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Evaluating monitoring methods for cetaceans

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Abstract

With increasing human pressures on wildlife comes a responsibility to monitor them effectively, particularly in an environment of declining research funds. Scarce funding resources compromise the level and efficacy of monitoring possible to detect trends in abundance, highlighting the priority for developing cost-effective programs. A systematic and rigorous sampling regime was developed to estimate abundance of a small, genetically isolated spinner dolphin (*Stenella longirostris*) population exposed to high levels of human activities. Five monitoring scenarios to detect trends in abundance were evaluated by varying sampling effort, precision, power and sampling interval. Scenario 1 consisted of monthly surveys, each of 12 days, used to obtain the initial two consecutive annual abundance estimates. Scenarios 2, 3 and 4 consisted of a reduced effort, while Scenario 5 doubled the effort of Scenario 1. Scenarios with the greatest effort (1 and 5) produced the most precise abundance estimates (CV=0.09). Using a CV=0.09 and power of 80%, it would take nine years to detect a 5% annual change in abundance compared with 12 years at a power of 95%. Under this best-case monitoring scenario, if the trend was a decline, the population would have decreased by 37% and 46%, respectively, prior to detection of a significant decline. With the potential of a large decline in a small population prior to detection, the lower power level should be used to trigger a management intervention. The approach presented here is applicable across taxa for which individuals can be identified, including terrestrial and aquatic mammals, birds and reptiles.

1 Introduction

With the ever-increasing human pressure on wildlife we have a responsibility to monitor and manage wildlife populations effectively (Geffroy et al. 2015; Tablado and Jenni 2015). Management decisions for the conservation of wildlife should be based on sound scientific investigations and rigorous monitoring regimes, particularly for those populations whose viability is threatened (Jaramillo-Legorreta et al. 2007; Turvey et al. 2007). These requirements, however, conflict with the perennial problem of scarce funding resources in conservation biology (Williams and Thomas 2009; Williams et al. 2011). The challenge that management agencies face is the effective allocation of scarce funding resources to conservation research and management, while still being able to fulfil their statutory obligations. Consequently, managers often cut the costs of research to estimate wildlife abundance (Williams and Thomas 2009; Williams et al. 2011). The trade-off for reduced funding for abundance estimation is a reduction in the precision of those estimates (Thomas et al. 2010), which has important implications for the power of detecting trends in abundance. Power analysis determines the ability of a study to detect an effect of a given size with a degree of confidence, and should be an integral part of any study that is investigating the demographic parameters of wildlife populations. Detecting changes in populations is critical for managing populations with low abundance.

Taylor *et al*. (2007) reviewed decades of monitoring data for marine mammal stocks under United States (U.S.) jurisdiction, and found that agencies had almost no statistical power to detect even catastrophic declines in many stocks, especially oceanic dolphins. For example, a study of the Atlantic spotted dolphin (*Stenella frontalis*) in the Western North Atlantic had only 11% power to detect a 50% decline in 15 years (Taylor et al. 2007). In the waters of the

U.S., marine mammals are data-rich by global standards, as exemplified by the fact that 75% of the world's ocean has never been surveyed to estimate cetacean density (Kaschner et al. 2012). In the face of such uncertainty, two broad approaches have been suggested as precautionary ways to conserve marine mammal populations when statistical power is low or data are scarce. One approach is to lower the burden of proof that a population is in decline before triggering a mitigation approach (e.g., Taylor et al. 2000). The other is to set allowable harm limits on an annual basis, so that populations should never decline below some predefined threshold, as long as those annual limits are not exceeded (e.g., Wade 1998). Although these harm limits are usually thought of in terms of lethal removals from a population (e.g., through incidental catch in fisheries or ship strikes), decision rules could be articulated equally well in terms of the number of sub-lethal takes that policy-makers are willing to allow animals to withstand (e.g., Higham et al. 2016).

Notwithstanding the difficulty in detecting declines in long-lived, slowly-reproducing mammals, managers often require proof that a population falls within either the classification of “small population” or “declining population” (Caughley 1994) before they act. Population monitoring programs designed to detect change and determine management strategies that hinge on proof of declines to trigger management intervention require precise and unbiased estimates of population parameters (Taylor and Gerrodette 1993; Taylor et al. 2007). To do this, these programs must be designed to satisfy the assumptions of the estimation methods to ensure that the estimates are unbiased and have sufficient sampling effort to produce precise abundance estimates (Wilson et al. 1999; Thompson et al. 2000).

The power to detect trends in abundance depends on the relationship between the rate of change in the abundance, the precision of the abundance estimate (*e.g.,* the coefficient of variation) and the acceptable levels of making errors to detect change (Type I (α) and Type II (β) errors). Variations in these parameters can then determine the efficacy of proposed monitoring programs to detect trends in abundance and provide a scientific basis for the level of precaution required to address management issues.

The U.S. National Oceanic and Atmospheric Administration (NOAA) has the mandate under the *Marine Mammal Protection Act 1972* (MMPA) to protect all cetaceans, seals and sea lions in U.S. waters and the National Marine Fisheries Service (NMFS) and the U.S. Fish and Wildlife Service have the responsibility for assessing the stocks of cetaceans and pinnipeds. The frequency of stock assessments depends on the classification of the stock: strategic stocks require annual reviews, while non-strategic stocks require reviews every three years or when new information becomes available (Carretta et al. 2014). A strategic stock is defined under the MMPA as a marine mammal stock "… (A) *for which the level of direct human-caused mortality exceeds the potential biological removal level;* (B) *which, based on the best available scientific information, is declining and is likely to be listed as a threatened species under the Endangered Species Act (ESA) within the foreseeable future; or* (C) *which is listed as threatened or endangered under the ESA, or is designated as depleted under the MMPA.*" Currently, Hawaiian spinner dolphins (*Stenella longirostris*) are not listed as threatened, endangered or depleted. Furthermore, the levels of serious injury and mortality due to anthropogenic causes do not exceed the estimated Potential Biological Removal (PBR) level for the stock (Carretta et al. 2014). Therefore, they are classified as a non-strategic stock (MMPA, 1972).

In Hawaii, spinner dolphins live in small (Tyne et al. 2014) , isolated stocks with restricted ranges (Andrews *et al.*, 2010) and have evolved a specialised behavioural ecology (Norris and Dohl 1980). They forage cooperatively offshore at night, and return to sheltered bays to socialise and rest during the day (Norris and Dohl 1980; Norris et al. 1994; Benoit-Bird and Au 2009; Tyne et al. 2015) during which time the bays are also used extensively by people for tourism, recreational and subsistence purposes (Heenehan et al. 2015). Some of these activities, in particular nature-based tourism, engage in repeated, close-up encounters with dolphins on a daily basis (Heenehan et al. 2015). These close-up encounters may have negative consequences for spinner dolphins, which is a major concern for managing the population. However, currently no data are available on the trends in abundance for any spinner dolphin stock in the Hawaiian archipelago (Carretta et al. 2014), which hampers the evaluation of potential impacts on Hawaiian spinner dolphins.

Here, data from a rigorous photo-identification study designed to estimate abundance were used to provide a second consecutive annual abundance estimate for the Hawaii Island spinner dolphin stock (see Tyne et al. 2014 for the first estimate) and evaluate the power of different sampling strategies to detect change in abundance. Five scenarios with different levels of sampling effort, based on the systematic approach employed in Tyne et al. (2014), were evaluated in terms of their efficacy to detect trends in abundance by varying sampling effort, the rate of change in abundance, precision, power and the interval between annual abundance estimates. The results from this research provide management with guidelines for evaluating sampling programs of different intensity to detect a trend in abundance, and to guide where limited funding resources may be directed. This approach is applicable across taxa for which individuals can be identified, including terrestrial and aquatic mammals (e.g., Pennycuick and Rudnai 1970; Parra et al. 2006), birds (Buckland et al. 2008; Williams and Thomson 2015) and reptiles (Sacchi et al. 2010). The results also provide fundamental information for the development of monitoring programs that evaluate the efficacy of management interventions (e.g., time-area closures) designed to reduce the number and intensity of human-wildlife interactions.

2 Materials and methods

2.1 Fieldwork

Hawaii Island is the largest, youngest and most southerly of the main Hawaiian Islands. On the leeward (west) side of the island is the Kona Coast, where four important dolphin resting bays are located: Makako Bay, Kealakekua Bay, Honaunau Bay and Kauhako Bay (Figure 1); (Norris et al. 1994; Thorne et al. 2012; Tyne et al. 2014; Tyne et al. 2015).

2.2 Sampling design

Abundance estimated from data that have been collected opportunistically can increase the risk of introducing sampling bias into the data, leading to inaccurate and imprecise abundance estimates. To mitigate this risk from September 2010–August 2012, boat-based photographic-identification was carried out in four important resting bays (Tyne et al. 2015) of the Hawaii Island spinner dolphin stock using the systematic sampling design presented in Tyne *et al*. (2014). Each bay was sampled on the same dates each month, regardless of whether dolphins were present or absent, thus providing consistent and even effort throughout the study period and area. This design, referred to as Scenario 1, consisted of 12 consecutive sampling days each month for each of the two years. Three additional sampling regimes of reduced intensity (Scenarios 2, 3 and 4) were evaluated, using subsets of Scenario 1 data, and compared with the results from Scenario 1. Finally, a fifth sampling regime of a two-fold increase in sampling intensity from Scenario 1, i.e., 24 consecutive sampling days each month, was also compared with the results from Scenario 1. Abundance and precision were estimated for each year.

2.3 Sampling effort

The sampling effort in each of the five scenarios was:

- Scenario 1 – 12 sampling days per month across four bays, two days in Makako Bay, four days in Kealakekua Bay, two days in Honaunau Bay and four days in Kauhako Bay (Figure 1).
- Scenario 2 – six sampling days per month, spread across the four bays, with the days chosen by randomly selecting half the number of days from each bay in Scenario 1.
- Scenario 3 – six sampling days per month, across the two bays where dolphins were encountered most frequently (two days in Makako Bay and four days in Kealakekua Bay).
- Scenario 4 – three sampling days per month, across two bays where dolphins were encountered most frequently, with the days chosen by randomly sampling half the number of days from each bay in Scenario 3 (one day in Makako Bay and two days in Kealakekua Bay).
- Scenario 5 – 24 sampling days per month across four bays chosen by randomly selecting double the number of days from each bay in Scenario 1, four days in Makako Bay, eight days in Kealakekua Bay, four days in Honaunau Bay and eight days in Kauhako Bay.

2.4 Estimating costs

The relative costs of the different sampling regimes were estimated by determining the number of hours required for field sampling and processing the images (including time to score photographs for quality, animal distinctiveness, and propose putative matches between photographic encounters) and multiplying this by an estimated labour costs of USD $10. This cost was that of a technician/undergraduate student trained to complete the tasks. In addition to labour costs, other costs are also associated with intensive boat-based photo-identification studies, e.g., access to research boat, boat fuel and maintenance, car fuel and maintenance, photo-identification equipment and computers.

2.5 Capture-recapture analysis

All photographs were graded according to photographic quality and distinctiveness to minimise the introduction of bias and to reduce misidentification (Urian et al. 2015). Only highly distinctive (D1) fins in photographs of excellent and good quality were included in the capture-recapture analyses (Gowans and Whitehead 2001; Urian et al. 2015). A capture was defined as a photograph of sufficient quality of an individual dolphin's distinctly marked dorsal fin. Capture histories corresponded to whether or not an individual dolphin was "captured" or "recaptured" during a sampling occasion. This information was compiled for each individual (calves excluded) after a photo-grading process. See Tyne et al. (2014) for more details of the photo-grading process.

For both years, open and closed capture-recapture models in the program MARK (White and Burnham 1999) were applied to the photo-identification data to estimate stock size, variability and evaluate the goodness-of-fit of the models. See Tyne *et al*. (2014) for full details on modelling approach. The POPAN approach is able to estimate probabilities of entry (immigration) and probabilities of exit (emigration and mortality), to and from the study area between sampling occasions (Schwartz and Arnason 1996). Under Scenario 2, 4 and 5, capture histories of individual dolphins were created based on six and three and 24 days respectively, subsampled 100 times from Scenario 1. Capture-recapture modelling was then applied to each of the 100 spinner dolphin capture histories for each Scenario. Annual abundance estimates and over-dispersion were each calculated from the mean of the 100 abundance estimates and over-dispersion ($\hat{c}=\chi^2/df$) for each year. Standard errors (SE) were then calculated for each of the annual abundance estimates from the standard deviation of the empirical sampling distributions of the estimates.

All capture-recapture models make the following assumptions (Williams et al. 2002): 1) marks are not lost during the study; 2) marks are correctly recognised on recapture; 3) individuals are instantly released after being marked; 4) intervals between sampling occasions are longer than the duration of a sample; 5) all individuals observed during a given sampling occasion have the same probability of surviving until the next one; 6) study area does not vary; and 7) homogeneity of capture probabilities, i.e. that all animals in a sampling occasion have equal probability of being captured. These assumptions are relaxed for certain models that allow heterogeneity in the capture probabilities. See Tyne *et al*. (2014) for more detail on the methods used to estimate abundance, mark rate and total stock size. To determine whether data were over-dispersed (when the variance is greater than the mean (Cox 1983)), the inflation factor ($\hat{c}$) was calculated for the abundance estimates (Anderson et al. 1994) and Quasi-likelihood adjustments were applied to take over-dispersion into account.

2.6 Detecting change in abundance

Detecting significant change in abundance over time requires that the null hypothesis (H_0) of no change in abundance is rejected. The probability of detecting a significant change in abundance when one doesn't exist, i.e., the Type I error, is generally set at α = 0.05, which is policy in the United States (Taylor et al. 2007). However, even when H_0 is not rejected, it is possible that the abundance has changed, *i.e.*, a Type II error is present. Power analysis can be used to identify the ability of sampling regimes to adequately detect trends in abundance and to minimise the probability of Type II errors occurring (Gerrodette 1987). The ability of five scenarios to detect change in abundance was investigated using Gerrodette's (1987) inequality model:

$$r^2 n^3 \geq 12CV^2\left(Z_{\alpha/2} + Z_\beta\right)^2$$

Where r = the rate of population change, n = the number of estimates, CV = the coefficient of variation of the abundance estimate (a measure of precision), $Z\alpha$ = normal deviate corresponding to the probability of making a Type I error, $Z\beta$= normal deviate corresponding to the probability of making a Type II error, α = the one-tailed probability of making a Type I error and β = the probability of making a Type II error. The probability of making a Type I error (α) was set at 0.05, and the r probability of making a Type II error (β) was set at 0.05 (i.e., power = 1 – β = 0.95) and 0.20 (power = 0.80).

The mean CVs obtained from the two annual abundance estimates from each sampling scenario were used to investigate the number of years required to detect varying rates of change (1 to 20%) in abundance at 80% and 95% power. A range of CVs (5% to 20%) were then used to determine the number of years required to detect 5% and 10% change in abundance at 80% and 95% power. Finally, we examined the number of years it would take to detect a 5% change in abundance under the five scenarios.

3 Results

3.1 Effort and summary statistics

A total of 276 days (> 2,350 h of on-water effort) of photo-identification was carried out in the four bays between September 2010 and August 2012. Approximately 4,000 h of effort was required to identify and grade the individual spinner dolphins from the more than 200,000 images. More than 64,500 of these images were of sufficient quality to be added to a photo-identification catalogue in which 235 individuals were classified as highly distinctive individuals (D1). The identification of new individuals reached a plateau (90% of all individuals identified) before the end of the two-year study period (August 2012, on sampling day 276), with 211 dolphins (90%) identified after 114 sampling days (July 2011) and 223 (95%) after 187 sampling days (February 2012, Figure 2).

3.2 Estimates of stock abundance

The abundance estimates were higher in 2012 than 2011 for all five scenarios. Although the abundance estimates were more precise from Scenarios 1 and 5 (CV = 0.09), there was very little difference in precision between the three scenarios (Scenarios 2, 3 and 4, CV = 0.10, 0.11 and 0.12 respectively). The goodness-of-fit measure ($\hat{c}=\chi^2/df$) suggested that the data were over-dispersed for eight of the ten estimates (Scenarios 1, 2, 4 and 5) (Table 1).

3.3 Detecting change in abundance

The number of abundance estimates required to detect a change in the dolphin stock decreased as the rate of change increased (Figure 3). For example, at a CV of 0.10 and a 5%

rate of change at 95% power, nine abundance estimates are needed to detect change, compared with five abundance estimates to detect a 10% change (Figure 3). Furthermore, as the precision decreased (*i.e.,* CV increased), the time necessary to detect a change increased (Figure 4).

The annual abundance estimates from the most intensive sampling Scenarios 1 and 5 were the most precise (CV = 0.09; Table 2). Under these scenarios, it would take seven annual abundance estimates over six years to detect a 5% annual change (decline/increase) with 80% power. Under the same scenarios with 95% power, it would take eight annual abundance estimates over seven years to detect a 5 % change (Table 2). Under Scenario 4 (three field-days, two bays) and at 80% power, it would take eight annual abundance estimates over seven years to detect a 5% change in abundance (Table 2). The annual labour cost of Scenario 4 at 80% power was 27% that of Scenario 1 (12 field-days, four bays) at 80% power (Table 2). As the time interval between abundance estimates increased from one to three years, the number of abundance estimates required to detect a change decreased, but the time taken to detect a change increased (Table 2). This is due to the increase in the effective percentage change in abundance per interval (Gerrodette 1987; Wilson et al. 1999). To detect an annual 5% change at 80% and 95% power, it would take four and five abundance estimates (at three year intervals), over nine and 12 years, respectively. If the change was a continuous decline, the abundance would have declined by 37% and 46% by the time of detection, equivalent to a decline from 668 ± 62 SE (95% CI 556-801) to 433 and 372. If the change in abundance was an increase, the abundance estimate would have increased by 55% (1,035) and 80% (1,202) at the time of detection.

4 Discussion

This study aimed to provide a scientific basis for management agencies to develop monitoring programs that are effective in fulfilling their statutory obligations, while also providing information on where they might direct their scarce funding resources. To achieve this aim, we estimated the abundance of Hawaii Island spinner dolphins in consecutive years, modelled the ability of different sampling scenarios to detect change in abundance over time and estimated the relative costs of these scenarios. Two main findings emerged from this research. Firstly, the additional abundance estimates of the Hawaii Island spinner dolphin stock were virtually identical to those from the first year (Tyne et al. 2014), suggesting that the sampling design, developed to satisfy the assumptions of capture-recapture models, is rigorous and that the estimates from the first year are reliable. Secondly, although there was little difference in the precision between sampling scenarios, sampling effort affected the ability of the sampling regime to detect a significant trend in abundance over time. However, a point is reached where an increase in effort does not improve the precision of the abundance estimates but that the costs of sampling continue to increase (e.g., results from Scenarios 1 vs 5).

4.1 Estimates of abundance

The systematic sampling approach developed in Tyne *et al*. (2014) was designed specifically to estimate the abundance of the Hawaii Island spinner dolphin stock using capture-recapture models. Here, the data from this approach were used to evaluate the ability of five different sampling scenarios to detect a change in abundance over time. The two most intensive sampling scenarios, Scenarios 1 and 5 (Scenario 1 = 12 days each month in four bays; Scenario 5 = 24 days each month, randomly resampled from Scenario 1, across four bays) produced the most precise annual abundance estimates. However, the standard errors of Scenarios 2 and 3 (half of the sampling effort in Scenario 1) were still similar to those of Scenario 1 and had only slightly higher coefficients of variation (10% and 11% cf 9%). This is partly a consequence of the relatively high recapture probabilities of Hawaiian spinner dolphins, even at the reduced sampling efforts of Scenarios 2 and 3. The annual abundance estimates in this study and in Tyne *et al*. (2014) are > 30% lower than the most recent previous estimate (Ostman-Lind et al. 2004). However, these comparisons should be made with caution, as previous research efforts were not designed specifically to estimate abundance (see also Tyne et al. 2014). Consequently, it is not possible to assess the current trend in population size of the Hawaiian spinner dolphins, except to acknowledge that the stock is smaller than previously thought (Norris et al. 1994; Ostman-Lind et al. 2004).

4.2 Monitoring changes in dolphin abundance over time

Caughley (1994), defines problems in conservation biology as falling into the “small” or “declining” population paradigm. Here, and the results from Tyne et al. (2014) clearly demonstrate that the Hawaii Island spinner dolphin stock is a “small” population. Through estimating the power of alternative sampling strategies, we provide the information needed to assess population decline with different degrees of certainty.

With the increasing pressure on coastal dolphin populations the ability to confidently detect trends in abundance over time is critical when making conservation decisions (Taylor and Gerrodette 1993; Wilson et al. 1999; Thompson et al. 2000). Degrees of precision, power, sampling effort and interval between abundance estimates were varied to evaluate the ability of five sampling scenarios to detect significant change in abundance over time. As the sampling effort increased, so did the precision of the abundance estimates, and thus changes in abundance could be detected earlier. This research provides the basis for evaluating future trends in abundance as the current trend in population size is unknown, and highlights the need for future systematic research designed to estimate abundance. Clearly, the need for future estimates and evaluation of change in the Hawaii Island spinner dolphin population size is a priority for managers because of the small population size (Tyne et al. 2014), its genetic isolation (Andrews et al. 2010) and the use of the four bays important for resting spinner dolphins (Tyne et al. 2015), where the dolphins encounter significant numbers of human activities on a daily basis (Heenehan et al. 2015) .

4.3 Applications for monitoring

Hawaiian spinner dolphins are currently classed as a non-strategic stock under the MMPA and under the current legislation, their abundance should be assessed once every three years (Carretta et al. 2014). The NOAA are considering a management approach to reduce the number and intensity of human-dolphin interactions in preferred resting habitat of spinner dolphins, including the introduction of time-area closures of the four spinner dolphin resting bays from this study (NOAA 2005). If time-area closures were introduced, a monitoring program to detect trends in dolphin abundance would help evaluate the effectiveness of this management strategy.

If the rate of change in abundance is small, then the level of precision will have a large effect on the time needed to detect a change (Figure 3; see also Wilson et al. 1999; Thompson et al. 2000; Taylor et al. 2007). The sampling effort for one of the most precise sampling scenarios (1, CV = 9%) in this study required a significant investment of time and field personnel and for the processing of the dolphin photo-identification images, and addition costs for equipment and logistic expenses, e.g. boats, cars, cameras and housing. The resources required for this research were only possible because of the presence of a dedicated PhD student, large numbers of volunteer research assistants and significant financial and logistical support through a NOAA grant. In general, the resources for population monitoring programs are chronically underfunded (Williams and Thomas 2009; Williams et al. 2011). Consequently, careful consideration on the distribution of funds for resourcing population assessments is required in developing the sampling designs and strategies for further estimates of the numbers in this spinner dolphin stock.

Management agencies can evaluate different monitoring options by comparing the different scenarios investigated in this study, for example, an annual monitoring program implemented under Scenario 4 (three field-days per month across two bays) is estimated to require eight annual abundance estimates and take seven years to detect a significant 5% change in abundance at 80% power. This is a year longer than the estimated time to detect change using the annual monitoring program of Scenario 1 (12 field-days per month, across four bays) at 80% power, a much more intensive sampling regime. If the change was consistent decline in abundance, the spinner dolphin population would have reduced by 26% to 494 dolphins under Scenario 1 and by 30% to 468 dolphins under Scenario 4, before a significant decline was detected. The annual cost of running a monitoring program implemented under Scenario 4, however, is only 27% of the cost of the monitoring program for Scenario 1. Furthermore, running an annual monitoring program implemented under Scenario 2 (six field-days per month, across four bays), at 80% power, is estimated to require seven surveys per year and take six years to detect a significant 5% change in abundance, the same time required to detect a 5% change as Scenario 1 but at half the cost.

Other considerations in the design of the program include the rate of change in abundance and the confidence of detecting significant change. By increasing power (confidence) to detect a change, both the number of annual abundance estimates and study duration required will increase (Gerrodette 1987; Taylor et al. 2007). The time taken to detect a decline is critical for small, genetically isolated stocks, such as those of the Hawaii Island spinner dolphins (Wilson et al. 1999; Thompson et al. 2000). A precipitous decline in abundance will have significant, negative biological consequences for this spinner dolphin stock. Consideration of these factors is a paramount concern, especially in determining the level of precaution required to address management issues. Our findings suggest that managers have an important decision to make: if current levels of monitoring are inadequate to detect precipitous declines in a timely manner, is it appropriate to increase monitoring efforts to improve statistical power or should a metric, other than population decline, be used to trigger management intervention? The measures of precision for our abundance estimates are enviably high (CVs of 9 to 11%) by the standards of even well-monitored marine mammal stocks e.g., Cuvier's beaked whale (*Ziphius cavirostris*) (CVs of 51 to 55%) (Moore and Barlow 2013), and managers in the region have other conservation issues competing for scarce funding for research and mitigation efforts (Forney et al. 2011). We see two, non-exclusive options for resolving the dilemma faced by managers: managers could consider legal listing for spinner dolphins (i.e. classifying them as a strategic stock) when the certainty of a decline is above 80%, rather than the conventional 95%; and/or managers could act in a precautionary way and consider mitigation measures (e.g., time-area closures) to mitigate impacts in hopes that population declines are prevented altogether.

Another consideration in developing monitoring strategies for different cetacean species is the proportion and distinctiveness of identifiable individuals in the population. For example, Hectors dolphins (*Cephalorhyncus hectori*) have a low proportion of subtly distinctive individuals, between 10%, (Gormley et al. 2005) and 35% (Bejder and Dawson 2001), whereas in general, bottlenose dolphins (*Tursiops* spp.) have a larger proportion of highly distinctive individuals of approximately e.g., 60%, (Wilson et al. 1999); 80%, (Nicholson et al. 2012). This spinner dolphin population had a relatively low proportion of distinctly marked individuals (35%) (Tyne et al. 2014). Clearly, the distinctiveness of individuals has implications for sampling precision and the ability of sampling programs to detect a change in abundance.

These results provide a scientific basis for the level of precaution required to address management issues, while assisting in the effective allocation of limited funding resources to monitoring programs. The sampling design adopted by Tyne et al. (2014) and in the current study to estimate the abundance of Hawaii spinner dolphins, when used in combination with power analyses, can effectively determine when a trend in abundance will be detected and should be considered as an integral part of any population management strategy. Here, at the most intensive sampling scenarios we considered (Scenarios 1 and 5), with annual surveys and abundance estimates assessed every three years at 95% power, the population of spinner dolphins may have declined by 46% at the time a significant trend is detected. This rate of decline is approximately 50% over 15 years, a rate that has been defined as “precipitous” (Taylor et al. 2007) and could lead to the stock being classed as ‘depleted’ under the MMPA (Taylor et al. 2007). This is a serious concern for a small and genetically isolated population, such as the one of Hawaii Island spinner dolphins. In order to be consistent with the legislation within the MMPA, it will be necessary to increase funding for monitoring or lower the burden of proof needed to trigger a change in classification from non-depleted to depleted status.

We have shown little difference in the precision of abundance estimates between five sampling scenarios of varying intensity but major differences in costs of the scenarios, with the least intensive program costing about 30% of the scenario implemented by Tyne et al. (2014) and 15% of the most intensive regime (Scenario 5 - 24 field-days per month, across four bays). Management agencies can evaluate these different monitoring options while considering the allocation of their available funding resources.

The objectives of population studies of other wildlife species with identifiable individuals may require that demographic parameters other than abundance are estimated. Although we have concentrated on the estimation of abundance and precision from different scenarios, survival and immigration/emigration have also been estimated using the data collected from this approach (Tyne et al. 2014). Delphinid sighting data have also been collected systematically along transects to estimate abundance and other demographic parameters, such as temporary immigration/emigration (Smith et al. 2013; Brown et al. 2016; Sprogis et al. 2016) using Pollock’s Robust Design (Pollock et al. 1990). The data from these studies could be used to estimate the power to detect change and evaluate alternative sampling strategies for monitoring in a similar manner to the current study by varying the number of transect cycles. Using line transect sampling to estimate the abundance of dolphins from a small boat, is not advisable however, as it can lead to biased estimates due to the movement response of the dolphins towards and away from the boat prior to detection (Turnock and Quinn 1991). The approach presented in the current study provides a model for developing sampling strategies to monitor other populations with identifiable individuals, including terrestrial and aquatic mammals (Pennycuick and Rudnai 1970; Wilson et al. 1999), birds (Buckland et al. 2008; Williams and Thomson 2015) and reptiles (Sacchi et al. 2010), whose abundance can be estimated through capture-recapture analyses.

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Tables

Table 1 Abundance, over-dispersion and coefficient of variation calculated for the different sampling scenarios and capture-recapture models. Scenario 1 = 12 days of sampling covering four bays (two days in Makako Bay, four days in Kealakekua Bay, two days in Honaunau Bay and four days in Kauhako Bay), Scenario 2 = six days randomly subsampled from the 12 days covering four bays (one day in Makako Bay, two days in Kealakekua Bay, one day in Honaunau Bay and two days in Kauhako Bay), Scenario 3 = six days covering two bays (two days in Makako Bay and four days in Kealakekua Bay), Scenario 4 = three days randomly subsampled from Scenario 3 covering two bays (one day in Makako Bay and two days in Kealakekua Bay) and Scenario 5 = 24 days randomly subsampled from the 12 days covering four bays (four days in Makako Bay, eight days in Kealakekua Bay, four days in Honaunau Bay and eight days in Kauhako Bay). SE = standard error, CI = 95% confidence interval, ĉ = over-dispersion (values > 1.2 indicate Overdispersion).[1]estimates from Tyne *et al*. (2014)

Scenario, effort	Year	Total abundance ± 1 SE (95% CI)	ĉ	CV
1: 12 d, 4 bays	2011[1]	631 ± 60 (524-761)	1.4	0.09
	2012	668 ± 62 (556-801)	1.5	0.09
2: 6 d, 4 bays	2011	552 ± 57 (448-680)	1.5	0.10
	2012	632 ± 62 (521-769)	1.7	0.10
3: 6 d, 2 bays	2011	557 ± 56 (458-678)	1.1	0.11
	2012	659 ± 69 (545-796)	1.2	0.11
4: 3 d, 2 bays	2011	542 ± 63 (436-674)	1.6	0.12
	2012	652 ± 76 (525-827)	1.5	0.12
5: 24 d, 4 bays	2011	617 ± 58 (514-741)	1.3	0.09
	2012	665 ± 62 (554-798)	1.5	0.09

Table 2 Number of annual abundance estimates, effective percentage change, years to detection, total percentage change at detection, at varying degrees of precision, to detect an annual 5% change (decline/increase) in abundance between one, two and three year monitoring intervals and annual labour costs based on Scenario 1 = 12 days of sampling covering four bays (two days in Makako Bay, four days in Kealakekua Bay, two days in Honaunau Bay and four days in Kauhako Bay), Scenario 2 = six days randomly subsampled from the 12 days covering four bays (one day in Makako Bay, two days in Kealakekua Bay, one day in Honaunau Bay and two days in Kauhako Bay), Scenario 3 = six days covering two bays (two days in Makako Bay and four days in Kealakekua Bay), Scenario 4 = three days covering two bays (one day in Makako Bay and two days in Kealakekua Bay) and Scenario 5 = 24 days randomly repeated subsamples from the 12 days covering four bays (four days in Makako Bay, eight days in Kealakekua Bay, four days in Honaunau Bay and eight days in Kauhako Bay). Probability of a Type I Error (α = 0.05) and a Type II Error (1 – β = 0.95 and 1 – β = 0.80). CV = coefficient of variation. Annual labour costs = four people paid $US10/hr working nine hrs/day on the boat, and processing time based on 2000 hours/year from Scenario 1.

Power	**CV**	**Monitoring interval (years) (*t*)**	**Annual abundance estimates (*n*)**	**Effective % decline per interval *t* ($0.95^t - 1$)**	**Effective % increase per interval *t* ($1.05^t - 1$)**	**Years to detection ($t(n\text{-}1)$)**	**Total % decline at detection ($0.95^{t(n\text{-}1)} - 1$)**	**Total % increase at detection ($1.05^{t(n\text{-}1)} - 1$)**	**Annual labour cost ($US)**
Scenario 1									
0.80	0.09	1	7	-5.0	5.0	6	-26	34	50,240
	0.09	2	5	-9.8	10.3	8	-34	48	41,600
	0.09	3	4	-14.3	15.8	9	-37	55	37,280
0.95	0.09	1	8	-5.0	5.0	7	-30	41	54,560
	0.09	2	6	-9.8	10.3	10	-40	63	45,920
	0.09	3	5	-14.3	15.8	12	-46	80	41,600
Scenario 2									
0.80	0.10	1	7	-5.0	5.0	6	-26	34	25,120
	0.10	2	5	-9.8	10.3	8	-34	48	20,800
	0.10	3	4	-14.3	15.8	9	-37	55	18,640
0.95	0.10	1	9	-5.0	5.0	8	-34	48	29,440
	0.10	2	7	-9.8	10.3	12	-46	80	25,120
	0.10	3	6	-14.3	15.8	15	-54	110	22,960
Scenario 3									
0.80	0.11	1	8	-5.0	5.0	7	-30	41	27,280
	0.11	2	6	-9.8	10.3	10	-40	63	22,960
	0.11	3	5	-14.3	15.8	12	-46	80	20,800
0.95	0.11	1	9	-5.0	5.0	8	-34	48	29,440
	0.11	2	7	-9.8	10.3	12	-46	80	25,120
	0.11	3	6	-14.3	15.8	15	-54	110	22,960
Scenario 4									
0.80	0.12	1	8	-5.0	5.0	7	-30	41	13,640
	0.12	2	6	-9.8	10.3	10	-40	63	11,480
	0.12	3	5	-14.3	15.8	12	-46	80	10,400
0.95	0.12	1	10	-5.0	5.0	9	-34	55	15,800
	0.12	2	8	-9.8	10.3	14	-46	98	13,640

	0.12	3	7	-14.3	15.8	18	-54	141	12,560
Scenario 5									
0.80	0.09	1	7	-5.0	5.0	6	-26	34	100,480
	0.09	2	5	-9.8	10.3	8	-34	48	83,200
	0.09	3	4	-14.3	15.8	9	-37	55	74,560
0.95	0.09	1	8	-5.0	5.0	7	-30	41	109,120
	0.09	2	6	-9.8	10.3	10	-40	63	91,840
	0.09	3	5	-14.3	15.8	12	-46	80	83,200

Figures

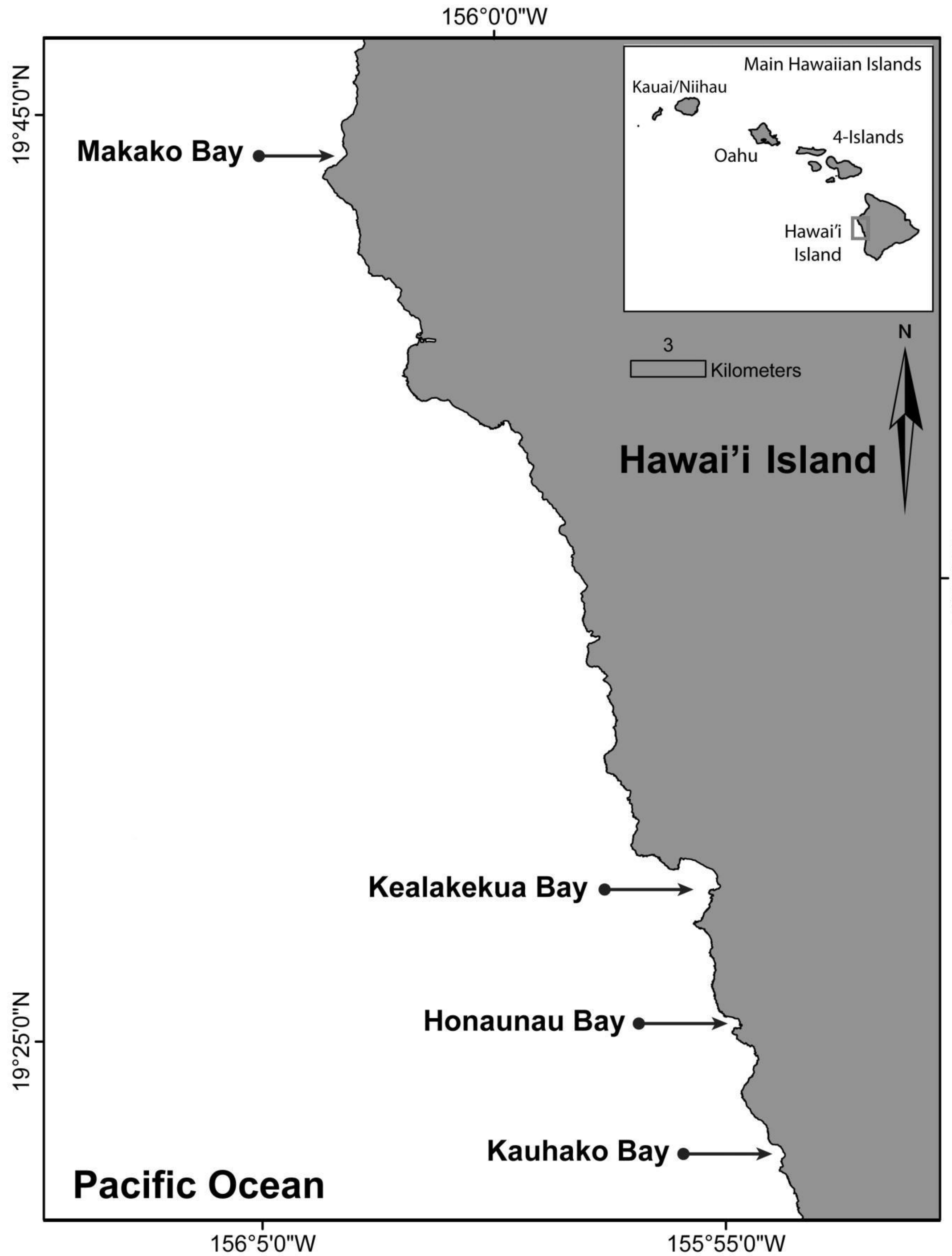

Figure 1 Map of the study area illustrating the four spinner dolphin resting bays, Makako Bay, Kealakekua Bay, Honaunau Bay and Kauhako Bay, along the Kona Coast of Hawaii Island.

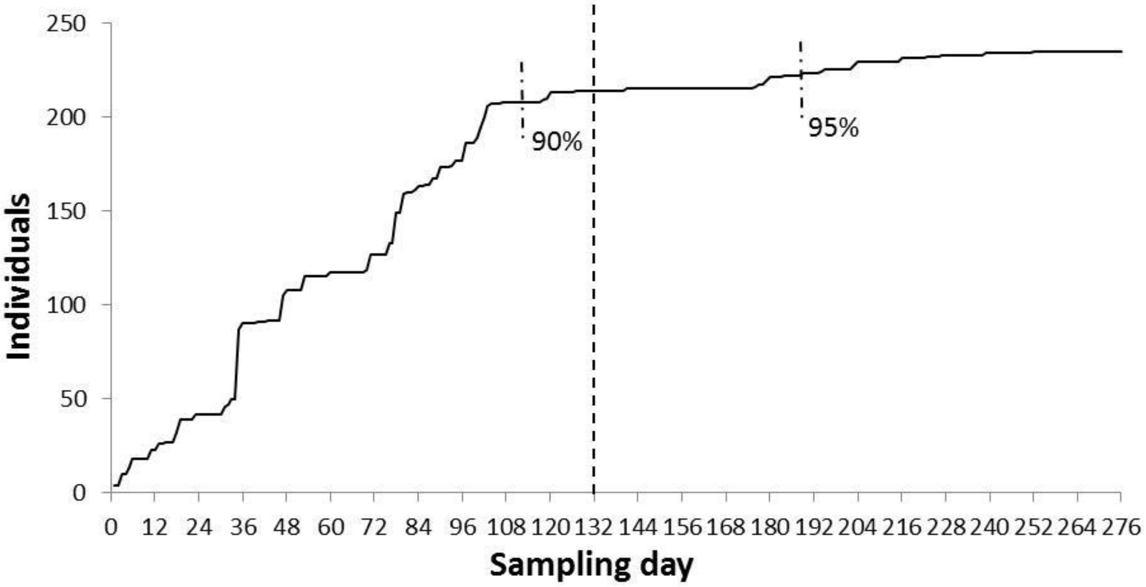

Figure 2 Cumulative discovery curve of highly distinctive (D1) spinner dolphins during 276 photographic identification sampling days from September 2010 to August 2012. Short, dashed, vertical lines indicate when 90% and 95% of the highly distinctive individuals had been identified. Long vertical dashed line indicates 12 months of sampling.

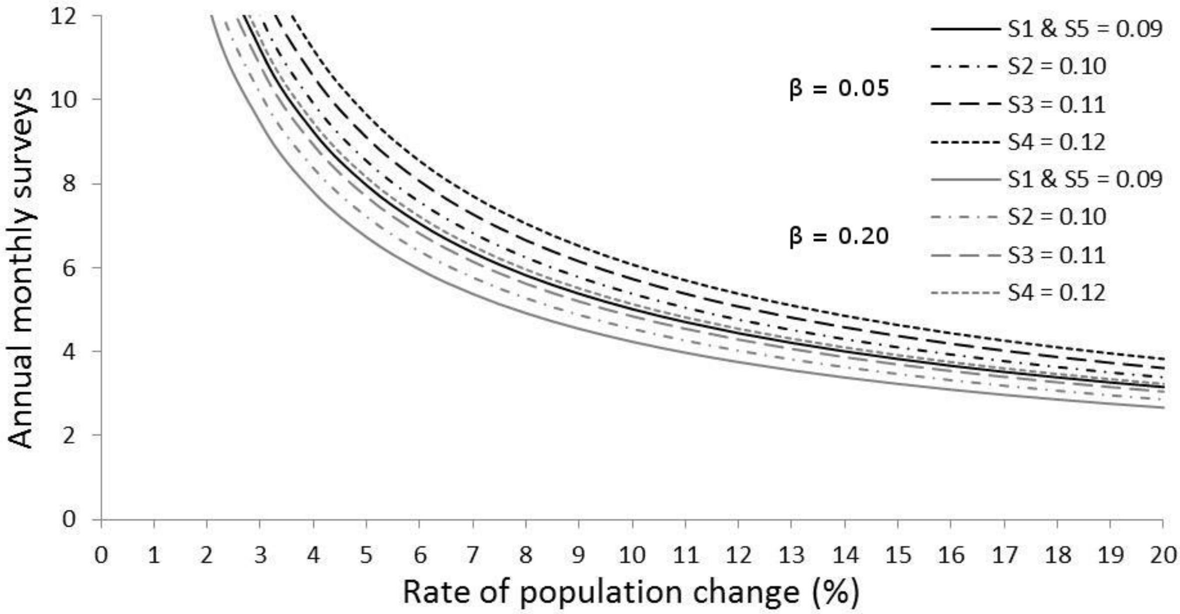

Figure 3 Number of annual abundance estimates required to detect various rates of change in stock size at varying levels of precision (coefficient of variation, CV) from five sampling scenarios. Scenario 1 (S1) = 12 days of sampling covering four bays (two days in Makako Bay, four days in Kealakekua Bay, two days in Honaunau Bay and four days in Kauhako Bay), Scenario 2 (S2) = six days randomly subsampled from the 12 days covering four bays (one day in Makako Bay, two days in Kealakekua Bay, one day in Honaunau Bay and two days in Kauhako Bay), Scenario 3 (S3) = six days covering two bays (two days in Makako Bay and four days in Kealakekua Bay), Scenario 4 (S4) = three days covering two bays (one day in Makako Bay and two days in Kealakekua Bay) Scenario 5 (S5) = 24 days randomly subsampled from the 12 days covering four bays (four days in Makako Bay, eight days in Kealakekua Bay, four days in Honaunau Bay and eight days in Kauhako Bay). Type I error (α) probabilities were set

at 0.05 and Type II error (β) probabilities were set at power = 1 – β = 0.95 (dark lines) and 1 – β = 0.80 (grey lines).

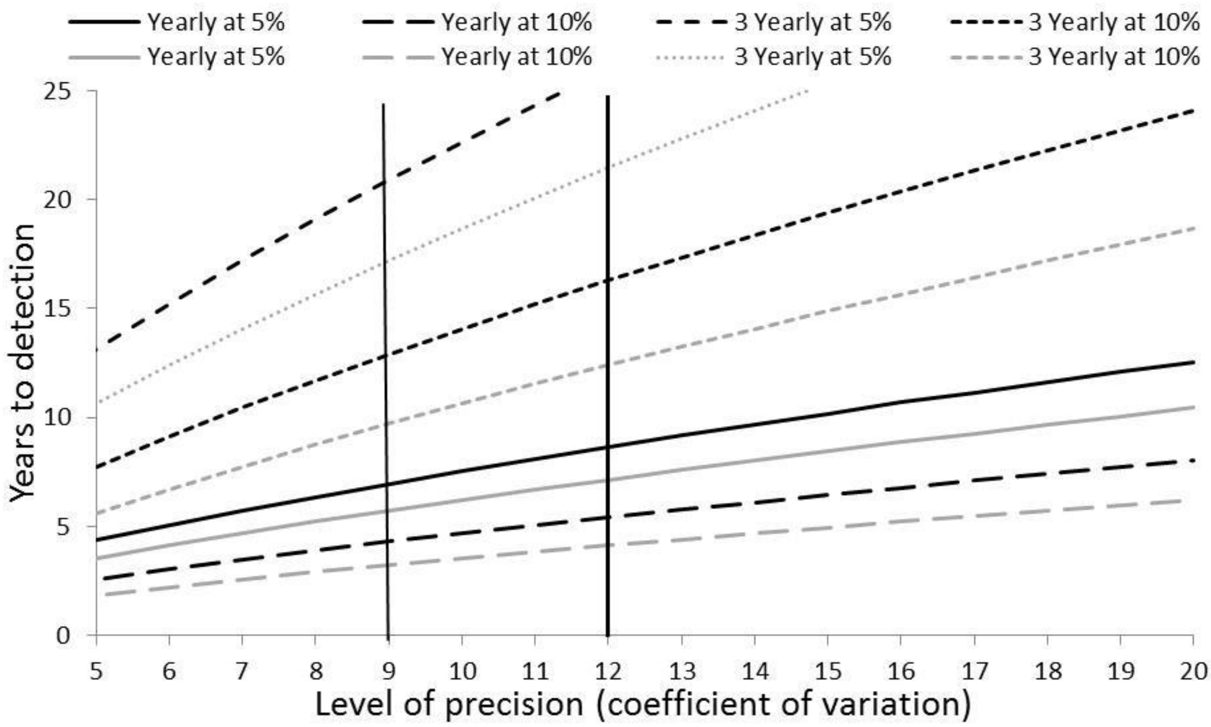

Figure 4 Predicted time it would take to detect an annual change of 5% and 10% with varying levels of precision (coefficient of variation, CV) using monitoring intervals of one year and three years. Type I error (α) probabilities were set at 0.05 and Type II error (β) probabilities were set at 0.20. Power = 1 – β = 0.80 (grey) and power = 1 – β = 0.95 (dark). Vertical lines indicate CV range from the five sampling scenarios.