



# Precautionary design of a marine protected area based on a habitat model

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**ABSTRACT:** A basic principle of effective resource management is that decisions should be conservative in the face of uncertainty. Due to limited data, there is often considerable uncertainty about species' habitat relationships and requirements. If the boundaries of a protected area are based on relationships estimated by a habitat model, effective management takes the uncertainty into account. The inclusion of uncertainty in the design of a hypothetical marine protected area is described for a coastal population of the long-beaked common dolphin *Delphinus capensis* off Baja California, Mexico. Line-transect and depth data were combined in a hierarchical Bayesian model. Two possible management goals were considered: protecting 100 000 animals or protecting 60% of the population. A precautionary approach was adopted, meaning that the management goal should be met with a high probability. The model estimated that a seaward boundary at 360 m would include 100 000 dolphins with a probability of 0.9. A conventional but less precautionary 'best estimate' boundary at 160 m would meet the management goal with a probability of 0.5. For the second goal of including 60% of the population, the precautionary and non-precautionary depths were 210 and 170 m, respectively. Habitat models are useful for management, but management decisions based on such models should consider the uncertainty inherent in estimating parameters from data. Models which include the data observation process can improve inference about habitat relationships.

**KEY WORDS:** Precautionary management · Marine protected area · *Delphinus capensis* · Cetacean habitat model · Hierarchical Bayes model

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## INTRODUCTION

Cetaceans face a variety of challenges, such as climate change, noise pollution, fisheries bycatch and collisions with ships. For reasons of conservation and management, it is important to understand the habitat requirements of cetaceans, and habitat models play a critical role, as shown by the papers in this special issue. When using the results of habitat models in management decisions, however, it is important to consider the uncertainty inherent in estimating model parameters from data. Insufficient recognition of uncertainty has led to repeated failures in resource management and conservation (Ludwig et al. 1993). The scientific issue is to estimate

uncertainty well and to report it in terms that can be clearly understood. The management issue is to recognize that uncertainty exists and to account for it when making decisions.

A basic principle of effective management of natural resources is that decisions should be more conservative when uncertainty is greater (Mangel et al. 1996). For marine mammals, an example of this precautionary principle in practice is the procedure for setting bycatch limits under the US Marine Mammal Protection Act. Bycatch limits are based on the lower end of a confidence interval of an abundance estimate (Wade 1998). Thus, the more uncertainty about marine mammal population size, the larger the confidence interval and the smaller the permitted

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bycatch. Uncertainty is explicitly taken into account for conservative management (Taylor et al. 2000).

Here we apply the precautionary use of uncertainty to the design of a marine protected area, when the design is based on habitat modeling. To be effective for the conservation of a species, the design of a protected area should consider, among other things: (1) how many animals should be protected and (2) where the boundaries of the area should be established in order to protect that number.

In the present paper we deal with the second question. We assume that the first question has already been considered, and that either of 2 potential management targets has been established for a cetacean population: (1) to protect at least 100 000 animals or (2) to protect at least 60 % of the population. Maintaining a marine mammal population at  $\geq 60\%$  of carrying capacity is a management goal called the 'optimum sustainable population' level under the US Marine Mammal Protection Act, and is based on the assumed inflection point of a generalized production model of large mammal population dynamics (Gerrodette & DeMaster 1990). Data to estimate population size and distribution may be limited, and there will often be considerable uncertainty about whether any proposed boundary actually contains 100 000 animals or 60 % of the population. A precautionary management approach recognizes the uncertainty, and specifies that the management target be met with reasonably high certainty. What constitutes 'reasonably high certainty' is a policy decision about how precautionary management will be. In the present paper, we assume that the level of certainty has been chosen to be 0.9. Given this policy decision, the scientific problem is to use available data to estimate the location of a boundary which contains 100 000 animals with a probability of 0.9 or 60 % of the population size with a probability of 0.9.

As a case study, we use data on the long-beaked common dolphin *Delphinus capensis*. This species occurs from southern California to the tip of Baja California off the west coast of North America, including the Gulf of California (Rice 1998). We use the long-beaked common dolphin simply as an illustrative example; we are not suggesting

that the species is in danger of extinction or that it requires any more protection than other cetaceans in the area. *D. capensis* was described as distinct from *D. delphis* in 1994 (Heyning & Perrin 1994, Rosel et al. 1994). From the locations of sightings, it is clear that the species occurs primarily in coastal waters. Given the management targets specified above, we need to estimate the location of the offshore boundary of a potential protected area that will meet the management objectives. This requires that we estimate the density of dolphins at a relatively fine spatial scale. Further, we need to convert the uncertainty inherent in the estimation of density into a probability that the true value is included. We use depth as a predictor variable for the habitat model because depth data are readily available on a fine scale, and depth is more likely than distance from shore to be a proxy for the actual processes that the dolphins are responding to, such as food supply.

## METHODS

Line-transect surveys were carried out in the range of *Delphinus capensis* off the coast of Baja California, Mexico, during 11 yr between 1986 and 2006 (Fig. 1A), as part of larger cetacean surveys in the eastern tropical Pacific Ocean. Beaufort sea state was recorded continuously during each survey. School size and distance from the trackline were recorded for each sighting. Further details on data collection

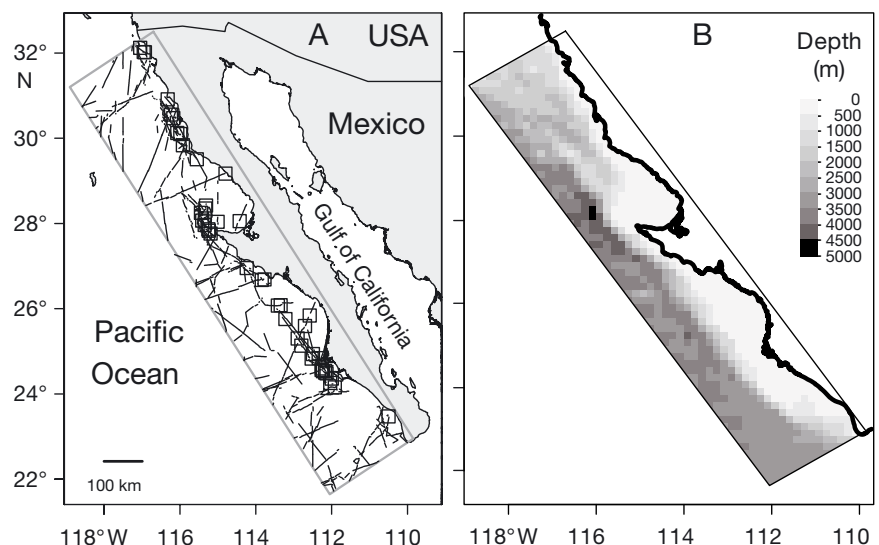


Fig. 1. *Delphinus capensis*. (A) Tracklines (thin black lines) and long-beaked common dolphin sightings (squares) off the peninsula of Baja California, Mexico, 1986 to 2006. The rectangle outlines the area within which data were considered for this analysis. (B) Grid of 992 cells within the study area, shaded by mean depth

are given in Kinzey et al. (2000) and Gerrodette & Forcada (2005).

For this analysis, we selected data within a rectangular area approximately 300 km from the coast (Fig. 1A). Approximately 87 000 depths within this area were extracted from the NOAA database ([www.ngdc.noaa.gov/mgg/gdas/gd\\_designagrid.html](http://www.ngdc.noaa.gov/mgg/gdas/gd_designagrid.html)) on a 1 min (~1 nautical mile) scale. We divided the study area into smaller subareas within which depth was reasonably uniform and could be represented by a single value. Subareas could be of arbitrary size and shape, but for convenience we used a grid of 992 rectangular cells, each 1/6 of a degree (~18 km) per side. The areas of the rectangular cells decreased slightly with latitude, but the mean area of non-boundary cells was 306 km<sup>2</sup>. There were about 90 depth values in each cell, with mean cell depths ranging up to nearly 5000 m (Fig. 1B).

Our analytical framework was a hierarchical Bayesian line-transect model, an extension of the basic model of Eguchi & Gerrodette (2009). If  $n$  objects are encountered in survey distance  $L$ , the density of objects  $d$  is:

$$d = \frac{n}{2wL} \quad (1)$$

Line-transect analysis estimates the 'effective' strip width  $w$  on each side of the trackline, on the basis of the distribution of distances of detected objects from the trackline. For long-beaked common dolphins, the number of dolphin schools  $n_i$  detected in each cell  $i$  with non-zero effort depended on the actual density  $d_i$  and the observation process summarized by  $w_i$  and  $L_i$ . We assumed that the  $n_i$  followed a Poisson distribution:

$$n_i \sim \text{Pois}(2w_i L_i d_i) \quad (2)$$

where survey distances  $L_i$  were known but  $w_i$  and  $d_i$  were estimated. For  $w_i$  we assumed that Beaufort sea state could affect the probability of detecting a school of dolphins, and modeled strip width as (Marques & Buckland 2004, Gerrodette & Forcada 2005):

$$w_i = \exp(\alpha_0 + \alpha_1 c_i) \quad (3)$$

where  $c_i$  was Beaufort sea state in cell  $i$  during the survey. Parameters  $\alpha_0$  and  $\alpha_1$  were estimated from the perpendicular distance  $y_j$  and sea state  $b_j$  for each sighting  $j$  with a normal likelihood, with mean zero and variance ( $\sigma^2$ ), such that:

$$y_j \sim \mathcal{N}(0, \sigma_j^2) \quad (4)$$

$$\sigma_j = \exp(\alpha_0 + \alpha_1 b_j) \sqrt{2/\pi}$$

that is, a half-normal detection function with a sea-state covariate ( $\mathcal{N}$ : normal distribution). We modeled the density of dolphin schools  $d_i$  as a function of depth

with linear, half-normal and hazard-rate functions, but report results only for the latter, which has the most flexible form of the three. The hazard-rate model was:

$$d_i = \beta_0 (1 - \exp(-(z_i/\beta_1)^{\beta_2})) \quad (5)$$

where  $z_i$  was the mean depth in cell  $i$  as a positive value, and  $\beta_0$ ,  $\beta_1$  and  $\beta_2$  were parameters to be estimated. To compute the density of animals, group size  $s$  was estimated with a normal likelihood from the  $n = \sum n_j$  observed dolphin school sizes  $g_j$ ,

$$g_j \sim \mathcal{N}(s, \sigma_s^2) \quad (6)$$

assuming a known variance  $\sigma_s^2 = \text{var}(g)/n$ .

The number of dolphins in each cell was  $sd_i A_i$ , where  $A_i$  was the water area of cell  $i$ . The cumulative abundance of dolphins occurring within an area shallower than depth  $k$  was:

$$N(k) = \sum sd_i A_i \text{ for cells } i \text{ with } z_i < k \quad (7)$$

and the cumulative percentage of abundance occurring within an area shallower than depth  $k$  was:

$$P(k) = 100N(k)/N_{\text{tot}} \quad (8)$$

where  $N_{\text{tot}}$  was the sum of the number of animals in all cells in the study area.

We used Markov Chain Monte Carlo methods, specifically the Gibbs sampler implemented in the BRugs package in R (R Development Core Team 2009), to estimate basic parameters  $\alpha_0$ ,  $\alpha_1$ ,  $\beta_0$ ,  $\beta_1$ ,  $\beta_2$  and  $s$ , as well as derived parameters  $N(k)$  and  $P(k)$ . We assumed flat prior distributions for all basic parameters. BUGS code (Lunn et al. 2000) for the model is given in the supplement at [www.int-res.com/articles/suppl/n015p159\\_supp/](http://www.int-res.com/articles/suppl/n015p159_supp/). After a burn-in phase of 20 000 samples, we ran 1 000 000 steps, retaining every tenth value, for a posterior sample of 100 000 values for inference. Convergence was checked by obtaining similar posterior distributions with different initial values. We further checked our results by obtaining similar posterior distributions with non-Markov Chain Monte Carlo methods (uniform sampling across a 6-dimensional array), and by obtaining point estimates for the detection function and total abundance with Distance software (Thomas et al. 2010); these estimates were similar to the medians of the posterior distributions.

## RESULTS

There was a total of 8545 km of survey effort within the study area, with non-zero effort in 531 of the 992 cells. Survey effort distances in individual cells

ranged from 0 to 65 km, with a predominance of lower values (Fig. 2A). Effort-weighted mean Beaufort sea state conditions in each cell ranged from 0 to 5, with a predominance of higher values (Fig. 2B).

There was a total of 44 sightings of long-beaked common dolphin *Delphinus capensis* schools in 36 cells, with group sizes ranging from 1 to 6393. Mean group size was 512 (SE = 154). The frequency of perpendicular distances from the trackline of the sightings declined with distance (Fig. 3A). Depths within the study area were bimodally distributed between 0 and 5000 m (Fig. 3B, dashed lines), and tracklines sampled all depths (Fig. 3B, solid lines). Sightings occurred in a restricted fraction of these depths, mainly <250 m (Fig. 3B, gray bars). Of the 44 sightings, 6 occurred deeper than 500 m, and only one occurred deeper than 1000 m.

Long-beaked common dolphins were estimated to occur at a mean density of about 2 animals  $\text{km}^{-2}$  in shallow water (Fig. 4A). The 0.1 and 0.9 quantiles (i.e. a central 80% credibility interval) of the posterior distribution at this depth were 1.6 and 2.8  $\text{km}^{-2}$ , respectively. The hazard-rate model predicted that density was constant from about 0 to 200 m, and then decreased with depth, falling to a mean density of 0.3  $\text{km}^{-2}$  by 1000 m, and <0.03  $\text{km}^{-2}$  by 1500 m. Based on this function, the highest densities of animals occurred on the continental shelf (Fig. 4B). A posterior distribution of density was calculated at each of the ~87 000 depths in the study area; the median value of each distribution is plotted in Fig. 4B.

Cumulative abundance  $N(k)$  and percentage of abundance  $P(k)$  both rose rapidly at depths <200 m and then approached an asymptote (Fig. 5). There was less uncertainty about the percentage of a population included at a given depth than about the absolute number (shaded areas in Fig. 5).

Setting the boundary of a protected area at 360 m would meet the first management goal of including 100 000 animals with a probability of 0.9 (Fig. 5A, dashed lines). Setting the boundary at

160 m could also include 100 000 animals, but only with a probability of 0.5 (the median, Fig. 5A, vertical dotted line).

Setting the boundary at 210 m would meet the second management goal of including 60% of the population within the area with a probability of 0.9 (Fig. 5B, dashed lines). Setting the boundary at 170 m would include 60% of the population with a probability of 0.5 (Fig. 5B, vertical dotted line).

Because these depth boundaries are on or near the continental slope, the areas within the depths are not very different along much of the Baja California Pacific coast (Fig. 6). The areas between the coastline and the 160, 170, 210 and 360 m isobaths within the study area were  $46.7 \times 10^3$ ,  $47.7 \times 10^3$ ,  $51.4 \times 10^3$  and  $61.3 \times 10^3 \text{ km}^2$ , respectively.

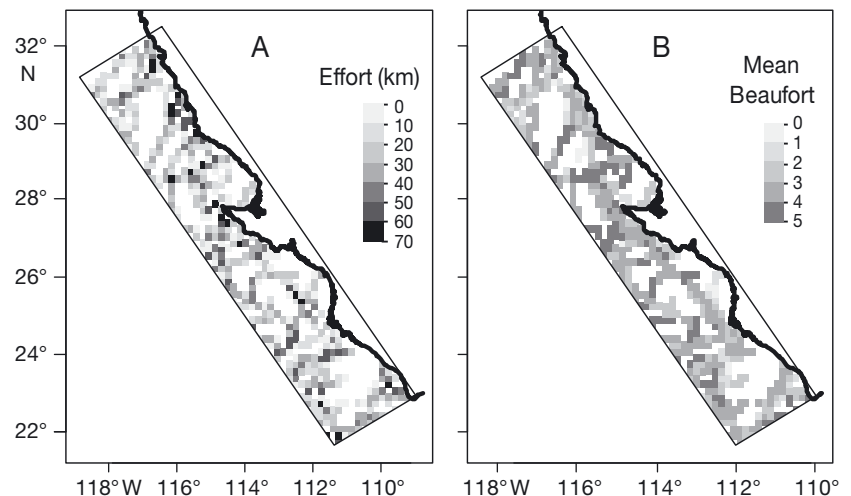


Fig. 2. *Delphinus capensis*. (A) Survey effort in each cell. (B) Effort-weighted mean Beaufort sea state conditions at the time of the survey in each cell. Blank cells had no survey effort

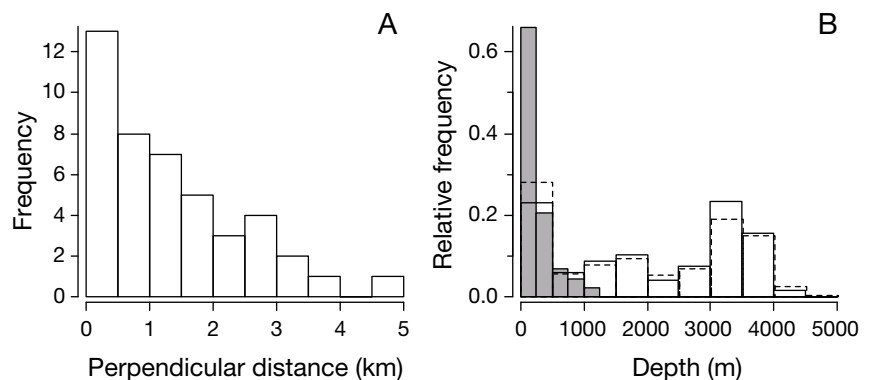


Fig. 3. *Delphinus capensis*. (A) Frequency of perpendicular distances of sightings from the trackline. (B) Relative frequencies of depths of cells with sightings (gray bars), cells with survey effort (solid lines), and all cells in the study area (dashed lines)

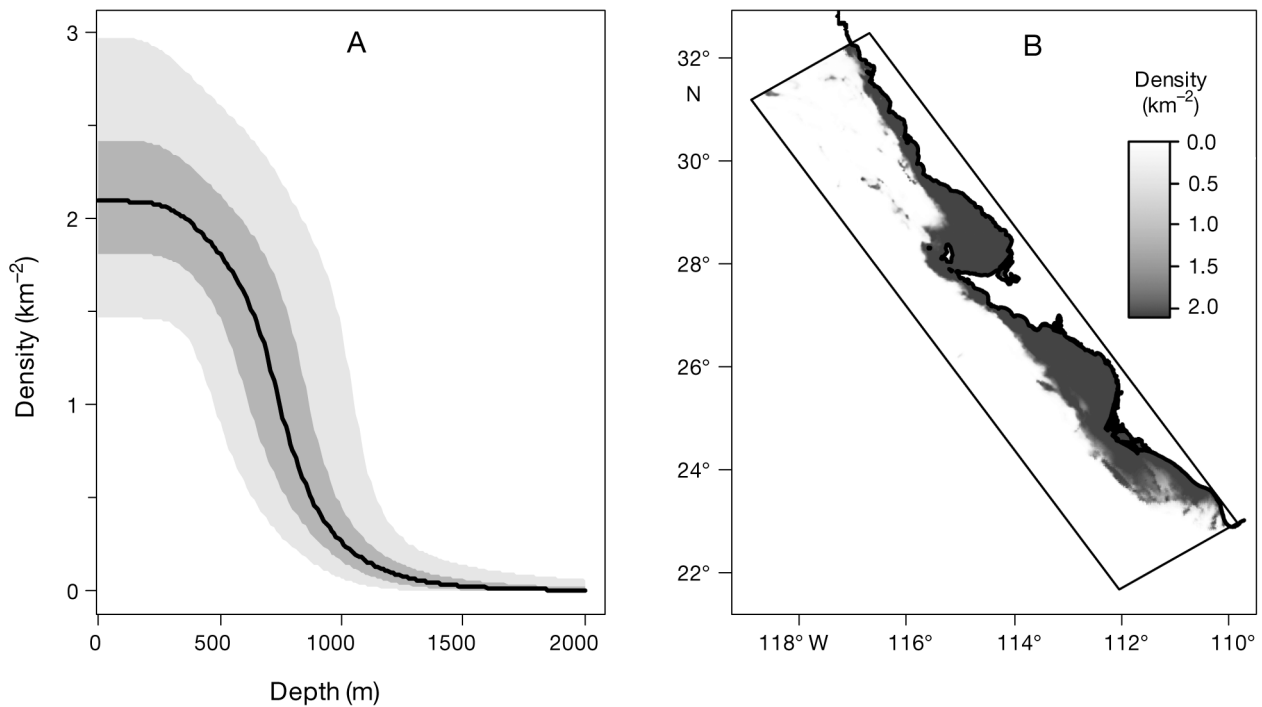


Fig. 4. *Delphinus capensis*. (A) Animal density as a hazard-rate function of depth. The line connects the medians; dark gray, central 50% and light gray, central 90% of the posterior distributions at each depth. (B) Spatial distribution of animal density based on depth at a 1 min scale, shaded by median posterior animal density

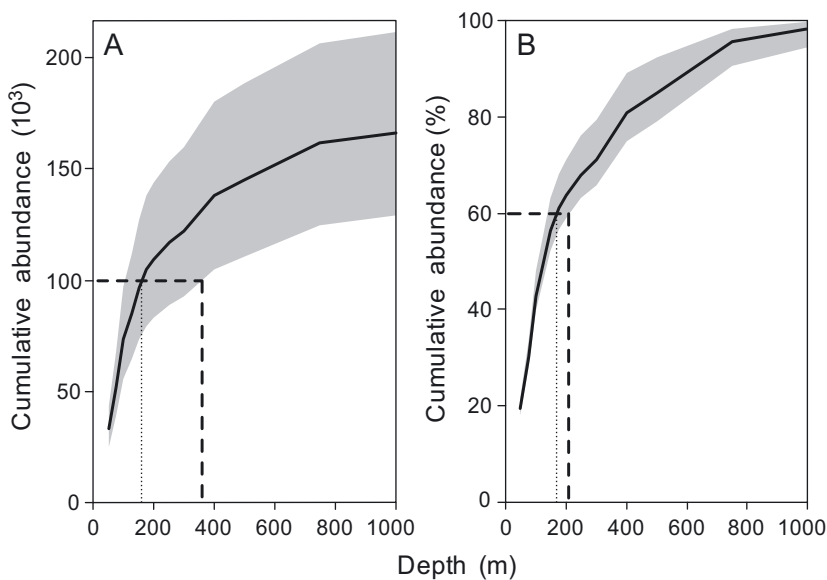


Fig. 5. *Delphinus capensis*. (A) Cumulative abundance by depth. (B) Cumulative percentage of abundance by depth. Solid lines connect the medians, and the shaded areas are bounded by the 0.1 and 0.9 quantiles of the posterior distributions. Horizontal dashed lines correspond to management targets of (A) protecting 100 000 dolphins or (B) protecting 60% of the population. Vertical dashed lines indicate the depths corresponding to a precautionary policy of achieving these targets with a probability of 0.9. Vertical dotted lines indicate the depths corresponding to a less precautionary policy of achieving these targets with a probability of 0.5

## DISCUSSION

A frequent goal of a protected area, such as a reserve, park or sanctuary, is to protect the critical habitat of a species. If 'critical' is defined in sufficiently quantitative terms, data can be used to determine whether a proposed area will meet or has met the management goal. For effective management, uncertainty should also be recognized and considered. If policy makers specify the level of precaution, scientists can estimate parameters consistent with those policy goals. Here we assumed that a quantitative management goal, and a desired probability of meeting that goal, had been articulated for a potential protected area of a coastal cetacean, the long-beaked common dolphin *Delphinus capensis*.

A hierarchical Bayesian line-transect habitat model estimated dolphin density as a hazard-rate function of depth (Fig. 4A). The depth which would represent a management goal

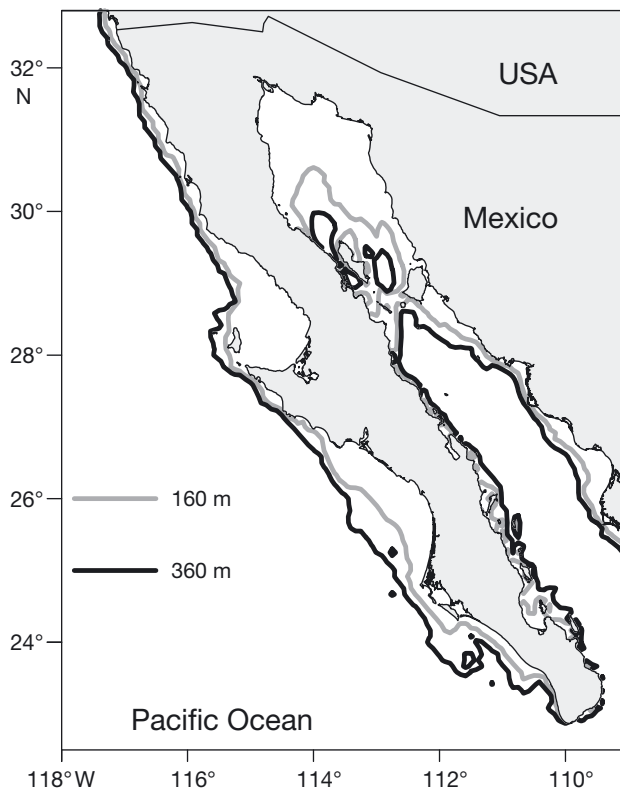


Fig. 6. Locations of 160 and 360 m isobaths around the peninsula of Baja California, Mexico

of including 100 000 dolphins in the protected area with a probability of 0.5 was 160 m (Fig. 5A). For many purposes this is a reasonable estimate, but it is not a precautionary estimate. There is a 50% probability that there are fewer than 100 000 dolphins in waters shallower than 160 m. In other words, there is only a 50:50 chance that the management goal would be met. The 'best' estimate does not lead to the best management with respect to conserving the species (Taylor & Wade 2000).

A precautionary approach achieves the management goal with a high probability. We postulated that the level of precaution had been set, as a matter of policy, at 0.9. For the management goal of including 100 000 dolphins to be met with this higher probability, the boundary of the protected area would have to be 360 m, on the basis of the habitat model (Fig. 5A). In this case, there was a considerable difference in depth (160 vs. 360 m) between the non-precautionary and precautionary boundary of the protected area.

For a second management goal of including at least 60% of the population, there was a smaller difference between the depth of the precautionary bound-

ary (210 m) and the non-precautionary one (170 m; Fig. 5B). The difference was smaller because there was less uncertainty about the cumulative percentage of the population contained within a given depth than about the absolute number of animals within the same depth.

We emphasize that the design of a protected area for long-beaked common dolphins was a hypothetical case study. *Delphinus capensis* is not endangered, nor has it been shown that the species is declining or in need of special protection. We chose the species for the case study because transect data were available and the distribution of *D. capensis* could be reasonably modeled by depth alone. Furthermore, the design of an actual reserve would consider social, political, economic and logistical factors, as well as biological data. Several programs are available to help optimize reserve design, such as Marxan ([www.uq.edu.au/marxan](http://www.uq.edu.au/marxan)), MarineMap (<http://marinemap.org/>) and Zonation ([www.helsinki.fi/science/metapop/Research/Project\\_spatial4.htm](http://www.helsinki.fi/science/metapop/Research/Project_spatial4.htm)).

To infer cetacean habitat use from line-transect data, the separate components of a density estimator, such as sighting rate, group density, group size and effective strip width, may be modeled as functions of environmental variables, then combined to estimate density at small spatial scales (Cañadas & Hammond 2006, Ferguson et al. 2006, Gómez de Segura et al. 2007, Cañadas & Hammond 2008, Becker et al. in press, Forney et al. in press). Estimation of density and habitat relationships may also be combined in a single analysis (Hedley et al. 2004, Royle et al. 2004, Johnson et al. 2010, Niemi & Fernández 2010). Inference about population processes is improved when combined with an observation model into a single likelihood framework (Goodman 2004, Buckland et al. 2007, Royle & Dorazio 2008).

Fortunately for cetaceans, factors which are related to abundance, such as temperature, primary productivity, or depth in this case, can often be separated from factors that affect detection probability, such as number of observers, height of observation, or sea state in this case. We assumed that depth had little or no effect on the probability of detection of dolphins and that sea state at the time of the survey had little or no effect on the abundance of dolphins. The analysis attempted to account for the imperfect detection of animals in order to relate the true, but unobserved, number of animals to habitat factors. Bayesian methods provide a coherent framework for quantifying uncertainty (Clark 2005, Royle & Dorazio 2006, Cressie et al. 2009). Furthermore, because a Bayesian analysis expresses uncertainty in terms of

probabilities, results can be used directly in decision-making (Punt & Hilborn 1997, Goodman 2009), such as setting the boundary of a protected area.

The habitat model in the present study, while adequate to illustrate the importance of accounting for uncertainty in the design of a protected area, was relatively simple. More flexible models with additional habitat predictor variables should be considered for comprehensive estimation of *Delphinus capensis* habitat. Cañadas & Hammond (2008), for example, found that abundance of *D. delphis* in the Mediterranean Sea off southern Spain tended to be bimodal with depth, a pattern that would not be modeled by the hazard-rate function used here. The probability of detecting dolphin schools may depend on additional variables, particularly group size (Gerrodette & Forcada 2005). The Poisson distribution assumed that the numbers of dolphin schools detected per cell were independent after adjusting for survey effort, sea state and depth. If the density of schools depended on other factors—patches of prey across several cells, for example—the numbers of sightings could be spatially correlated.

Spatial management based on sea-surface temperature or other dynamic habitat variables without fixed geographic boundaries is natural and ecologically sensible in the ocean (Norse & Crowder 2005). Habitat variables which are not geographically fixed can be modeled, but pose challenges for implementation and enforcement of protected areas based on such variables. Nevertheless, fishing restrictions based on dynamic habitat conditions have been implemented to reduce bycatch of loggerhead sea turtles *Caretta caretta*. Along the coast of southern California, USA, fishing with drift gill-nets is prohibited from June 1 to August 31 if El Niño conditions exist or are predicted (Federal Register 2002, 2007). Around the waters of Hawaii, fishers are warned of higher risk of interaction with turtles in areas within a certain sea-surface temperature range (Howell et al. 2008). As more knowledge about the interactions between protected species and environment accumulates, habitat-based management rules based on dynamic variables may become more prevalent, but it is important to take the uncertainty about the estimated habitat relationship into account.

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