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A DOUBLE-OBSERVER APPROACH FOR ESTIMATING DETECTION PROBABILITY AND ABUNDANCE FROM POINT COUNTS

JAMES D. NICHOLS,[1,4] JAMES E. HINES,[1] JOHN R. SAUER,[1] FREDERICK W. FALLON,[2] JANE E. FALLON,[1] AND PATRICIA J. HEGLUND[3]

[1]*U.S. Geological Survey, Biological Resources Division, Patuxent Wildlife Research Center, Laurel, Maryland 20708 USA;*
[2]*AScI Corporation, 1365 Beverly Road, McLean, Virginia 22101 USA; and*
[3]*Department of Biological Sciences, University of Idaho, Moscow, Idaho 83844 USA*

ABSTRACT.—Although point counts are frequently used in ornithological studies, basic assumptions about detection probabilities often are untested. We apply a double-observer approach developed to estimate detection probabilities for aerial surveys (Cook and Jacobson 1979) to avian point counts. At each point count, a designated "primary" observer indicates to another ("secondary") observer all birds detected. The secondary observer records all detections of the primary observer as well as any birds not detected by the primary observer. Observers alternate primary and secondary roles during the course of the survey. The approach permits estimation of observer-specific detection probabilities and bird abundance. We developed a set of models that incorporate different assumptions about sources of variation (e.g. observer, bird species) in detection probability. Seventeen field trials were conducted, and models were fit to the resulting data using program SURVIV. Single-observer point counts generally miss varying proportions of the birds actually present, and observer and bird species were found to be relevant sources of variation in detection probabilities. Overall detection probabilities (probability of being detected by at least one of the two observers) estimated using the double-observer approach were very high (>0.95), yielding precise estimates of avian abundance. We consider problems with the approach and recommend possible solutions, including restriction of the approach to fixed-radius counts to reduce the effect of variation in the effective radius of detection among various observers and to provide a basis for using spatial sampling to estimate bird abundance on large areas of interest. We believe that most questions meriting the effort required to carry out point counts also merit serious attempts to estimate detection probabilities associated with the counts. The double-observer approach is a method that can be used for this purpose. *Received 16 November 1998, accepted 1 October 1999.*

A BEWILDERING VARIETY of methods exists for assessing animal abundance (e.g. Ralph and Scott 1981, Seber 1982, Lancia et al. 1994). However, all methods involve the collection of some sort of count statistic. Count statistics are as varied as the methods by which they are obtained and include number of birds seen and heard at a point-count location, number of ungulates seen while walking a line transect, number of small mammals caught on a trapping grid, number of kangaroos seen from an airplane flying an aerial transect, and number of tigers photographed by camera traps. The relationship between a count statistic and the quantity of interest, abundance or population size, can be written as follows (see Barker and Sauer 1992, Nichols 1992, Lancia et al. 1994):

$$E\,(C_i) = N_i\,p_i, \tag{1}$$

where C_i denotes the count, N_i the true abundance, and p_i the detection probability, all associated with time and location i.

Two basic approaches use count statistics to draw inferences about animal abundance and changes in abundance over time (Lancia et al. 1994, Wilson et al. 1996). One approach is to collect the count data in a manner that permits estimation of the associated detection probability. Such estimates then permit direct estimation of population size:

$$\hat{N}_i = \frac{C_i}{\hat{p}_i}, \tag{2}$$

where the hats denote estimates. Resulting estimates of population size can be used to draw inferences about changes in abundance over time and/or space. If the estimates of detection

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[4] E-mail: jim_nichols@usgs.gov

probabilities provide strong evidence that they are similar for different times or locations, then the count statistics themselves can be used to draw inferences about differences in abundance (Skalski and Robson 1992).

The other approach is not to estimate detection probability, but to use standardized methods to obtain the count statistic in the hope that detection probabilities will be similar for the times or places for which abundance comparisons are to be made (i.e. that $p_i = p$ for all i in the comparison). Under this approach, the count statistic is viewed as an index to abundance (Conroy 1996). In some cases, the collection of index statistics is accompanied by the measurement of some small number of covariates (e.g. weather variables) that are thought to influence detection probability. Under the assumption that these covariates influence only detection probability (and not abundance), they can be incorporated into analyses that use index statistics to draw inferences about abundance (Conroy 1996).

Data resulting from point counts nearly always are treated as indices (Ralph et al. 1995). Standardized methods have been incorporated into large-scale surveys such as the North American Breeding Bird Survey, or BBS (Robbins et al. 1986, Peterjohn et al. 1997). In the BBS, standardization includes such features as duration of count, length of survey route, distance between stops, weather conditions under which surveys are conducted, time of year, etc. Observer identity and experience are recognized as covariates that are likely to be relevant to variation in detection probability (Sauer et al. 1994b, Kendall et al. 1996) and have been incorporated into most serious efforts to draw inferences about abundance from BBS data (Link and Sauer 1997, 1998). Unfortunately, in any count-based survey, many sources of variation in detection probability that are not associated with observable covariates are likely to exist, and these cannot be accommodated in analyses (e.g. Burnham 1981, Johnson 1995).

Here, we make no claim that inferences emerging from historical analyses of data from the BBS or other point-count surveys necessarily are wrong. Instead, we simply express discomfort with the knowledge that such inferences depend on untested assumptions. When the ratio of count statistics is used to estimate the ratio of abundances (e.g. this is termed relative abundance for two locations or population growth rate for the same location at two points in time), it performs best when $p_i = p$ for the i (places or times) involved in the comparison. Such use of the ratio of count statistics can also be viewed as reasonable in the situation where values of p_i are themselves viewed as random variables arising from some distribution that does not change over the times or locations being compared. However, variation in habitat over time and space and temporal changes in climatic variables that affect bird activity and behavior (e.g. Crick et al. 1997) make even this distributional assumption unlikely to be true for many comparisons.

Although use of point-count data as indices may be necessary in some instances, we believe it is sensible to investigate alternative ways to conduct point counts that might permit estimation of detection probabilities associated with the counts. This is the general approach taken in most estimation methods for animal populations, such as capture-recapture sampling (Seber 1982, Lancia et al. 1994). One approach permitting estimation from point-count data is the variable circular plot (Ramsey and Scott 1979, Reynolds et al. 1980) in which distances to detected birds are recorded and resulting data used with distance sampling methods to estimate density. This approach has been used in avian studies (Mountainspring and Scott 1985, Scott et al. 1986, Fancy 1997) but is not widely used by ornithologists. We recommend that variable circular plot methods be given serious consideration for future point-count surveys.

In this paper, we present a double-observer approach that permits estimation of detection probability from point count data. The approach uses two observers and is a modification of a method developed by Cook and Jacobson (1979) to estimate abundance from aerial survey data. We first describe the field-sampling situation and the basic estimation approach. We then discuss alternative estimation models and their implementation using program SURVIV (White 1983). We describe 17 experimental point-count surveys conducted in spring and early summer 1998 to test this double-observer approach, and we present the results of our modeling and estimation efforts with these data. Finally, we discuss the potential utility of this approach for point-count surveys of birds and make recommendations regarding implementation of the method.

METHODS

Field methods.—We assume a sampling situation where multiple locations are selected for point counts within some general area of interest. In the BBS, for example, each route contains 50 stops at which 3-min point counts are conducted. In other studies, we might select, for example, a sample of 10 to 40 points within an area of interest or in patches of similar habitat within a larger area of interest. The approach is most appropriately used when the points are placed in areas of similar habitat, and stratification is recommended when a set of point counts is obtained from discrete habitats between which differences in detection probability are suspected.

Two observers are present during all point counts. At each count (a visit to a single point), one observer is designated as "primary" and the other as "secondary." The primary observer identifies all birds seen and heard and communicates (via speech and gesture) to the secondary observer the species detected and the direction and general distance of the detection. The secondary observer records the species detected by the primary observer but also surveys the area. Birds detected by the secondary observer but not by the primary observer also are recorded by the secondary observer. At the end of each point count, the data are the number of birds of each species (1) detected by the primary observer and (2) missed by the primary observer but detected by the secondary observer.

A key element of the design is that each observer serves both primary and secondary roles on any group of counts. We recommend that observers alternate roles on consecutive counts, with one observer serving as primary at the first point count, secondary at the second count, primary at the third count, and so on. Under this design, each observer will serve as primary observer for half of the point counts. Although reasons exist for preferring the design with alternating primary observers, it is necessary only for each observer to serve as a primary observer on at least one count. This general design leads to stop-level data that are then aggregated over the counts in the group (e.g. all stops on a BBS route, all counts conducted in a particular habitat type on one day) to yield the basic count statistics needed for estimation of abundance for each species detected.

Estimators of Cook and Jacobson (1979).—Although the sampling situation differs from that studied by Cook and Jacobson (1979), for convenience we follow their general notation. Define x_{ij} as the number of individuals counted by observer i ($i = 1, 2$) on stops when observer j ($j = 1, 2$) was the primary observer. As noted above, the counts for the primary observer include all birds detected, whereas the counts for the secondary observer include only birds detected by this observer that were missed by the primary observer. Define p_i as the detection probability for observer i, which is assumed to be the same whether observer i is serving as the primary or the secondary observer. Further, let N_1 denote the true number of birds exposed to sampling efforts (for fixed-radius point counts, we can specify the area covered, whereas for unlimited-radius counts, we cannot) in the point-count samples for which observer 1 served as primary observer. We can view x_{11} as a binomial random variable with parameters N_1 and p_1, denoted as having distribution $B(N_1, p_1)$. For a given x_{11}, we similarly can view x_{21} as a binomial random variable $B(N_1 - x_{11}, p_2)$. The joint distribution of (x_{11}, x_{21}) can thus be written as the product $B(N_1, p_1)\, B(N_1 - x_{11}, p_2)$. Similarly, the distribution of (x_{22}, x_{12}) can be written as $B(N_2, p_2)\, B(N_2 - x_{22}, p_1)$. Finally, assuming that the pairs (x_{11}, x_{21}) and (x_{22}, x_{12}) are independent, the joint distribution for all four random variables is $B(N_1, p_1)\, B(N_1 - x_{11}, p_2)\, B(N_2, p_2)\, B(N_2 - x_{22}, p_1)$.

Because values of N_i are unknown, it would be difficult to use the above distribution directly for estimation. Following the recommendation of Cook and Jacobson (1979), we thus condition on the total birds detected in the samples of point counts for which each observer served as primary observer. The probability that a bird in a sampled area is detected at a point count by at least one observer is $p = 1 - (1 - p_1)(1 - p_2)$. This detection probability applies to each of the point counts (or stops) on the route for which it is estimated, and thus to each area ($i = 1, 2$) and the entire area sampled by the counts. Thus, the distribution of $(x_{11} + x_{21})$ is $B(N_1, p)$, and that of $(x_{22} + x_{12})$ is $B(N_2, p)$. Further, the probability of a bird having been detected by observer 1 in area 1, given that it was detected in area 1 (i.e. the probability that a bird was a member of x_{11}, given that it was a member of $x_{11} + x_{21}$) is p_1/p. The complement of this probability, the probability that a bird in area 1 was missed by observer 1 and detected only by observer 2, given that it was detected in area 1, is $(1 - p_1)\, p_2/p$. For estimation purposes, we thus rewrite the joint distribution of the four random variables as: $B(N_1, p)\, B(x_{11} + x_{21}, p_1/p)\, B(N_2, p)\, B(x_{22} + x_{12}, p_2/p)$.

The approach to estimation begins by using the two conditional (on detections) distributions, $B(x_{11} + x_{21}, p_1/p)$ and $B(x_{22} + x_{12}, p_2/p)$, to estimate detection probabilities. Cook and Jacobson (1979) present the following maximum-likelihood estimators for the general model in which detection probability differs for the two observers:

$$\hat{p}_1 = \frac{x_{11}x_{22} - x_{12}x_{21}}{x_{11}x_{22} + x_{22}x_{21}}, \quad \hat{p}_2 = \frac{x_{11}x_{22} - x_{12}x_{21}}{x_{11}x_{22} + x_{11}x_{12}}, \quad \text{and}$$

$$\hat{p} = 1 - \frac{x_{12}x_{21}}{x_{22}x_{11}}. \tag{3}$$

Large-sample variance estimators for the detection probability estimates were also provided by Cook and Jacobson (1979) and are presented in Appendix 1.

Note that the estimators in equation 3 can also be obtained simply by equating the four sufficient statistics with their expectations:

$$E(x_{11}) = N_1 p_1, \qquad E(x_{21}) = N_1(1 - p_1)p_2,$$

$$E(x_{22}) = N_2 p_2, \quad \text{and} \quad E(x_{12}) = N_2(1 - p_2)p_1.$$

These equations then can be solved to yield the estimators in equation 3. Examination of these expectations provides a good basis for the intuition underlying the double-observer approach. For example, the expected number of birds detected by observer 1 on the stops at which this observer is primary is given simply as the product of bird abundance at these stops and the detection probability for that observer. The number of additional birds detected by observer 2 on the stops at which observer 1 is primary is given as the product of bird abundance, the probability that a bird is missed by observer 1, and the probability that a bird is detected by observer 2.

Once estimates of detection probability are obtained, the natural estimator (see equation 2) for population size on the sampled area is:

$$\hat{N} = \frac{x..}{\hat{p}}, \tag{4}$$

where $x.. = x_{11} + x_{21} + x_{22} + x_{12}$. An associated variance estimator is:

$$\widehat{\text{var}}(\hat{N}) = \frac{(x..)^2 \widehat{\text{var}}(\hat{p})}{\hat{p}^4} + \frac{(x..)(1 - \hat{p})}{\hat{p}^2}. \tag{5}$$

The above estimators for abundance (equation 4) and its associated variance (equation 5) are used in all of our work on estimation under the double-observer approach, regardless of the exact model selected for estimation of detection probability.

Confidence intervals for $\hat{N}$ were approximated using the approach of Chao (1989; also used and recommended by Rexstad and Burnham 1991). The estimation is based on the estimated number of birds not detected, $\hat{f}_0 = N - x..$ The $\ln(\hat{f}_0)$ is treated as an approximately normal random variable, yielding the following 95% confidence interval, $(x.. + \hat{f}_0/C, x.. + \hat{f}_0 C)$, where

$$C = \exp\left(1.96\left[\ln\left(1 + \frac{\widehat{\text{var}}(\hat{N})}{\hat{f}_0^{\,2}}\right)\right]^{1/2}\right).$$

Additional models and estimators.—For each group of point counts, we consider the modeling of two possible sources of variation in detection probability, observers and bird species. Following Cook and Jacobson (1979), we assume differences in detection probabilities for the two observers. If we also assume different detection probabilities for each bird species, then we have a very general model and must estimate two parameters (a detection probability for each observer) for each species observed. However, large numbers of parameters lead to large sampling variances, so we would like to reduce the number of parameters and model the data parsimoniously (Burnham and Anderson 1992, 1998). Consequently, analyses of double-observer point-count data should include consideration of models in which detection probabilities are similar for the two observers and for different bird species. Most North American point counts contain many species for which only small numbers of individuals are detected, making estimation of species-specific detection probability problematic or impossible. Thus, we would like to consider grouping species for which small samples are obtained. Detection probabilities can then be estimated for these multispecies groups.

Consequently, for reasons of parsimony and small sample sizes for some species, we recommend consideration of grouping of species for modeling and estimation purposes. Because of the binomial nature of detection-probability modeling, such grouping should be done only when detection probabilities of the grouped species are similar. We thus recommend *a priori* grouping of species into general categories associated with predicted variation in detection probabilities (e.g. easy to detect, difficult to detect). Although universal agreement on any such *a priori* grouping is virtually impossible (e.g. Sauer et al. 1996), this approach is subject to *a posteriori* testing. For example, group-specific detection probabilities can be compared and the results used to guide the modeling of detection probabilities in the current analysis (e.g. if no difference between detection probabilities of two groups is evident, then these groups could be modeled with a common detection probability) and in future analyses.

To fit and obtain estimates under different models, to test between models, and to apply model-selection criteria to choose among them, we implemented a series of product-binomial models using program SURVIV (White 1983). Denote a particular species, s, by the use of a superscript. The most general model is based on the following product binomial for each species $B(x_{11}^s + x_{21}^s, p_1^s/p^s)\, B(x_{22}^s + x_{12}^s, p_2^s/p^s)$. These conditional binomials are multiplied together over all species to obtain the general model, which we denote as (p_i^s) to indicate the dependence of detection probability on observer identity (i) and bird species (s). This very general model permits an "interaction" between observer and species effects on detection probability such that an observer with a relatively high probability of detecting birds of one species can have a relatively low probability of detecting individuals of another species.

We also considered models with a variety of parameter constraints. For example, model (p^s) has the constraint that detection probability differs by species but within species is the same for each observer ($p_1^s = p_2^s$). Because many species are detected a small number of times on a route, models with species-specific detection probabilities will be too general for reasonable estimation and use. Thus, we identified broad categories of species based on expected detectability. Model (p_i^g) retains different detection probabilities for the two observers but imposes a constraint on detection probabilities of the different species. The g superscript indicates that species within an *a priori* defined group (e.g. easily detected vs. difficult to detect) exhibit the same detection probability but that this probability differs between groups. Model (p_i) retains different detection probabilities for the two observers but constrains detection probability for all species to be equal.

For a given data set involving species-specific data for all species encountered on point counts, we fit several models and then used Akaike's Information Criterion (AIC) to make decisions about the most appropriate model(s) for use in estimation. AIC is an information-theoretic measure used to select a parsimonious model that adequately explains the variation in the data using as few parameters as necessary (Burnham and Anderson 1992, 1998). Because our sample sizes were not large relative to the number of parameters in our general model, we used AIC_c, a second-order AIC with small-sample bias adjustment.

We then used the resulting estimates, $\hat{p}_i^s$, in conjunction with species-specific data (e.g. $x_{..}^s$) to estimate abundance for species s using equation 4. Note that even when we selected a model that did not retain species-specific detection probabilities, we still applied the detection probability estimate (e.g. for a group of species or for all species) to the number of individuals observed in the species of interest to estimate abundance for that species. Thus, our approach yielded an estimate of abundance, $\hat{N}^s$, for each species observed in the set of counts.

Regardless of whether a model with detection probability subscripted by i (observer) is selected, the detection probabilities on which the modeling is based correspond to the probability that an individual observer detects a bird that is present in the surveyed area. However, to estimate abundance, we must then translate the estimates for observers 1 and 2 ($\hat{p}_1^s$, $\hat{p}_2^s$) into an estimate of the probability that a bird of species s is detected by at least one of the two observers. For the general Cook-Jacobson model (p_i^s), the closed-form estimator, $\hat{p}^s$, is given in equation 3. However, we also need to compute this estimate for the other reduced-parameter models. This is accomplished using the equality:

$$\hat{p}^s = 1 - (1 - \hat{p}_1^s)(1 - \hat{p}_2^s) \qquad (6)$$

that is, in order to go undetected in the survey ($1 - p^s$), a bird must be missed by both observers. Following model selection using SURVIV, we reparameterize the model using the identity:

$$p_1^s = \frac{p_2^s - p^s}{1 - p_2^s}. \qquad (7)$$

Expression 7 is then substituted for p_1^s in the SURVIV code to obtain direct estimates of p^s and associated sampling variances and covariances.

TABLE 1. Descriptive information on the point count surveys conducted using the double-observer approach.

Survey	Observer		Route[a]	No. of stops	Date
	A	B			
1	1	2	PWRC-W1	20	6-14-98
2	1	2	PWRC-F1	10	6-14-98
3	1	2	BBS-A	50	6-20-98
4	1	2	PWRC-W2	20	6-22-98
5	1	2	PWRC-F2	20	6-24-98
6	3	2	PWRC-W1	20	6-25-98
7	3	1	PWRC-W2	20	6-26-98
8	4	1	BBS-B	50	6-28-98
9	5	2	PWRC-W1	20	6-28-98
10	6	1	BBS-C	50	6-30-98
11	6	2	BBS-D	50	7-07-98
12	7	3	PWRC-W1	20	7-07-98
13	7	2	PWRC-F2	20	7-09-98
14	6	3	PWRC-W2	20	7-09-98
15	3	2	PWRC-F2	20	7-14-98
16	8	3	PWRC-F2	20	7-15-98
17	8	3	PWRC-F2	20	7-16-98

[a] PWRC-W1 and -W2 are routes conducted in the woods at Patuxent Wildlife Research Center. PWRC-F1 and -F2 are routes conducted in fields at Patuxent Wildlife Research Center. The BBS routes are actual Maryland BBS routes.

FIELD TRIALS

We carried out the double-observer approach on 17 different sets of point counts (Table 1). Each set consisted of a route of 10 to 50 points. At each point, 3-min point counts were conducted, and all birds seen and heard (unlimited-radius counts) were recorded. Observers then drove to the next site. Most of the routes contained 20 stops and were located at the Patuxent Wildlife Research Center in either field/scrub habitat or woods. In addition, four Maryland BBS routes containing 50 stops were run using the double-observer approach. Stops were located at 0.5-mile intervals. With the exception of the double-observer sampling, point counts were conducted using BBS protocol. Counts occurred in the morning hours and were conducted under reasonable weather conditions. An abbreviated protocol was prepared

TABLE 2. ΔAIC_c values for the six models of detection probability fit to each data set. $\Delta AIC_c = 0.00$ for the model judged to be most appropriate for each data set. Smaller values of ΔAIC_c indicate models that describe the variation in the data more parsimoniously.

		Models					
Data set	Total birds	p_i^s	p^s	p_i^g	p^g	p_i	p
1	231	9.65	0.00	10.47	6.42	7.53	5.58
2	83	7.08	0.42	4.23	0.00	3.17	1.32
3	619	3.40	12.61	—[a]	—	0.14	0.00
4	219	12.78	8.93	3.59	4.92	0.00	2.89
5	321	26.25	16.14	4.05	0.00	5.41	3.41
6	300	10.13	22.32	—	—	0.00	24.08
7	232	6.50	1.91	—	—	4.15	0.00
8	675	24.36	6.17	—	—	2.00	0.00
9	176	6.04	0.00	—	—	1.35	1.97
10	970	0.00	20.50	—	—	10.30	8.51
11	773	0.00	11.29	—	—	12.30	19.74
12	408	29.35	22.94	2.32	11.84	0.00	10.10
13	492	37.77	89.63	0.59	77.59	0.00	77.27
14	228	0.00	4.61	7.30	14.35	4.21	12.54
15	484	9.25	43.41	—	—	0.00	76.54
16	474	39.94	20.92	0.00	9.61	0.07	11.24
17	535	12.11	40.19	—	—	0.00	20.59

[a] Too few individuals in the "difficult detection" group to merit analysis, so only "easy detection" birds were used. In this case, models with a "g" superscript were not relevant.

by observers 1 and 2 following the first few routes and distributed to the other observers prior to their participation in the surveys. The protocol was slightly different for the very last survey (data set 17), because a third person accompanied the two observers to serve as recorder for the primary observer.

The data obtained from these trial routes were analyzed using the SURVIV (White 1983) code developed for this purpose. We used the approach described above with observer, bird species, and species group as potential sources of variation. Under the more general models, we estimated separate parameters for each species for which at least 10 individuals were detected. The remaining species were pooled into one of two groups, "difficult" or "easy," for estimation of a group-level detection probability. We were conservative in our species grouping because we placed only the following species with high-frequency calls in the "difficult detection" group: Brown Creeper (*Certhia americana*), Blue-gray Gnatcatcher (*Polioptila caerulea*), Cedar Waxwing (*Bombycilla cedrorum*), Black-and-white Warbler (*Mniotilta varia*), Prairie Warbler (*Dendroica discolor*), and Grasshopper Sparrow (*Ammodramus savannarum*). For a small number of species, the numbers of individuals detected by the different observers assumed values that led to problems with parameter identifiability (see below). In such cases, the data were pooled with data from the appropriate species group ("difficult" or "easy").

ΔAIC_c values were computed for all 6 models for each of the 17 data sets. These values reflect the difference between the AIC_c value of the model in question and the model with the lowest AIC_c (the model considered the most appropriate for the data set; Burnham and Anderson 1998). Small differences (e.g. $\Delta AIC_c < 2$) indicate models that are very similar in their abilities to explain the data in a parsimonious manner (Burnham and Anderson 1998). The number of detections of birds in the "difficult" category was too small for analysis in nine data sets, so the two models using these species groups (p^g, p_i^g) were not used with these data.

Model p_i showed the lowest AIC_c for the largest number (6) of data sets (Table 2). Models p_i^s and p each showed the lowest AIC_c value for three data sets (Table 2). Models p^g and p^s each were judged most appropriate for two data sets, and model p_i^g showed the lowest AIC_c for a single data set (Table 2). Based on these results, all of the factors hypothesized *a priori* to be potential sources of variation in detection probabilities indeed were important on at least some routes. Variation between the two observers on each route was an important model factor in 10 of the 17 data sets (models p_i, p_i^g and

TABLE 3. Mean detection probabilities (based on model p_i) for the different observers.

Observer (i)	Number of counts	$\hat{p}_i$	$\widehat{\mathrm{SE}}\ (\hat{p}_i)$[a]
1	7	0.88	0.013
2	10	0.81	0.025
3	7	0.85	0.042
4	1	0.89	0.018
5	1	0.82	0.042
6	3	0.84	0.045
7	2	0.93	0.010
8	2	0.85	0.045

[a] Estimated standard errors are based on replication except for observers 4 and 5, who ran only a single set of counts. Model-based standard error estimates are presented for these observers.

p_i^s). Point estimates of detection probability for individual observers showed substantial variation, with averages on specific routes ranging from 0.65 to 0.97 (Appendix 2). The average estimated detection probabilities for individual observers over all data sets ranged from 0.81 to 0.93 (Table 3).

Our ability to draw inferences about the difference in detection probabilities of "difficult" and "easy" species was greatly limited by the small number of individuals in the "difficult" category. Nevertheless, model selection results indicated that this distinction was important in three of the six data sets that contained both difficult and easy species and that did not require species-specific detection probabilities. Species group or identity was included in the selected models for 8 of the 17 data sets (Table 2). We used point estimates of detection probability under model p^g to reflect average detection probability for species in the two detection categories (Table 4). The average detection probabilities over all eight routes for which such estimates could be obtained were 0.67 for difficult species and 0.86 for easy species. A one-tailed paired t-test yielded a test statistic with probability $P = 0.01$ under the null hypothesis of no difference. Thus, despite the poor precision of estimates for the difficult species, our results provided evidence of a true difference in the detection probabilities for these two groups.

To illustrate the actual estimation approach, we computed estimates of abundance for all bird species encountered on one of the sample routes, BBS-C (data set 10). On this route, the general Cook-Jacobson model (p_i^s) was selected as most appropriate for the data set (Table 2). Under this model, separate detection probabilities were estimated for species for which at least 10 individuals were detected (and for which the sufficient statistics did not yield identifiability problems; such problems occurred in two species). Species not meeting the criteria for separate estimation of detection probabilities were categorized as belonging to the "difficult" or "easy" detection groups to estimate group-level detection probabilities. On this particular route, no "difficult" species were detected. We note that model (p_i^s) was a fairly clear choice for data set 10, based on the magnitudes of the $\Delta\mathrm{AIC_c}$ values for the other models. For data sets where model selection is not so clear, model-averaged estimates of detection probabilities (based on estimates from different models weighted using the $\Delta\mathrm{AIC_c}$ values; Buckland et al. 1997, Burnham and Anderson 1998) may be a more reasonable approach to estimation of detection probability

TABLE 4. Number of birds observed (n) and estimated detection probability (standard error) for birds in the "difficult detection" and "easy detection" groups based on model p^g.

	Difficult		Easy	
Data set	n	$\hat{p}$ ($\widehat{\mathrm{SE}}$ [$\hat{p}$])	n	$\hat{p}$ ($\widehat{\mathrm{SE}}$ [$\hat{p}$])
1	6	0.50 (0.433)	225	0.82 (0.033)
2	11	0.63 (0.254)	72	0.93 (0.035)
4	12	0.91 (0.095)	207	0.90 (0.024)
5	12	1.00 (0.213)	309	0.86 (0.024)
12	5	0.75 (0.280)	403	0.87 (0.020)
13	9	0.50 (0.354)	483	0.82 (0.023)
14	4	0.67 (0.385)	224	0.81 (0.034)
16	11	0.43 (0.358)	463	0.85 (0.021)
$\bar{x}$	9	0.67 (0.072)[a]	298	0.86 (0.015)[a]

[a] Standard errors of the mean detection probability estimates were obtained using the data sets as replicates.

and bird abundance. This approach basically involves computing a weighted estimate (e.g. of detection probability) using the estimates from different models weighted by their respective ΔAIC_c values, such that the estimates from models with smaller ΔAIC_c values have larger weights (Burnham and Anderson 1998). Consequently, the parameter estimate is not based solely on the low-AIC_c model, but is most strongly influenced by the models that are judged to be the most appropriate for the data set.

The detection probabilities used to estimate abundance (Table 5) were those corresponding to the probability of a bird being detected by at least one observer (equation 6), as estimated using the substitution of equation 7. It is important to recall that these are not equivalent to the observer-specific detection probabilities that were presented in previous tables and on which modeling was based. For many species, the estimated detection probability was 1 (Table 5). This occurred, for example, when at least one observer detected all of the individuals of a given species that were detected while that person served as primary observer (i.e. the secondary observer detected no additional birds of that species). In such cases, the best estimate of abundance is the number of birds detected, and the variance of $\hat{p}$ (see Appendix 1), and hence of $\hat{N}$, are undefined.

The high detection probabilities produced abundance estimates that are very precise and that are only slightly higher than the actual counts (Table 5). This should not be taken as evidence that standard point counts perform reasonably well in the absence of estimation efforts, because the detection probability estimates for individual observers are substantially lower (Tables 3 and 4, Appendix 2). To obtain abundance estimates that correspond to standard point counts with single observers, we focus on the half of the point counts for which one specific observer served the primary role. We estimate abundance for the survey stops at which primary observer i serves as primary observer by dividing the number of birds detected on these stops by both observers by the estimated detection probability for both observers for the species in question (e.g. $\hat{N}_1^s = x_{.1}^s/\hat{p}^s$). Such abundance estimates corresponding to half of the survey route, $\hat{N}_i^s$, can differ substantially from the number counted by the primary observer on these stops, x_{11}^s (Table 6), clearly demonstrating the bias associated with use of a count from a standard point-count survey route as an estimate of actual population size.

DISCUSSION

PROBLEMS IN APPLYING THE DOUBLE-OBSERVER APPROACH

Results from our field trials indicate that the double-observer approach to estimation of detection probabilities can be applied usefully to point counts. The field methods and the subsequent modeling and estimation appear to be reasonable and to yield reasonable results. As in any field implementation of an estimation procedure, our attempts to use this approach were not without problems. Here, we discuss the main problems and difficulties that we encountered.

Field application.—This approach requires that detection of a bird by the primary observer be independent of detection by the secondary observer. If the primary observer notices the secondary observer focusing attention in a particular direction, then the primary observer may focus attention similarly. The act of the secondary observer writing down an observation when the primary observer has not indicated a detection can serve as a cue to the primary observer. To minimize the provision of cues by the secondary observer, we recommend that the secondary observer attempt to remain directly behind the primary observer and out of his/her field of vision. Clearly, this is easier said than done, because the primary observer will be constantly turning his/her head to detect birds, so the recommendation is simply that the secondary observer stay behind the primary observer to the extent possible.

If it appears that recording observations by the secondary observer is serving as a cue to the primary observer (this will likely be a problem only when few birds are present), then the secondary observer should probably go through the motions of recording (even to the point of scribbling on the data sheet) at times when no birds are detected. Similarly, the secondary observer must sometimes focus binoculars on a specific position to identify a detected bird. Again, we recommend that the secondary observer attempt to disguise the location of the observed bird to the degree possible by scanning areas and focusing on locations without, as well as with, detected birds. In many (perhaps most) point counts, most birds are detected by hearing, and such detections are least likely to provide cues to the other observer.

We have not formally investigated the consequences of dependent detection probabilities, but we believe that they will yield estimates of detection probability that are biased high (and abundance estimates that are biased low). Although every effort should be made to reduce dependence among detection probabilities, even with such dependence, the double-observer approach is preferable to counts in which detection probabilities are assumed to be 1. That is, the positive bias in detection probability estimates will never be larger for the double-observer approach than for standard point counts, and it will nearly always be smaller.

Another potential problem involves the assumption that an observer's detection probability is the same regardless of whether the person is serving a primary or secondary role. At points with small to moderate numbers of birds, this assumption was not perceived to be a problem. In areas with many birds, however, secondary observers sometimes believed that their detection probabilities were reduced because of their recording duties. If this is believed to be a substantial problem, then it may be necessary to use a third person who would serve as recorder for the primary observer. As noted, we followed this approach on the last survey (data set 17), and it appeared to work reasonably well. Another possible solution is to have both the primary and secondary observers record the data from the primary observer. This redundancy would serve no purpose with respect to the actual data collection but would serve to make detection probabilities as similar as possible for a person in the two different observation roles.

The problem that we view as potentially the most serious involves differences in distances at which different observers detect birds. The double-observer approach deals well with simple differences in detection probabilities (one observer is more likely to detect a bird of a particular species than is the other observer), and our results provided strong evidence of variation among observers in detection probabilities. However, the above models were developed assuming that the same group of birds was potentially detectable by both observers, whereas in reality it may be that one observer detects birds from a much larger distance than the other observer. In this situation, a group of birds may be undetectable by one observer and detectable by the other. This situation can lead to the detection probabilities for a particular observer appearing to change according to the identity of the observer with whom he/she is paired. Of course, this problem is not unique to the double-observer approach.

A reasonable approach to dealing with this problem is to use fixed-radius point counts rather than unlimited-radius counts. The fixed radius would be set to a value for which the possibility that birds are undetectable approaches zero (i.e. the radius would be sufficiently short that all observers would be able to detect birds at that distance). The argument against fixed-radius counts is that it is difficult to judge distances accurately, and that such inaccuracies will translate into ambiguity and variation among observers in actual distances over which birds are detected. Certainly, this is true to some extent, and no two observers will be recording birds from the same exact distances. Nevertheless, we suspect that variation among observers in distances at which birds are detected will be much smaller for fixed-radius counts than for unlimited-radius counts. Training can be used to increase an observer's ability to distinguish distance to a fixed counting radius. An alternative approach for dealing with differences among observers in detection radii involves development of models that specifically incorporate parameters associated with these differences (see below).

Other minor problems exist in application of the double-observer approach. In some cases, the secondary observer will disagree with the identity of a species determined by the primary observer. In cases of a passing flock or group of birds, the counts of the primary and secondary observers may differ. In the absence of any information indicating greater faith in one observer over the other, we have assumed that the primary observer has correctly identified and enumerated detected birds. Such disagreements did not occur frequently, and arbitrary resolution (primary observer is always right) seems as reasonable as any approach. Obviously, this sort of problem is not unique to the double-observer approach. Errors made by a single

TABLE 5. Number of birds counted, and estimated detection probability and abundance, for species detected on BBS-C (data set 10).

		Detection probability		Abundance		
Species	$x_{..}$	$\hat{p}$	$\widehat{\mathrm{SE}}(\hat{p})$	$\hat{N}$	$\widehat{\mathrm{SE}}(\hat{N})$	95% CI
Great Blue Heron (*Ardea herodias*)	1	0.9625	0.0159	1.04	0.20	1.00 to 2.39
Cattle Egret (*Bubulcus ibis*)	2	0.9625	0.0159	2.08	0.29	2.00 to 3.92
Turkey Vulture (*Cathartes aura*)	47	0.9865	0.0159	47.64	1.11	47.06 to 53.46
Canada Goose (*Branta canadensis*)	21	0.9625	0.0159	21.82	0.99	21.13 to 26.26
Mallard (*Anas platyrhynchos*)	1	0.9625	0.0159	1.04	0.20	1.00 to 2.39
American Kestrel (*Falco sparverius*)	4	0.9625	0.0159	4.16	0.41	4.01 to 6.60
Ring-necked Pheasant (*Phasianus colchicus*)	2	0.9625	0.0159	2.08	0.29	2.00 to 3.92
Northern Bobwhite (*Colinus virginianus*)	44	0.9808	0.0218	44.86	1.37	44.10 to 51.77
Killdeer (*Charadrius vociferus*)	6	0.9625	0.0159	6.23	0.50	6.02 to 9.08
Rock Dove (*Columba livia*)	38	1.0000	—	38.00	—	
Mourning Dove (*Zenaida macroura*)	29	1.0000	—	29.00	—	
Yellow-billed Cuckoo (*Coccyzus americanus*)	1	0.9625	0.0159	1.04	0.20	1.00 to 2.39
Chimney Swift (*Chaetura pelagica*)	5	0.9625	0.0159	5.19	0.46	5.01 to 7.85
Ruby-throated Hummingbird (*Archilochus colubris*)	3	0.9625	0.0159	3.12	0.35	3.01 to 5.30
Red-bellied Woodpecker (*Melanerpes carolinus*)	6	0.9625	0.0159	6.23	0.50	6.02 to 9.08
Downy or Hairy woodpecker (*Picoides pubescens, P. villosus*)	1	0.9625	0.0159	1.04	0.20	1.00 to 2.39
Northern Flicker (*Colaptes auratus*)	7	0.9625	0.0159	7.27	0.55	7.02 to 10.28
Pileated Woodpecker (*Dryocopus pileatus*)	2	0.9625	0.0159	2.08	0.29	2.00 to 3.92
Eastern Wood-Pewee (*Contopus virens*)	7	0.9625	0.0159	7.27	0.55	7.02 to 10.28
Acadian Flycatcher (*Empidonax virescens*)	1	0.9625	0.0159	1.04	0.20	1.00 to 2.39
Eastern Phoebe (*Sayornis phoebe*)	1	0.9625	0.0159	1.04	0.20	1.00 to 2.39
Great Crested Flycatcher (*Myiarchus crinitus*)	5	0.9625	0.0159	5.19	0.46	5.01 to 7.85
Eastern Kingbird (*Tyrannus tyrannus*)	2	0.9625	0.0159	2.08	0.29	2.00 to 3.92
Red-eyed Vireo (*Vireo olivaceus*)	28	1.0000	—	28.00	—	
Blue Jay (*Cyanocitta cristata*)	22	0.9899	0.0150	22.22	0.58	22.01 to 25.71
American Crow (*Corvus brachyrhynchos*)	16	1.0000	—	16.00	—	
Fish Crow (*Corvus ossifragus*)	8	0.9625	0.0159	8.31	0.59	8.03 to 11.46
Horned Lark (*Eremophila alpestris*)	2	0.9625	0.0159	2.08	0.29	2.00 to 3.92
Purple Martin (*Progne subis*)	15	0.9625	0.0159	15.58	0.82	15.08 to 19.52
Tree Swallow (*Tachycineta bicolor*)	1	0.9625	0.0159	1.04	0.20	1.00 to 2.39
Barn Swallow (*Hirundo rustica*)	12	1.0000	—	12.00	—	
Carolina Chickadee (*Poecile carolinensis*)	2	0.9625	0.0159	2.08	0.29	2.00 to 3.92
Tufted Titmouse (*Baeolophus bicolor*)	9	0.9625	0.0159	9.35	0.62	9.03 to 12.64
White-breasted Nuthatch (*Sitta carolinensis*)	1	0.9625	0.0159	1.04	0.20	1.00 to 2.39
Carolina Wren (*Thryothorus ludovicianus*)	11	1.0000	—	11.00	—	
Eastern Bluebird (*Sialia sialis*)	5	0.9625	0.0159	5.19	0.46	5.01 to 7.85
Wood Thrush (*Hylocichla mustelina*)	16	1.0000	—	16.00	—	
American Robin (*Turdus migratorius*)	72	0.9924	0.0083	72.55	0.96	72.05 to 77.60
Gray Catbird (*Dumetella carolinensis*)	5	0.9625	0.0159	5.19	0.46	5.01 to 7.85
Northern Mockingbird (*Mimus polyglottos*)	34	1.0000	—	34.00	—	
Brown Thrasher (*Toxostoma rufum*)	1	0.9625	0.0159	1.04	0.20	1.00 to 2.39
European Starling (*Sturnus vulgaris*)	55	0.9778	0.0193	56.25	1.58	55.18 to 63.51
Northern Parula (*Parula americana*)	1	0.9625	0.0159	1.04	0.20	1.00 to 2.39
Kentucky Warbler (*Oporornis formosus*)	1	0.9625	0.0159	1.04	0.20	1.00 to 2.39
Common Yellowthroat (*Geothlypis trichas*)	13	1.0000	—	13.00	—	
Summer Tanager (*Piranga rubra*)	1	0.9625	0.0159	1.04	0.20	1.00 to 2.39
Scarlet Tanager (*Piranga olivacea*)	4	0.9625	0.0159	4.16	0.41	4.01 to 6.60
Eastern Towhee (*Pipilo erythrophthalmus*)	3	0.9625	0.0159	3.12	0.35	3.01 to 5.30
Chipping Sparrow (*Spizella passerina*)	15	1.0000	—	15.00	—	
Field Sparrow (*Spizella pusilla*)	6	0.9625	0.0159	6.23	0.50	6.02 to 9.08
Song Sparrow (*Melospiza melodia*)	8	0.9625	0.0159	8.31	0.59	8.03 to 11.46
Northern Cardinal (*Cardinalis cardinalis*)	21	1.0000	—	21.00	—	
Blue Grosbeak (*Guiraca caerulea*)	17	0.9815	0.0279	17.32	0.75	17.02 to 21.71
Indigo Bunting (*Passerina cyanea*)	24	0.9545	0.0550	25.14	1.82	24.13 to 34.31
Red-winged Blackbird (*Agelaius phoeniceus*)	114	0.9973	0.0024	114.31	0.63	114.03 to 117.76

TABLE 5. Continued.

		Detection probability		Abundance		
Species	$x_{..}$	$\hat{p}$	$\widehat{SE}(\hat{p})$	$\hat{N}$	$\widehat{SE}(\hat{N})$	95% CI
Eastern Meadowlark (*Sturnella magna*)	5	0.9625	0.0159	5.19	0.46	5.01 to 7.85
Common Grackle (*Quiscalus quiscula*)	87	0.9661	0.0205	90.06	2.61	87.72 to 100.05
Brown-headed Cowbird (*Molothrus ater*)	11	1.0000	—	11.00	—	
Orchard Oriole (*Icterus spurius*)	6	0.9625	0.0159	6.23	0.50	6.02 to 9.08
Baltimore Oriole (*Icterus galbula*)	4	0.9625	0.0159	4.16	0.41	4.01 to 6.60
House Finch (*Carpodacus mexicanus*)	11	1.0000	—	11.00	—	
American Goldfinch (*Carduelis tristis*)	11	1.0000	—	11.00	—	
House Sparrow (*Passer domesticus*)	56	0.9969	0.0039	56.17	0.47	56.01 to 59.02

observer conducting a point count simply go unchallenged. The best way to circumvent this problem is to try to insure that all observers are experts at bird identification and observation.

Some bird species are virtually undetectable in daytime surveys such as those reported here (e.g. owls and nightjars). Even if an individual of such a species is detected now and then, it will be impossible to estimate associated detection probabilities. Thus, although the double-observer approach holds promise for species with reasonable detection probabilities (e.g. >0.40), the approach will not be useful for species with detection probabilities that approach 0. Similarly, in some situations certain classes of individuals (e.g. females) will have detection probabilities that approach 0, in which case estimates of detection probability and abundance for the species would correspond to the classes of individuals that have non-zero detection probabilities. Clearly, undetectable species and individuals present problems in any type of survey, and if these species or classes are of primary interest, then an alternative sampling approach should be used (e.g. capture-recapture methods rather than observation-based methods).

Computations.—Under certain combinations of values of the sufficient statistics, the parameters of interest are not identifiable and cannot be well estimated. One such situation is when only one observer detects individuals of a particular species (e.g. $x_{11} > 0$, $x_{12} > 0$, $x_{22} = 0$, $x_{21} = 0$). In this situation, the denominator of the estimator (equation 3) for the observer who detected birds is 0, and the estimator is undefined. If $x_{11}x_{22} - x_{12}x_{21} = 0$, and $x_{ij} > 0$ ($i = 1, 2$; $j = 1, 2$), then the two detection probabilities are not identifiable. When we encountered such situations for particular species in our analyses, we did not attempt to estimate a species-specific detection probability but pooled the data for the problem species with the other species in the same detection group (i.e. difficult or

TABLE 6. Number of birds counted by observer 1 (x_{11}), estimated abundance[a] ($\hat{N}_1$), and estimated species-specific detection probabilities for stops at which observer 1 was the primary observer for selected bird species[b] detected on BBS-C (data set 10).

		Abundance			Detection probability	
Species	x_{11}	$\hat{N}_1$	$\widehat{SE}(\hat{N}_1)$	95% CI	$\hat{p}_1$	$\widehat{SE}(\hat{p}_1)$
Turkey Vulture	33	37.51	0.94	37.05 to 42.52	0.8799	0.0581
Northern Bobwhite	13	19.37	0.75	19.03 to 23.53	0.6711	0.1119
Blue Jay	11	12.12	0.40	12.01 to 14.62	0.9074	0.0892
American Robin	22	29.22	0.53	29.01 to 32.33	0.7529	0.0816
European Starling	27	29.66	1.01	29.08 to 34.67	0.9103	0.0619
Blue Grosbeak	6	7.13	0.42	7.01 to 9.76	0.8413	0.1479
Red-winged Blackbird	54	58.16	0.42	58.01 to 60.71	0.9285	0.0346
Common Grackle	39	45.55	1.59	44.29 to 52.19	0.8563	0.0615
House Sparrow	19	20.06	0.26	20.00 to 21.78	0.9471	0.0516

[a] $\hat{N}_1 = x_1/\hat{p}$.

[b] Selected species were those for which species-specific detection probabilities were estimated and for which $\hat{p} < 1$.

easy) that did not have adequate data for separate estimation. Finally, detection probability estimates of 0 or 1 produce undefined variances (see Appendix 1).

ADDITIONAL MODELING OF DETECTION PROBABILITY

Our intent is to present the basics of the double-observer approach to the conduct of point counts. In the process of examining our data and considering the approach, we identified several other possible extensions to the modeling of detection probabilities. Our results indicate that observer identity and bird species are sources of variation that should be incorporated into virtually all attempts to model detection probability. During our field trials, bird detections were categorized as occurring by visual or by auditory means. Detection probabilities associated with these two modes of detection are likely to be different, and it would be possible to build models that incorporate mode of detection. We suspect that any gains in ability to model detection probabilities would not merit the extra parameters associated with such models, but we do not know this and believe that such modeling should be investigated.

Habitat may be an important source of variation in detection probabilities. It would be possible to classify habitats associated with different point counts according to a simple classification scheme and then incorporate habitat type into models of detection probability.

We found it necessary to group species into broad categories based on ease of detection because small numbers of individuals were detected for many bird species. Certainly, it would be possible to consider different classification schemes and to test their efficacy with data from our field trials or from new efforts. In particular, our "difficult" detection category contained a small number of species, none of which was very abundant in the areas surveyed in our field trials. If the "difficult" category contained more species, then it would be more likely that at least a group-specific detection probability could be estimated. We can also envision species being placed into different detection categories depending on phenology and survey timing, as when males of some species stop singing earlier in the breeding season than do males of other species.

Point counts are used in a variety of types of investigation ranging from broad surveys such as the BBS, to intensive studies of particular sites or locations. Multiple counts by specific observers will permit additional modeling of detection probability that should prove useful in estimating bird abundance. Our field trials perhaps are analogous to intensive research investigations in that some individuals served as observers on many routes and occasions. In such situations, we can create models containing multiple surveys (surveys at different times and places) that share at least some observers. Then, reduced-parameter models can be considered in which species-specific detection probabilities for a particular observer are modeled as constants over time/space or perhaps time/habitat. Even in large-scale surveys in which a pair of observers may conduct only one survey route per year, it may be possible to exploit data from a single observer obtained over multiple years. Such modeling should result in gains in precision.

Multiple routes with specific pairings of investigators also may be an approach to deal with the problem of two observers having different distances from which they can detect birds (different detection radii). Such modeling might require that each individual be paired with every other individual in a small group of investigators. Given data from such multiple routes, parameters reflecting variation in observer detection radius can be incorporated into modeling efforts to standardize detection-probability estimates to correspond to birds that are potentially detectable.

We might categorize the Cook-Jacobson model and our various extensions as "conditional" in that estimation is conducted by first conditioning on the numbers of birds observed, estimating detection probability from such a conditional distribution, and then applying the estimates of detection probability to numbers of birds observed to estimate abundance. In the future, we will consider the possibility of developing unconditional models that incorporate abundance or annual population growth rate directly as model parameters.

RECOMMENDATIONS

We were sufficiently encouraged by the double-observer approach that we believe it should be strongly considered for use in future point-count studies. In particular, the variation in estimated detection probabilities we document for single-observer counts provides a strong argument against use of these counts when results are to be compared over space or time. Because detection probabilities could vary among the counts being compared (e.g. associated with an experimental treatment), investigators cannot make statements about differences in population sizes based on observed differences in counts. Based on our results, we see little justification for use of standard point counts unaccompanied by some effort to estimate detection probability. The variable circular plot and the double-observer approach described here offer two distinctly different approaches to estimation of detection probability, and hence bird abundance, from point counts. Both require additional effort beyond that required for simple counts, but it is our opinion that most questions that are sufficiently important to merit the effort required to conduct point counts in the first place also are sufficiently important that estimation should be taken seriously.

Computations associated with estimation under the general Cook-Jacobson model are straightforward (e.g. equations 3 and 4) and can be done easily on a hand calculator. The SURVIV models are available at <www.mbr-pwrc.usgs.gov/software/dobserv.html>, as is a more user-friendly Visual Basic program to implement detection probability modeling.

We have pointed out potential problems with our initial efforts to apply the double-observer approach, but most of these problems are even more serious for standard point counts. The situation with point counts that do and do not incorporate attempts to estimate detection probability is analogous to uses of capture-recapture data that do and do not attempt to estimate capture probability. Proponents of the use of raw catch statistics once claimed that they preferred their approach because it was free of the assumptions required by efforts to model and estimate capture probability. This claim was shown to be false, and indeed the "estimators" based on catch statistics were shown to be much more sensitive to assumption violations than were the probabilistic estimators based on modeling capture probability (Jolly and Dickson 1983, Nichols and Pollock 1983, Skalski and Robson 1992). Although this has not been formally investigated with point counts, we believe that abundance and trend estimates based on the double-observer approach are likely to be much more robust to the various problems discussed above than are estimates based on single-observer counts.

Our primary recommendation regarding implementation of the double-observer approach is the restriction to fixed-radius counts. We believe that two very important advantages are associated with use of a fixed radius. The first advantage has been discussed above and involves an attempt to minimize the probability that a group of birds (e.g. at a particular distance) will be undetectable by one observer, yet detectable by another. The second involves the issue of geographic or spatial sampling. In our treatment above, we followed the traditional treatment of point-count data and omitted discussion of the area sampled and of spatial variation in bird abundance and density. However, spatial variation is easily (and usefully) included in the double-observer approach.

Consider the goal of density or abundance estimation for some large area of interest. One approach to such estimation would be to randomly select locations for the conduct of point counts from all possible locations in the area of interest (stratification could also be used with random selection within strata). The double-observer sampling at the selected points would then cover a known area (equal to $k\pi r^2$, where k denotes the number of point counts conducted and r denotes the fixed radius) and a known fraction of the total area of interest. The abundance estimates from the sampled area can then be used to estimate the total density and abundance on the entire area of interest. The variance of this overall estimate of abundance or density will then depend not only on the precision of the estimate of detection probability, but also on the fraction of the total area on which counts were conducted and on the spatial variation in bird density and abundance (Cook and Jacobson 1979, Lancia et al. 1994). This latter spatial variation results in the need to include in the overall variance estimator a variance component associated with the count-to-count (and place-to-place) variance in number of birds detected. Such estimation of overall abundance or density and its variance is straightforward and is presented in Cook and

Jacobson (1979). Whether the objective of the point-count survey involves monitoring goals or specific study goals, inclusion of spatial variation in bird abundance or density likely will yield stronger and more widely applicable inferences.

A final recommendation is to investigate the potential for use of independent observers to collect point-count data. Two or more observers would detect birds at the same point and the same time, recording the approximate locations and detection times of birds seen and heard on a rough map. After the point count, the different maps would be used to determine which birds were detected by which observer(s). Resulting data would have the form of a capture history, with a vector of 0s and 1s indicating for each bird the observers that did (1) and did not (0) detect it. If detections of the different observers are really independent, then the resulting data can be used with the entire suite of closed-population capture-recapture models (Otis et al. 1978, Rexstad and Burnham 1991). This model set includes models that permit detection probability to be different for each individual bird in the sampled area, and we suspect that such models would prove useful for point-count data. Our primary reason for not exploring this approach was our *a priori* belief that it would be very difficult in the field to insure independence of observers who were counting birds at the same point. However, Ted Simons (pers. comm.) has experimented with this approach, and his initial results suggest that this sort of sampling is possible.

Note that this final recommendation involves multiple observers sampling at the same point in space and time. This approach is not the same as a single observer surveying the same point(s) on multiple occasions (e.g. days). Although data from this latter approach can be used to estimate species-specific detection probabilities, the estimates are very model dependent and relatively imprecise (Carrol and Lombard 1985, Sauer et al. 1994a). Sampling using variable circular plots and the double-observer approach should be preferable to this latter approach. Multiple surveys by the same pair of observers using the double-observer approach at each survey can be modeled using the approach described here and should produce more precise estimates of detection probability and abundance, as well as inferences about possible changes in abundance over the repeat visits.

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APPENDIX 1. Estimation of variances of detection-probability estimates based on Cook and Jacobson (1979).

Large-sample variances and covariances for individual detection probability estimates are given by Cook and Jacobson (1979) as:

$$\mathrm{var}(\hat{p}_1) = \frac{p_1(1 - p)(1 - \beta_1 p)}{x_{..} p_2(1 - p_2)\beta_1\beta_2},$$

$$\mathrm{var}(\hat{p}_2) = \frac{p_2(1 - p)(1 - \beta_2 p)}{x_{..} p_1(1 - p_1)\beta_1\beta_2},$$

$$\mathrm{cov}(\hat{p}_1, \hat{p}_2) = \frac{(1 - p)}{x_{..}\beta_1\beta_2}, \tag{8}$$

where $\beta_i = x_{.i}/x_{..}$ They also give the following asymptotic variance of the estimated detection probability for both observers, $\hat{p}$:

$$\mathrm{var}(\hat{p}\,|\,x_{..}) = \frac{(1 - p)^2 p}{x_{..}}\left[\frac{1}{p_1\beta_1} + \frac{1}{p_2\beta_2} + \frac{1}{p_2(1 - p_1)\beta_1} + \frac{1}{p_1(1 - p_2)\beta_2}\right]. \tag{9}$$

These expressions can be used to compute estimates of the variances of detection probability estimates under a general model in which detection probabilities are assumed to be different for the two observers. In practice, we obtain our variance and covariance estimates for $\hat{p}_1$ and $\hat{p}_2$ directly from the appropriate model in program SURVIV. To compute a variance estimate for the overall detection probability, $\hat{p}$, we rewrite p_1 as a function of p (equation 7). This expression (equation 7) is substituted for p_1, and the SURVIV output then contains estimates of p_2, p, and their variances.

APPENDIX 2. Estimated average detection probability (from model p) and detection probabilities for specific observers (from model p_i).

	Observers		Detection probability, $\hat{p}_i$ ($\widehat{SE}$ [$\hat{p}_i$])		
Data set	A	B	A	B	Average
1	1	2	0.82 (0.039)	0.81 (0.043)	0.82 (0.033)
2	1	2	0.91 (0.049)	0.88 (0.051)	0.89 (0.040)
3	1	2	0.88 (0.020)	0.84 (0.023)	0.86 (0.017)
4	1	2	0.94 (0.024)	0.86 (0.036)	0.90 (0.024)
5	1	2	0.88 (0.025)	0.87 (0.033)	0.87 (0.022)
7	3	1	0.86 (0.034)	0.87 (0.035)	0.87 (0.027)
6	3	2	0.96 (0.019)	0.77 (0.035)	0.85 (0.026)
15	3	2	0.97 (0.013)	0.70 (0.034)	0.84 (0.021)
8	4	1	0.89 (0.018)	0.89 (0.018)	0.89 (0.014)
9	5	2	0.82 (0.042)	0.90 (0.038)	0.85 (0.034)
10	6	1	0.86 (0.017)	0.85 (0.017)	0.86 (0.014)
11	6	2	0.90 (0.017)	0.83 (0.020)	0.86 (0.015)
14	6	3	0.75 (0.042)	0.90 (0.034)	0.81 (0.034)
13	7	2	0.94 (0.017)	0.66 (0.035)	0.81 (0.023)
12	7	3	0.92 (0.021)	0.81 (0.030)	0.87 (0.020)
16	8	3	0.89 (0.022)	0.78 (0.030)	0.84 (0.021)
17	8	3	0.80 (0.031)	0.65 (0.034)	0.72 (0.029)