



AN UNRECONCILED DOUBLE-OBSERVER METHOD FOR ESTIMATING DETECTION PROBABILITY AND ABUNDANCE

JASON D. RIDDLE,^{1,4} KENNETH H. POLLOCK,² AND THEODORE R. SIMONS³

¹*Department of Biology, North Carolina Cooperative Fish and Wildlife Research Unit, North Carolina State University, Campus Box 7617, Raleigh, North Carolina 27695, USA;*

²*Department of Biology, North Carolina State University, Campus Box 7617, Raleigh, North Carolina 27695, USA; and*

³*U.S. Geological Survey, Cooperative Fish and Wildlife Research Unit, Department of Biology, North Carolina State University, Raleigh, North Carolina 27695, USA*

ABSTRACT.—Multiple-observer point-count methods allow estimation of detection probability and have some advantages over other point-count methods. We introduce the unreconciled double-observer method, an independent double-observer method that does not require observers to match or otherwise reconcile individual observations. The modeling of the counts uses the repeated-counts model (Royle 2004). We compared estimates of detection probability and abundance from the unreconciled double-observer method with estimates from the traditional independent double-observer method (which requires matching of individual animals) using field-simulated bird-point-count data. The unreconciled double-observer method provided point estimates of detection probability and abundance that were essentially identical to the results of the independent double-observer method, even though much less effort was required to collect data with the unreconciled method. Estimates of detection probability from the unreconciled double-observer method were usually less precise—and estimates of abundance always less precise—than those from the independent double-observer method, because there is less information available in the unreconciled double-observer approach. We also evaluated the unreconciled double-observer method on 12 Breeding Bird Survey (BBS) routes. The unreconciled double-observer method provided estimates of route-level abundance for most routes and for most of the 20 species we considered. We believe that this method has potential for established bird-monitoring programs such as the BBS because no changes in historical data-collection methods are required other than collecting data simultaneously using two or more observers. *Received 5 August 2009, accepted 30 March 2010.*

Key words: abundance, detection probability, double-observer, PRESENCE, repeated counts.

Un Método de Doble Observador sin Reconciliación para estimar Probabilidades de Detección y Abundancia

RESUMEN.—Los métodos de conteo en puntos con múltiples observadores permiten la estimación de probabilidades de detección y tienen algunas ventajas sobre otros métodos de conteo en puntos. Aquí presentamos el método de doble observador sin reconciliación, un método de doble observador independiente que no requiere que los observadores coincidan o reconcilien sus observaciones individuales. El modelado usa el modelo de conteos repetidos (Royle 2004). Comparamos los estimados de probabilidad de detección y abundancia calculados con el método sin reconciliación de doble observador con los estimados del método tradicional de doble observador independiente (el cual requiere que los individuos coincidan) utilizando datos de puntos de conteo de aves en campo simulados. El método de observador doble sin reconciliación brindó estimados puntuales de detectabilidad y abundancia que fueron esencialmente idénticos a los resultados obtenidos con el método de observador doble independiente, a pesar de que el esfuerzo para recolectar los datos con el método sin reconciliación fue mucho menor. Los estimados de la probabilidad de detección con el método sin reconciliación de doble observador fueron generalmente menos precisos —y los estimados de abundancia fueron siempre menos precisos— que los estimados del método de observador doble independiente. También evaluamos el método de observador doble sin reconciliación en 12 rutas del Conteo de Aves Reproductivas (BBS, por sus siglas en inglés). El método de doble observador sin reconciliación entregó estimados de abundancia a nivel de las rutas para la mayoría de las rutas y para la mayoría de las 20 especies que consideramos. Creemos que este método tiene potencial para programas de monitoreo establecidos tales como el BBS porque no se requieren cambios en los métodos históricos de colección de datos fuera de recolectar datos simultáneamente utilizando dos o más observadores.

⁴Present address: College of Natural Resources, University of Wisconsin—Stevens Point, Stevens Point, Wisconsin 54481, USA.
E-mail: jason.riddle@uwsp.edu

THE IMPORTANCE OF accounting for detection probability in abundance estimation has received much attention in recent years. Detection probability (p) can be represented as the product of several components: the probability that an individual bird associated with the sample area is present during the count (p_p), the probability that an individual bird is available (i.e., vocalizing or not visually obscured) given that it is present (p_a), and the probability that an individual bird is detected given that it is present and available (p_d) (see Johnson 2008, and the recent review by Nichols et al. 2009). Therefore, the full detection process can be represented as $p = p_p p_a p_d$.

Various methods for estimating one or more components of p are now available, including distance (Buckland et al. 2001), multiple observers (Nichols et al. 2000, Alldredge et al. 2006), time-of-removal (Farnsworth et al. 2002), time-of-detection (Alldredge et al. 2007a), and repeated counts (Royle 2004). Distance sampling and multiple-observer methods provide only estimates of p_d . Therefore, estimators of abundance from these methods will be biased low when p_p and p_a are not equal to 1. Time-of-removal and time-of-detection provide an estimate of $p_a p_d$, but p_a and p_d are not separable unless these methods are combined with distance or multiple observers. Estimators of abundance from time-of-removal and time-of-detection will be biased low when p_p is not equal to 1. Repeated-counts methods provide the full estimate of $p_p p_a p_d$, but none of the components of the detection process are separable unless this method is combined with time-of-removal or time-of-detection and distance or multiple observers. Also, the repeated-counts abundance estimate (N) is technically a super-population estimate and may be difficult to translate or relate to habitat area or bird density in many instances (Royle and Dorazio 2008). In other words, some methods are theoretically and mathematically superior to others in terms of the estimates of detection probability and abundance they provide, but this can come at the cost of interpretability. In addition to the technical advantages of particular methods over others, some methods are likely more appropriate than others, depending on study objectives, the species under investigation, and logistical constraints. For example, observers often have difficulty estimating distance in forested environments, where the vast majority of detections are auditory (Alldredge et al. 2007b). Therefore, distance-based methods may be more appropriate in environments where visual detections are more likely. Time-of-removal and time-of-detection methods are more intensive in that they require observers either to record the time interval in which a bird is first detected or to record detections over multiple time intervals. These methods may work well when only one or a few focal species in moderate densities are the focus of investigation (e.g., Riddle et al. 2008), but they can be cumbersome when the number of individual birds tracked is large. Repeated-counts methods usually rely on multiple visits to a site over time. These methods are often easier to execute than the methods just described because distance estimation and the tracking of individual birds are not required. Therefore, repeated counts may be more appropriate for situations in which there are many focal species encountered by either sight or sound. However, repeated-counts methods assume that detections in each visit are independent of those from other visits, and this may be difficult to accomplish in many circumstances (Riddle et al. 2010). Repeated-counts methods also have a closure assumption that may be difficult

to meet if counts are conducted over long periods. Moreover, it may not be logistically feasible for practitioners to make repeated visits to locations of interest.

Multiple-observer methods have some features that make them appealing when compared with other methods. In particular, multiple-observer methods require only one visit to each point-count location. Also, these methods do not require observers to track individual birds across time intervals. Therefore, observers can focus on a greater number of focal species without the logistical constraints of multiple visits. Multiple-observer methods require at least two observers. This may be viewed as a logistical constraint in terms of the personnel required, but in many situations, field conditions or other field-work components make two or more observers a safer and sometimes a necessary option. Traditional multiple-observer methods also have their own unique constraints. For example, the independent double-observer method requires observers to map the location of birds during the course of a count in order to facilitate matching observations that were common to both observers (Moore et al. 2004, Alldredge et al. 2006). Observers often have difficulty in localizing sound sources, and so the matching process itself may generate errors (Alldredge et al. 2007b, 2008). Moreover, the matching process should ideally occur immediately following each point count, and on high-density or species-rich counts this process can be time consuming. The dependent double-observer method does not require reconciliation (Nichols et al. 2000). Instead, observers alternate roles as primary and secondary observer. The primary observer communicates all his or her observations to the secondary observer. The secondary observer makes note of these observations, but also records any observations he or she detected that the primary did not. Although this essentially excludes errors and time constraints associated with the matching process, the process of communicating observations during the count can be cumbersome and distracting. Moreover, this method is often less efficient (i.e., larger SEs) than the independent double-observer method (Alldredge et al. 2006).

Here, we present an unreconciled double-observer method that relies on independent observations but does not require matching observations or any other communication between observers regarding detections. Site-specific abundances are estimated in a similar manner to that of repeated-counts methods except that each observer is treated as a "visit." We also compare estimates of detection probability and abundance from the unreconciled double-observer method with those from the independent double-observer method using data from a field-based bird-song-simulation system. Finally, we use real field data from actual Breeding Bird Survey (BBS) routes to obtain route-level estimates of abundance for species of varying levels of apparent abundance using the unreconciled double-observer method. Here, we use the term "apparent abundance" to refer to abundance based on raw counts.

METHODS

The unreconciled double-observer method is a very easy method to execute. All that is required is for two observers to be present at the same point-count location to conduct simultaneous point counts. It is important that the observers do not provide any cues to each other regarding their observations. In other words,

observers should do their best to ignore each other so that the count proceeds as if each observer were the only one present. This is to satisfy the assumption that the two counts obtained are independent. When the count is over, there is no need to match observations or discuss results because there is no reconciliation of observations between the observers. The only data necessary from each site are simply each observer's counts. For example, if observer 1 detected 1 individual of a species at site A and observer 2 detected 3 individuals of the same species at site A, then the resulting site history for A is simply 1,3.

The underlying mathematical model of this method is exactly that of the hierarchical model that Royle (2004) developed for repeated counts obtained from multiple visits, except that in this case each observer functions as a "visit." Because both "visits" occur simultaneously, the detection estimate provided by this method is only p_d , even though the mathematics involved are the same as with the repeated-counts models. Note that Royle and Dorazio (2008:177) were the first to suggest that unreconciled independent multiple-observer counts could be modeled in this way. This two-stage hierarchical model allows for an ecological-state-process model and an observation model. Here, the ecological state process is the actual abundance at each site (point-count location). Abundance can be modeled as Poisson, and this is often the most intuitive choice (Royle 2004). However, negative-binomial or zero-inflated Poisson may perform better in cases in which count data are overdispersed. For example, Etterson et al. (2009) found that zero-inflated Poisson mixtures performed very well with overdispersed count data in numerous removal models. For the purposes of demonstration, we consider abundance as a simple Poisson process only. The observation process for this model is the detection probability component, which allows for imperfect observations. Here, it is modeled as a simple binomial process. Mathematically, this hierarchical model can be represented as

$$Y_{ij} \sim \text{Binomial}(N_i, p_{ij})$$

$$N_i \sim \text{Poisson}(\lambda)$$

where N_i is the unobserved true abundance at site i , $i = 1, \dots, n$; y_{ij} is the vector of observed abundance values at site i by the j th observer; and p_{ij} is the probability of detection at site i by observer j . Additional details about these kinds of models can be found in Royle (2004) and Royle and Dorazio (2008).

EXAMPLE DATA

Field-simulated data.—We use two data sets that were generated from experiments with a field-based bird-song-simulation system (Simons et al. 2007, 2009). The system uses a laptop computer to send commands to play bird-song recordings from remotely located MP3 players and amplified speakers that can be arranged at known distances and orientations around a central point. Therefore, entire point counts can be simulated in which the population of singing birds is known (along with the distance and direction of each song in relation to the observer). In particular, we utilize data from two experiments in which field-simulated bird populations were sampled by multiple observers using the independent double-observer method. In the simple experiment, 8 birds were simulated at each of 60 point counts. The species of interest for

the present study are the Acadian Flycatcher (*Empidonax virens*), Black-throated Blue Warbler (*Dendroica caerulescens*), and Black-throated Green Warbler (*D. virens*). One hundred individuals of each focal species were simulated, and two pairs of observers conducted all 60 counts using the independent double-observer method. In the complex experiment, 12 birds were simulated at each of 60 point counts. For the present study, the species of interest from this experiment are Acadian Flycatcher, Black-and-white Warbler (*Mniotilta varia*), Black-throated Blue Warbler, Black-throated Green Warbler, Hooded Warbler (*Wilsonia citrina*), and Scarlet Tanager (*Piranga olivacea*). One hundred individuals of each focal species were simulated, and three pairs of observers conducted all 60 counts using the independent double-observer method. The detection histories from these experiments are the same as those to which Alldredge et al. (2008) applied relatively complex model sets that incorporated estimated and true distances, song rate, song orientation, and observer variation for each individual bird. Here, our interest was in converting the detection histories from each point count into simple site histories for use with the unreconciled double-observer method to determine whether the estimates of abundance and detection probability were comparable to the independent double-observer method. Data were converted from detection histories to site histories in the following manner. Suppose that 3 Scarlet Tanagers are recorded at a point count; 2 are noted as matches (i.e., observations that both observers in a pair agree were shared between them), and 1 is unique to the second observer. The detection histories for these birds would be 11, 11, and 01, respectively. The site history would simply be the sum of all observations for each observer: 2,3.

Breeding Bird Survey data.—As part of a study to determine the feasibility of potential changes to BBS survey protocol methods, 6 observers sampled 12 BBS routes in central and eastern North Carolina. The unreconciled double-observer method was used on all 600 stops associated with the 12 routes (50 stops route⁻¹). Each pair of observers sampled each stop for a total of 6 min because of other methods that we were evaluating. In order to sample the route within the time typically allotted for BBS protocols, we had to use two teams of double observers on each route (total of 4 observers on each route). One team sampled even-numbered stops, and the other sampled odd-numbered stops. For our present purposes, we use observations from the first 3 min of each count only, to make our data more comparable to typical BBS data. Also, we restrict our analysis to the 20 apparently most abundant species that did not occur in large mixed flocks, excluding, for our purposes, the European Starling (*Sturnus vulgaris*), Common Grackle (*Quiscalus quiscula*), and Brown-headed Cowbird (*Molothrus ater*). The 20 most abundant species along these routes were the Northern Cardinal (*Cardinalis cardinalis*), American Crow (*Corvus brachyrhynchos*), Chipping Sparrow (*Spizella passerina*), Northern Mockingbird (*Mimus polyglottos*), Indigo Bunting (*Passerina cyanea*), Mourning Dove (*Zenaidura macroura*), Carolina Wren (*Thryothorus ludovicianus*), Tufted Titmouse (*Baeolophus bicolor*), Eastern Bluebird (*Sialia sialis*), Red-eyed Vireo (*Vireo olivaceus*), Blue Jay (*Cyanocitta cristata*), Carolina Chickadee (*Poecile carolinensis*), American Robin (*Turdus migratorius*), Blue-gray Gnatcatcher (*Poliophtila caerulea*), Red-bellied Woodpecker (*Melanerpes carolinus*), Canada Goose

(*Branta canadensis*), Eastern Towhee (*Pipilo erythrophthalmus*), Barn Swallow (*Hirundo rustica*), Pine Warbler (*Dendroica pinus*), and Chimney Swift (*Chaetura pelagica*).

Analysis

Field-simulated data.—We converted detection histories for each focal species at each point count for each experiment (simple and complex) to site histories as previously demonstrated. We analyzed these data in program PRESENCE using the Royle Biometrics option (Royle 2004, Hines 2006). We used indicator variables to identify individual observers and allow detection probability to vary by observer. For each species in the simple and complex experiments we considered two models: one with constant site abundance ($\lambda(\cdot)$) and constant detection probability among observers ($p(\cdot)$), and one with constant site abundance and detection probability that varied among observers ($p(\text{obs})$). We present parameter estimates from both models in each set.

To facilitate meaningful comparisons of the unreconciled double-observer and independent double-observer methods for these data, we reanalyzed the original detection histories from Alldredge et al. (2008) but excluded information about distance, song rate, and song orientation. In other words, the data were reduced so that we were considering only the same model sets for the independent double-observer data that were possible for the unreconciled double-observer data (i.e., $p(\cdot)$ and $p(\text{obs})$). These data were reanalyzed in Program MARK (White and Burnham 1999) using the Huggins Closed Captures option (Huggins 1989, 1991). We present parameter estimates from both models in each set.

Breeding Bird Survey data.—We entered site histories into and analyzed these data in PRESENCE. We used indicator variables to identify individual observers and allow detection probability to vary by observer. We also used indicator variables as site-level covariates to identify individual routes and allow stop-level abundance to vary by route. For each species, we considered models that allowed site-level abundance to be constant across routes or vary by route and that allowed detection probability to be constant or vary by route or observer. Specifically, we considered the following models for each species: $p(\cdot)\lambda(\cdot)$, $p(\text{obs})\lambda(\cdot)$, $p(\text{route})\lambda(\cdot)$, $p(\cdot)\lambda(\text{route})$, $p(\text{obs})\lambda(\text{route})$, and $p(\text{route})\lambda(\text{route})$. We used Akaike's information criterion (AIC) model-selection criteria to select the top model from each set.

RESULTS

Field-simulated data.—Estimates of N and p were similar for analogous models between methods. Estimates of p from the unreconciled double-observer method were almost always less precise, and estimates of N were always less precise, than those from the independent double-observer method. However, point estimates of N from the unreconciled double-observer method tended to be closer to the true population size of 100 (26 of 48 models, or ~54%) than point estimates of N from the independent double-observer method. Moreover, estimates of N from the unreconciled double-observer method were within 1 SE of the true population size ~54% of the time (26 of 48 models), whereas estimates of N from the independent double-observer method were within 1 SE of the true population size only ~8% of the time (4 of 48 models; Table 1).

Breeding Bird Survey data.—There was overwhelming support for model $p(\text{obs})\lambda(\text{route})$ for nearly every species based on AIC weights (Table 2). Most species had enough data to fit all six models. We had to supply initial values for p and λ for models with abundance that varied by route in the Mourning Dove model set. We were unable to fit $p(\text{route})\lambda(\text{route})$ to the Eastern Bluebird and Pine Warbler data sets, and we were unable to fit models with route-level variation on p or λ for the Red-eyed Vireo. We were unable to fit the Barn Swallow models unless either p or λ was held constant, and we were able to fit Chimney Swift models only with constant p . We were unable to fit any of the models to the Canada Goose data set.

DISCUSSION

The unreconciled double-observer method provided point estimates of N and p that were essentially identical to those from the independent double-observer method based on our analysis of field-simulated data. This is remarkable, given that the two methods represent extremes in terms of effort. This is because observers using the independent double-observer method must confer with each other regarding each observation on each count whereas observers using the unreconciled double-observer method can simply conduct each count and move on to the next. The main difference between the estimates provided by each method is in the precision of N . Estimates of N from the unreconciled double-observer method were always less precise than those from the independent double-observer method. Typically, this would be an undesirable trait when comparing estimates. However, in our field-simulated experiments, the unreconciled double-observer estimates of N were more often than not within 1 SE of the true population size, whereas the independent double-observer estimates of N were rarely within 1 SE. In other words, the unreconciled double-observer method was less precise, but it was also less biased, perhaps because of a lack of matching errors. Practitioners must decide for themselves what level of precision is acceptable for their study or management objectives, but inaccurate estimates with small SEs can lead to erroneous inference with a false sense of confidence.

It is important to note that we compared estimates from both methods from an equal number of counts. In reality, it is possible to conduct more counts in a given amount of time with the unreconciled double-observer method than with the independent double-observer method, because no time is spent matching observations. This would result in larger SEs for the independent double-observer method. For example, Stanislav (2009) compared efficiency (size of SEs) of the independent double-observer and dependent double-observer methods via simulation and demonstrated that if the time requirements of the matching process reduce the overall number of survey points by 25–50%, then the dependent double-observer method may be more efficient (smaller SEs).

It is also important to note that when one or more observers tended to double-count birds (e.g., Black-throated Blue Warblers and Black-throated Green Warblers in the complex experiment) or when observers had difficulty hearing birds (e.g., Black-and-white Warblers in both experiments), both methods had estimators of N that were badly biased.

TABLE 1. Estimates of abundance (N) and detection probability (p) using both the independent double-observer and unreconciled double-observer methods for multiple pairs of observers for species from the simple and complex experiments. Species abbreviations: ACFL = Acadian Flycatcher, BTBW = Black-throated Blue Warbler, BTNW = Black-throated Green Warbler, BAWW = Black-and-white Warbler, HOWA = Hooded Warbler, and SCTA = Scarlet Tanager. Scientific names are given in the text.

Experiment	Species	Observer Group	Model	Independent double-observer						Unreconciled double-observer						
				N		p		N		p		Observer 1		Observer 2		
				N	SE	p	SE	N	SE	p	SE	N	SE	p	SE	p
Simple	ACFL	A	p(.)	91.22	1.76	0.84	0.03	0.84	0.03	90.25	9.96	0.84	0.04	0.84	0.04	
			p(obs)	91.08	1.71	0.88	0.04	0.81	0.04	89.54	9.84	0.89	0.04	0.80	0.05	
		B	p(.)	78.20	1.25	0.88	0.03	0.88	0.03	80.14	9.29	0.85	0.04	0.85	0.04	
			p(obs)	77.87	1.06	0.82	0.04	0.94	0.03	79.24	9.13	0.81	0.05	0.92	0.04	
	BTBW	A	p(.)	88.47	0.74	0.93	0.02	0.93	0.02	88.06	9.47	0.93	0.02	0.93	0.02	
			p(obs)	88.26	0.55	0.88	0.03	0.97	0.02	87.63	9.41	0.89	0.03	0.97	0.02	
		B	p(.)	98.89	1.04	0.91	0.02	0.91	0.02	96.48	9.94	0.92	0.02	0.92	0.02	
			p(obs)	98.86	1.03	0.92	0.03	0.89	0.03	96.25	9.91	0.95	0.03	0.89	0.03	
	BTNW	A	p(.)	100.22	0.50	0.95	0.02	0.95	0.02	99.49	10.01	0.95	0.02	0.95	0.02	
			p(obs)	100.15	0.41	0.93	0.03	0.98	0.02	99.37	9.99	0.94	0.03	0.98	0.02	
		B	p(.)	102.74	0.94	0.91	0.02	0.91	0.02	100.20	10.10	0.93	0.02	0.93	0.02	
			p(obs)	102.70	0.91	0.90	0.03	0.93	0.03	100.16	10.09	0.92	0.03	0.94	0.03	
Complex	ACFL	A	p(.)	87.86	2.07	0.82	0.03	0.82	0.03	96.00	11.39	0.76	0.06	0.76	0.06	
			p(obs)	87.85	2.06	0.83	0.04	0.81	0.05	95.98	11.39	0.76	0.06	0.75	0.06	
		B	p(.)	103.14	3.63	0.74	0.04	0.74	0.04	100.53	11.93	0.74	0.06	0.74	0.06	
			p(obs)	103.13	3.62	0.75	0.05	0.73	0.05	100.15	11.83	0.77	0.06	0.72	0.06	
		C	p(.)	72.81	2.09	0.80	0.04	0.80	0.04	71.58	9.07	0.80	0.05	0.80	0.05	
			p(obs)	72.38	1.92	0.75	0.05	0.87	0.05	70.93	8.93	0.76	0.06	0.86	0.05	
		BAWW	A	p(.)	67.51	1.96	0.81	0.04	0.81	0.04	68.80	8.96	0.79	0.05	0.79	0.05
				p(obs)	66.82	1.66	0.73	0.06	0.90	0.04	67.13	8.61	0.73	0.06	0.89	0.05
			B	p(.)	89.09	2.57	0.79	0.04	0.79	0.04	91.36	11.05	0.76	0.06	0.76	0.06
				p(obs)	88.20	2.27	0.71	0.05	0.87	0.04	89.20	10.54	0.71	0.06	0.84	0.06
		C	p(.)	72.45	2.80	0.75	0.05	0.75	0.05	78.96	11.37	0.68	0.07	0.68	0.07	
			p(obs)	71.41	2.44	0.67	0.06	0.85	0.05	76.13	10.52	0.63	0.07	0.79	0.08	
	BTBW		A	p(.)	97.52	2.31	0.81	0.03	0.81	0.03	98.76	10.95	0.79	0.05	0.79	0.05
				p(obs)	97.27	2.23	0.85	0.04	0.77	0.05	97.54	10.71	0.85	0.05	0.75	0.05
	B	p(.)	p(.)	145.92	5.12	0.70	0.04	0.70	0.04	165.79	23.60	0.62	0.08	0.62	0.08	
			p(obs)	144.92	4.90	0.65	0.05	0.77	0.04	159.05	20.92	0.59	0.07	0.70	0.08	
		C	p(.)	86.92	1.63	0.85	0.03	0.85	0.03	88.44	9.91	0.84	0.04	0.84	0.04	
			p(obs)	86.52	1.45	0.91	0.03	0.80	0.05	87.29	9.71	0.91	0.04	0.79	0.05	
	BTNW	A	p(.)	121.28	2.55	0.81	0.03	0.81	0.03	132.70	14.35	0.74	0.05	0.74	0.05	
			p(obs)	121.13	2.50	0.78	0.04	0.84	0.04	132.16	14.21	0.72	0.06	0.76	0.06	
		B	p(.)	144.45	4.13	0.74	0.03	0.74	0.03	141.79	15.26	0.74	0.06	0.74	0.06	
			p(obs)	144.38	4.11	0.76	0.04	0.73	0.04	139.85	14.73	0.79	0.06	0.71	0.06	
		C	p(.)	p(.)	112.59	3.04	0.78	0.03	0.78	0.03	107.36	11.72	0.79	0.05	0.79	0.05
				p(obs)	112.56	3.03	0.76	0.05	0.79	0.04	107.23	11.69	0.80	0.06	0.77	0.06
			A	p(.)	95.30	1.79	0.84	0.03	0.84	0.03	100.37	10.98	0.80	0.05	0.80	0.05
				p(obs)	95.29	1.79	0.85	0.04	0.84	0.04	100.36	10.98	0.81	0.05	0.80	0.05
		B	p(.)	p(.)	104.65	1.94	0.84	0.03	0.84	0.03	109.54	11.60	0.80	0.05	0.80	0.05
				p(obs)	104.16	1.74	0.90	0.03	0.79	0.04	107.42	11.17	0.88	0.05	0.75	0.05
			C	p(.)	87.70	1.51	0.86	0.03	0.86	0.03	87.38	9.70	0.86	0.04	0.86	0.04
				p(obs)	87.66	1.50	0.84	0.04	0.88	0.04	87.33	9.69	0.85	0.05	0.87	0.04
	SCTA	A	p(.)	96.23	0.51	0.95	0.02	0.95	0.02	95.50	9.81	0.95	0.02	0.95	0.02	
			p(obs)	96.21	0.48	0.97	0.02	0.94	0.03	95.38	9.79	0.98	0.02	0.93	0.03	
		B	p(.)	104.65	1.47	0.87	0.03	0.87	0.03	101.68	10.32	0.89	0.03	0.89	0.03	
			p(obs)	104.28	1.29	0.82	0.04	0.93	0.03	100.91	10.21	0.85	0.04	0.94	0.03	
		C	p(.)	94.12	1.71	0.85	0.03	0.85	0.03	91.41	9.91	0.86	0.04	0.86	0.04	
			p(obs)	93.99	1.66	0.88	0.04	0.82	0.04	90.71	9.79	0.92	0.04	0.83	0.04	

TABLE 2. Model selection criteria and route-level estimates of abundance for the 20 apparently most abundant species on 12 Breeding Bird Survey routes in North Carolina. Species abbreviations: NOCA = Northern Cardinal, AMCR = American Crow, CHSP = Chipping Sparrow, NOMO = Northern Mockingbird, INBU = Indigo Bunting, MODO = Mourning Dove, CARW = Carolina Wren, TUTI = Tufted Titmouse, EABL = Eastern Bluebird, REVI = Red-eyed Vireo, BLJA = Blue Jay, CACH = Carolina Chickadee, AMRO = American Robin, BGGN = Blue-gray Gnatcatcher, RBWO = Red-bellied Woodpecker, CANG = Canada Goose, EATO = Eastern Towhee, BARS = Barn Swallow, PIWA = Pine Warbler, and CHSW = Chimney Swift. Scientific names are given in the text.

Species	Model	AIC	AIC weight	Parameters	Deviance	Route 1	SE	Route 2	SE	Route 3	SE	Route 4	SE
NOCA	p(obs)λ(route)	2,733.46	1.00	18	2,697.46	30.25	6.11	63.18	9.63	93.01	11.29	77.58	10.46
AMCR	p(obs)λ(route)	2,533.59	1.00	18	2,497.59	83.17	11.29	63.26	10.08	34.11	6.95	52.85	8.46
CHSP	p(obs)λ(route)	2,251.29	1.00	18	2,215.29	48.58	8.29	82.46	11.56	62.52	9.57	57.76	9.72
NOMO	p(obs)λ(route)	2,085.30	1.00	18	2,049.30	19.92	5.04	14.70	4.48	53.56	8.65	69.53	9.85
INBU	p(obs)λ(route)	2,066.04	1.00	18	2,030.04	40.10	7.06	60.85	8.43	41.51	7.22	38.89	6.76
MODO	p(obs)λ(route)	2,115.09	0.97	18	2,079.09	18.04	5.10	21.55	5.95	56.72	9.49	61.08	10.57
CARW	p(obs)λ(route)	1,983.10	1.00	18	1,947.10	31.69	6.46	21.65	5.17	48.89	8.16	44.55	7.75
TUTI	p(obs)λ(route)	1,695.12	0.62	18	1,659.12	31.00	6.66	37.62	7.78	30.27	6.65	30.50	6.56
EABL	p(obs)λ(route)	1,504.16	1.00	18	1,468.16	25.43	7.26	18.47	5.33	75.11	13.92	51.70	10.17
REVI	p(obs)λ(.)	1,337.23	1.00	7	1,323.23	21.96	1.69	21.96	1.69	21.96	1.69	21.96	1.69
BLJA	p(obs)λ(route)	1,256.47	0.76	18	1,220.47	11.18	3.76	13.77	4.22	21.54	5.33	40.97	7.63
CACH	p(obs)λ(route)	1,341.77	0.99	18	1,305.77	13.76	4.45	26.06	6.94	33.19	7.35	23.00	6.01
AMRO	p(obs)λ(route)	1,304.29	1.00	18	1,268.29	12.41	4.01	16.43	5.21	35.09	7.05	8.60	3.92
BGGN	p(obs)λ(route)	1,224.18	1.00	18	1,188.18	20.91	5.64	25.85	6.49	24.52	6.05	30.01	6.36
RBWO	p(obs)λ(route)	1,057.25	0.98	18	1,021.25	10.14	3.40	18.19	5.01	23.09	5.25	28.45	6.12
CANG	—	—	—	—	—	—	—	—	—	—	—	—	—
EATO	p(obs)λ(.)	1,091.97	0.84	7	1,077.97	17.18	1.70	17.18	1.70	17.18	1.70	17.18	1.70
BARS	p(.)λ(route)	1,239.05	1.00	13	1,213.05	19.25	6.58	1.87	1.88	34.09	9.13	9.49	4.41
PIWA	p(obs)λ(route)	1,015.49	1.00	18	979.49	38.02	11.10	20.11	7.66	21.02	7.27	31.21	9.93
CHSW	p(.)λ(route)	1,203.88	1.00	13	1,177.88	34.08	10.32	10.60	5.00	83.44	18.70	25.44	8.26

TABLE 2. Continued.

Species	Model	AIC	AIC weight	Parameters	Deviance	Route 5	SE	Route 6	SE	Route 7	SE	Route 8	SE
NOCA	p(obs)λ(route)	2,733.46	1.00	18	2,697.46	75.66	10.47	89.87	11.05	91.85	11.55	63.59	9.35
AMCR	p(obs)λ(route)	2,533.59	1.00	18	2,497.59	102.40	13.92	73.13	9.86	50.14	8.10	39.86	7.72
CHSP	p(obs)λ(route)	2,251.29	1.00	18	2,215.29	54.18	9.10	50.27	8.36	27.19	5.90	92.32	12.97
NOMO	p(obs)λ(route)	2,085.30	1.00	18	2,049.30	33.90	6.79	39.69	7.17	75.64	11.05	49.40	8.25
INBU	p(obs)λ(route)	2,066.04	1.00	18	2,030.04	81.15	10.28	37.55	6.95	29.99	5.93	25.56	5.37
MODO	p(obs)λ(route)	2,115.09	0.97	18	2,079.09	45.09	8.42	33.72	7.14	115.84	15.59	41.71	8.31
CARW	p(obs)λ(route)	1,983.10	1.00	18	1,947.10	65.75	9.70	48.35	7.94	48.16	8.16	31.93	6.38
TUTI	p(obs)λ(route)	1,695.12	0.62	18	1,659.12	32.82	6.76	33.16	6.86	16.18	4.75	36.07	7.36
EABL	p(obs)λ(route)	1,504.16	1.00	18	1,468.16	16.05	5.60	47.32	9.86	19.68	5.47	18.25	6.08
REVI	p(obs)λ(.)	1,337.23	1.00	7	1,323.23	21.96	1.69	21.96	1.69	21.96	1.69	21.96	1.69
BLJA	p(obs)λ(route)	1,256.47	0.76	18	1,220.47	7.43	3.06	16.45	4.45	36.43	6.88	19.98	5.30
CACH	p(obs)λ(route)	1,341.77	0.99	18	1,305.77	20.44	5.93	39.34	8.53	15.44	5.05	25.49	6.29
AMRO	p(obs)λ(route)	1,304.29	1.00	18	1,268.29	21.57	5.46	19.74	5.11	26.64	5.91	4.76	2.78
BGGN	p(obs)λ(route)	1,224.18	1.00	18	1,188.18	32.21	7.16	19.74	5.06	1.49	1.49	25.54	6.14
RBWO	p(obs)λ(route)	1,057.25	0.98	18	1,021.25	13.78	4.23	8.17	3.11	9.43	3.36	14.51	4.25
CANG	—	—	—	—	—	—	—	—	—	—	—	—	—
EATO	p(obs)λ(.)	1,091.97	0.84	7	1,077.97	17.18	1.70	17.18	1.70	17.18	1.70	17.18	1.70
BARS	p(.)λ(route)	1,239.05	1.00	13	1,213.05	9.41	4.37	30.72	8.66	31.57	8.95	56.07	12.39
PIWA	p(obs)λ(route)	1,015.49	1.00	18	979.49	23.29	7.79	21.81	7.58	7.28	4.46	29.37	8.80
CHSW	p(.)λ(route)	1,203.88	1.00	13	1,177.88	16.96	6.51	6.50	3.89	20.17	7.46	26.92	8.81

TABLE 2. Continued.

Species	Model	AIC	AIC weight	Parameters	Deviance	Route 9	SE	Route 10	SE	Route 11	SE	Route 12	SE
NOCA	p(ops)λ(route)	2,733.46	1.00	18	2,697.46	64.90	9.54	87.14	10.85	97.28	11.61	87.06	10.94
AMCR	p(ops)λ(route)	2,533.59	1.00	18	2,497.59	64.52	9.23	48.46	7.79	50.71	7.96	87.49	11.70
CHSP	p(ops)λ(route)	2,251.29	1.00	18	2,215.29	63.95	10.18	38.46	7.36	30.79	6.42	63.29	10.18
NOMO	p(ops)λ(route)	2,085.30	1.00	18	2,049.30	37.00	7.02	70.17	9.92	70.73	9.79	39.45	7.23
INBU	p(ops)λ(route)	2,066.04	1.00	18	2,030.04	21.40	4.94	53.11	8.28	50.60	8.07	43.28	7.11
MODO	p(ops)λ(route)	2,115.09	0.97	18	2,079.09	32.27	7.38	76.63	11.36	51.27	9.31	48.88	7.67
CARW	p(ops)λ(route)	1,983.10	1.00	18	1,947.10	22.42	5.35	46.44	8.09	61.86	9.60	48.88	8.44
TUTI	p(ops)λ(route)	1,695.12	0.62	18	1,659.12	31.54	6.64	28.80	6.30	62.87	9.71	44.50	7.91
EABL	p(ops)λ(route)	1,504.16	1.00	18	1,468.16	37.29	8.62	58.78	11.18	41.76	8.92	33.33	8.39
REVI	p(ops)λ(.)	1,337.23	1.00	7	1,323.23	21.96	1.69	21.96	1.69	21.96	1.69	21.96	1.69
BLJA	p(ops)λ(route)	1,256.47	0.76	18	1,220.47	16.11	4.54	16.66	4.51	22.49	5.25	19.70	5.02
CACH	p(ops)λ(route)	1,341.77	0.99	18	1,305.77	14.78	4.81	17.85	5.09	42.46	8.34	39.87	8.07
AMRO	p(ops)λ(route)	1,304.29	1.00	18	1,268.29	10.49	4.38	29.70	6.60	55.69	9.68	53.65	9.68
BGGN	p(ops)λ(route)	1,224.18	1.00	18	1,188.18	26.37	5.96	11.40	4.08	34.90	7.43	27.30	6.91
RBWO	p(ops)λ(route)	1,057.25	0.98	18	1,021.25	8.86	3.38	9.17	3.26	25.91	5.65	21.72	5.23
CANG	—	—	—	—	—	—	—	—	—	—	—	—	—
EATO	p(ops)λ(.)	1,091.97	0.84	7	1,077.97	17.18	1.70	17.18	1.70	17.18	1.70	17.18	1.70
BARS	p(.)λ(route)	1,239.05	1.00	13	1,213.05	13.27	5.29	27.10	8.06	17.28	6.17	35.46	9.25
PIWA	p(ops)λ(route)	1,015.49	1.00	18	979.49	57.79	15.91	16.42	6.89	7.04	4.26	50.29	13.88
CHSW	p(.)λ(route)	1,203.88	1.00	13	1,177.88	21.44	7.52	46.64	12.12	16.96	6.51	25.84	8.43

The unreconciled double-observer method provided estimates of route-level abundance for most routes and most species that we considered from our BBS data. Models that allowed for observer differences in p and route differences in N were favored 75% of the time (15 of 20 model sets). These $p(\text{obs})\lambda(\text{route})$ models were relatively complex, with 18 parameters each, and we were encouraged that unreconciled data were able to support such models with only 12 routes and 6 observers. We believe that this method may have enormous potential for already established bird-monitoring programs, such as the BBS, because no changes in historical data-collection methods are required other than collecting data simultaneously by two or more observers.

As with any sampling method, the unreconciled double-observer method will not work well for every species or every observer. For example, we were unable to fit any models to our Canada Goose data. Moreover, we had difficulty fitting models to our Mourning Dove data despite the fact that it was our sixth apparently most abundant species. Both Canada Geese and Mourning Doves tended to occur in groups when present. This “clumpiness” tends to result in situations where counts are either zero or relatively large. For example, 5 of our routes had <3 records for Canada Geese (both observers combined), whereas 2 of our routes had no records. However, observers recorded 30 to 40 Canada Geese on a single stop on 1 route. Similarly, of the 600 stops that were sampled on our 12 routes, 386 did not have records of Mourning Doves. However, the maximum count for the other 214 stops was 19 Mourning Doves. This extreme overdispersion in the observed N values is not handled well by a Poisson distribution. The negative binomial or zero-inflated Poisson may be a more appropriate model of abundance for such species (Etterson et al. 2009).

Some reviewers questioned whether or not our adjusted estimates were better than our raw counts for the BBS data and whether it is worth the effort to devote two observers to half the counts that they could survey if they were not paired. Unfortunately, we cannot answer the first part of this question. If one knew how reliable the raw BBS counts were to begin with, it would not be necessary to attempt to adjust them for imperfect detection. Indeed, a lack of certainty in raw count reliability is why methods for estimating detection probabilities exist in the first place. However, we can address both of the issues that reviewers raised with the data from the bird-song-simulation system because the true population of singing birds is known. To do this, we determined the absolute bias for the adjusted counts as the percent difference between the estimated population size from $p(\cdot)$ models and the true population size of 100 for each pair of observers for each species from each experiment. We also determined the absolute bias for the sum of the raw counts as the percent difference between the total counted number of birds and a true population size of 200 (i.e., we treated the data set as if it were gathered by two observers on 120 total counts instead of two paired observers on 60 counts) for both observers for each species from each experiment. The absolute bias was worse for the raw counts >87% of the time (Table 3). Thus, researchers have little to gain by increasing sample sizes with biased methods. To put it another way, large sample sizes simply do not remedy biased estimators. The primary disadvantage of the unreconciled double-observer method and other multiple-observer methods is that they do not account for p_p

TABLE 3. Percent absolute bias of estimates of total population size from the unreconciled double-observer method and raw counts. Species abbreviations: ACFL = Acadian Flycatcher, BTBW = Black-throated Blue Warbler, BTNW = Black-throated Green Warbler, BAWW = Black-and-white Warbler, HOWA = Hooded Warbler, and SCTA = Scarlet Tanager. Scientific names are given in the text.

Experiment	Species	Observer pair	Absolute bias (%)	
			Unreconciled double-observer	Raw counts
Simple	ACFL	A	9.8	24.0
		B	19.9	31.5
	BTBW	A	11.9	18.5
		B	3.5	11.5
	BTNW	A	0.5	5.0
		B	0.2	7.0
Complex	ACFL	A	4.0	27.5
		B	0.5	25.5
		C	28.4	42.5
	BAWW	A	31.2	45.5
		B	8.6	31.0
		C	21.0	46.0
	BTBW	A	1.2	22.0
		B	65.8	2.5
		C	11.6	26.0
	BTNW	A	32.7	2.0
		B	41.8	4.5
		C	7.4	15.5
	HOWA	A	0.4	19.5
		B	9.5	12.5
		C	12.6	25.0
	SCTA	A	4.5	9.0
		B	1.7	9.5
		C	8.6	21.0

and especially p_a . However, practitioners should carefully weigh both the theoretical and practical advantages of recently developed point-count methods when choosing the most appropriate method for their study and monitoring objectives.

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LITERATURE CITED

- ALLDREDGE, M. W., K. PACIFICI, T. R. SIMONS, AND K. H. POLLOCK. 2008. A novel field evaluation of the effectiveness of distance and independent observer sampling to estimate aural avian detection probabilities. *Journal of Applied Ecology* 45:1349–1356.
- ALLDREDGE, M. W., K. H. POLLOCK, AND T. R. SIMONS. 2006. Estimating detection probabilities from multiple-observer point counts. *Auk* 123:1172–1182.
- ALLDREDGE, M. W., K. H. POLLOCK, T. R. SIMONS, J. A. COLLAZO, AND S. A. SHRINER. 2007a. Time-of-detection method for estimating abundance from point-count surveys. *Auk* 124:653–664.
- ALLDREDGE, M. W., T. R. SIMONS, AND K. H. POLLOCK. 2007b. A field evaluation of distance measurement error in auditory avian point count surveys. *Journal of Wildlife Management* 71:2759–2766.
- BUCKLAND, S. T., D. R. ANDERSON, K. P. BURNHAM, J. L. LAAKE, D. L. BORCHERS, AND L. THOMAS. 2001. *Introduction to Distance Sampling: Estimating Abundance of Biological Populations*. Oxford University Press, New York.
- ETTERSON, M. A., G. J. NIEMI, AND N. P. DANZ. 2009. Estimating the effects of detection heterogeneity and overdispersion on trends estimated from avian point counts. *Ecological Applications* 19:2049–2066.
- FARNSWORTH, G. L., K. H. POLLOCK, J. D. NICHOLS, T. R. SIMONS, J. E. HINES, AND J. R. SAUER. 2002. A removal model for estimating detection probabilities from point-count surveys. *Auk* 119:414–425.
- HINES, J. E. 2006. PRESENCE2: Software to estimate patch occupancy and related parameters. U.S. Geological Survey Patuxent Wildlife Research Center. [Online.] Available at www.mbr-pwrc.usgs.gov/software/presence.html.
- HUGGINS, R. M. 1989. On the statistical analysis of capture experiments. *Biometrika* 76:133–140.
- HUGGINS, R. M. 1991. Some practical aspects of a conditional likelihood approach to capture experiments. *Biometrics* 47:725–732.
- JOHNSON, D. H. 2008. In defense of indices: The case of bird surveys. *Journal of Wildlife Management* 72:857–868.
- MOORE, J. E., D. M. SCHEIMAN, AND R. K. SWIHART. 2004. Field comparison of removal and modified double-observer modeling for estimating detectability and abundance of birds. *Auk* 121:865–876.
- NICHOLS, J. D., J. E. HINES, J. R. SAUER, F. W. FALLON, J. E. FALLON, AND P. J. HEGLUND. 2000. A double-observer approach for estimating detection probability and abundance from point counts. *Auk* 117:393–408.
- NICHOLS, J. D., L. THOMAS, AND P. B. CONN. 2009. Inferences about landbird abundance from point count data: Recent advances and future directions. Pages 201–235 *in* *Environmental and Ecological Statistics, vol. 3: Modeling Demographic Processes in Marked Populations* (D. L. Thomson, E. G. Cooch, and M. J. Conroy, Eds.). Springer Science and Business Media, New York.
- RIDDLE, J. D., C. E. MOORMAN, AND K. H. POLLOCK. 2008. A comparison of methods for estimating Northern Bobwhite covey detection probabilities. *Journal of Wildlife Management* 72:1437–1442.
- RIDDLE, J. D., R. S. MORDECAI, K. H. POLLOCK, AND T. R. SIMONS. 2010. Effects of prior detections on estimates of detection probability, abundance, and occupancy. *Auk* 127:94–99.
- ROYLE, J. A. 2004. *N*-mixture models for estimating population size from spatially replicated counts. *Biometrics* 60:108–115.
- ROYLE, J. A., AND R. M. DORAZIO. 2008. *Hierarchical Modeling and Inference in Ecology: The Analysis of Data from Populations*,

- Metapopulations, and Communities. Academic Press, San Diego, California.
- SIMONS, T. R., M. W. ALLDREDGE, K. H. POLLOCK, AND J. M. WETTROTH. 2007. Experimental analysis of the auditory detection process on avian point counts. *Auk* 124:986–999.
- SIMONS, T. R., K. H. POLLOCK, J. M. WETTROTH, M. W. ALLDREDGE, K. PACIFICI, AND J. BREWSTER. 2009. Sources of measurement error, misclassification error, and bias in auditory avian point count data. Pages 237–254 *in* *Environmental and Ecological Statistics*, vol. 3: Modeling Demographic Processes in Marked Populations (D. L. Thomson, E. G. Cooch, and M. J. Conroy, Eds.). Springer Science and Business Media, New York.
- STANISLAV, S. J. 2009. Developments and applications of a closed capture–recapture robust design model to avian point count data. Ph.D. dissertation, North Carolina State University, Raleigh.
- WHITE, G. C., AND K. P. BURNHAM. 1999. Program MARK: Survival estimation from populations of marked animals. *Bird Study* 46 (Supplement):S120–S139.

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