

OPTIMAL ALLOCATION OF POINT-COUNT SAMPLING EFFORT

RICHARD J. BARKER^{1,2}, JOHN R. SAUER³, AND WILLIAM A. LINK³

¹Florida Cooperative Fish and Wildlife Research Unit,
Department of Wildlife and Range Science,
University of Florida, Gainesville, Florida 32611, USA;

²Department of Statistics, Massey University, Palmerston North,
New Zealand; and

³U.S. Fish and Wildlife Service, Patuxent Wildlife
Research Center, Laurel, Maryland 20708, USA

ABSTRACT.—Both unlimited and fixed-radius point counts only provide indices to population size. Because longer count durations lead to counting a higher proportion of individuals at the point, proper design of these surveys must incorporate both count duration and sampling characteristics of population size. Using information about the relationship between proportion of individuals detected at a point and count duration, we present a method of optimizing a point-count survey given a fixed total time for surveying and travelling between count points. The optimization can be based on several quantities that measure precision, accuracy, or power of tests based on counts, including (1) mean-square error of estimated population change; (2) mean-square error of average count; (3) maximum expected total count; or (4) power of a test for differences in average counts. Optimal solutions depend on a function that relates count duration at a point to the proportion of animals detected. We model this function using exponential and Weibull distributions, and use numerical techniques to conduct the optimization. We provide an example of the procedure in which the function is estimated from data of cumulative number of individual birds seen for different count durations for three species of Hawaiian forest birds. In the example, optimal count duration at a point can differ greatly depending on the quantities that are optimized. Optimization of the mean-square error or of tests based on average counts generally requires longer count durations than does estimation of population change. A clear formulation of the goals of the study is a critical step in the optimization process. Received 7 February 1992, accepted 25 November 1992.

POINT COUNTS are a popular method for surveying birds (Dawson 1981), and the method is used for extensive monitoring programs such as the North American Breeding Bird Survey (Robbins et al. 1986). Point counts are conducted by recording the number of individuals of the target species that are observed during a specified time interval at a sampling point. Because not all individual animals associated with the sampling point are observed during the count period, the data provide only an index of animal abundance (Dawson 1981). The count of individuals at point i , c_i , is related to the total number of animals associated with that point, N_i , by an unknown detection probability p_i , such that the expected count at point i is

$$E(c_i) = p_i N_i. \quad (1)$$

To use point-count data to compare populations over time or space, assumptions must be made about the constancy of p_i . Unfortunately,

environmental factors have been demonstrated to influence the p_i 's (Dawson 1981). Numerous papers in Ralph and Scott (1981) were devoted to documenting seasonal, temporal, observer, and species-specific influences on the p_i 's. The duration of the point count is one of the most obvious factors influencing the p_i 's. Functions relating p_i to count duration under a variety of conditions have been considered (e.g. Scott and Ramsey 1981). In a recent analysis, Gutzwiller (1991) used an empirical approach to examine how the mean number of species detected during unlimited distance point counts in winter was affected by factors such as count duration, time of day, and environmental covariates, and offered suggestions on allocation of sampling effort.

Verner (1988) has simulated the optimization of point-count surveys based on duration of the point count. He maximized expected total count of individuals as a function of various combi-

nations of counting and noncounting times, where number of birds counted was a function of counting time. He derived detection functions from all species and individuals detected during point counts conducted over varying intervals of time at two study sites in the Sierra National Forest, California. He concluded that efficiency of the survey increased with duration of count, but recommended an upper limit of 10 min to minimize double counting of individuals (Verner 1988).

Although total count may be a reasonable indicator of survey performance, it is important when designing a survey to remember that the goal is not to maximize total count, but rather to provide data with which relevant hypotheses can be addressed. Usually, formal testing of these hypotheses will be conducted within some statistical framework; thus, it may be useful to allocate sampling effort on the basis of the potential performance of the statistical procedures that will be used to analyze the data. The allocation of sampling effort that leads to maximum total count may not optimize performance of the chosen statistical procedure.

The allocation of sampling effort involves a trade-off between time spent at each point and the number of points sampled. In this paper we propose an objective means of finding the "best" trade-off possible given the total available time for surveying, travel time between counts, certain population characteristics, and detection functions. We illustrate the method using optimization criteria derived from commonly used methods of statistical analysis, and apply the method to published data on Hawaiian birds (Scott and Ramsey 1981).

METHODS

THE MODEL

We assume that the animal population sizes (N_i) at distinct points are independent with mean μ and variance σ^2 . Conditional on N_i , the number counted at the i th point c_i is a binomial random variable with parameter p , the detection probability. The detection probability p is assumed to be a function of count duration, T_i . For simplicity, $p = f(T_i)$ is assumed to be the same at all points. Some of the consequences of variation in p will be discussed later in the paper.

There are two closely related ways to consider the binomial counting process. In the first, exemplified by unlimited-distance methods, counts can be considered as arising from a population of individual birds of a single species that are located within a fixed

radius (ρ) of the observer. Within ρ of the observer, individuals have some probability of detection less than or equal to one, and detection probabilities may differ among birds. At some distance ρ from the observer, the birds are not perceptible to the observer and probability of detection becomes effectively zero.

In the second case, exemplified by limited-distance point-count methods, the circle of radius ρ^* describes the radius within which a bird must be present to be counted. All birds within this distance are counted with probability 1, and the binomial detection probability p in the above model corresponds to the probability that a bird located within ρ of the observer, occurs within ρ^* of the observer at the time of the count.

Despite the difference in the two sampling approaches, they can be modelled in the same way. In each case a bird that is in some sense "located" at the point being surveyed is either heard or not heard, at random, during the survey. In the unlimited-distance method they are not heard because they failed to call or simply were missed by the observer. In the limited-distance method they were missed because they were not located within the sampling radius at the time of the survey.

We assume that survey cost can be expressed in units of time, of which a fixed total T must be allocated to travel time between points and sampling time at points. Let T_i denote the average traveling time between points. The number of points sampled, n , and the duration of counts at individual points, T_s , are constrained by the relationship

$$T = (n - 1) T_i + n T_s. \quad (2)$$

Thus, either T_s can be large and n small, or vice versa. In practice, actual costs can be assigned for person time and travel for each of these components.

OPTIMIZATION CRITERIA

An important problem in sampling theory is the optimization of estimator performance given a fixed sampling effort. The first step in the optimization process is choosing a criterion for measuring estimator performance. Because this choice may affect the outcome of the optimization, as we demonstrate below, it is important that a reasonable choice be made. This choice is itself determined by the goals of the study and the methods that will be used to meet these goals. We discuss several alternative optimization criteria.

Mean-square error of counts.—For optimal allocation of sampling effort, one traditional measure of estimator performance is the sample variance (Cochran 1977). Many of the estimators of population size based on point counts are biased; thus, the mean-square error (MSE) is a more appropriate measure of estimator performance than the sample variance. For example, consider the mean count as an estimator of

the mean number of animals present at each possible survey point. Under the model described in the previous section, the mean and variance of the counts are given by

$$E(c_i) = E[E(c_i | N_i)] = E(N_i p) = p\mu \tag{3}$$

and

$$\begin{aligned} \text{Var}(c_i) &= E[\text{Var}(c_i | N_i, p)] + \text{Var}[E(c_i | N_i, p)] \\ &= E[N_i p(1 - p)] + \text{Var}(N_i p). \end{aligned} \tag{4}$$

Thus,

$$\text{Var}(\bar{c}) = (\mu p + \mu p^2 d) / n, \tag{5}$$

where d is $(\sigma^2 / \mu) - 1$.

Choosing T_s to minimize the variance of the counts leads to choosing T_s so that p is zero, in which case all counts are zero, and the variance of the counts is zero. Obviously, minimizing the variance of the counts is an inappropriate criterion because this maximizes the bias. Note that the bias (i.e. $E[c_i] - \mu$) increases as p decreases.

An alternative approach is to minimize the mean-square error (MSE, where $MSE = \text{bias}^2 + \text{variance}$). Given that $p = f(T_s)$ and the results above, MSE of the mean count is

$$MSE(\bar{c}) = \mu^2 [1 - f(T_s)]^2 + [\mu f(T_s) + \mu f(T_s)^2 d] / n. \tag{6}$$

By incorporating bias and error into the optimization, we simultaneously address the issues of precision and accuracy of the counts.

Maximum expected total count.—It has been suggested that total count is a valid criterion for optimization; studies based on small sample sizes of individuals are difficult to analyze and lead to statistical tests of low power (Verner 1988). The expected value of the total number of animals counted is given by the product of the total number of individuals at a point, the probability of detecting each individual for the count duration, and the number of points, or

$$E\left(\sum_{i=1}^n c_i\right) = n\mu f(T_s). \tag{7}$$

Power of test for difference in means.—If point counts are used for comparison of counts between study sites or within study sites over time, the strong assumption of no differences in mean detection probabilities must be made. Under our model, power of a one-sided z-test for a difference in means between two sets of counts (denoted by subscripts i and j) with identical detection probabilities and equal sampling effort is given by

$$\text{Power} = \Phi[z_{\alpha} \sigma_0 - f(T_s)k\mu_i / \sigma_1], \tag{8}$$

where $\Phi(z)$ denotes the upper-tail probability of the standard normal distribution, σ_0 denotes the standard deviation of the difference in means under the null hypothesis ($H_0: \mu_i = \mu_j$), σ_1 denotes the standard deviation of the difference in means under the alter-

native hypothesis ($H_1: \mu_i \geq \mu_j$), and $\mu_j = (1 - k)\mu_i$. The factor k represents a proportional difference between the means. The standard deviation of the difference in mean counts under the null and alternative hypotheses can be computed using expression (5).

MSE of ratio estimator of population change.—Estimation of population change at n points counted on two occasions (time periods t and $t + 1$) can be done using the ratio of the total count for all points at time $t + 1$ and the total count for all points at time t or

$$\hat{\beta} = \left(\sum_{i=1}^n c_{i,t+1}\right) / \left(\sum_{i=1}^n c_{i,t}\right). \tag{9}$$

The theoretical MSE for this estimator under our model can be obtained using the expressions for bias and variance

$$\text{Bias}(\hat{\beta}) = (\beta / (n\mu)) \{[1 - f(T_s)] / f(T_s)\} \tag{10}$$

and

$$\begin{aligned} \text{Var}(\hat{\beta}) &= (1/n) \left\{ [\beta(1 + \beta) / \mu] \{[1 - f(T_s)] / f(T_s)\} \right. \\ &\quad \left. + \sigma_{\beta}^2 \left(1 + \frac{\sigma^2}{\mu^2}\right) \right\}, \end{aligned} \tag{11}$$

where β and σ_{β}^2 denote the conditional mean and variance of N_{t+1} / N_t among points, and σ^2 the variance of the number of individual animals among points in the first time period. Here, $\hat{\beta}$ denotes an estimate of the true population change β . Equations (10) and (11) were derived from (9) using the method of statistical differentials (Seber 1982).

OPTIMIZATION PROCEDURE

From calculus theory, the maximum and minimum values of a function with respect to one variable occur at the point where the slope of the function is zero. To find out if this is a maximum or minimum value we look at the rate of change of the slope (the second derivative) at this point. If this is negative (i.e. slope is going from being positive to negative) then we know we have found a maximum.

Where our function depends on more than one variable, the gradient vector corresponds to the slope, and the matrix of second partial derivatives corresponds to the second derivative. Thus, the values of n and T_s that correspond to either maximum or minimum values of the function describing efficiency of our estimation or testing procedures, occur at the points where the gradient of that function with respect to n and T_s equals zero. If the matrix of second partial derivatives (Hessian) is positive-definite at these points then they correspond to local minima. If the Hessian is negative-definite, then the points correspond to local maxima. For simple functions, closed-form solutions can often be obtained, but in more complex cases (such as those described above) nu-

TABLE 1. Maximum-likelihood estimates of exponential (r) and Weibull parameters (a and b), and results of generalized likelihood-ratio test between models for three species of Hawaiian forest birds (data from Scott and Ramsey 1981).

Species	Exponential r		Weibull b		X^2	P
	$\hat{r} \pm SE$	$\hat{a} \pm SE$	$\hat{b} \pm SE$			
Red-billed Leiothrix	0.149 \pm 0.024	0.143 \pm 0.018	1.255 \pm 0.144		3.324	0.068
Omao	0.234 \pm 0.031	0.236 \pm 0.033	0.984 \pm 0.095		0.027	0.869
Apapane	0.061 \pm 0.008	0.058 \pm 0.011	0.962 \pm 0.080		0.233	0.629

merical techniques such as the Newton-Raphson method (Seber 1982:17-18) must be used. A computer program that will optimize the allocation of effort using the above estimators and measures of survey performance is available in executable code from the authors.

ESTIMATION OF $f(T_s)$

The function $f(T_s)$ describes the way in which the proportion of birds counted increases with count duration. Ideally, $f(T_s)$ could be estimated by explicitly estimating p using a known population of animals. Unfortunately, this is rarely possible, so alternative estimation procedures must be sought.

Associated with each bird is a random variable x , denoting the time until first sighting of the bird. The function $f(T_s)$ is the cumulative distribution function of the random variable x ; $f(T_s)$ should increase rapidly at first and then slowly approach one.

We consider two models for $f(T_s)$. In the first, times until first detection are modeled as independent and identically distributed exponential random variables with mean r . In this case

$$f(t) = 1 - e^{-t/r} \tag{12}$$

In practice, the simple curve provided by the exponential model may be too restrictive to mimic the shape of $f(T_s)$. A more flexible model is the Weibull, in which the probability that the time to first detection is less than t is given by

$$f(t) = 1 - e^{-(t/a)^b} \tag{13}$$

This model includes the exponential model as a special case corresponding to a b of one.

Given estimates of the parameters, the percentage of animals sighted in the sampling period T_s can be estimated by

$$\hat{f}(T_s) = 1 - e^{-T_s/r} \tag{14}$$

under the exponential model, or by

$$\hat{f}(T_s) = 1 - e^{-(T_s/a)^b} \tag{15}$$

under the Weibull model.

Under the Weibull model, parameter estimates must be obtained using numerical maximization of the

likelihood function because MLEs or other efficient estimators are not available in closed form. If t_1, t_2, \dots, t_k are the distinct times to detection for all animals detected in the observation period of duration τ , then the likelihood function to be maximized is

$$L = \prod_{i=1}^k [ab(t_i/a)^{b-1} e^{-(t_i/a)^b}] / [1 - e^{-(\tau/a)^b}] \tag{16}$$

Maximum likelihood can also be used in the exponential model using the likelihood function above by constraining the parameter b to equal one. Alternatively, a closed-form method of moments estimator for the exponential parameter can be obtained. Let \bar{t} denote the average length of time to detection, and S^2 the variance of these times, then

$$\hat{r} = ((\bar{t})^2 + S^2 - \tau\bar{t}) / (2\bar{t} - \tau) \tag{17}$$

is a consistent estimator of r , and is almost as efficient as the maximum-likelihood estimator. Consistency means that the error of estimation tends to zero as the sample size becomes large. If the maximum-likelihood estimator is used, then a likelihood-ratio test can be used to test between the Weibull and exponential models. Executable computer code for fitting the models is available from the authors.

EXAMPLE

Scott and Ramsey (1981), in a study of Hawaiian forest birds presented data on the cumulative proportion of Red-billed Leiothrix (*Leiothrix lutea*), Omao (*Myadestes obscurus*), and Apapane (*Himatione sanguinea*) counted as a function of time spent counting within a 32-min interval. Using their data we fitted the exponential and Weibull models. For the Red-billed Leiothrix the likelihood-ratio test indicated marginal evidence of the need for the Weibull model ($P = 0.068$; Table 1). For the Omao and Apapane, however, the likelihood-ratio tests were not significant ($P = 0.869$ and 0.629 , respectively), indicating that the Weibull model did not lead to an improved fit over the exponential model.

Suppose that the Omao study was to be used as the basis for planning a future study. We illustrate the optimization procedure, using the exponential-parameter estimate from the Omao data, for a study area

TABLE 2. Optimal sampling allocation and associated expected values of $f(T_s)$ for hypothetical study with mean number of animals present at each point of 20, variance of number of animals at each point of 20, total sampling time available of 180 min, 10 min required for travel between points, and function relating detection probability at each point (p) to time spent sampling at each point (T_s) given by $p = 1 - e^{-rT_s}$, where r is 0.23.

Statistic	Locations	T_s	$f(T_s)$
Count MSE	4.863	29.073	0.999
Total count	11.307	6.803	0.798
Power	11.390	6.681	0.792
Ratio	12.958	4.663	0.666

with mean number of birds present (μ) of 20, variance of 20, total survey time (T) of 180 (min), travel time between stations (T_s) of 10 (min), and exponential-parameter r of 0.23 (as estimated from the data). Note that the exponential parameter is the only value estimated from the pilot data, and the other values can be varied for any particular experimental situation. To compare optimal sampling effort under the constraint (equation 2), we: (1) minimized MSE of the average count; (2) maximized power of a one-sided z-test for a difference in means between two sets of counts with identical $f(T_s)$; (3) minimized MSE of the ratio estimator for population change between two time periods with identical $f(T_s)$; and (4) maximized expected total count. We set k at 0.1 (proportional difference in population means = 10%), and α at 0.05. For the two-year population-change analysis, we considered a case where $\mu_{t+1} = \mu_t$, and where the coefficient of variation among points of the ratio of animals present during the two years (σ_r/β) was 0.2.

RESULTS

For the Hawaiian forest birds discussed by Scott and Ramsey (1981), the MSE of the average count was minimized with a combination of few points and a long sampling time at each point (Table 2). A detection probability of 0.99 would occur under this combination. Thus, with this particular combination of parameters and optimality criterion, avoidance of bias plays a dominant role in determining the allocation of sampling effort.

Optimal allocation of the sampling effort to obtain maximum power of the one-sided z-test and maximum total count were nearly coincident in this case. However, unlike the expected value of total counts, the power of the z-test is sensitive to the variance of the distribution of animals through space (i.e. σ^2). For example if

we change σ^2 so that $\sigma^2/\mu = 0.5$, but keep all other parameters the same, optimal allocation of sampling effort occurs for 11.3 points when expected total count is maximized, but when power is maximized the optimal number of sampling points is 9.8. If $\sigma^2/\mu = 2$, the optimal number of points sampled when expected total count is maximized remains at 11.3, but for power the optimal number of sampling points is 13.0.

In contrast to the result for the MSE of the average count, the minimum MSE of the population change estimator occurred for a combination of a relatively large number of points, and much less time sampling at each point, with a predicted detection probability of 0.67.

DISCUSSION

Because estimator performance is sampling-scheme dependent, it is necessary to have an objective means of best allocating sampling effort that explicitly incorporates the estimator of interest. We have demonstrated a method of allocating point-count sampling effort, based on a framework that relates underlying population characteristics and detection probabilities to the numbers of individual animals counted. Our results emphasize the importance of defining clear objectives, because the results of the optimization can differ greatly depending on the goals of the study and the methods used to achieve these goals. If goals that require estimates of population size tend to require long-duration counts at each point as is suggested by our example, actual implementation of point counts as surrogates of population size estimates is unlikely to be feasible. However, optimal point-counting periods for other objectives, such as the estimation of population trends, seem reasonable. Of course, while some generalizations can be made from our example, we recommend that investigators collect pilot data and actually assess the feasibility of their study goals using these methods before actually implementing a study.

Verner (1988) used total counts as an optimization criterion with the justification that maximizing counts maximized statistical power. However, a statistical test must be defined before power can be assessed. Also, many of the estimation methods that use point-count data are biased (e.g. ratio estimator for trend). Considering power alone and ignoring bias over-

looks the fact that power is a function of type I error rates. The type I error rate (α level) corresponds to the power for the smallest possible departure from the null hypothesis (i.e. H_0 is true). Thus, increasing the α -level automatically increases test power. Usually, the α -level is considered to be pre-set by the experimenter; however, biased testing procedures usually lead to α -levels higher than the nominal values. In this way bias can lead to increased power simply through increasing the type I error rate.

If one can assume that bias is constant between comparisons, testing procedures such as a comparison of means can be used. Because expected maximum total count is unaffected by the variance of the distribution of animals, it does not always act as a good surrogate for maximum power, and can lead to a quite different allocation of sampling effort than that which maximizes power.

The method we have described above is most easily applied where a single species is of interest, or where there is some simple way of characterizing the collection of species, such as species richness (number of species associated with a point). In many studies, however, point-count-sampling schemes provide data on a multitude of species and, in monitoring programs, all species may be of interest. In this latter case, optimal allocation of sampling effort may be an ill-defined concept because the allocation of sampling effort that leads to optimal performance of estimators or testing procedures is species specific. The process of allocating sampling effort in a multispecies program must involve reconciling the differing sampling requirements of the species. Many approaches can be used to develop a composite optimization. For example, it is conceivable that a measure of survey performance could be computed for the entire assemblage of species (e.g. total MSE), but in practice this will be extremely difficult for anything other than a few species. Alternatively, key species could be picked from the assemblage associated with the study area, and effort optimized with respect to the hardest species to sample. This will lead to a tendency to spend more time sampling at each point. If too little time is spent at each point, bias may dominate estimator performance.

It is tempting to use the method we have described above for modeling the manner in which detection probability changes with count duration as a method of estimating detection

probability for a fixed-duration count, and then to use this estimated detection probability to obtain an estimate of exact population size. We hesitate to recommend this approach because of the difficulty in testing the necessary assumptions. Incorrect model specification is liable to have far more serious consequences for estimation than for planning of studies. The consequence of error in the first case may be biased inference, but in the second the same error may only lead to weaker inference.

The feasibility of the methods we suggest depends on the actual function $f(T_s)$, which relates the probability of detection to sampling effort (time spent counting) at a sampling point. The shape of this function ultimately determines the efficacy of any point-count study through the effects of detection probabilities on estimators. Because point counts rarely sample all the animals present, bias is an important component of estimation procedures. Consequently, the optimal allocation of sampling effort involves a trade-off between bias and the precision of the estimate. This trade-off depends in large measure on $f(T_s)$. Therefore, optimization based on $f(T_s)$ should be the basis of all point-count studies and studies based on similar methods.

Given expressions for bias, variance, $f(T_s)$, and a function describing sampling constraints, it is possible to optimize sampling effort using the methods we have outlined. The solutions will depend on the model for $f(T_s)$, the estimator used, and the optimality criterion. Consequently, it is difficult to make general statements about how sampling effort should be allocated.

All modeling of animal population involves assumptions that must be carefully considered in any application. For our model, we first assume that the detection function is a realistic reflection of the mechanics of counting. This assumes that double counting of individuals does not occur. Verner (1988) suggested that the maximum time at a point is limited by increased probability of double counting after 10 min. Disturbance associated with the observer also may attract or repel birds (Scott and Ramsey 1981). Finally, sexes of most songbird species have greatly different detection functions, as the females are only occasionally observed. A detection function based on singing males can only account for part of the population, and the optimization depends on the validity of the model.

It must be recognized that the assumption

that $f(T_s)$ is constant between points and over time is unrealistic. However, two points must be made. First, the assumption that some consistent $f(T_s)$ exists is implicit to most existing analyses of point-count data, because all hypothesis tests will be biased if based on point-count data in which $f(T_s)$ is changing among the items to be compared. Second, even if our model for $f(T_s)$ is imperfect because of violation of this assumption, the consequence is a slightly less-than-optimal sampling scheme, which will still be more efficient than sampling based entirely on a subjectively chosen regimen. The procedure outlined here is objective, and it places appropriate emphasis on the critical underlying assumption of all point-count studies: the probability of detecting a bird at a point increases with time spent counting at the point. Furthermore, the procedure is flexible; optimization can be carried out under various assumptions about the population parameters, allowing for the examination of the effects of these assumptions on optimal sampling schemes. Consequently, the use of $f(T_s)$ in optimization of point counts makes explicit the importance of our assumptions about $f(T_s)$ in the analysis.

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