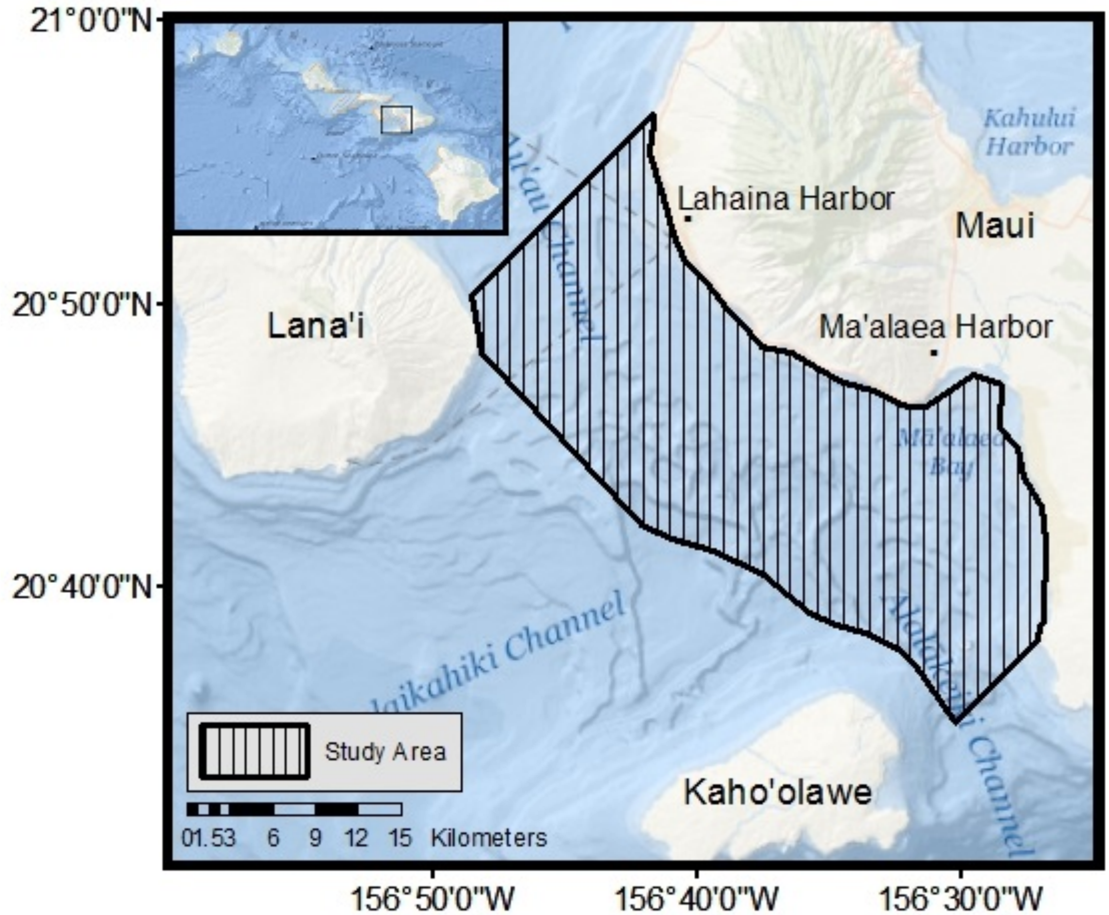


**Fig. 1:** Study area surveyed within the four-island region of Maui, Hawai′i, in 2014 and 2015. Shaded area depicts boundary of prediction grid.

### *Data collection*

Data were collected simultaneously on two separate platforms utilizing opportunistic and systematic sampling methods over two years. All research was conducted under National Marine Fisheries Service Permit No. 16749, with special activities permits obtained annually from the Department of Lands and Natural Resources. All field research and data collection was authorized and approved by the National Oceanic and Atmospheric Administration.

*Systematic transect surveys*

Line transects (average length = 14.3 km) separated by one nautical mile were mapped over study area to ensure equal sampling probability. Three to eight transects were completed per survey day and start position was chosen randomly at the beginning of each survey. An 8m catamaran research vessel departed from either Lahaina or Ma'alaea harbor and surveyed between 07:00 and 16:00 over two seasons: December 2013 -April 2014 and December 2014 - April 2015. Approximately 5-6 days was required to survey all transect lines once. The furthest distance covered was 20 km from shore, traveling an average of 13 kts, covering an area of 604.44 km$^2$. Following line transect methodology (Buckland *et al*., 2004), observations were made by two observers stationed on the port and the starboard side of the vessel scanning equal sections of water, from abeam to forward with a third person recording data. Data on number, composition, distance, and angle from the observer to the center of focal group (measured with Bushnell 7x50 mm reticle binoculars) were recorded. In addition, data on sighting time, location (obtained from global positioning system, GPS), percent cloud cover, Beaufort sea state (BSS), Douglas sea state (DSS), and percent glare were recorded.

*PoP surveys*

PoP surveys were conducted from either Lahaina or Ma'alaea harbor between 06:30 and 18:30 onboard eco-tour vessels over two seasons: December 2013 -April 2014 and December 2014 - April 2015. Surveys took place on the same days as systematic transects within the same survey area, and were conducted on one of five 20 m power catamarans. A single observer stationed at the helm scanned the surface of the water and collected data during each trip. Distance and angle to sightings were measured using reticle binoculars (Bushnell 7x50 mm) and recorded along with information on group size, composition, location (obtained from GPS), percent cloud cover, BSS, DSS, percent glare, and vessel speed.

*Environmental Covariates*

To predict humpback whale abundance the following spatial covariates were used: (1) latitude (*y*) and longitude (*x*); (2) distance from nearest shoreline (*ds*) obtained using Hawaii coastline data provided by the U.S. Geological Survey and the "near" tool in ArcMAP (ESRI, 2011); (3) depth (*d*) extracted from multi-beam bathymetry data provided by Hawaii Mapping Research Group (HMRG, 2011), and slope (*sl*) averaged within each grid cell calculated from the HMRG bathymetry data, using the "Slope" tool in ArcMAP's spatial analyst toolbox (ESRI, 2011). Spatial covariates (*x*) and (*y*) were tested in both their univariate and bivariate forms during model selection, with the univariate forms providing better fits and therefore presented in final models.

### *Data Analysis*

*Data organization*

All transect survey effort was divided into equal 1.5 km segments using ArcGIS 10.1 (ESRI, 2011). The distance of 1.5 km was chosen to minimize the number of segments without sightings, reducing problems with model fits (de Segura *et al*., 2007), and maintaining high resolution of environmental covariates. To ensure homogenous effort type, segments at the end of each survey transect with a distance <1.5 km were dropped and not used in subsequent analysis, as done in de Segura *et al*. (2007). It was assumed that environmental features would have minimal variability within each segment. Each segment and associated effort was characterized by number and size of each pod as well as the arithmetic mean values of each environmental covariate used in analysis. Models were fitted to segment data to predict humpback whale abundance along transects as a function of environmental covariates.

The study area, consisting of 798 $km^2$ was divided into 355 grid cells measuring 1.5 km by 1.5 km. Each grid cell was characterized by the mean of each environmental covariate. Histograms showing the distribution of depths and distances from shore among the 355 grid cells are presented in **Fig 2**. Predicted model densities were extrapolated to each grid cell as a function of covariates to estimate humpback whale abundance for the entire study area. Collinearity among predictor variables was tested using the cor() function in "stats" package (R Core Team, 2014). If collinearity was observed, the term contributing least to improving overall model fit was dropped.

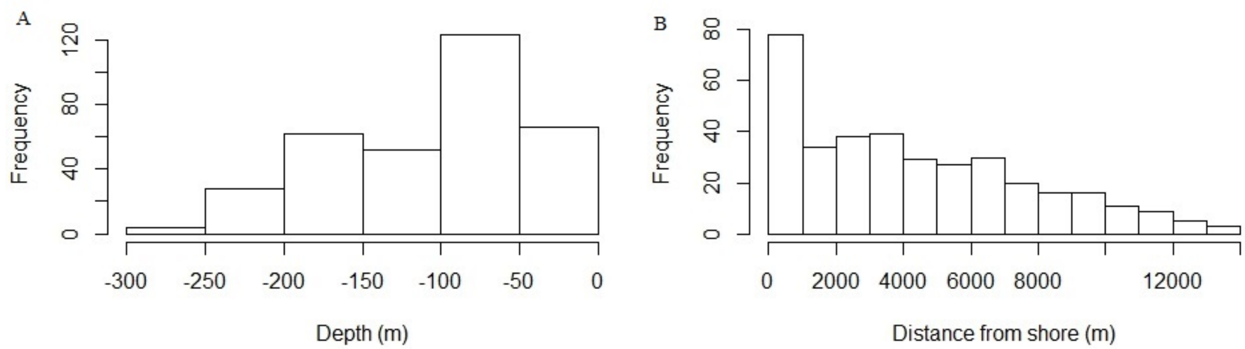


**Fig 2:** Histograms showing distribution of depths (A) and distances from shore (B) among the 355 grid cells within the four-island region of Maui, Hawaii.

*Spatial modeling*

A model-based approach was used to predict abundance and density estimates within the study area. PoP surveys do not adhere to systematic-design based principles. To account for this, spatial modelling was used which allowed for relaxing of assumptions associated with systematic sampling methods (Williams *et al*., 2014; Miller, 2013). Similar to Cañadas & Hammond (2006), five steps were followed to derive model-based abundance estimates: (1) detection function was estimated; (2) number of individuals per segment was estimated; (3) group size was modeled as a function of detection and environmental covariates; (4) abundance of animals was estimated in each grid cell; and (5) final estimates were corrected for availability.

*Perception Bias*

The detection function, *g(y)*, was used to estimate the probability of detecting an animal at distance *y* from the vessel. Collection of sighting distances and associated covariates from PoP surveys in an area of high whale density proved to be problematic. PoP vessels operate independently of observers; whalewatch vessels pursue pods opportunistically based on proximity to the whale and level of activity. This resulted in partial documentation of some pods by the observer; therefore maximum sighting distances were implemented in data collection methodologies. The distance chosen to represent sighting distance limits represented the distance at which whales were generally approached by vessel captain and therefore allowed for complete observations and data recording. For 2014 PoP and systematic sampling distances were truncated to $w$ = 300 m, while in 2015 the PoP truncation distance was changed to $w$ = 500 m to correct the underestimates of PoP density estimates in the 2014 analysis and to better align with systematic survey results. In addition to perpendicular distance, additional explanatory variables (**Table 1**) which influence detectability were included in the detection function using multiple covariate distance sampling (MCDS) (Marques, 2001). Half-normal, hazard-rate, and uniform forms of the detection function model were tested and second order cosine series adjustments were also considered. Models were fitted using the "Distance" package (Miller, 2014) in R (R Core Team, 2014). Adjustments terms were evaluated via forward selection based on Akaike's information criterion (AIC), and model covariates evaluated by comparison of AIC. A range of candidate detection functions were considered, combining the functional forms and covariates, and the function having the lowest AIC value selected. A separate detection function was fit to each survey type, systematic and PoP, pooling data across years.

**Table 1:** Covariates incorporated in modelling the detection functions, indicating variable type and levels, if applicable.

| **Covariate** | **Type** | **Levels** |
|---|---|---|
| Group size | *continuous* | - |
| Distance | *continuous* | - |
| Cloud cover | *continuous* | - |
| Glare | *continuous* | - |
| Wind speed (BSS) | *Factor* | 5 levels: 1, 2, 3, 4, >5 (BSS) |
| Wind direction | *Factor* | 8 levels: N, NE, E, SE, S, SW, W, NW |
| Sea state (DSS) | *Factor* | 4 levels: 1, 2, 3, >4 (DSS) |
| Visibility | *Factor* | 4 levels: excellent, good, fair, poor |
| Rain | *Factor* | 2 levels: yes, no |

*Estimation of number of individuals per segment*

To formulate the spatial model of abundance, estimates on the numbers of whales per segment were determined using a Horvitz-Thompson estimator (Horvitz and Thompson, 1952) with the inclusion probabilities (Borchers and Burnham, 2004):

$$Ni = j{=}1ni1Pij$$

Where: $ni$ is the number of whales detected in the $i$th segment

$Pij$ is the estimated probability of detection of individual $j$ in segment $i$

Modelling abundance estimates as a function of spatial covariates was completed using a GAM (Wood, 2006) with a poisson or quasi-poisson response distribution and logarithmic link function with the following general model structure:

$$Ni{=}exp\ln ai{+}\ \beta 0{+}kqfk(zik)$$

Where: $ai$ is the offset calculated as the search area for the $ith$ segment

$ai$ for line transects = $2wl$

where: $w$ is the width

$l$ is the length

$\beta 0$ is the intercept

$f_k$ are smooth functions of the $q$ spatial covariates $z$

$z_{ik}$ is the value of the $k^{th}$ spatial covariate in the $i^{th}$ segment

Models were fitted using the "dsm" package (Miller *et al*., 2014) in R (R Core Team, 2014) and final model selection was based on the generalized cross validation (GCV) statistic (Wood, 2006), percentage of deviance explained, and diagnostic plots (to check model assumptions). Smoothness selection for model terms was based on GCV. Distributions tested were negative binomial, Tweedie, poisson, and quasi-poisson. Poisson and quasi-poisson were utilized in final analysis as they provided best fits based on above evaluation criteria.

*Availability Bias*

To account for the likely underestimates arising from some animals being underwater and therefore undetectable during the sighting window, an availability bias correction factor ($PA$) for whales within the study area was calculated. Data for the calculations were obtained from Baird *et al*. (2000), who deployed time-depth recorders on 21 whales within the same study region of Maui in 2000, 2001, and 2011. Whales tagged consisted of lone adults, non-mother-calf pairs, primary and secondary escorts of competition pods, and mother-calf groups. The estimate for $PA$ within time ($t$) was derived by Laake *et al*. (1997) and subsequently used for humpback whales estimates in Greenland (Heide-Jorgensen *et al*., 2012):

$$PA = \frac{E[s]}{E[s]+E[d]} + \frac{E[d](1-e^{-t/E[d]})}{E[s]+E[d]}$$

Where: $E[s]$ is the average time the whale is at the surface

$E[d]$ is the average time the whale is below the surface

$t$ is the window of time the whale is within visual range of the observers

It should be noted that age class and uncertainty in parameter estimate was not considered when calculating availability bias correction factor. Final abundance corrected for availability bias where then estimated as:

$$N_c = \frac{N}{PA}$$

*Variance*

Variance was estimated using the "dsm.var.prop" function (Miller *et al*., 2014) in R (R Core Team, 2014) utilizing variance propagation as outlined in Williams *et al.* (2011).

## Results

In all years, surveys covered the four-island region of Maui, with PoP surveys sampling more heavily within 12 km of Lahaina and Ma'alaea harbors. The total survey effort was 12,745.3 km for PoP surveys (**Fig. 3**) and 2,381.7 km for systematic surveys (**Fig. 4**). PoP surveys had a total of in 1,621 sightings and systematic surveys recording a total of 520 sightings.

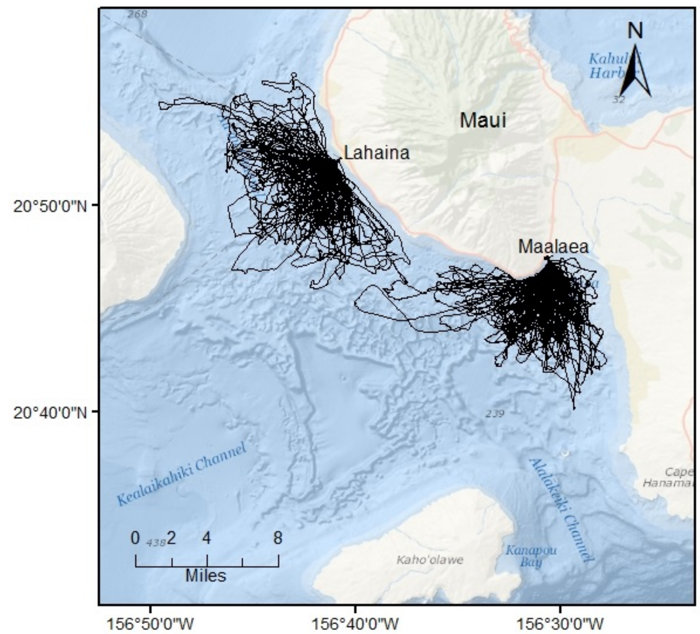


**Fig. 3:** Platform of Opportunity effort track lines completed within the four-island region of Maui, Hawaii from December to April 2014 and 2015

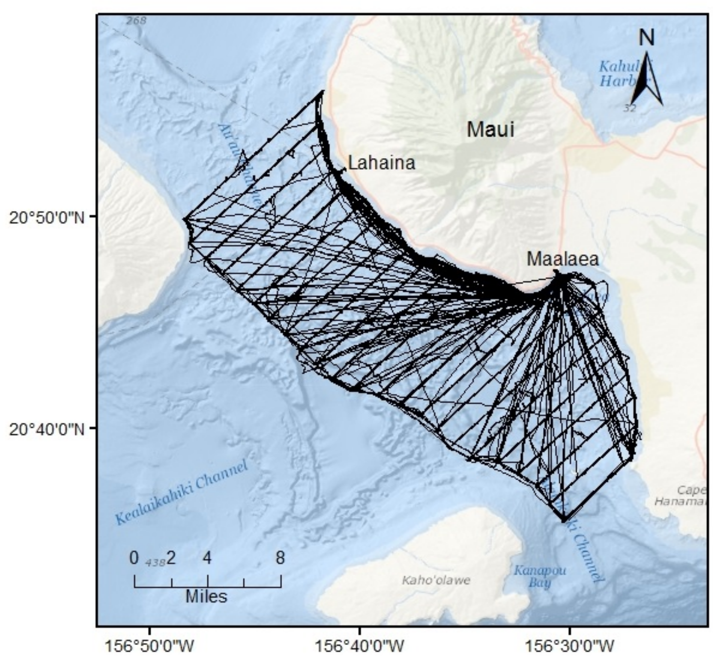


**Fig. 4:** Systematic effort track lines completed within the four-island region of Maui, Hawaii from December to April 2014 and 2015

*Perception Bias*

Models were fitted with single covariates initially and continuing with combinations of up to four covariates. Data showed no significant improvement in fit of detection function when month and year were considered, and therefore it was assumed detection probability did not change over time and data were pooled across both years. The goodness of fit of top detection functions were checked using the ddf.gof() function in the "mrds" package in R (Lake *et al*., 2015) and results including Kolmogorov-Smirnov test statistic presented in Appendix 1. The quantile-quantile plot of the final detection function utilized for PoP and systematic surveys is also presented in Appendix 1

*Systematic Transect Surveys*

Inspection of observed distances of systematic sightings showed minimal sightings at <50m (n=3). As such, a left truncation of 10% was applied post-survey to account for likely failure in model convergence due to limited sightings. Further, a right truncation distance of 300m was implemented, owing to field data collection methodologies. The half-normal function with cosine series expansion and 0 adjustment terms (**Fig. 5**) was identified as the best-fitting model for the systematic detection function according to AIC (Appendix 1). The next best model was a half-normal function with DSS and BSS as covariates (Appendix 1).

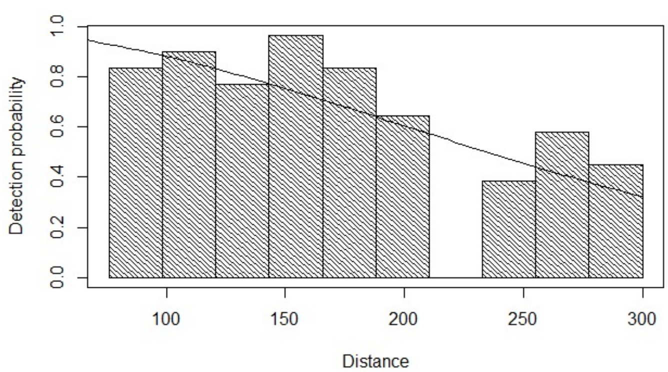


**Fig 5**: Frequency distribution of perpendicular distances from the systematic surveys lines and fitted detection function.

*Opportunistic Surveys*

Inspection of observed distances of systematic sightings showed minimal sightings at <100m (n=6). This is to be expected for whalewatch vessels as they legally cannot approach whales closer than 100m in Hawaiian waters. As such, a left truncation of 100 m was applied post-survey to account for likely failure in model convergence due to limited sightings. A right truncation distance of 500 m was implemented, owing to field collection methodologies. The hazard-rate function with cosine series expansion and 0 adjustment terms (**Fig. 6**) was identified as the best-fitting model for the PoP detection function according to AIC (Appendix 1). The next best model was a half-normal function key only model (Appendix 1).

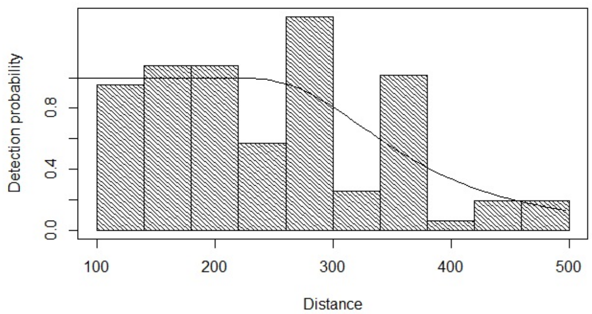


**Fig 6**: Frequency distribution of perpendicular distances from opportunistic survey lines and fitted detection function.

### *Availability Bias*

Data obtained from time-depth recorders indicated that humpback whales in Hawaiʻi spent, on average, 44% of their time at the surface (≤ 4 m) and therefore during that time are available for detection. Surface times ranged from 1-29 mins (C.V. = 8.79) and dive times ranged from 3-26 mins (C.V. = 6.54).

### *Density Surface Model*

The deviation explained by the best-fit DSM's in 2014 and 2015 ranged from 13.8-52.1% and 15.5-65.2% for systematic and PoP surveys, respectively (**Table 2**).

Analysis of systematic surveys found distance to shore and depth were significant predictors in 7 of the 10 models. Slope was included in 3 of 10 models, having minimal impact on predicting densities.

Analysis of PoP surveys found distance from shore in 7 of 10 models representing a strong predictor of density. Latitude had minimal impact on predicting densities, found in 4 of 10 models (**Table 2**).

*Monthly Trends*
Longitude and depth were significant predictors of density, regardless of survey methods, in 18 of 20 models (**Table 2**).

**Table 2:** Environmental covariates selected as the best-fitting spatial model for monthly estimates of humpback whale abundance in Maui, Hawaiʻi between December 2013 and April 2015.

| Month | Year | Survey | Co-variables | Expl. Dev. % |
|---|---|---|---|---|
| December | 2013 | Systematic | ds + d + sl | 24.2 |
| January | 2014 | Systematic | s(x) + s(y) + s(ds) | 19.5 |
| February | 2014 | Systematic | s(x) + s(y) s(ds) + s(d) | 20.8 |
| March | 2014 | Systematic | s(x) + s(y) + s(d) | 52.1 |

| | | | | |
|---|---|---|---|---|
| April | 2014 | Systematic | s(x) + s(d) + s(ds) + s(sl) | 20.2 |
| December | 2013 | PoP | x + y + d + ds | 18.1 |
| January | 2014 | PoP | s(x) + s(ds) + s(sl) | 17.2 |
| February | 2014 | PoP | s(y) + s(ds) + s(sl) | 19.0 |
| March | 2014 | PoP | s(x) + s(y) + s(d) + s(ds) + s(sl) | 31.9 |
| April | 2014 | PoP | s(d) | 15.5 |
| December | 2014 | Systematic | s(d) + s(ds) | 36.6 |
| January | 2015 | Systematic | s(y) + s(ds) | 19.5 |
| February | 2015 | Systematic | s(y) + s(d) + s(sl) | 20.0 |
| March | 2015 | Systematic | s(y) + s(d) + s(ds) | 30.7 |
| April | 2015 | Systematic | s(x) + s(y) + s(d) + s(ds) | 13.8 |
| December | 2014 | PoP | s(x) + s(y) + s(d) + s(ds) + s(sl) | 36.2 |
| January | 2015 | PoP | s(d) + s(ds) + s(sl) | 23.3 |
| February | 2015 | PoP | s(ds) | 21.3 |
| March | 2015 | PoP | Intercept only | NA |
| April | 2015 | PoP | s(d) + s(x) | 65.2 |

*Note:* *x* = longitude; *y* = latitude; *d* = depth; *ds* = distance to shore; *sl* =slope
s() = spline based smooths

The monthly abundance estimates within the study area varied both within and between seasons (**Fig. 7**)

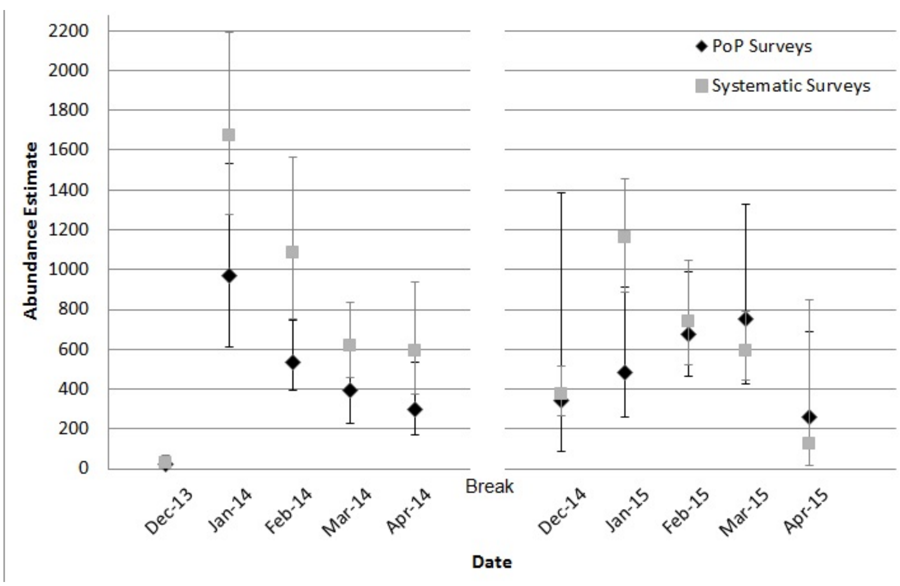


**Fig. 7** Trends in abundance estimates of humpback whales within the four-island region of Maui, Hawai'i as measured using PoP and systematic survey methods between December 2013 and April 2015.
*Note:* bars represent confidence intervals associated with each estimate.

In 2014, when systematic and PoP surveys both utilized a truncation distance of 300m, PoP's differed from systematic estimates by ~40% (**Table 3**). Increasing the truncation distance to 500m in 2015 allowed for similar abundance estimates between both survey types (**Table 3**).

**Table 3** Estimates of monthly abundance (corrected for perception and availability bias) and density of humpback whales, with coefficient of variation (CV) and calculated 95% confidence interval (CI) obtained from spatial analysis.

| **Month** | | **Survey** | **Abundance Estimate** | **CV** | **95 % Confidence Interval** | **Whales/km$^2$** |
|---|---|---|---|---|---|---|
| December | 2013 | Systematic | 27 | 0.38 | 15-65 | 0.04 |
| January | 2014 | Systematic | 1,672 | 0.14 | 1,276 – 2,190 | 2.09 |
| February | 2014 | Systematic | 1,087 | 0.19 | 753 – 1,567 | 1.36 |
| March | 2014 | Systematic | 619 | 0.15 | 461 - 833 | 0.78 |
| April | 2014 | Systematic | 593 | 0.24 | 375 - 938 | 0.74 |
| December | 2013 | PoP | 23 | 0.23 | 14-38 | 0.03 |
| January | 2014 | PoP | 970 | 0.24 | 611-1,543 | 1.21 |
| February | 2014 | PoP | 534 | 0.16 | 391-534 | 0.67 |
| March | 2014 | PoP | 391 | 0.27 | 225-645 | 0.48 |
| April | 2014 | PoP | 299 | 0.30 | 168-534 | 0.37 |
| December | 2014 | Systematic | 372 | 0.17 | 269-516 | 0.47 |
| January | 2015 | Systematic | 1,159 | 0.14 | 886-1,458 | 1.45 |
| February | 2015 | Systematic | 738 | 0.18 | 519-1,049 | 1.22 |
| March | 2015 | Systematic | 593 | 0.15 | 447-788 | 0.74 |
| April | 2015 | Systematic | 123 | 1.21 | 18-851 | 0.16 |
| December | 2014 | PoP | 345 | 0.81 | 86-1,386 | 0.43 |
| January | 2015 | PoP | 456 | 0.33 | 258-915 | 1.08 |
| February | 2015 | PoP | 677 | 0.19 | 464-988 | 0.85 |
| March | 2015 | PoP | 753 | 0.30 | 427-1,327 | 0.94 |
| April | 2015 | PoP | 57 | 0.71 | 16-201 | 0.32 |

## Discussion

Data presented show the potential utility of PoP data collection by comparison of data collected from systematic surveys during the same time period. Biases inherit in data collection methodologies from PoPs, particularly whalewatch vessels, are obvious in the presented methods, and were accounted for in all subsequent analysis. The use of spatial DSM showed potential for comparable results when data are collected on PoP and systematic surveys.. The use of DSM's for cetacean abundance estimates has been a proven method in the past, with several advantages over conventional distance sampling (de Segura *et al*., 2007; Hedley & Buckland, 2004; Hedley *et al*., 1999). It is recommended that the numbers presented in this paperbe used with caution, as GAMs are flexible (de Segura *et al*., 2007; Hedley & Buckland, 2004) and estimates represent monthly predictions or "snapshots" of the survey region in a given month.

Results from this study included both perception and availability biases to allow for estimates of absolute abundance and as opposed to surface abundance. To the knowledge of the authors this is the first use of spatial DSM, which bases abundance estimates on the observed relationship between animals and spatial covariates, to estimate abundance of humpback whale population within the Hawaiian Islands.

Abundance estimates presented in this study are the first to focus on humpback whales specifically within the four-island region of Maui since estimates published by Barlow *et al.* (2011), based on 2004-2006 surveys carried out by Calambokidis *et al.* (2008). The increase in PoP abundance estimates from 2014 to 2015 is likely attributed to increasing the truncation distance to 500m, as this distance will impact the conversion of counts within each segment into estimates of abundance (Buckland *et al.*, 2004). Utilizing truncation distances of 500m for whalewatching PoP tends to produce most similar estimates to systematic surveys

The average deviance explained by all models between systematic and PoP surveys is very similar, at 25.7% and 27.5%, respectively. This result, in conjunction with similar monthly abundance estimates, supports the use and efficacy of PoPs for collection of annual humpback whale abundances within the spatial resolution of this study. The low deviance explained by some models could be as a result of the low density of sightings, often associated with the end and beginning of whale season as whales return to feeding grounds (Currie *et al.*, 2015). Migratory whales can move rapidly over long distances (Constantine *et al.*, 2015) and as a result estimates of density will change depending on the time of year.

Depth and location strongly influenced sightings within the study area. Stratification by depth is consistent with humpback whale observations made in other breeding grounds (Craig *et al.*, 2014; Cartwright *et al.*, 2012; Félix and Haase, 2005; Smultea, 1994). Although not the focus of this study, this consistency further supports the potential use of PoPs and spatial DSM as an alternative to systematic survey designs, particularly in areas with a lack of resources to conduct systematic studies.

The availability of humpbacks within the study area was estimated at 44% of the population. This value is in conjunction with previous availability biases calculated for humpback whales (Heide-Jørgensen, 2012). Humpback whales are known to have short surface intervals with extended dive times (Heide-Jørgensen, 2012), indicating the importance of including a perception bias when assessing relative abundances.

The goal of this study was to compare monthly abundance estimates collected using PoP and systematic survey methods. The principle of using spatial DSM in cases where a survey design has unknown coverage probability has been proven effective (de Segura *et al.*, 2007; Cañadas & Hammond, 2006), with results presented here further supporting this outcome. Although results presented here are limited to abundance estimates, data collected on PoPs can also provide information on habitat use, furthering our understanding of animal distribution (de Segura *et al.*, 2007).

**Acknowledgements**

This work was made possible by the members and supporters of the Pacific Whale Foundation. We extend our gratitude to Dr. Robin Baird for donating dive interval data on humpback whales that contributed greatly to data analysis. The authors thank Emmanuelle Martinez, Betsy Davidson, and Shannon Easterly for their help in field work and data collection. Additionally, we thank Pacific Whale Foundation's interns, naturalists, and captains for PoP logistical support. Finally, our gratitude goes to all research interns between 2013 and 2015 who contributed significantly to research efforts. The systematic portion of this research was conducted under NMFS permit #16479.

## References


Alpizar-Jara R, Pollock KH. A combination of line transect and capture–recapture sampling model for multiple observers in aerial surveys. Environ. Ecol. Stat. 1996; 3: 311–327.

Baird RW, Ligon AD, Hooker SK. Sub-surface and night-time behavior of humpback whales off Maui, Hawaiʻi: a preliminary report. Report prepared under Contract #40ABNC050729 from the Hawaiian Islands Humpback Whale National Marine Sanctuary, Kihei, HI, to the Hawaiʻi Wildlife Fund, Paia, HI. 2000. 18 p.

Barlow J, Calambokidis J, Falcone EA, Baker CS, Burdin AM, Clapham PJ *et al*. Humpback whale abundance in the North Pacific estimated by photographic capture-recapture with bias correction from simulation studies. Mar Mamm Sci. 2011; 27(4): 793-818.

Borchers DL, Buckland ST, Goedhart PW, Clarke ED, Hedley SL. Horvitz-Thompson estimators for double platform line transect surveys. Biom. 1998; 54: 1221–1237.

Borchers DL, Burnham KP. General formulation for distance sampling. In: Buckland ST, Anderson DR, Burnham KP, Laake JL. Borchers DL, Thomas L, editors. Advanced Distance Sampling. Oxford University Press, Oxford; 2004. pp. 6–30.

Buckland ST, Anderson DR, Burnham KP, Laake JL, Borchers DL. Thomas L. Advanced Distance Sampling. Oxford: Oxford University Press; 2004.

Buckland ST, Rexstad EA, Marques TA, Oedekoven CS. Distance Sampling: Methods and Applications. Springer International Publishing. 2015.

Calambokidis J, Steiger GH, Straley JM, Herman LM, Cerchio S, Salden DR, et al. Movements and population structure of humpback whales in the North Pacific. Mar Mamm Sci. 2001;17: 769–974.

Calambokidis J, Falcone EA, Quinn TJ, Burdin AM, Clapham PJ, Ford JKB, et al. SPLASH: Structure of Populations, Levels of Abundance and Status of Humpback Whales in the North Pacific. Final report for Contract AB133F-03-RP-00078 U.S. Dept of Commerce Western Administrative Center. 2008. Seattle, Washington. 57 p.

Cañadas A, Hammond PS. Model-based abundance estimates for bottlenose dolphins (*Tursiops truncates*) off southern Spain: implications for management. J Cetecean Res Manag. 2006; 8(1): 13-27.

Cartwright R, Gillespie B, LaBonte K, Mangold T, Venema A, Eden K, et al. Between a rock and a hard place: habitat selection in female-calf humpback whale (*Megaptera novaeangliae*) pairs on the Hawaiian breeding grounds. PLoS One. 2012; 7: e38004, DOI:10.1371/journal.pone.0038004.

Currie JJ, Stack SH, Easterly SK, Kaufman GD, Martinez E. Modeling whale-vessel encounters: the role of speed in mitigating collisions with humpback whales (*Megaptera novaeangliae*). Document SC/66a/HIM/3. 2015. 17 p.

Constantine R, Steel D, Allen J, Anderson M, Andrews O, Baker CS, et al. Remote Antarctic feeding ground important for east Australian humpback whales. Mar Biol. 2014; 161(5): 1087-1093.

Craig AS, Herman LM. Habitat preferences of female humpback whales *Megaptera novaeangliae* in the Hawaiian Islands are associated with reproductive status. Mar Ecol Prog Ser. 2000; 193: 209-216.

Craig AS, Herman LM, Pack AA, Waterman JO. Habitat segregation by female humpback whales in Hawaiian waters: avoidance of males? Behav. 2014; 151: 613-631.

de Segura AG, Hammond PS, Cañadas A, Raga JA. Comparing cetacean abundance estimates derived from spatial models and design-based line transect methods. Mar Ecol Prog Ser. 2007; 239: 289-299.

ESRI. ArcGIS Desktop: Release 10. Redlands, CA: Environmental Systems Research Institute. 2011.

Evans MD, Raphael MG, Laake JL. Probability of detecting Marbled Murrelets at sea: Effects of single versus paired observers. J Wildl Manag. 2002; 66: 865–873.

Félix F, Haase B. Distribution of humpback whales along the coast of Ecuador and management implications. J Cetacean Res Manag. 2005; 7: 21-31.

HMRS. Main Hawaiian Islands Multibeam Bathymetry Synthesis: 1-km Bathymetry and Topography. School of Ocean and Earth Science and Technology, University of Hawaii at Manoa. Distributed via THREDDS Data Server (TDS) by PacIOOS. 2011

Heide-Jørgensen MP, Laidre KL, Hansen RG, Burt ML, Simon M, Borchers DL, et al. Rate of increase and current abundance of humpback whales in West Greenland. J Cetacean Res Manag. 2012; 12: 1-14.

Hedley SL, Buckland ST. Spatial models for line transect sampling. J Agric Biol Environ Stat. 2004; 9(2): 181-199.

Hedley SL, Buckland ST, Borchers DL. Spatial modeling for line transect data. J Cetacean Res Manag. 1999; 1(3): 255-264.

Hedley SL, Buckland ST, Borchers DL. Spatial distance sampling models. *In*: Buckland ST, Anderson DR, Burnham KP, Laake JL, Borchers DL. Thomas L, editors. Advanced Distance Sampling. Oxford University Press, Oxford; 2004. 440 p.

Johnston DW, Friedlaender AS, Read AJ, Nowacek DP. Initial density estimates of humpback whales *Megaptera novaengliae* in the inshore waters of the western Antarctic Peninsula during the late autumn. Endanger Species Res. 2012; 18: 63-71.

Horvitz DG, Thompson DJ. A generalization of sampling without replacement from a finite universe. J Am Stat Assoc. 1952; 47(260): 663-685.

Laake JL, Calambokidis JC, Osmek SD, Rugh DJ. Probability of detecting harbor porpoise from aerial surveys: Estimating *g*(0). J Wildl Manag. 1997; 61: 63–75.

Laake J, Borchers D, Thomas L, Miller D, Bishop J. mrds: Mark-Recapture Distance Sampling. R package version 2.1.14. https://CRAN.R-project.org/package=mrds. 2015.

Marques FFC. Estimating wildlife distribution and abundance from line transect surveys conducted from platforms of opportunity. PhD Dissertation, University of St. Andrews. 2001. Available: https://research-repository.st-andrews.ac.uk/bitstream/10023/3727/3/FernandaFCMarquesPhDThesis.pdf

Massey Jr FJ. The Kolmogorov-Smirnov test for goodness of fit. J Am Stat Assoc 1951; 46(253): 68-78.

McCallum DA. A conceptual guide to detection probability for point counts and other count-based survey methods. USDA Forest Service General Technical Report PSW–GTR–191. 2005. pp 754-761.

Miller DL, Burt ML, Rexstad EA, Thomas L. Spatial models for distance sampling data: recent developments and future directions. Methods Ecol Evol. 2013; 4(11): 1001-1010.

Miller DL. Distance: A simple way to fit detection functions to distance sampling data and calculate abundance/density for biological populations. 2014. R package version 0.8.1. http://github.com/dill/Distance/wiki.

Miller DL, Rexstad E, Burt L, Bravington MV, Hedley S. dsm: Density surface modelling of distance sampling data. 2014. R package version 2.2.2. http://github.com/dill/dsm.
Mobley, JR., Jr., S. Spitz and R. Grotefendt. 2001. Abundance of humpback whales in Hawaiian waters: Results of 1993–2000 aerial surveys. Report for the Hawaiian Islands Humpback Whale National Marine Sanctuary. 16 p.
Moore SE, Waite JM, Mazzuca LL, Hobbs RC. Mysticete whale abundance and observations on prey association on the central Bering Sea shelf. J Cetac Res Manag. 2000 2(3): 227-234.
R Core Team R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. 2014. ISBN 3-900051-07-0. http://www.R-project.org/
Smultea MA. Segregation by humpback whale (Megaptera novaeangliae) cows with a calf in coastal habitat near the island of Hawai'i. Can J Zool. 1994; 72:805-811.
Williams R, Kelly N, Boebel O, Friedlaender AS, Herr H, Kock KH, et al. Counting whales in a challenging, changing environment. Sci Rep. 2014; doi:10.1038/srep04170
Williams R, Hedley SL, Branch TA, Bravington MV, Zerbini AN, Findlay KP. Chilean Blue Whales as a Case Study to Illustrate Methods to Estimate Abundance and Evaluate Conservation Status of Rare Species. Conserv Biol. 2011; 25(3): 526-535.
Wood SN. Generalized Additive Models: An Introduction with R. Taylor & Francis, 2006 CRS Press, United Kingdom; 384 p.

## Appendix 1: Detection Function

**Table 1:** List of top candidate detection function models considered for systematic transect surveys and associated AIC and goodness of fit statics

| Detection Model | | | | | Goodness of fit | |
|---|---|---|---|---|---|---|
| Key Function | Adjustment | # of adjustment terms | Covariate(s) | AIC | K-S stat | p-value |
| Half normal | Cos | 0 | - | 1065.0 | 0.0773 | 0.5951 |
| Half normal | - | - | DSS,BSS | 1065.7 | 0.0607 | 0.8581 |
| Half normal | - | - | BSS | 1065.9 | 0.0659 | 0.7832 |
| Hazard rate | - | - | DSS,BSS | 1067.5 | 0.0663 | 0.7768 |
| Hazard rate | Cos | 0 | - | 1073.1 | 0.1813 | 0.0030 |
| Uniform | - | 0 | - | 3403.2 | 0.3441 | <0.001 |

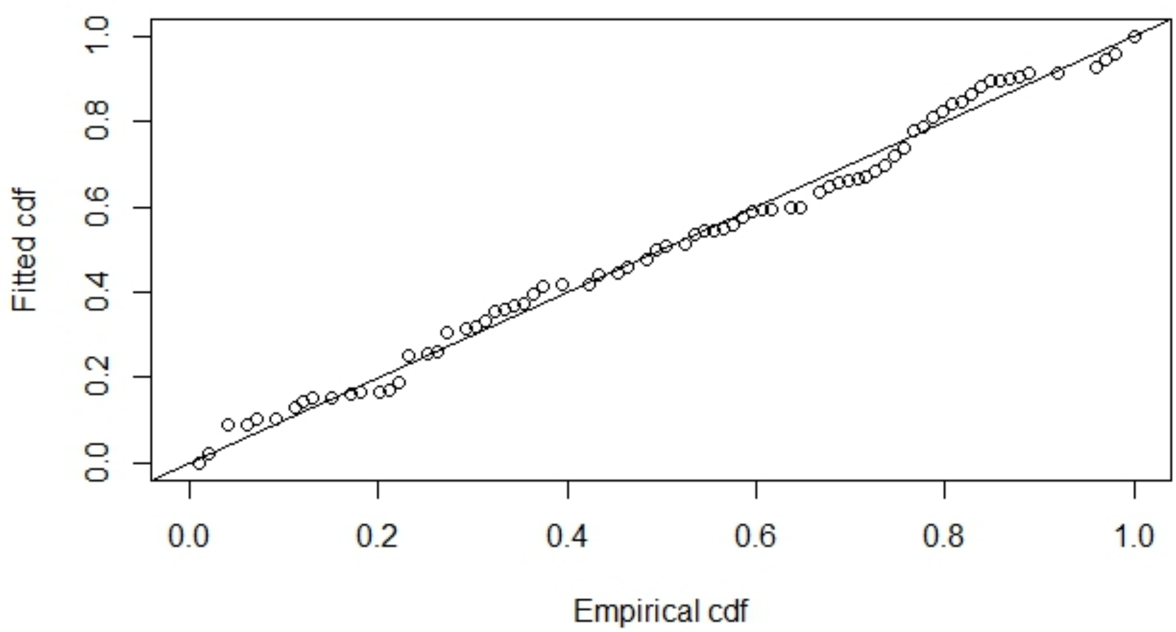


**Figure 1:** Quantile-Quantile plot used for evaluating goodness of fit of top detection function model for systematic transect surveys.

**Table 2:** List of top candidate detection function models considered for opportunistic surveys and associated AIC and goodness of fit statics

| Detection Model | | | | | Goodness of fit | |
|---|---|---|---|---|---|---|
| Key Function | Adjustment | # of adjustment terms | Covariate(s) | AIC | K-S stat | p-value |
| Hazard rate | Cos | 0 | - | 1257.1 | 0.0861 | 0.4061 |
| Half normal | - | 0 | - | 1257.8 | 0.0863 | 0.4027 |
| Half normal | Cos | 2 | - | 1258.3 | 0.0866 | 0.3987 |
| Hazard rate | - | - | DSS | 1258.9 | 0.0625 | 0.7971 |
| Hazard rate | Cos | 2 | - | 1259.1 | 0.0870 | 0.3927 |
| Hazard rate | - | - | DSS, BSS | 1260.5 | 0.0565 | 0.8838 |
| Half normal | - | - | DSS, BSS | 1261.2 | 0.0792 | 0.5131 |
| Uniform | - | 0 | - | 1282.1 | 0.2944 | <0.001 |

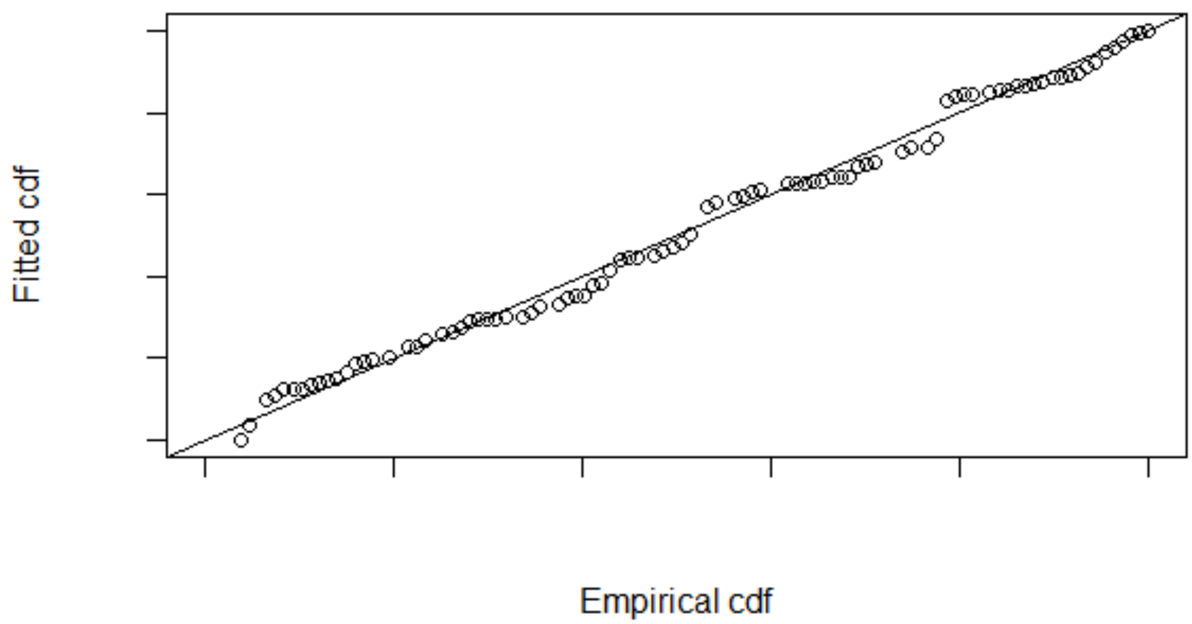


**Figure 2:** Quantile-Quantile plot used for evaluating goodness of fit of top detection function model for opportunistic surveys.