Comparison of Methods for Estimating Bird Abundance and Trends From Historical Count Data

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ABSTRACT The use of bird counts as indices has come under increasing scrutiny because assumptions concerning detection probabilities may not be met, but there also seems to be some resistance to use of model-based approaches to estimating abundance. We used data from the United States Forest Service, Southern Region bird monitoring program to compare several common approaches for estimating annual abundance or indices and population trends from point-count data. We compared indices of abundance estimated as annual means of counts and from a mixed-Poisson model to abundance estimates from a count-removal model with 3 time intervals and a distance model with 3 distance bands. We compared trend estimates calculated from an autoregressive, exponential model fit to annual abundance estimates from the above methods and also by estimating trend directly by treating year as a continuous covariate in the mixed-Poisson model. We produced estimates for 6 forest songbirds based on an average of 621 and 459 points in 2 physiographic areas from 1997 to 2004. There was strong evidence that detection probabilities varied among species and years. Nevertheless, there was good overall agreement across trend estimates from the 5 methods for 9 of 12 comparisons. In 3 of 12 comparisons, however, patterns in detection probabilities potentially confounded interpretation of uncorrected counts. Estimates of detection probabilities differed greatly between removal and distance models, likely because the methods estimated different components of detection probability and the data collection was not optimally designed for either method. Given that detection probabilities often vary among species, years, and observers investigators should address detection probability in their surveys, whether it be by estimation of probability of detection and abundance, estimation of effects of key covariates when modeling count as an index of abundance, or through design-based methods to standardize these effects. (JOURNAL OF WILDLIFE MANAGEMENT 72(8):1674–1682; 2008)

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Estimating abundance and trends in abundance is an objective of many wildlife monitoring programs, with point-count surveys being the most popular approach for monitoring avian populations (Rosenstock et al. 2002). For most avian point-count surveys, counts are treated as an index of relative abundance, even though there have been long-standing concerns about the use of counts that have not been adjusted for detectability (Burnham 1981, Barker and Sauer 1995). Recently this practice has come under increasing scrutiny (Rosenstock et al. 2002, Thompson 2002, Farnsworth et al. 2005). The use of counts as a measure of relative abundance requires the basic assumption that differences in counts reflect differences in the true population, or in other words, the proportion of animals detected is constant across all plots or times (Thompson 2002). Sources of bias in counts include differences in detectability originating from differences in observers, habitats, birds, and weather conditions. Studies that utilize counts as a measure of relative abundance typically use a design-based approach that relies on the study design to control for sources of bias (Verner 1985, Bart et al. 2003). In contrast, a model-based approach attempts to correct for biases by estimating their effects in a model. For example, model-based approaches have been used to correct for observer effects when estimating relative abundance and trends for the North American Breeding Bird Survey (Link and Sauer 1998).

Models are also used to directly estimate detection probabilities but these methods require the collection of additional data during the count. Distance estimation methods estimate detection probabilities as a function of distance to detection (Buckland et al. 1993, 2001). Capture–recapture methods have been used with 2 observers conducting counts at the same time at a point (Nichols et al. 2000) or when detections of individual birds are recorded during each time interval of a multiple-interval count (Alldredge et al. 2007), and capture–removal models have been used when only the time or interval of first detection is recorded (Farnsworth et al. 2002).

The observation that most avian surveys do not employ model-based approaches to address detectability suggests investigators are not aware of these methods, or they believe the improvement in reliability of knowledge derived from surveys is not great enough to warrant increased field and computational effort required by these approaches, the procedures are too difficult in the field or when analyzing the data, or if methods are changed during long-term monitoring programs earlier data will have to be discarded. We used data from the United States Forest Service Southern Region bird monitoring program to compare several common approaches to estimating annual abundance and trends. Our objective was to determine 1) the applicability of model-based methods that directly estimate detectability to potentially large amounts of existing data collected by agencies such as the United States Forest Service, 2) if there was evidence that detectability differed

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among species and years (which would invalidate common assumptions for treating counts as indices), and 3) if different methods would lead to different conclusions and potentially different management decisions. As in any comparison of methods based on real survey data, we can only compare estimates from different methods in a relative sense, because we do not know the actual abundance or trend. Nevertheless, we can evaluate support for whether detectability differs among species, years, and areas; evaluate the applicability of these methods to existing data; and identify potential discrepancies among the approaches.

METHODS

The Forest Service Southern Region adopted a region-wide program of monitoring avian populations based on point counts as part of the Southern National Forest's Migrant and Resident Landbird Conservation Strategy (Gaines and Morris 1996) to improve monitoring, research, and management programs involving birds and their habitats. Sampling strategy and point-count methodology are described in detail by Gaines and Morris (1996). Individual National Forests implemented surveys but points were stratified by physiographic areas that included ≥ 1 national forests (of portions thereof). We selected for use in our analysis 2 physiographic areas that had many points that were consistently sampled from 1997 to 2004, which included 508 points from the Ozark–Ouachita Interior Highlands and 890 points from the Southern Blue Ridge, in the Southeastern United States. We only included points where ≥ 1 of the 7 focal species occurred in ≥ 1 year to reduce the number of zero values in our analysis. We included 6 species that represented a gradient from common to uncommon species: red-eyed vireo (*Vireo olivaceus*), ovenbird (*Seiurus aurocapilla*), prairie warbler (*Dendroica discolor*), Acadian flycatcher (*Empidonax virescens*), wood thrush (*Hylocichla mustelina*), and blue-winged warbler (*Vermivora pinus*).

Point-count methodology followed Hamel et al. (1996). Counts at each point were conducted for 10 minutes between sunrise and 1000 hours and between 12 April and 30 June. All birds seen or heard during this time period were recorded. The distance interval (0–25 m, 25–50 m, and >50 m) and time interval (0–3 min, 4–5 min, 6–10 min) in which a bird was detected was recorded. These intervals were designed to facilitate comparison of results with other bird surveys rather than for model-based estimation of detectabilities.

Estimating Abundance

We compared 4 methods for estimating abundance or an index of abundance. We used each method to estimate abundance of each species in each year in each physiographic area and then used models to assess trends in abundance by treating year as a continuous fixed effect. For the 2 methods that estimate detection probabilities, we evaluated support for species and year effects on detection probability.

The means method consisted simply of calculating the arithmetic mean of the observed detections per point of each species for each year in each physiographic area. This is a design-based approach that treats the mean of the counts as an index of abundance (Bart et al. 2003). We consider this a naïve method because it ignores observer effects or any other factors that might affect detectability by averaging across these; the implied assumption is that the design controls for these effects or they represent random error.

For the Poisson method, we fit a Poisson regression model to the data for each species and physiographic area. We treated counts of a species at a point (the response variable) as an index of abundance and included year as a categorical, fixed effect so we could estimate annual counts. To account for variability among observers, we included observer as random effect, which allowed the intercept term to vary by observer. We also included point as a repeated or residual random effect with a first-order autoregressive correlation structure to account for covariance among counts at the same points over time (yr) when estimating trend (see below). We chose a first-order autoregressive correlation structure because we assumed counts in adjacent years would be the most correlated. We used this model to estimate detections per point for each species and year in each physiographic area.

In the removal method, we estimated absolute abundance of each species using a closed-capture-removal model where we estimated total number of individuals based on the probability of the species being detected during each of 3 consecutive time intervals (3 min, 2 min, and 5 min) composing the 10-minute count period. We used the Huggins closed capture model (Huggins 1989) with a logit link function in Program MARK, version 5.0 (White and Burnham 1999). We included year, species, physiographic area, and interval length (3 min, 2 min, and 5 min) as covariates. To implement this approach in MARK with unequal time intervals required a slightly different approach than Farnsworth et al. (2002) or Alldredge et al. (2007). Farnsworth et al. (2002) define failure of detection on a per-minute basis and expand the estimate exponentially to the length of the interval, whereas Alldredge et al. (2007) estimated detection probability for equal-length intervals. Because we had unequal-length intervals we modeled detection probability for each discrete interval with the length of the interval as a covariate. To evaluate support for our hypotheses that detection probability varied by species and year we examined support for candidate models with species, year, and species and year included as covariates based on Akaike's Information Criterion corrected for small sample size (AIC_c; Burnham and Anderson 2002). We had no a priori reason to hypothesize detection probabilities would be the same between physiographic areas, so we included physiographic area in all models and the model with physiographic area and interval length was our null model. We produced population estimates for each species in each year in both physiographic areas using the most supported model, which we divided by the number of points surveyed to express it as number of birds per point to standardize the estimate by effort.

In the distance method, we estimated probability of detection and density for of each of the 7 species using distance-sampling methods (Reynolds et al. 1980; Buckland et al. 1993, 2001) and Program DISTANCE, version 5.0 (Thomas et al. 2005). This approach used the distance species were detected from the center of the point to estimate detection probability for a species. We were limited to simple models because distances were recorded in 3 distance intervals (0–25 m, 25–50 m, and >50 m). Program DISTANCE uses the midpoint of each interval to model the detection function; because our outer interval was unbounded, we assumed an outer boundary of 100 m (midpoint = 75 m). Based on our experience, most species we considered are detected at distance <100 m; thus, we thought it better to make this assumption than discard observations >50 m. We used the multiple covariate distance sampling method and a half-normal detection function with a cosine series expansion for the distance function because of its common application in bird studies, its simplicity (which was important because we were limited in model parameters by the no. of distance intervals), and preliminary analyses indicated the hazard-rate function did not perform better. We examined support for the same set of candidate models described above for the removal method based on AIC_c. Then, based on the most supported model, we fit separate models either for each year, species, or year and species for each physiographic area. We had to fit separate models at this stage because DISTANCE has limited options for number and level (i.e., physiographic area, yr, and species) of density and detectability estimates. We converted density estimates to individuals per point so we could directly compare them with the other estimates.

Estimating Population Trends

We defined trend as the annual rate of change in abundance. We used the same model to estimate trend for each species in each physiographic region based on the estimates of annual abundance from each method. Neither MARK nor DISTANCE are capable of analyzing trends in abundance directly, and we wanted to use a similar analysis across estimates to address our primary objective of assessing comparability of different methods for estimating abundance. We fit an exponential model for each method to the abundance estimates for year. We used the model $\mathrm{Log_e}(N_t) = \beta_0 + \beta_1 \mathrm{Year} + \varepsilon_t$, where N_t is the abundance estimate, β_0 is the intercept, β_1 is the trend, and ε_t is the error term. The exponential model is relevant in distance sampling because it corresponds to assumptions about sampling error and its correspondence with the exponential growth model and interpretation of $\exp(\beta_1)$ as rate of change (Buckland et al. 2004); it is also frequently used with count data. The error term actually consists of 2 components, the sampling error and the non-trend population variation or process error. More sophisticated variance components approaches are possible, which more appropriately address these sources of variation, but for applications with a limited time series, fitting a simple model such as this to abundance estimates can be adequate (Buckland et al. 2004). Because of the inherent auto-correlative nature of population time series (Barker and Sauer 1992), and because counts were conducted at the same points each year, we further modified the above model by adding an autoregressive model for the error term using the AUTOREG procedure in SAS (SAS Institute, Cary, NC). We used maximum-likelihood estimates for first-order autoregressive models because we hypothesized observations in adjacent years were most correlated and correlations declined rapidly after that. More sophisticated approaches to time-series analyses are available (Ryding et al. 2007); however, because of our short time-series, we were limited to simple approaches. We fit the above model to annual abundance estimates from each of the 4 methods used to estimate abundance and refer to these results as the autoregressive means, Poisson, removal, and distance trend estimates. We estimated percent annual change as $[\exp(\beta_1) - 1] \times 100$ and compared this estimate and its confidence limit and P values for the significance of β_1 among the 4 methods.

One potential advantage of the Poisson method we used to model abundance is that by including year as a continuous covariate we can directly estimate the percent annual change in relative abundance; this approach also properly incorporates temporal correlation in counts at the point level and eliminates the need for the autoregressive model we described above. So in addition to the autoregressive trend model that we applied to results from the 4 abundance estimation models, we also directly estimated population trend with year as a continuous covariate in the Poisson model described for estimating abundance and refer to this as mixed-model Poisson trend estimates. This allowed us to compare trend estimates that were based on the same trend model (the autoregressive model) applied to all abundance estimates as well as to consider some of the advantages of directly estimating trend with the mixed-model Poisson trend model.

RESULTS

From 1997 to 2004, 565 to 688 points were sampled in the Ozark–Ouachita Interior Highlands and 436 to 479 points were sampled in Southern Blue Ridge (Table 1). Most points were surveyed in all years of the survey; however, variation in the number of points sampled each year was a consequence of some points being added or dropped by national forests during the survey. Blue-winged warbler had the lowest number (3–52) and red-eyed vireo the greatest number (795–1,108) of detections per year in a physiographic area of the 6 species we considered (Table 1). We estimated abundance by the means, Poisson, removal, and distance methods for all species and years in both physiographic areas (with one exception, see below; Figs. 1, 2).

The removal model with year and species had overwhelming support (Table 2) providing evidence that detection probabilities varied by these factors. Therefore, to estimate abundance, we fit separate models for each species in each physiographic area and allowed detection probability to vary by year. We estimated detection probabilities and abundance for all species. Estimates of detection probabilities were high for all species (Fig. 3). There were 4 negative, 1

Table 1. Number of points (N) and bird detections from United States Forest Service point-count surveys in the Ozark–Ouachita Interior Highlands and Southern Blue Ridge physiographic areas in the Southeastern United States, 1997–2004, used in a comparison of methods for estimating abundance or indices of abundance.

			No. of detections					
Area	Yr	N	Acadian flycatcher	Blue-winged warbler	Ovenbird	Prairie warbler	Red-eyed vireo	Wood thrush
Interior Highlands								
	1997	586	94	43	485	62	999	158
	1998	565	106	44	508	50	928	178
	1999	573	88	52	480	56	849	164
	2000	569	81	42	509	49	836	186
	2001	634	106	17	587	58	1,043	189
	2002	681	115	16	523	55	1,108	230
	2003	672	119	12	564	68	1,030	153
	2004	688	106	24	609	41	1,086	198
Southern Blue Ridge								
	1997	456	67	12	243	125	795	47
	1998	464	75	12	239	112	808	38
	1999	465	102	12	217	111	906	42
	2000	442	108	7	229	88	825	39
	2001	436	95	14	212	78	843	50
	2002	472	84	3	232	97	964	39
	2003	479	99	9	285	106	1,013	58
	2004	459	92	6	280	82	952	30

positive, and 7 nonsignificant trends based on abundance estimates by the removal method (Figs. 1, 2).

As with the removal method, the distance model with year and species had overwhelming support (Table 2), providing evidence that detection probabilities varied by these factors. We fit separate models for each species within each physiographic area with year as a covariate to estimate density for each year. We were unable to produce estimates of abundance by the distance method for wood thrush in the Southern Blue Ridge because the model would not converge. We visually examined the goodness-of-fit of the detection functions in Program DISTANCE and 16, 11, 15, 16, 16, and 6, of 16 possible functions (8 yr and 2 physiographic areas) years for Acadian flycatcher, blue-winged warbler, ovenbird, prairie warbler, red-eyed vireo, and wood thrush, respectively, had good fit with detections decreasing monotonically with distance (Fig. 4) and detection probabilities that ranged 0.07–0.60 (Fig. 3).

Correlations among abundance estimates were all high and ranged from 0.835 to 0.998. Comparison of abundance estimates and trend estimates among methods indicated considerable agreement but also several differences (Figs. 1, 2). Estimates of abundance were similar between the means and Poisson methods. Abundance estimates by the removal method, on average, were only slightly greater than the means and Poisson methods because detection probabilities were generally close to one. Abundances estimated by the distance method were approximately 2–4 times greater because of lower detection probabilities.

We fit the autoregressive exponential model to annual abundance estimates from each method for all species in both physiographic regions to estimate population trends (Figs. 1, 2). We detected significant autocorrelation in only 11 of 48 models (6 species $\times$ 4 methods $\times$ 2 physiographic areas). Estimates of percent change were nearly identical and estimates of variances only slightly greater than estimates not corrected for autocorrelation. We also fit the mixed-Poisson model with year as a continuous covariate to all species in both physiographic areas to estimate population trends (Figs. 1, 2). All comparisons of significant trends ($P \leq 0.1$) among methods, for a species in a physiographic area, were in agreement (increasing or decreasing; Figs. 1, 2). When we compared 3 possible conclusions (no significant trend, significant decrease, and significant increase) conclusions among models were in agreement 36–100% of the time (Table 3). Disagreement was often the result of one trend being significant whereas the second was not (Figs. 1, 2). There were 3 instances, however, where the difference was more notable. Trends based on the means method for ovenbird, red-eyed vireo, and wood thrush in the Ozark–Ouachita Interior Highlands were negative with non-significant P-values; however, those based on the distance method were positive, large, and had P-values of 0.002–0.113 (Fig. 1). Examination of the detection probabilities (Fig. 4) for these species by year indicated a decrease in detection probability over time.

DISCUSSION

We were able to apply the Poisson, removal, and distance methods to data collected by traditional point-count methods (Ralph et al. 1995, Hamel et al. 1996) even though the survey was not initially designed for estimation of detection probabilities. Distance bands and time intervals for observations were recorded primarily to facilitate comparison of results among different studies, and not necessarily for estimation of detectability.

We found strong evidence that detection probabilities varied among species and years. A basic assumption for

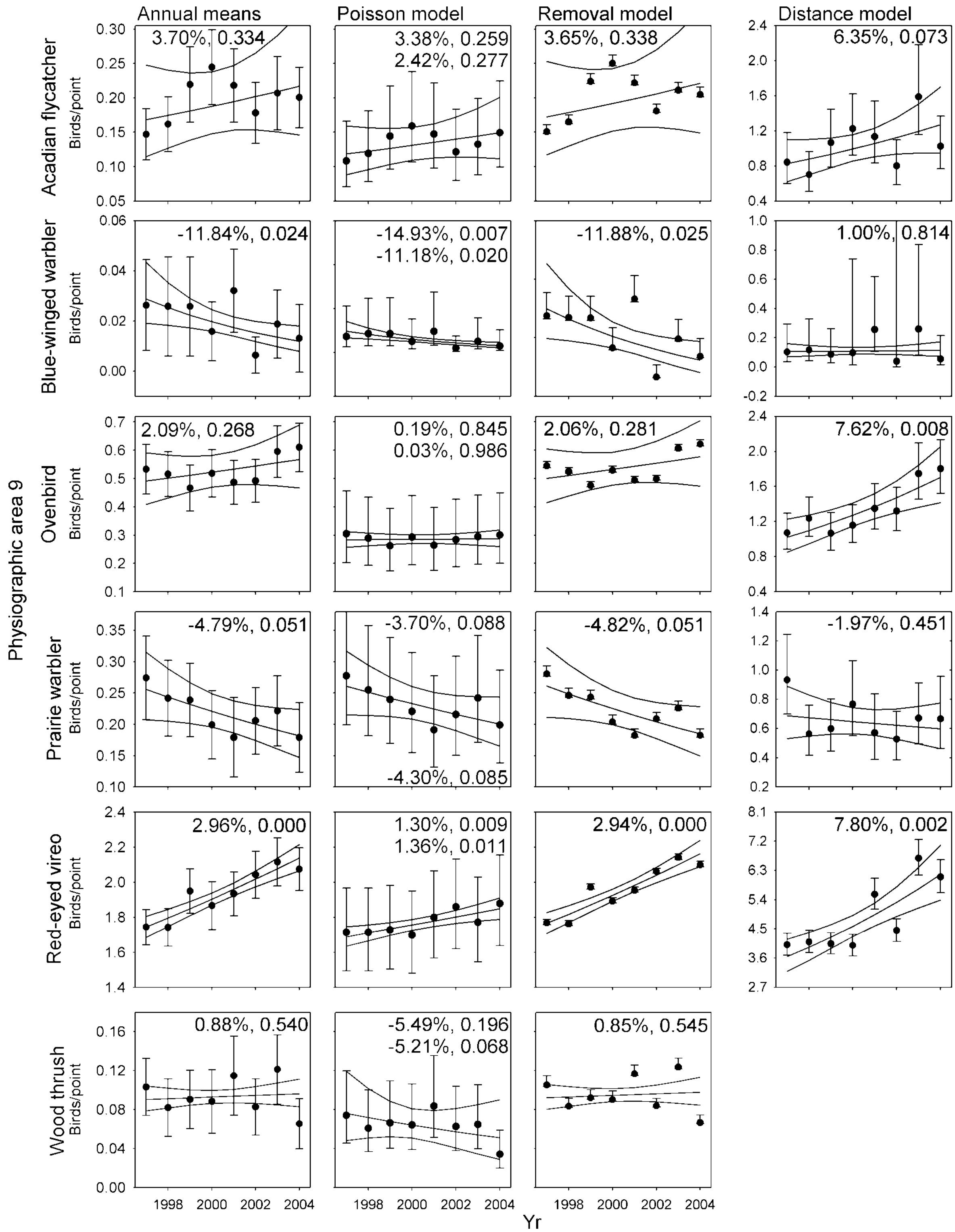

Figure 1. Estimated abundance (±95% CI), trend lines (±95% CI), and percent annual change and *P*-value for hypothesis that percent annual change = 0, based on annual means, Poisson models, capture–removal models, and distance models and data from point-count surveys of forest songbirds in the Ozark–Ouachita Interior Highlands in the southeastern United States, 1997–2004. Percent annual change estimates for all species are based on autoregressive, exponential model fit to annual abundances; the second estimate presented for Poisson models is based on the year coefficient from a mixed-Poisson model fit to the point-level data while accounting for temporal correlation. The abundance axis for the distance models has a different scale than the other models because of greater abundance values.

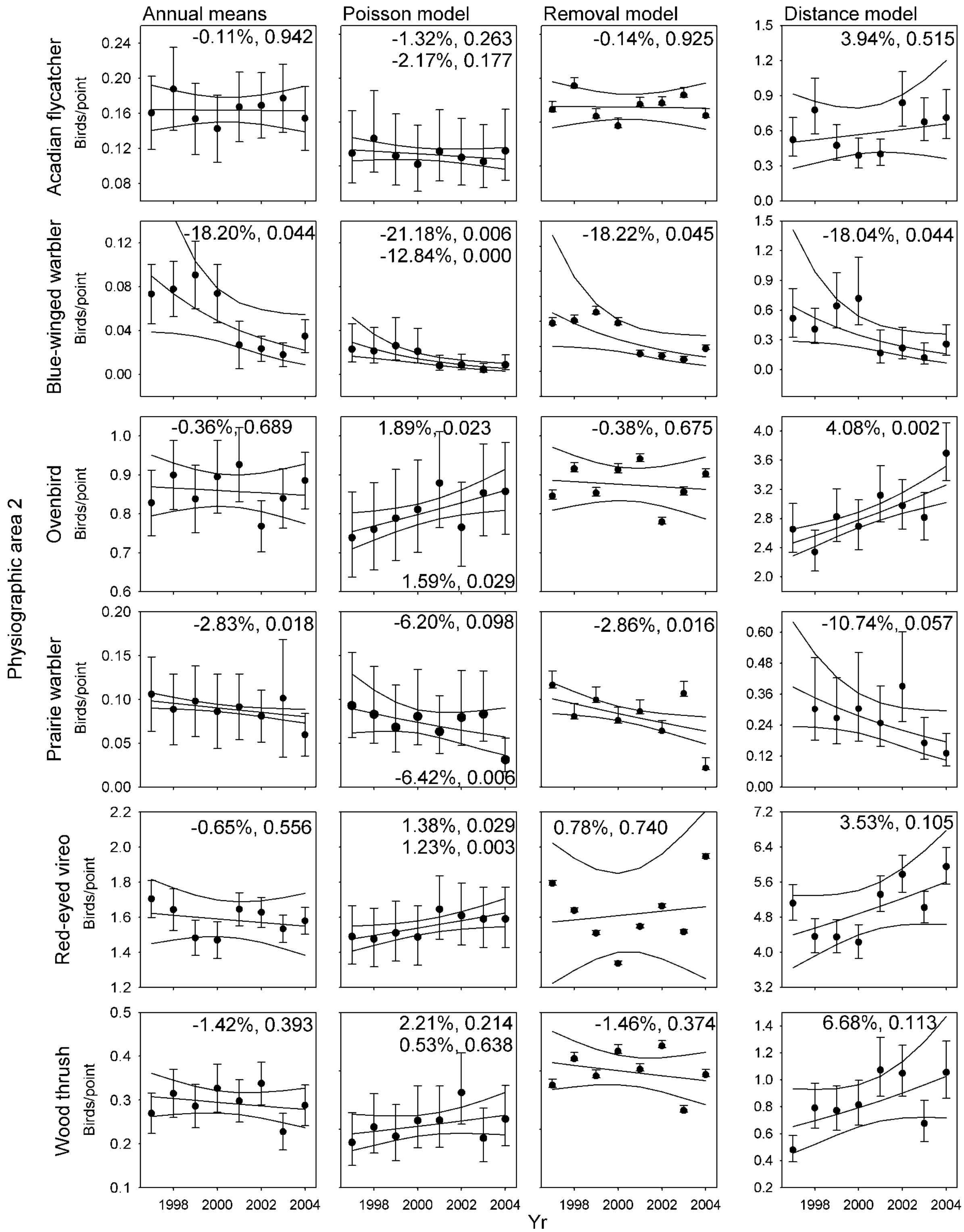

Figure 2. Estimated abundance (±95% CI), trend lines (±95% CI), and percent annual change and *P*-value for hypothesis that percent annual change = 0, based on annual means, Poisson models, capture–removal models, and distance models and data from point-count surveys of forest songbirds in the Southern Blue Ridge in the southeastern United States, 1997–2004. Percent annual change estimates for all species are based on autoregressive, exponential model fit to annual abundances; the second estimate presented for Poisson models is based on the year coefficient from a mixed-Poisson model fit to the point-level data while accounting for temporal correlation. The abundance axis for the distance models has a different scale than the other models because of greater abundance values.

Table 2. Support for capture-removal models and distance models used to estimate detection probabilities and abundance of 6 forest bird species in 2 physiographic areas in the southeastern United States, 1997–2004. Models vary by the covariates included to explain variability in detection probabilities and appear in order of ascending ΔAIC_c.[a]

Method and models	K	$-2(L)$	AIC_c	ΔAIC_c	w_i
Removal method					
Yr + Species + Physiographic area	16	44,504.74	44,536.75	0.00	0.998
Species + Physiographic area	9	44,531.16	44,549.16	12.58	0.002
Yr + Physiographic area	10	44,632.60	44,652.60	116.02	0.000
Physiographic area	3	44,660.35	44,666.35	129.77	0.000
Distance method					
Yr + Species + Physiographic area	15	41,211.38	41,241.40	0	1.000
Species + Physiographic area	8	41,348.14	41,364.15	122.75	0.000
Yr + Physiographic area	9	41,415.74	41,433.74	192.34	0.000
Physiographic area	2	41,548.12	41,552.11	310.71	0.000

[a] K = no. of parameters; $-2(L) = -2 \times$ log likelihood; AIC_c = Akaike's Information Criterion corrected for small sample size; w_i = Akaike's model wt.

treating counts as an index of abundance is that the proportion of animals detected was constant among years and points. This assumption was apparently violated in this study, as it has been in other studies that examined detection probabilities (Diefenbach et al. 2003, Norvell et al. 2003). Nevertheless, we found many examples of general agreement across the 4 methods, as evidenced by high correlations among estimates and by simple visual comparison of the results (Figs. 1, 2). Not unexpectedly, results were most similar when trends were large. For example, trends for prairie warbler in both physiographic areas were all large (>3% decline/yr) and in each case significant for 3 of 4 methods (Figs. 1, 2).

We did, however, find several examples where patterns in detection probabilities potentially confounded interpretations based on uncorrected counts. In 3 cases (ovenbird, red-eyed vireo, and wood thrush in the Ozark–Ouachita Interior Highlands), trend estimates based on the means method were small, negative, and nonsignificant, whereas the trend estimate based on the distance method was large, positive, and significant or nearly so, the result of decreasing detection probabilities over time. Decreasing detectability over time could have been the result of turnover in observers over time, which by chance resulted in observers with lower detection probabilities in later years. We could not estimate detection probabilities for each observer because there were many observers and an inconsistent pattern of observers across years. Therefore we relied on the year covariate to capture observer effects as well as other temporal effects.

We expected abundance estimates from the removal and distance methods to be greater than those from the means and Poisson methods because the former account for birds present but not detected; however, this was only partly true. Estimates of detectability by the removal method were unexpectedly high (0.78–0.98, $\bar{x} = 0.96$) and greater than those by the distance method (0.07–0.60, $\bar{x} = 0.26$).

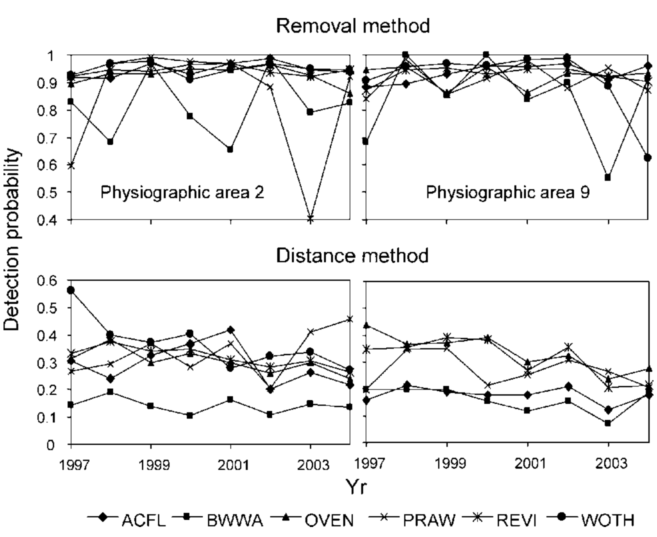

Figure 3. Estimated detection probabilities for Acadian flycatcher (ACFL), blue-winged warbler (BWWA), ovenbird (OVEN), prairie warbler (PRAW), red-eyed vireo (REVI), and wood thrush (WOTH) based on removal models and distance models applied to point-count surveys in 2 physiographic areas in the southeastern United States, 1997–2004.

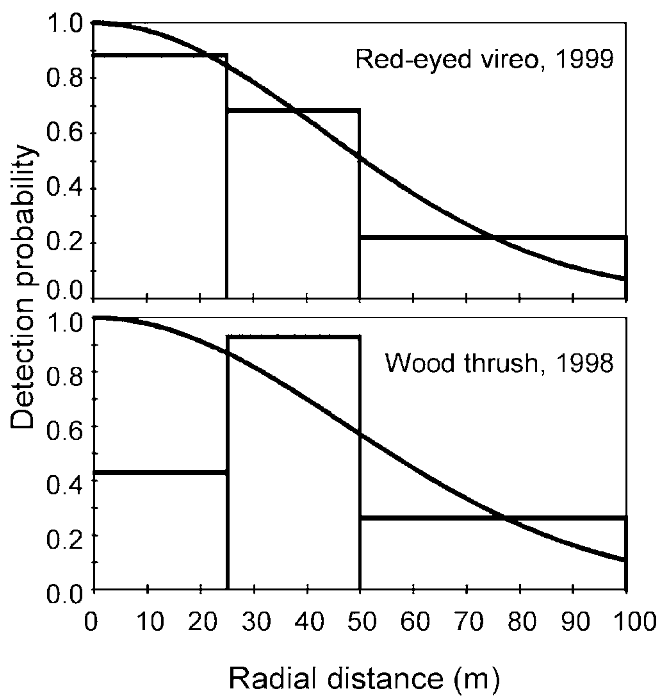

Figure 4. Comparison of the estimated detection function (smooth curve) to the distribution of observations in distance classes (bars) for a function with good fit (red-eyed vireo) and poor fit (wood thrush) from Program DISTANCE, southeastern United States, 1997-2004.

Table 3. Proportion of comparisons ($n = 12$,[a] 6 species, 2 physiographic areas) with the same conclusion (significant decrease, no change, or significant increase in index or abundance; $P < 0.10$) between 5 methods used to estimate abundance and percent annual change in forest bird populations from point-count surveys in the southeastern United States, 1997–2004.

	Method				
Method	**Means**[b]	**Poisson 1**[b]	**Poisson 2**[c]	**Removal**[b]	**Distance**[b]
Means	1.00	0.83	0.75	1.00	0.36
Poisson 1	0.83	1.00	0.92	0.83	0.55
Poisson 2	0.75	0.92	1.00	0.75	0.55
Removal	1.00	0.83	0.75	1.00	0.36
Distance	0.36	0.55	0.55	0.36	1.00

[a] 11 for comparisons with distance method.
[b] Means, Poisson 1, removal, and distance methods are based on fitting an autoregressive model to the log of annual abundance estimates by these methods.
[c] Poisson 2 represents an estimate of annual change by treating yr as a continuous covariate in a mixed-Poisson model.

Therefore abundance estimates by the removal method were only slightly greater than those by the means and removal methods. Farnsworth et al. (2002) used the removal method to estimate detection probabilities of 0.51–0.91 for forest birds in Great Smokey Mountains National Park (USA), which is lower than we observed using a similar model. Alldredge et al. (2007) used mark–recapture models based on the full detection-history from a time-of-detection survey for birds in the same park and estimated detection probabilities of 0.86–0.95. In a similar application of distance methods to riparian birds in Utah (USA), Norvell et al. (2003) estimated detection probabilities of 0.12–0.61, similar to those we reported.

It is not surprising that estimates of detection probabilities differed between methods because the removal and distance methods used different methods for estimating detection probabilities, and in fact, estimate different components of detectability. For aural surveys, detection probability (P) has 2 main components: probability that a bird sings (availability, P_a) and probability a bird is detected, given that it sings (detectability, $P_{d|a}$), where $P = P_a \, P_{d|a}$ (Farnsworth et al. 2002, McCallum 2005, Diefenbach et al. 2007). Distance methods estimate $P_{d|a}$ as a function of distance from the observer and assume that all animals at distance zero are detected, essentially assuming $P_a = 1$. In contrast, the removal method estimates P if there are sufficient sampling intervals (Farnsworth et al. 2005), but with ≤ 3 sampling intervals, at least some portion of the population must be assumed to have a $P_{d|a} = 1$ (McCallum 2005, Diefenbach et al. 2007). Farnsworth et al. (2005) proposed an approach based on time of detections and ≥ 2 distance categories for detections that addresses both of the main components of P and allows density estimation; however, these methods are not yet readily available.

We have some evidence that distance-based methods and time-of-detection methods produce similar estimates of detection probability and abundance when studies are better designed for these methods. In 3 ongoing studies we are measuring actual distances to detections and recording detections in 5 1- or 2-minute intervals; estimates from these studies of detection probability and density from time-of-detection methods and distance methods are similar (F. R. Thompson, United States Forest Service Northern Research Station, unpublished data). In this study we were limited to 3 distance and time intervals. Three intervals can only provide a partial representation of how species detections changed by distance and time, which likely limited our ability to generate robust estimates of detection probability and abundance. Unequal time intervals were also not optimal for the removal method, nor was the lack of an outer radius for the largest distance band (>50 m) for the distance method. Program DISTANCE uses the midpoint of each distance band to fit a detection function, so we assumed an outer boundary of 100 m and midpoint of 75 m for the >50-m band. We examined the sensitivity of estimates to this assumption by estimating densities and detection probabilities for Acadian flycatcher (a species of moderate abundance) for several assumed outer radii. Estimated densities were 0.160/ha, 0.175/ha, and 0.177/ha for assumed outer radii of 75 m, 100 m, and 125 m, respectively. Estimated detection probabilities were 0.527, 0.266, and 0.168 for an assumed outer radius of 75 m, 100 m, and 125 m, respectively. Because density estimates varied very little with this assumption we do not believe it greatly affected our comparisons of abundances and trends. However, estimates of detection probability did vary substantially with this assumption.

MANAGEMENT IMPLICATIONS

Distance and removal models can be successfully applied to existing data from bird surveys based on point-counts if observation times and at least some distance intervals were recorded; however, for new studies detection probabilities can be better estimated with ≥ 4 distance or time categories. Proponents of abundance estimation will likely interpret this study as support for the growing concern that counts of bird detections from point counts should not be used as indices of abundance. Proponents of indices, however, will likely interpret our results as support that even with moderate departures from assumptions, in most cases, indices will result in similar conclusions or management decisions. Given that detection probabilities often vary among species, years, and observers we believe investigators should address detection probability in their surveys; whether it be by estimation of the probability of detection and abundance, estimation of the effects of key covariates when modeling count as an index of abundance, or through design-based methods to standardize these effects. The degree to which naïve methods that treat counts as indices result in unbiased estimates or valid conclusions will partly depend on the amount of standardization in the design of those surveys. We believe further investigation of the use of model-based methods that treat counts as indices while accounting for factors that affect detection probability (i.e., observer, yr, etc.) is warranted. Most readers are likely aware of these types of approaches applied to the North American Breeding Bird Survey (Sauer et al. 1994, Link and Sauer 1998), but they have not been widely used elsewhere. These models also allow inclusion of other effects of interest, such as treatment effects or year effects, something not easily accomplished with current programs for abundance estimation.

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