Bird Populations 2:23-32

ESTIMATING EQUATIONS ESTIMATES OF TRENDS[1]

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Abstract. The North American Breeding Bird Survey (BBS) monitors changes in bird populations through time using annual counts at fixed survey sites. The usual method of estimating trends has been to use the logarithm of the counts in a regression analysis. This procedure is reasonably satisfactory for more abundant species, but produces biased estimates for less abundant species. We present an alternative estimation procedure based on estimating equations. Results presented here suggest that the estimating equations approach to estimating population trends has several advantages over the usual approach. It avoids the arbitrary scaling of the data associated with adding a constant, and the trend is estimated directly on the appropriate scale. Simulation results indicate that the new estimator reduces the bias of estimation relative to the standard regression estimator. We present a comparison of trend estimates for 348 species of birds (based upon BBS data). Trend estimates based upon the alternative methods are generally similar for more abundant species, but the estimating equations estimator appears to provide more realistic results for low abundance species.
Key words: Breeding Bird Survey; trends; estimating equation; route-regression.

ECUACIONES ESTIMATIVAS DE LAS TENDENCIAS ESTIMADAS

Resumén. El BBS (siglas en inglés para Breeding Bird Survey) de Norteamèrica monitorea cambios en las poblaciones de las aves a través de conteo anuales y censos. El método común usado para calcular las tendencias ha sido el del logaritmo de conteo regresivo. Este procedimiento es razonablemente satisfactorio para las especies abundentes pero, para las especies no-abundantes causa parcialidad. Presentamos una alternativa al procedimiento de estimación basado en ecuaciones estimativas. Los resultados aqui dados sugieren que las ecuaciones estimativas se aproximan a las tendencias de la poblaciones estimadas y tienen varias ventajas sobre el acercamiento normal. Evita la escala arbitraria de una suma constante de los datos asociades y la tendencia se calcula directamente en una escala adecuada. Resultados simulados indican que el estimador nuevo reduce la parcialidad de estimación en relación con la regresión estándar. Damos una comparación de las tendencias calculadas para 348 especies de aves en base a datos del BBS. Estas tendencias calculadas basadas en métodos alternativos son generalmente similar para las especies mas abundantes, pero las ecuaciones estimativas parece proveer resultados mas reales para especies con poca abundancia.
Palabras clave: Censo de Aves Reproductivas; tendencias; ecuaciones estimativas; regresivo de ruta.

[1]Received: 23 September 1994. Accepted: 21 December 1994.

ESTIMATION DE TENDANCES PAR LES ÉQUATIONS D'ESTIMATION

Résumé. Le Suivi des Oiseaux Nicheurs d'Amérique du Nord (North American Breeding Bird Survey (BBS)) suit les variations affectant les populations d'oiseaux à travers le temps en utilisant des dénombrements annuels sur des sites d'étude déterminés. La méthode habituelle pour estimer les tendances a été d'utiliser le logarithm des résultats des dénombrements dans une analyse de régression. Cette démarche est raisonnablement satisfaisante pour les espèces les plus abondantes, mais produit des estimations biaisées pour les espèces moins abondantes. Nous proposons une autre procédure d'estimation basée sur les équations d'estimation. Les résultats présentés ici suggèrent que l'utilisation de ces équations d'estimation pour estimer les tendances des variations de populations a plusieurs avantages par rapport à la méthode habituelle. Elle évite le changement d'échelle arbitraire des données associé à l'addition d'une constante, et la tendance est estimée directement l'échelle appropriée. Les résultats des simulations indiquent que ce nouvel estimateur réduit les biais d'estimation relatifs à l'estimateur standart de la régression. Nous fournissons une comparaison des estimations de tendance pour 348 espèces d'oiseaux (basées sur les données du BBS). Les estimations de tendance basées sur les nouvelles méthodes sont en général similaires pour les espèces les plus abondantes, mais l'estimateur des équations de regression semble fournir des résultats plus réalistes pour les espèces de faible abondance.

Mots-clés: Suivi des oiseaux nicheurs; tendances; équations d'estimation; regression d'itineraire.

ERMITTLUNG VON BESTANDSTRENDS MIT HILFE VON SCHÄTZGLEICHUNGEN

Zusammenfassung. Das Nordamerikanische Brutvogelmonitoring-Programm (BBS) ermittelt Bestandsveränderungen der Brutvogelpopulationen über die Zeit anhand jährlicher Erfassungen an festen Zählstellen. Die übliche Methode Bestandstrends zu berechnen bestand darin, die logarithmierten Zählwerte in einer Regressionsanalyse zu überführen. Für die häufigeren Arten brachte diese Vorgehensweise durchaus zufriedenstellende Ergebnisse, allerdings ergaben sich nicht unerhebliche Fehler bei den weniger häufigen Arten. Wir stellen eine alternative Berechnungsmethode vor, die auf Schätzgleichungen beruht. Die hier dargestellten Ergebnisse legen nahe, daß der Ansatz Bestandstrends mit Schätzgleichungen zu berechnen mehrere Vorteile gegenüber der gängigen Berechnungsmethode bietet. Zum einen wird die willkürliche Skalierung der Daten vermieden, die durch die Addition mit einer Konstanten entsteht, und zum anderen wird der Bestandstrend in der betreffenden Größenordnung direkt ermittelt. Die Ergebnisse einer Simulation deuten an, daß der neue Schätzwert den Fehler gegenüber der Standardregressionsberechnung verringert. Wir geben Vergleichswerte der Trendberechnungen für 348 Vogelarten (anhand von BBS-Daten). Die Trendwerte für die häufigeren Arten unterscheiden sich kaum zwischen den beiden Berechnungsmethoden, während die Berechnung anhand der Schätzgleichungen bei den selteneren Arten offensichtlich realistischere Werte liefert.

Schlüsselwörter: Nordamerikanische Brutvogelmonitoring-Programm; Bestandstrends; Schätzgleichungen; Route-regressionsanalyse.

INTRODUCTION: THE NEED FOR A NEW ANALYSIS

Over the past decade, many analyses of data from large-scale surveys such as the North American Breeding Bird Survey (BBS) have used an analytical approach called route-regression analysis (e.g., Robbins et al. 1989). In this analysis, trends are estimated on individual survey routes and a composite regional trend estimate is derived from a weighted average of the route-specific trends (Geissler and Sauer 1990, Peterjohn and Sauer 1993). This approach has several advantages: it allows for variation in trends among routes, it allows for the easy accommodation of route-specific covariates in estimating these trends, and it differentially weights route-specific trend estimates in accordance with their precision.

At the very heart of the route-regression procedure is the analytical procedure used to estimate the trends for individual routes. The route-specific analyses in current use add a small positive constant to the counts (0.50: Geissler and Sauer 1990, 0.23: Collins 1990), take logarithms, and perform regression analysis on the transformed data. For reasons that will soon be apparent, we refer to this as an approximate ANCOVA. Approximate ANCOVA procedures yield satisfactory estimates of trends for relatively abundant species, but are unsatisfactory for less common species. For these species, route-regression analysis could be substantially improved by the incorporation of better route-specific analyses.

Approximate ANCOVA procedures are based on a model of geometric population growth (or decline) and multiplicative observer effects. It is assumed that changes in the actual population size are mirrored in changes in expected counts for each observer, but at distinct levels governed by the observers' abilities. If observer j provides the count X_i in year y_i, then the expected count for year y_i is

$$E(X_i) = \gamma_j \beta^{y_i}, \tag{1}$$

where γ_j accounts for baseline abundance of the species and the multiplicative effect of observer j, and β is the annual rate of change in the population size. (Here and throughout, our attention is focused on the analysis of data from a single route.) It follows then that

$$\log\{E(X_i)\} = \log(\gamma_j) + y_i \log(\beta), \tag{2}$$

which is deceptively similar to

$$E\{\log(X_i)\} = \log(\gamma_j) + y_i \log(\beta). \tag{2'}$$

If $\log(X_i)$ were normally distributed with constant variances, (2') would specify the familiar and appealing analysis of covariance model (ANCOVA), used in the analysis of continuous data.

That the variances are not constant is not particularly troublesome; if this were the only problem, the resultant estimates would be inefficient but unbiased. A slight problem is that the unbiased estimate of log β cannot be directly translated by exponentiation into an unbiased estimate of β; this is only a minor problem, however, since an unbiased estimator of β can be obtained by an appropriate transformation of the estimate of log β (Bradu and Mundlak 1970), though this transformation is derived under normality assumptions. However, even that the errors are not normally distributed is not too much of a problem in applying the approximate ANCOVA models.

What is a problem is that the logarithm of an expected count is not the same as the expected logarithm of a count (cf. (2) and (2')). Approximate ANCOVA analyses fit model (2'), not (2). The distinction is not inconsequential. Its most obvious manifestation is the difficulty associated with zero counts: there is no such thing as the logarithm of zero, so one is forced to change zeros to something else. The usual expedient is the addition of a small positive constant, c, to all observations.

The addition of c seems innocuous enough: suppose that counts {0, 1, 1} are obtained in years {1, 2, 3}; we simply change the counts to $\{c, 1+c, 1+c\}$ and proceed. The addition of c has no effect at all on the slope of the regression line through the untransformed points; the slope is 0.50, regardless of the value of c. If the counts are log-transformed, however, the slope on the log-scale is 0.84 for $c = 0.23$, and 0.55 if $c = 0.50$. We can in fact make the slope equal to any (positive) value at all by judicious choice of c. Suppose that we want the slope to be 3.00; this is accomplished by setting $c = 0.00248$. If we wish the slope to be 0.10, we set $c = 4.5167$.

This is not to suggest that previous uses of approximate ANCOVA procedures were completely unreliable. The ambiguity resulting from the addition of c to counts is of little consequence when counts are larger. If instead of {0, 1, 1} the counts are {24, 30, 28}, setting $c = 0.23$ yields a slope on the log-scale of 0.0764, while $c = 0.50$ yields 0.0756; even the extreme values $c = 0.00248$ and $c = 4.5167$ yield reasonably similar slopes of 0.0771 and 0.0656.

Thus the ANCOVA approximation can be expected to provide a reasonable trend analysis for species that are not too uncommon. When counts are low, however, the addition of a constant and the approximation of (2) by (2') are liable to have a profound effect on the analysis of trends. We describe an alternative method of fitting the relationship (2) in the next section, which does not require the addition of c or taking logarithms.

THE ESTIMATING EQUATIONS ESTIMATOR

The only model assumption that we require is that the mean counts are as given by equation (1) [which is equivalent to (2)]. The estimator we propose is not calculated from a formula, but rather is the solution of an equation known as an "estimating equation"; the estimator obtained is called an "estimating equations estimator" (Godambe 1991).

To describe the estimating equations estimator algebraically, we need to define some data summaries (statistics). Let $\underset{\sim}{X} = (X_1, X_2, \ldots, X_n)$, where X_i denotes the count in year y_i, and let $I_j(y_i)$ be 1 if observer j counted in year y_i, and zero otherwise. The statistics we use are

$$T_j(\underset{\sim}{X}) = \sum_i I_j(y_i)\, X_i\,,$$

the total number of birds counted by observer j, and

$$S(\underset{\sim}{X}) = \sum_i y_i X_i.$$

The statistics $T_j(\underset{\sim}{X})$ and $S(\underset{\sim}{X})$ contain all of the information needed to construct an estimator of β, without any assumptions other than those of equation (1).

Using the statistics $T_j(\underset{\sim}{X})$ and $S(\underset{\sim}{X})$, we define a function of β given by

$$F(\beta;\underset{\sim}{X}) = \sum_j T_j(\underset{\sim}{X}) \left\{ \frac{\sum_i I_j(y_i)\, y_i\, \beta^{y_i - 1}}{\sum_i I_j(y_i)\beta^{y_i}} \right\} - \frac{S(\underset{\sim}{X})}{\beta}.$$

Since the expected value of $T_j(\underset{\sim}{X})$ is

$$E\{T_j(\underset{\sim}{X})\} = \gamma_j \sum_i I_j(y_i)\, \beta^{y_i}\,,$$

and the expected value of $S(\underset{\sim}{X})$ is

$$E\{S(\underset{\sim}{X})\} = \sum_j \sum_i \gamma_j I_j(y_i)\, y_i \beta^{y_i}\,,$$

it follows that

$$E\{F(\beta;\underset{\sim}{X})\} = 0\,. \tag{3}$$

Given the data for a BBS route, we can compute the statistics $T_j(\underset{\sim}{X})$ and $S(\underset{\sim}{X})$, but the true value of β is unknown. However, from (3) it is clear that a reasonable guess at the true value of β is the value $\hat{\beta}$ for which $F(\hat{\beta};\underset{\sim}{X}) = 0$. Thus $F(\beta;\underset{\sim}{X}) = 0$ is an "estimating equation"; the value $\hat{\beta}$ satisfying $F(\hat{\beta};\underset{\sim}{X}) = 0$ is an "estimating equations estimator."

The remarkable feature of this estimating equations estimator is that its reasonableness does not depend on any distributional assumptions other than the structure imposed by (1). Regardless of the variance structure of the data, regardless of the existence of autocorrelations in the data, regardless of anything other than equation (1), equation (3) remains true.

In passing, it is interesting to note certain properties of $\hat{\beta}$ which hold if the counts are Poisson random variables. Then equation (1) describes a Poisson regression model, the statistics $T_j(\underset{\sim}{X})$ are sufficient statistics for the nuisance parameters γ_j, and $\hat{\beta}$ is the maximum likelihood estimator conditional on the values of the sufficient statistics $T_j(\underset{\sim}{X})$. We reiterate, however, that the validity of equation (3) does not depend on any such distributional assumptions.

The solution to the equation $F(\beta;\underset{\sim}{X}) = 0$ is not available in closed form; nevertheless the estimate $\hat{\beta}$ can be readily obtained using Newton's method or other numerical procedures. In the next section we investigate the performance of this estimator relative to that of the ANCOVA approximation estimators.

SIMULATION RESULTS

We carried out a simulation to compare the performance of the ANCOVA procedures with that of the estimating equations estimator. Discrete counts were generated to simulate 20 years of observations. The counts had negative binomial distributions, chosen to reflect population trends β = 0.97, 0.98, 0.99, ..., 1.03. The mean count in the mid-year was set at μ = 0.5, 1.0, 2.0, and 5.0. The variance was set at twice the mean; thus the data were overdispersed relative to Poisson observations. Each parameter configuration was replicated 10,000 times; each time the trend analysis was performed via three ANCOVA procedures [adding c = 0.01, c = 0.23 (Collins 1990), and c = 0.50 (Geissler and Sauer 1990)] and by the estimating equations method. The results are summarized in Table 1.

The simulations reveal that all of the estimators are significantly biased, though the practical significance of the bias is typically quite small for the estimating equations estimator. Under the conditions simulated, the estimating equations estimator tended to have smaller absolute bias than the ANCOVA-based

TABLE 1. Simulation results based on 20 years of negative binomial counts with population trends β, mean count in midyear μ, and variance equal to twice the expected value. Data were analyzed by three ANCOVA estimators (adding constant c = 0.01, 0.23, or 0.50) and by the estimating equations estimator (EEE). Each parameter configuration was replicated 10,000 times; results are summarized by estimated bias (mean estimate of β minus true value) and z-statistics to assess the statistical significance of the estimated bias.

		Estimated Bias				z-Statistic for Bias			
μ	β	c=.01	c=.23	c=.50	EEE	c=.01	c=.23	c=.50	EEE
0.5	0.97	-0.007	0.015	0.019	0.000	-7.733	40.275	74.365	0.183
0.5	0.98	-0.005	0.009	0.012	0.001	-6.106	25.845	48.555	0.526
0.5	0.99	-0.004	0.004	0.006	0.001	-4.577	11.165	22.502	1.244
0.5	1.00	-0.000	-0.000	-0.000	0.005	-0.485	-0.291	-0.209	4.672
0.5	1.01	0.003	-0.005	-0.006	0.007	2.748	-13.052	-24.355	6.590
0.5	1.02	0.006	-0.009	-0.012	0.008	6.270	-25.155	-47.730	7.952
0.5	1.03	0.007	-0.014	-0.019	0.010	8.154	-38.811	-72.617	9.079
1.0	0.97	-0.026	0.004	0.011	-0.001	-27.431	10.482	36.510	-1.119
1.0	0.98	-0.019	0.002	0.007	-0.000	-19.390	5.842	23.247	-0.311
1.0	0.99	-0.010	0.001	0.004	0.000	-9.656	2.628	11.192	0.635
1.0	1.00	-0.001	-0.000	-0.000	0.002	-0.876	-0.440	-0.223	3.419
1.0	1.01	0.010	-0.001	-0.003	0.004	9.891	-2.292	-10.843	5.788
1.0	1.02	0.018	-0.003	-0.008	0.003	17.701	-6.677	-23.805	4.734
1.0	1.03	0.029	-0.004	-0.011	0.004	27.017	-9.410	-34.996	6.409
2.0	0.97	-0.034	-0.004	0.003	-0.000	-40.023	-9.840	10.303	-0.113
2.0	0.98	-0.025	-0.004	0.002	-0.000	-28.796	-8.617	4.849	-0.909
2.0	0.99	-0.013	-0.002	0.001	0.001	-14.281	-4.258	2.458	1.386
2.0	1.00	0.001	0.000	0.000	0.001	1.064	0.986	0.919	2.356
2.0	1.01	0.013	0.002	-0.001	0.001	13.734	4.199	-2.380	3.094
2.0	1.02	0.026	0.004	-0.002	0.002	27.112	7.998	-5.141	4.180
2.0	1.03	0.038	0.004	-0.003	0.002	38.491	9.937	-9.838	3.875
5.0	0.97	-0.018	-0.006	-0.002	-0.000	-37.775	-21.218	-9.048	-0.896
5.0	0.98	-0.013	-0.005	-0.002	-0.000	-27.592	-15.717	-7.360	-0.541
5.0	0.99	-0.004	-0.001	0.000	0.001	-9.298	-3.175	0.949	4.787
5.0	1.00	-0.001	-0.000	-0.000	0.000	-1.140	-0.901	-0.806	0.955
5.0	1.01	0.006	0.002	0.001	0.000	12.803	7.068	3.017	1.690
5.0	1.02	0.012	0.004	0.001	0.000	23.954	13.183	5.261	1.736
5.0	1.03	0.018	0.006	0.002	0.000	33.986	18.379	6.693	1.145

estimates (≤ minimum absolute bias of ANCOVA-based estimates in 20 of 28 cases). For estimating equations estimators, the bias appears to be related to abundance, with perhaps a slight increase in bias associated with larger trends. For ANCOVA-based estimators, the bias varies as a function not only of abundance but also of the true trend. Also, it is clear that the choice of c can have a substantial effect on the performance of the estimator; for fixed values of abundance and trend, bias can differ greatly among the ANCOVA estimates.

Simulations cannot prove the uniform superiority of one analytic method over another. However, the superior performance of the estimating equations estimator in these simulations, taken together with the fact that they are not based on the approximations involved in the ANCOVA procedures, argues strongly in their favor.

ANALYSIS OF BREEDING BIRD SURVEY DATA: A COMPARISON OF THE TWO APPROACHES

METHODS

To demonstrate the practical consequences of using the estimating equations estimator in route regression analysis, we estimated trends for each bird species encountered in the BBS using both estimating equations and ANCOVA to estimate the trends on survey routes. We used data from the period 1966-1993 and conducted the analysis for each species as described in Geissler and Sauer (1990), except that the trend estimate for each route was either based on the estimating equations or the ANCOVA, depending on the analysis. Observer effects were incorporated into both analyses (Sauer et al. 1994). To estimate composite trends, the route trends in both cases were weighted by a measure of relative precision (the inverse of the $(X'X)^{-1}$ element corresponding to the slope from the ANCOVA model), a mean abundance measure (the marginal mean relative abundance from the ANCOVA model), and the area of the state-stratum region in which the survey route was located. See Geissler and Sauer (1990) for the rationale for these weights. Each composite trend estimate is based on all survey routes on which trends could be estimated and, therefore, represents a survey-wide estimate.

The estimating equations approach cannot be used for survey routes with extremely sparse data. (Specifically, the estimating equations approach provides an estimate unless all observers have counts of zero for every year after their first year, or all observers have counts of zero for every year except their last year.) As a minimum data requirement, we restricted our analyses of a species to those routes on which there was at least one observer with two non-zero counts. In practice, this has little effect on the analysis because the routes that were eliminated have very small weights in the composite trends. Variances of the composite trend estimates were estimated using bootstrapping. To ensure that trends and variances are estimated with reasonable precision, we restricted our analysis to species that appeared on at least 40 routes.

We anticipated that the primary consequences of use of the estimating equations relative to the ANCOVA model would be (1) that the ANCOVA-based estimates would be closer to 1.0 than the estimating equations estimates, and (2) that the ANCOVA-based estimates would have smaller variances. Further, we anticipated that both these consequences would be associated with abundance; the differences between the methods should be greatest for species with low relative abundances. This is not only because the estimates are least precise for low abundance species (in both methods) but also because we anticipated that the effect of adding the constant c would be most noticeable for low counts.

To address the first of these issues, we estimated the difference between the two trend estimates for each species, standardized to a z-statistic by dividing them by the square root of the sum of their variances. The standardization removes the effects of variances in the comparisons. We plotted these z-statistics against the natural logarithm of mean abundance of the species, and correlated the absolute magnitude of the z-statistics with the log abundance to demonstrate the association between abundance and the differences in estimated trends. The second issue was addressed by finding the difference between the estimated variances of the two estimates for each species, and plotting the differences in variances against the natural logarithm of mean abundance of the species.

We anticipate that managers will be interested to know whether differences between the estimating equations and ANCOVA-based trend estimates are evident in summaries for groups of species. A summary used commonly in recent years is the percentage of species in a group having positive trend estimates. Peterjohn and Sauer (1993) used tests of the null hypothesis that this percentage is 50% to establish whether trends are consistent among species in groups. Recently, Link and Sauer (in press) described empirical Bayes estimates of the percentage of species with increasing trends. Empirical Bayes procedures examine attributes of collections of parameter estimates, accounting for the sampling variation implicit in the individual estimates. Empirical Bayes estimates of the percentage of positive trends place more weight on "better" estimates (i.e., those with less sampling error).

We obtained empirical Bayes estimates for several groupings of bird species and assessed the differences in the percentage of species with increasing trends between the two methods. The groupings are by breeding habitat (grassland, wetland, scrub, woodland, urban), nest type (closed vs open), nest height (low or high), migration type (Neotropical, short-distance, nonmigratory); constituent species for these groups are listed in Peterjohn and Sauer (1993). For each group, we estimated the percentage of increasing species and calculated a 95% confidence interval.

RESULTS

ANCOVA and estimating equations estimates of trend were obtained for 348 species. The ANCOVA estimates for White-winged Crossbills *(Loxia leucoptera)* were so extreme (indicating a 17.6% annual rate of increase) that we excluded them from summary analyses. The composite estimates of trend based on the estimating equations are presented elsewhere (Peterjohn et al. 1994). Here, we discuss the relationships between the ANCOVA-based estimates and the estimating equations-based estimates.

Comparison of the *z*-statistics of the differences indicates that differences between the methods are associated with abundance (Figure 1). The correlation of the absolute magnitude of the *z*-statistics and log abundance is -0.32 ($P < 0.01$), indicating that the results are more consistent when species are more abundant. This is also reflected in the spread of the *z*-statistics in Figure 1; for low abundance species the *z*-statistics are large, and 13 of the lower abundance species exceed the 1.96 (or -1.96) values associated with a significant difference for the species results. It should also be noted that the slope of the relationship in Figure 1 is negative ($P < 0.05$). This suggests that for more abundant species the estimating equations estimates tend to be less than the ANCOVA-based estimates. Because each composite estimate of trend is based on a variety of low and high abundance routes, and because trends are not consistent over species' ranges, the causes of this pattern are unclear.

The differences in variances are also associated with relative abundance on survey routes (Figure 2). Estimating equations-based estimates have larger variances for low

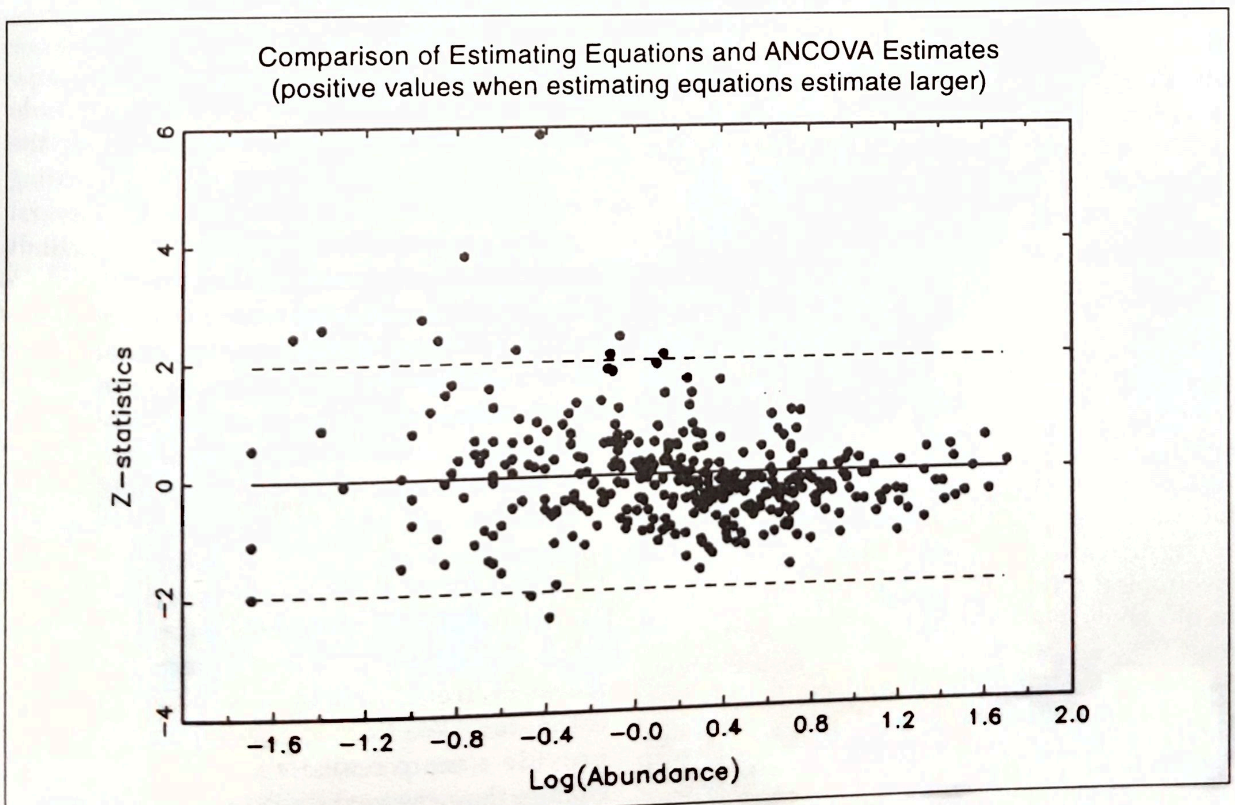

FIGURE 1. Plot of standardized differences between estimating equation estimates and ANCOVA estimates (*z*-statistics) of trend ($\hat{\beta}$) against natural logarithm of abundance. The dashed lines indicate the critical values ($P < 0.05$) for statistical significance of the *z*-statistic.

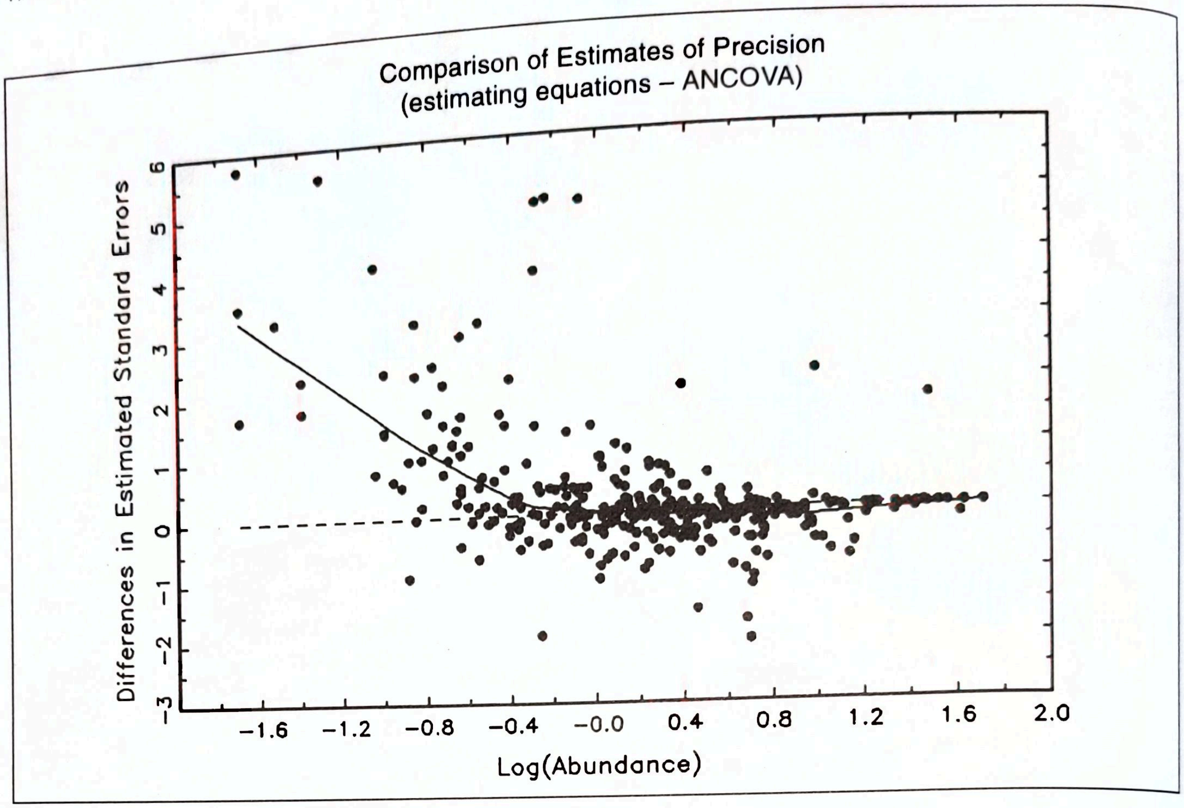

FIGURE 2. Plot of differences in estimated variances between estimating equations and ANCOVA-based trend estimates against natural logarithm of abundance. A LOESS smooth is added to illustrate the pattern.

abundance species, but for abundant species the variances are similar between the methods. A LOESS smooth through the data (tension parameter, $f = 0.30$) shows the pattern (Figure 2), and a regression through the data shows a significant negative slope estimate ($P < 0.05$).

Percentages of increasing species by groups show a general pattern of slightly lower percentage of increasing species for the estimating equations results (Figure 3). Overall, the estimating equations results show <50% of species with increasing populations (47.5%), while the ANCOVA-based results show >50% increasing (52.3%), although neither percentage is significantly different from 50%. For Neotropical migrant birds, estimating equations results show 43.4% increasing, significantly less than 50%, while ANCOVA-based results show 54.8% increasing. In general, the large scale patterns of population change such as declines in grassland bird species, open-cup nesting, and ground nesting bird species are reflected in both analyses (Peterjohn and Sauer 1993).

DISCUSSION

Results presented here suggest that the estimating equations approach to estimating population trends on BBS routes has several advantages over the ANCOVA approach. It avoids the arbitrary scaling of the data associated with adding a constant, and the trend is estimated directly on the appropriate scale, which avoids the sometimes controversial transformation to the multiplicative scale (Geissler and Sauer 1990). Simulation results indicate that the method is less biased than the ANCOVA approach. Finally, the trends estimated using estimating equations are generally similar to those estimated using the ANCOVA approach, but they show larger variances (and consequently more deviation from no trend) than the ANCOVA-based estimates. We therefore conclude that they provide a more realistic view of population change than the earlier estimates and suggest that they be adopted in future analyses.

Estimating equations results are generally

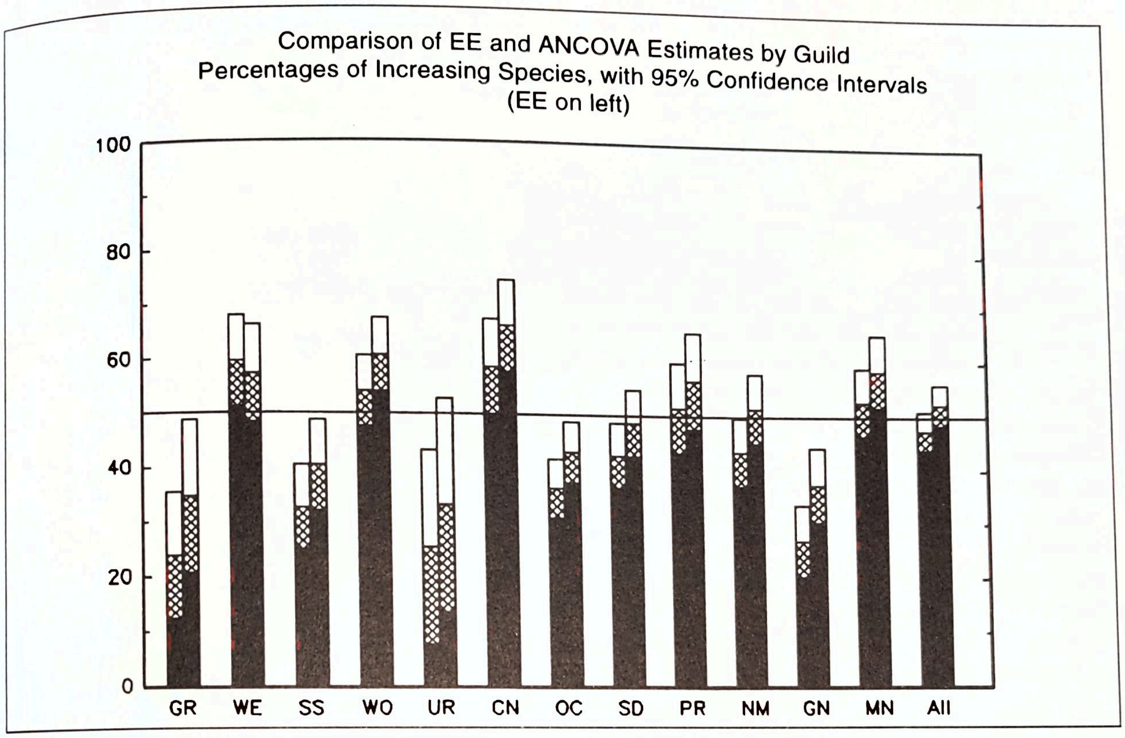

FIGURE 3. Histogram of percentage of species with increasing population for 12 groupings of bird species and overall for estimating equations estimates (left bar) and ANCOVA-based estimates (right bar). 95% confidence intervals are indicated by shading for each percentage (i.e., the mean percentage is indicated by the top of the cross-hatched area while the 95% confidence intervals are indicated by the tops of the open and filled areas, respectively). Groupings are by breeding habitat (GR: grassland, WE: wetland, SS: scrub, WO: woodland, UR: urban), nest type (CN: closed vs OC: open cup), migration type (SD: short-distance, PR: nonmigratory, NM: Neotropical), nest height (GN: low or MN: high), and for all species (All).

similar to those from the ANCOVA for more abundant species, and appear to provide more realistic results for low abundance species. In the past, BBS coordinators have attempted to avoid the problems associated with scaling of low abundance species by eliminating low (< 1 bird/route) abundance data from summary analyses and "flagging" the data in Tables (Peterjohn and Sauer 1994). Estimating equations-based results allow use of these data, providing more complete species lists. However, low abundance species are still imprecisely estimated; the improvement offered by estimating equations estimates is a reduction of bias. Summary analyses should incorporate the precision of the estimates (e.g., Link and Sauer, in press).

One important difference between earlier analyses of BBS data and the estimating equations-based results is that estimating equations results tend to be slightly more negative, resulting in a slightly higher percentage of species with trend estimates indicating decline. It has been suggested that ANCOVA-based results may have a sight positive bias (Barker and Sauer 1992), and our simulation results do indicate a slight tendency for positive bias (Table 1). Unfortunately, comparison of two sets of results does not necessarily provide insight into which, or indeed whether either, is correct. We can only document differences, and speculate as to which is more likely to mimic truth. Our simulation results provide a more objective comparison of the methods and favor the estimating equations estimator. The estimating equations estimators differ from the ANCOVA estimators precisely when we had anticipated the ANCOVA estimators to be most biased. We conclude that estimating equations provide a more realistic view of population change.

FUTURE MODIFICATIONS OF TREND ANALYSES

Estimating equations can be modified to incorporate a variety of special modeling situations. We are presently exploring several modifications that will make the model a more realistic description of bird population change. First, we are investigating the incorporation of a quadratic component into the model. By comparing the quadratic results to the linear results, we can directly test for nonlinearity in population trends and, if they exist, incorporate the more complex (and realistic) model into the analysis. Second, we are investigating the incorporation of parameters to measure "start-up effects", in which the counts from the first year of an observer are lower than those of subsequent years. These effects have been documented in BBS data (Kendall and Peterjohn, unpublished manuscript), and can be directly modeled in the estimating equations.

Estimation of population trends can be very controversial for index surveys such as the BBS (see James et al. 1990), in which a variety of biological and sampling constraints make the indices biased, imprecise, and unevenly spaced both geographically and temporally (Barker and Sauer 1992). The first step in these analyses is to estimate correctly rates of change on single survey routes. We believe that the estimating equations approach does a better job than the ANCOVA-based method in addressing this first consideration.

The next step in these analyses involves combining information among routes to derive regional estimates. For our examples in this paper, we have retained the weighting procedure described by Geissler and Sauer (1990), so that comparisons of composite estimates based on the different methods are not confounded by differences in weightings. In general, this weighting procedure provides more efficient (and less biased) composite estimates than alternative weightings (Pendleton, Sauer, and Link, unpublished analyses). However, further elaborations are needed to model spatial aspects of the sampling in combining route-specific results into composite regional results. The estimating equations approach can be extended in combination with empirical Bayes procedures and spatial modeling procedures to provide composite estimates.

ACKNOWLEDGMENTS

We thank Paul Geissler, Clinton Moore, Barry Noon, Nadav Nur, and Bruce Peterjohn for helpful reviews of early versions of this paper.

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