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Comparative Analysis of Mourning Dove Population Change in North America

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ABSTRACT Mourning doves (*Zenaida macroura*) are surveyed in North America with a Call-Count Survey (CCS) and the North American Breeding Bird Survey (BBS). Analyses in recent years have identified inconsistencies in results between surveys, and a need exists to analyze the surveys using modern methods and examine possible causes of differences in survey results. Call-Count Survey observers collect separate information on number of doves heard and number of doves seen during counting, whereas BBS observers record one index containing all doves observed. We used hierarchical log-linear models to estimate trend and annual indices of abundance for 1966–2007 from BBS data, CCS-heard data, and CCS-seen data. Trend estimates from analyses provided inconsistent results for several states and for eastern and central dove-management units. We examined differential effects of change in land use and noise-related disturbance on the CCS indices. Changes in noise-related disturbance along CCS routes had a larger influence on the heard index than on the seen index, but association analyses among states of changes in temperature and of amounts of developed land suggest that CCS indices are differentially influenced by changes in these environmental features. Our hierarchical model should be used to estimate population change from dove surveys, because it provides an efficient framework for estimating population trends from dove indices while controlling for environmental features that differentially influence the indices.

KEY WORDS Call-Count Survey, hierarchical model, North American Breeding Bird Survey, route regression, trend analysis, *Zenaida macroura*.

Mourning doves (*Zenaida macroura*) are widely distributed and common throughout the continental United States, with an estimated autumn population of 350 million birds (Otis et al. 2008). A popular game bird, approximately 20 million doves were harvested in the 2006 and 2007 hunting seasons (Richkus et al. 2008). Management of the species is based on roadside, point-count–based surveys, primarily a Call-Count Survey (CCS), supplemented with data from the North American Breeding Bird Survey (BBS; United States Department of the Interior 2005, Dolton et al. 2007, Sauer et al. 2008*a*). In the CCS, doves heard cooing are recorded separately from doves seen; in the BBS, total numbers of doves perceived by sight or sound are recorded. Analysis results from both the heard and seen indices from the CCS and from BBS data have routinely been provided in annual administrative reports that summarize mourning dove population status (e.g., Dolton et al. 2007).

Sauer et al. (1994) conducted a comparative analysis of dove population trends from the CCS-heard index and BBS dove data. Different patterns of population change as estimated by the 2 independent surveys were identified in that analysis in several states, although overall changes were generally similar. In recent years, differences in trends estimated from the BBS and the CCS have become increasingly evident, and trends estimated from CCS-heard and -seen indices have also begun to show inconsistencies (Dolton et al. 2007).

These differences between the indices highlight a key limitation of index data. Because detectability is not estimated as part of the survey, the indices vary both due to real population changes and due to changes in the environment that are not population-related such as observer ability, phenology of breeding, counting conditions such as weather and amount of noise-related disturbance, or land use around the site (e.g., Bibby et al. 2000). It is likely that the processes of encountering birds by hearing and seeing are differentially affected by ≥1 of these environmental features.

Any analysis of index data must control for factors influencing detectability, and recent analyses of BBS and CCS dove data control for baseline observer differences that are known to influence counts (Link and Sauer 1994). Different estimates of trends in continental dove populations based on the alternative indices indicate presence of unmodeled features that are differentially influencing the indices. Identifying these lurking covariates that are influencing the indices and controlling for their effects in the analysis must be a high priority for mourning dove surveys. Unfortunately, the route-regression analysis presently used in dove analyses is limited in its ability to model covariates that might influence detectability (Dolton et al. 2007). New statistical methods recently implemented for the BBS and the Christmas Bird Count provide the flexibility needed for these covariate analyses (Link and Sauer 2002, Link et al. 2006).

We implemented a new analysis of CCS data, a Bayesian analysis of log-linear hierarchical models that permits accommodation of covariates of population change (Link and Sauer 2002, Sauer et al. 2008*b*). We compared results of these models to results from the presently used route-

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regression analysis approach for CCS data and to BBS results based on hierarchical models. To identify covariates that may improve our estimation of dove population change, we evaluated several hypotheses regarding environmental features that might be acting to differentially influence the CCS dove indices. We evaluated whether changes in noise disturbance along routes differentially affects heard and seen indices in the CCS; we associated trends in temperature by state with trends in indices to determine whether phenological changes differentially affected the indices, and we associated trends in land uses by state with trends in indices to evaluate whether land-use–associated visibility changes differentially affected the indices.

METHODS

The CCS is optimized for counting mourning doves. Timed to coincide with the most stable period of cooing activity, the CCS collects 2 indices of abundance for the species (Dolton 1993). The CCS is a roadside survey, initiated across the continental United States in 1966. Each of the 1,255 survey routes contains 20 listening stations (stops) located 1.6 km (1 mile) apart, at which all doves heard and seen are recorded during 3-minute point counts conducted starting 30 minutes before sunrise on a day between 20 May and 5 June. At each stop, data on doves heard and seen are recorded separately; doves seen are also recorded while traveling between stops. Disturbance, defined as presence of traffic or other noise likely to interfere with counting, is also recorded at each stop as a categorical variable with levels of no, low, moderate, or high disturbance. The example provided in the survey instructions for low disturbance is distant tractor noise; for moderate and high disturbance intermittent and continuous traffic are used as examples (D. D. Dolton, United States Fish and Wildlife Service, unpublished report).

Although information collected along a route could be summarized in several ways, 2 indices of abundance have historically been used to characterize dove populations: 1) the CCS-heard index is the sum of the counts of doves heard over the 20 stops; and 2) the CCS-seen is the sum of the counts of doves seen at and between stops. See Dolton (1993) for a detailed summary of survey procedures and design issues.

The BBS is also a roadside survey, but is generally conducted in June and has 50 3-minute point-count stops separated by 0.8 km (0.5 miles). A single index to abundance, the total number of birds perceived by sight or sound, is collected for each species at each stop, and species totals over the 50 stops are used as the route summary. Counts of numbers of vehicles passing during the surveys were collected starting in 1998, but no noise disturbance measure was collected for most of the survey period. The BBS includes information from >4,000 survey routes in the continental United States and southern Canada. The survey was initiated in the eastern United States in 1966 and routes in the western United States and in Canada were first surveyed in 1968.

Analysis of CCS and BBS Indices

Between 1995 and 2007, the route-regression analysis method (Geissler and Sauer 1990, Link and Sauer 1994) was used for analysis of mourning dove population change for management reports and other summaries (e.g., Dolton et al. 2007). In the route-regression analysis method, interval-specific population change (trend) is estimated on each survey route as the slope of a Poisson regression with log links, in which observer data are included as covariates to allow each observer to have a separate intercept (baseline counting ability). Regional trends are estimated by a weighted average of the route trends, with weights of mean route abundance, a factor representing consistency of coverage, and an area weight. Variances are estimated via bootstrapping. Annual indices are estimated by calculating the average (on the log-scale) difference between yearly counts and predicted counts based on the regional estimated trends.

Link and Sauer (2002) and Sauer et al. (2008*b*) described a log-linear hierarchical model to estimate population change from count surveys. In hierarchical models, some parameters (e.g., stratum-specific yr effects) are governed by additional underlying hyperparameters (e.g., stratum means depend on a distribution based on a national mean). This structure is well-suited for national surveys, because the surveys are naturally hierarchical and we are interested in estimating attributes at many scales: survey routes that occur within strata and strata that occur within larger regions. Covariates can be easily added and evaluated at any scale in the hierarchical model, an important attribute for use of the model as a framework for evaluating environmental effects on counts.

We used the overdispersed Poisson regression model described in Sauer et al. (2008*b*). The means $\lambda_{i,j,t}$ of counts $Y_{i,j,t}$ (i indices stratum, j for unique combinations of route and observer, and t for yr) are a log-linear combination of several explanatory variables:

$$\log(\lambda_{i,j,t}) = S_i + \beta_i(t - t^*) + \omega_j + \gamma_{i,t} + \eta I(j,t) + \varepsilon_{i,j,t}. \quad (1)$$

This model has the standard structure of a linear model, but model parameters are random rather than fixed effects and we must specify their distributions. Variables S and β are stratum-specific intercepts and slopes, ω are observer–route combination effects, γ is a year effect for year and stratum, η is a start-up effect [$I(j,t) = 1$ for the first yr of survey for an observer, 0 otherwise], and ε represents overdispersion. We set the baseline year t^* to 1984.

We estimated annual indices of abundance and an interval-specific estimate of population change (trend) as functions of components of the log-linear model. Stratum-specific annual indices of abundance ($n_{i,t}$) index the number of birds per route in stratum i at year t (Link and Sauer 2002) and we estimated them from year effects, stratum, and trend effects:

$$n_{i,t} = \exp\left[S_i + \beta_i(t - t^*) + \gamma_{i,t} + 0.5\sigma^2_\omega + 0.5\sigma^2_\varepsilon\right].$$

We defined stratum level population indices $N_{i,t} = A_i n_{i,t}$, where A_i is area of the stratum, and composite indices for groups of strata as sums of $N_{i,t}$ divided by total areas in the collection. Indices $N_{i,t}$ are not unbiased estimates of population totals because $n_{i,t}$ are not area-specific population estimates. We defined trend as an interval-specific geometric mean rate of change of indices (c.f., Link and Sauer 2002), presented as a yearly percentage change. From year t_a to year t_b, for stratum i, trend is $100(b_i - 1)\%$, where

$$b_i = \left(\frac{n_{i,t_b}}{n_{i,t_a}} \right)^{\frac{1}{t_b - t_a}}.$$

We calculated regional trends $\bar{b}$ analogously as $100(\bar{b} - 1)\%$, using the composite indices $N_t = \Sigma_i N_{i,t}$, to calculate

$$\bar{b} = \left(\frac{N_{t_b}}{N_{t_a}} \right)^{\frac{1}{t_b - t_a}}.$$

For presentation, we scaled composite indices N_t by total areas, obtaining a summary on the scale of birds/route, $n_t = N_t \,/\, \Sigma_i A_i$.

Modeling Disturbance Effects

We incorporated an effect of noise-related disturbance as an additional component of the model for CCS data. We summarized route-level disturbance as the sum of stops with recorded moderate and high disturbance levels, because no and low disturbance levels reflect either background noise or noise produced at a distance, whereas the higher levels reflect traffic and other noises occurring close to the observers. Disturbance data were only available from 1968 to 2007 and were occasionally missing. To model effects of disturbance on counts without imposing a predefined shape of the relationship, we used the flexible 2-parameter family of models developed for effort adjustments in Christmas Bird Counts (Link et al. 2006), $B\,(\xi_{i,j,t}^{\,p} - 1) \,/\, p$, which is added to the log-linear model. In this model, effort $\xi_{i,j,t}$ is scaled to an overall mean effort. The parameter p defines the shape of the relationship between counts and effort, and B is the coefficient of the effort adjustment.

To use this model for disturbance, we transformed disturbance data as $d = 21 -$ (sum of moderate and high disturbance levels), allowing a realistic decline in counts associated with larger levels of disturbance; d ranges from 1 to 21. We also scaled disturbances to their overall mean and the model became $B\,(d_{i,j,t}^{\,p} - 1) \,/\, p$. If disturbance associated with count $Y_{i,j,t}$ is equal to overall mean disturbance, then $d_{i,j,t} = 1$ and the effort effect is zero.

We conducted an analysis of change in disturbance, using the log-linear model described above for CCS analysis but substituting our disturbance measure (sum of moderate and high levels of disturbance) for the count $Y_{i,j,t}$. We calculated annual indices and trend in disturbance as described above.

Fitting Hierarchical Models to CCS and BBS

We used Bayesian methods to fit the hierarchical models to all data sets. In Bayesian methods, we assume all quantities to be random variables and the goal of inference is to make probability statements about these unknown quantities by estimating their distribution (the posterior distribution), given our prior knowledge of their distributions (e.g., they are normally distributed) and the likelihood of data conditional on the parameters. The posterior distribution is the basis of all Bayesian inference: its mean (or sometimes its median or mode) is used as a point estimator; its percentiles are used to create interval estimates, called credible intervals. We present 95% credible intervals (CrI) extending from the 2.5th to the 97.5th percentile. Historically, direct calculation of posterior distributions from prior distributions and likelihoods by integration has been difficult; modeling such as that we described would not have been feasible using the traditional integration-based approaches. However, simulation-based numerical procedures such as Markov-chain Monte Carlo (MCMC) allow us to approximate posterior distributions of the parameters (Gilks et al. 1996). The MCMC produces samples of posterior distributions through iterative procedures. One of the most efficient methods of MCMC is Gibbs sampling, in which individual parameters are sampled from their full conditional distributions. The full conditional distribution of a given parameter is its posterior distribution given fixed values of the other parameters. Cyclical sampling of full conditional distributions produces samples from the joint posterior distributions of the model parameters. We can use the mean and percentiles of sampled values to compute point estimates and credible intervals for inference. Furthermore, we can compute functions of parameters (such as annual indices) based on the MCMC output, easily obtaining samples of their posterior distributions. Program WinBUGS (Lunn et al. 2000) implements Gibbs sampling and includes diagnostic tools for monitoring the process, and tools for summarizing the results.

We used WinBUGS to fit the log-linear model for BBS and CCS data. We assigned S_i and β_i diffuse normal prior distributions; other effects were modeled as mean zero normal random variables, with unknown variances. These variances were assigned flat inverse gamma prior distributions. The ω were identically distributed, with common variance σ^2_ω, ε were identically distributed with variance σ^2_ε, and variance of γ varied among strata ($\sigma^2_{\gamma,i}$). We used standard noninformative priors in the disturbance analysis. For parameter p we used a uniform prior on the interval $[-4, 4]$ and gave B a diffuse normal distribution (Link et al. 2006).

Breeding Bird Survey and CCS mourning dove data sets are large, and to implement the model with limited computer resources we thinned the results, storing each sixth iteration result for summary. We conducted 60,000 iterations of each chain as a burn-in, and then based the analysis on an additional 60,000 iterations. We evaluated convergence by inspection of graphs of iterated results and autocorrelation functions (e.g., Sauer et al. 2008*b*).

Geographic Regions Used in Analysis

We conducted analyses of mourning dove population change for 1966–2007 from CCS and BBS data. The CCS provided information from the 48 conterminous United States, and the BBS covered that area and southern Canada. In this analysis, we analyzed CCS and BBS using

Bird Conservation Regions (BCRs) physiographic strata within states; these state–physiographic regions are used in BBS analyses as the fundamental strata for analysis (Sauer et al. 2003). See Sauer et al. (2003) and Sauer et al. (1994) for a discussion of strata and an analysis of BBS data within BCR-based strata.

We summarized results by state and for the Eastern [EMU], Central [CMU], and Western [WMU] Management Units (Dolton et al. 2007; see Table 1 for states included in the management units) for CCS-seen, CCS-heard, and BBS indices. We calculated long-term (1966–2007) trends and annual indices. Due to small sample sizes in the CCS, we present composite results for New England states (denoted as NEE: CT, ME, MA, NH, RI, and VT), and for Delaware and Maryland (denoted as DM; Dolton et al. 2007), although we occasionally used trends for individual states in subsequent analyses.

We compared results by evaluating differences in trends by states and regions and present 95% CrI to assess significance of differences. We evaluated whether consistent differences existed in magnitude of trends from CCS-seen and CCS-heard indices by calculating mean differences among states and associated 95% confidence intervals. Dolton (1994) suggested that the CCS-seen index tended to be less precise than the CCS-heard index. We also compared relative precision of the indices by comparing half-width of credible intervals of estimated trends by states, estimating mean size of credible intervals and associated 95% confidence intervals.

Why Do Trends Differ Among Indices: 3 Hypotheses

Observed differences in population trends estimated from dove indices suggest that environmental factors differentially influenced the indices. The indices are collected simultaneously in the CCS; hence, we can interpret changes in indices as being a consequence of regional changes in factors that differentially affect the indices rather than actual population change. If we can document associations between hypothesized factors and differences in the indices, we can get insights both into possible causes of differences between indices and into means of controlling for the factors in the analysis.

Several possible explanations exist.

1. *Differential disturbance effects.*—Presumably, increased noise disturbance will influence observers' ability to count doves. Effects of disturbance are likely to be greater on the heard index, because noise competes with hearing but not with visual effects. We can directly address this differential disturbance hypothesis using the hierarchical model and the disturbance index collected in the CCS. We evaluated the relative importance of disturbance for the indices, estimated the shape parameter p and the slope parameter B for heard and seen indices, and compared the magnitude of these parameters for each index. We also assessed the consequences of disturbance for the analysis of both indices by estimating annual indices of abundance and trend while controlling for disturbance.

2. *Differential effects of land-use change along routes.*—Development along roads tends to create perches and increase observers' ability to see birds, and the CCS-seen index may differentially increase after development due to the increased visibility of doves. We associated state-level trends in dove populations with 2 sources of information on land-use change: the National Resource Inventory and change of general land-use types from the National Land Cover Database (NLCD; Fry et al. 2009). States with larger changes in amount of open land uses having greater divergence between CCS-heard and CCS-seen indices would support the land-use hypothesis.

Information on changes in developed versus rural nonfederal land acreages are summarized by the National Resources Inventory for 1982–1997 (Nusser and Goebel 1997). We obtained reports of developed and rural nonfederal land analyses of the National Resources Inventory (NRI) conducted by the Natural Resources Conservation Service (United States Department of Agriculture 2000). The NRI provides estimates at the state level and estimates were available for 1982 and 1997. We estimated yearly percentage change between those years and used simple linear regression to estimate the slope in a linear regression of population trend estimates on change in amount of developed land, by state for CCS-seen and CCS-heard, estimated for the period 1982–1997.

Land-use change data were also available from the NLCD 1992–2001 Land Cover Change Retrofit Product (Fry et al. 2009). Although based on a short interval, this data set is a consistent analysis of Landsat data from the starting and ending time periods using a consistent categorization, allowing comparisons of broadly defined land-use categories (open water, urban, barren, forest, grassland–shrub, agriculture, wetlands, ice–snow). We estimated percentage change in urban land use by state.

We also summarized change in combined agricultural and grassland–shrub land uses by state, and evaluated change in these open land uses as a predictor of population trends in CCS-heard and CCS-seen estimated over the 1992–2001 interval, as well as to differences in the trends from the indices by state. Although the actual population consequences for changes in agricultural land uses may vary by crop type (Martin and Sauer 1993), it is likely that increases in these land uses will influence visibility of doves and may, therefore, be associated with differences in trends for the indices.

3. *Differential phenology effects.*—Spring has been arriving sooner, and bird reproductive activities are beginning earlier in the year (Dunn and Winkler 1999). Earlier breeding may cause the cooing rates to be declining during the dove survey time (see review in Baskett 1993), and change in the timing of reproduction may have a differential effect on number of doves heard relative to seen. Although no phenology data exist that document changes in breeding times of doves, associations between surface air temperature increases and earlier spring breeding have been shown in tree swallows (*Tachycineta bicolor*) and other taxa (Dunn and Winkler 1999, Abu-Asab et al. 2001).

We evaluated the hypotheses that differences in the CCS-seen and CCS-heard indices were associated with

Table 1. Estimated population trend (%/yr and 95% credible intervals [CrI]) from hierarchical model analysis for 1966–2007, based on Mourning Dove Call-Count Survey (CCS) heard and seen data and North American Breeding Bird Survey (BBS) data for states (NEE represents combined New England states; DM is DE and MD) and Eastern (EMU), Central (CMU), and Western (WMU) Management Units.

	CCS-heard			CCS-seen			BBS		
		CrI			CrI			CrI	
Region	%/yr	2.5%	97.5%	%/yr	2.5%	97.5%	%/yr	2.5%	97.5%
DM	−0.76	−1.79	0.34	0.92	−0.4	1.63	0.58	0.26	0.91
FL	−0.06	−0.82	0.72	3.03	1.95	4.76	2.82	2.22	3.43
GA	−1.15	−1.9	−0.38	−0.83	−1.71	0.37	−0.80	−1.25	−0.38
IL	−0.36	−1.53	0.68	0.39	−1.42	2.79	1.10	0.6	1.59
IN	−1.43	−2.14	−0.73	−1.08	−2.11	−0.10	0.04	−0.51	0.59
KY	−0.17	−0.94	0.63	0.83	−0.28	2.29	0.88	0.36	1.43
LA	2.11	1.24	2.98	3.01	1.86	4.58	2.84	2.11	3.55
MI	1.25	0.52	2.05	3.25	2.29	4.27	1.72	1.21	2.25
MS	−1.24	−1.9	−0.57	−1.47	−2.35	0.12	−0.48	−1.27	0.34
NC	0.28	−0.28	0.85	0.21	−0.57	1.19	0.38	−0.12	0.87
OH	−0.28	−0.99	0.42	1.28	0.36	1.88	1.55	1.03	2.08
PA	0.43	−0.63	1.41	2.30	0.8	3.86	1.91	1.44	2.37
SC	−0.70	−1.29	−0.08	0.90	0.08	2.02	0.05	−0.58	0.67
TN	−1.96	−2.72	−1.17	0.06	−0.88	1.23	−0.18	−0.78	0.42
VA	−2.09	−4.54	−1.04	−0.22	−1.33	1.07	−0.08	−0.54	0.38
WI	0.45	−0.42	1.31	3.48	2.37	4.23	1.98	1.48	2.47
WV	1.38	0.43	2.39	3.57	1.87	5.57	5.19	4.48	5.98
NEE	1.63	−0.29	2.63	2.24	0.05	3.72	3.10	2.62	3.58
NJ	−2.98	−4.10	−1.80	−0.63	−2.14	1.02	0.76	−0.06	1.51
NY	2.44	1.55	3.33	4.66	3.25	5.40	2.29	1.87	2.70
EMU	−0.31	−0.61	−0.09	0.70	0.39	1.15	0.77	0.63	0.90
AR	−0.68	−1.59	0.29	−0.81	−1.96	0.58	0.71	−0.08	1.5
CO	−0.13	−1.06	0.84	−0.13	−1.33	1.19	0.23	−0.34	0.82
IA	0.21	−0.56	0.97	0.34	−0.55	1.71	0.46	−0.12	1.05
KS	−0.17	−0.79	0.46	0.11	−0.67	0.87	0.43	−0.16	1.03
MN	−1.19	−2.02	−0.35	−1.63	−2.97	−0.30	−1.17	−1.72	−0.61
MO	−2.47	−3.22	−1.78	−2.10	−2.91	−1.09	−1.61	−2.15	−1.04
MT	−0.72	−1.90	0.45	−0.01	−1.24	1.18	−0.78	−1.44	−0.08
NE	−0.88	−1.39	−0.35	−0.37	−1.19	0.13	−0.17	−0.73	0.41
NM	0.17	−0.67	1.00	0.83	−0.26	2.01	−0.15	−0.94	0.61
ND	0.08	−0.72	0.88	0.57	−0.40	1.43	0.77	0.16	1.39
OK	−0.66	−1.62	0.33	0.31	−0.76	1.43	−1.32	−1.87	−0.73
SD	−0.09	−0.79	0.65	0.33	−0.58	1.12	0.23	−0.37	0.87
TX	−0.57	−1.01	−0.14	0.94	0.40	1.60	−0.80	−1.18	−0.43
WY	−1.60	−2.62	−0.61	−2.83	−4.37	−1.56	−0.75	−1.55	0.05
Central	−0.53	−0.74	−0.31	0.11	−0.17	0.39	−0.33	−0.51	−0.16
AZ	−0.98	−1.60	−0.37	−3.52	−4.38	−2.31	−1.14	−2.04	−0.27
CA	−1.90	−2.47	−1.32	−1.89	−2.64	−0.84	−0.52	−1.03	−0.01
ID	−1.05	−1.93	−0.15	0.15	−1.15	2.33	−0.10	−1.17	0.94
NV	−2.64	−3.89	−1.33	−2.48	−4.09	0.50	−0.71	−1.92	0.52
OR	−0.89	−1.93	0.17	−2.21	−3.49	−0.04	−0.46	−1.48	0.51
UT	−1.66	−2.68	−0.68	−2.66	−4.20	−1.41	−0.55	−1.54	0.46
WA	−0.50	−2.22	1.23	1.85	−1.80	2.03	0.54	−1.24	2.28
Western	−1.47	−1.81	−1.15	−1.95	−2.42	−1.05	−0.70	−1.11	−0.30

changes in temperatures for May, the month of the survey. Monthly estimated temperature by state was available from the National Oceanic and Atmospheric Administration (National Climatic Data Center 2009). Most doves initiate breeding considerably earlier in the year, and we used the temperature from the survey period as a measure of the seasonal progression by the time of the survey. If the heard index decreased as more doves paired, the trend in birds seen would increase differentially relative to trends based on the CCS-heard index as temperature increased. We used simple linear regression to evaluate this hypothesis. States were the replicates in the analysis ($N = 47$); we did not include Rhode Island in the analysis due to small sample size of routes in the state.

RESULTS

We conducted 5 primary hierarchical model analyses and 2 route-regression analyses. We based the CCS-heard analysis on 40,013 counts by 8,077 observers, the CCS-seen analysis on 39,894 counts by 8,048 observers, the CCS-heard-disturbance analysis on 37,065 counts by 7,537 observers, the CCS-seen-disturbance analysis on 37,032 counts by 7,519 observers, and the BBS analysis on 77,116 counts by 13,294 observers. Minor differences in sample sizes reflect occasional missing data and other inconsistencies in route data.

Population Trend Estimated From CCS-Heard and CCS-Seen Indices

Trend estimates based on CCS-heard and CCS-seen indices differed in some states and regions. In the EMU, the 1966–

2007 mourning dove population trend was −0.31 (CrI = −0.061, −0.09) based on CCS-heard data and 0.70 (CrI = 0.39, 1.15) based on CCS-seen data. Trends between CCS-heard and CCS-seen indices were different (as defined by nonoverlapping CrIs) in Florida, Michigan, South Carolina, Tennessee, and Wisconsin (Table 1). Trends from CCS-seen indices were more positive in 19 of the 21 EMU states. On average, CCS-seen trends were larger by 1.5% (CI = 1.07, −1.95). However, trends based on the CCS-heard index were more precise, because half-widths of the credible intervals of the CCS-seen indices were 0.26 (CI = 0.15, 0.37) larger than those based on CCS-heard indices.

Estimated trends from CCS indices were not consistent among regions. In the CMU, the 1966–2007 trend was −0.53 (CrI= −0.74, −0.31) based on CCS-heard data and 0.11 (CrI= −0.17, 0.39) based on CCS-seen data. Trends were different (as defined by nonoverlapping CrIs) only in Texas (Table 1). Trends based on the CCS-seen index were more positive in 11 of the 14 CMU states, but on average, CCS-seen trends were only slightly larger than the CCS-heard trends (0.3; CI = −0.04, −0.64). Trends based on the CCS-heard index were more precise, because half-widths of the credible intervals of the CCS-seen indices were 0.23 (CI = 0.15, 0.30) larger than those based on CCS-heard indices.

In the WMU, the 1966–2007 trend was −1.47 (CrI = −1.81, −1.15) based on CCS-heard data and −1.94 (CrI = −2.42, −1.05) based on CCS-seen data. Trends differed (as defined by nonoverlapping CrIs) only in Arizona, where the CCS-seen trend was more negative than the CCS-heard trend (Table 1). Relative to CCS-heard trends, CCS-seen trends were more positive in 4 of the 7 WMU states. On average, CCS-seen trends were similar (−0.16 mean difference; CI = −1.37, −1.05). Trends based on the CCS-heard index were more precise, because half-widths of the credible intervals of the CCS-seen indices were 0.58 (CI = 0.10, 1.06) larger than those based on CCS-heard indices.

Estimating equation (EE) results and hierarchical model (HM) results were similar for CCS-heard and CCS-seen indices. Estimates for CCS-heard were similar in magnitude by region (EMU: −0.31 [HM] vs. −0.37 [EE]; CMU: −0.53 [HM] vs. −0.70 [EE]; WMU: −1.47 [HM] vs. −1.86 [EE]). For heard data, confidence intervals from EE trend estimates were larger than the CrI from HM estimates in all regions (0.65 [CI = 0.43, 0.86] in EMU, 0.73 [CI = 0.34, 1.11] in CMU, and 0.80 [CrI = 0.38, 1.21] in WMU). Estimates for CCS-seen showed similar patterns and were similar in magnitude by region (EMU: 0.70 [HM] vs. 0.39 [EE]; CMU: 0.11 [HM] vs. 0.06 [EE]; WMU: −1.94 [HM] vs. −2.09 [EE]). In only 11 of the 42 states were estimating equation estimates larger than hierarchical model estimates. For seen data, confidence intervals from EE trend estimates were larger than the CrI from HM estimates in all regions (0.71 [CI = 0.40, 1.01] in EMU, 0.69 [CI = 0.35, 1.03] in CMU, and 1.29 [CI = 0.48, 2.19] in WMU).

Disturbance and CCS Trends

Change in amounts of noise-disturbance varied within and among regions. In the EMU, Florida, Michigan, Pennsylvania, South Carolina, and New York had a positive trend in disturbance; Mississippi and North Carolina had declining rates of disturbance. Overall in the EMU, disturbance changed little over 1966–2007 (Fig. 1). In the CMU no state had increasing disturbance; Nebraska and South Dakota had negative trends, and overall disturbance declined at a rate of 0.3%/yr in the CMU. In the WMU, only Washington had credible intervals indicating an increase in disturbance over time. Overall in the WMU, the credible interval of the estimated trend in disturbance of 0.34%/yr overlapped zero (Fig. 1).

Disturbance influenced CCS-heard indices but had less effect on CCS-seen indices. For CCS-heard, we estimated the parameter p that determined shape of the relationship between disturbance and counts as −0.52 (CrI = −0.82, −0.23) and the coefficient B that described strength of the relationship as 0.04 (CrI = 0.03, 0.06). For CCS-seen, the estimated shape parameter p was 0.73 (CrI = −1.19, 3.7) and B was 0.02 (CrI = −0.01, 0.06). Differences in p had large effects on the shape of the disturbance effects, as the significant disturbance effects predicted extensive diminution of the CCS-heard index with higher levels of disturbance (Fig. 2).

Although effort effects were significant for CCS-heard, controlling for effort in the analysis of population change had only minor consequences for regional estimation of population change. Estimates of long-term trend were almost identical in the EMU (−0.31 without disturbance covariable, −0.32 with the covariable), similar in the CMU (−0.53 vs. −0.51), and in the WMU the estimate was less negative when we included disturbance (−1.47 without, −1.19 with), although overlapping credible intervals indicated a lack of significance. Incorporating the disturbance covariate led to trend estimates larger in magnitude in 27 of the 42 states in the analysis.

Incorporating disturbance effects had little influence on comparison of CCS-heard and CCS-seen indices. In the EMU, the 1966–2007 trend was −0.32 (CrI = −0.62, −0.09) based on CCS-heard data and 0.86 (CrI = 0.56, 1.15) based on CCS-seen data. In the CMU, the 1966–2007 trend was −0.51 (CrI = −0.74, −0.29) based on CCS-heard data and 0.07 (CrI = −0.25, 0.39) based on CCS-seen data. In the WMU, the 1966–2007 trend was −1.18 (CrI = −1.55, −0.83) based on CCS-heard data and −1.55 (CrI = −2.07, −1.05) based on CCS-seen data.

Temperature and Land-Use Associations with CCS Trends

Trends based on the CCS-seen index tended to be more negative in states where there was a positive trend in May temperatures (Fig. 3; slope of regression −2,335 [CI = −4,051, −618]). Trends based on the CCS-heard index had a weaker association (slope = −934 [CI = −2,300, 432]), and the difference between the 2 indices also was associated with trends in May temperature (slope = −1,400 [CI = −2,369, −433]).

There was a positive, although weak, relationship between differences in CCS indices (CCS-seen − CCS-heard) and

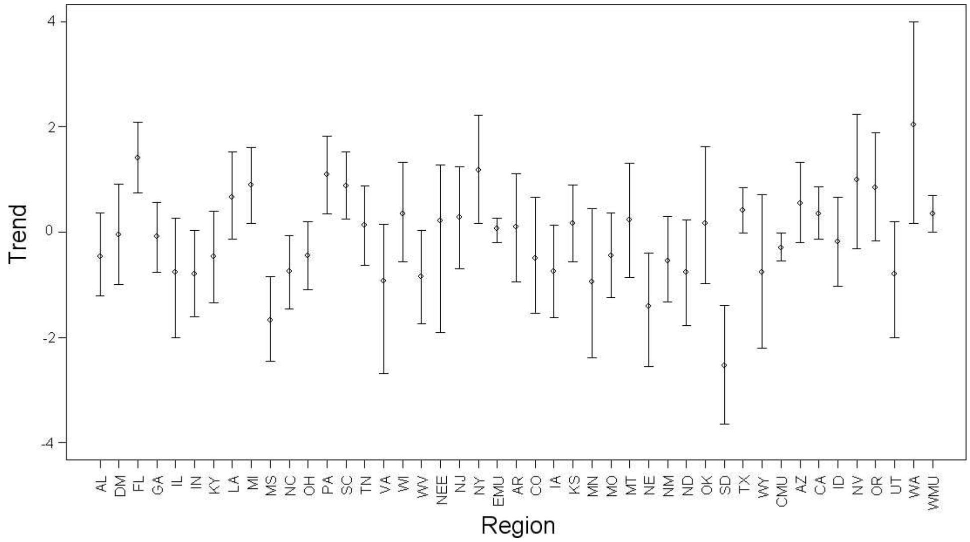

Figure 1. Estimated trend in noise-related disturbance (% change/yr ± 95% credible intervals) for 1968–2007 based on data collected during the Mourning Dove Call-Count Survey for states across the United States (NEE is New England; DM is DE and MD combined) and Eastern (EMU), Central (CMU), and Western (WMU) Management Units.

change in the NRI measure of developed land by state (slope = 0.51 [CI = −0.15, 1.17]; Fig. 4). This relationship also appeared when we used the longer term (1966–2007) dove change estimates in the analysis (slope = 0.40 [−0.03, 0.83]).

For the 1992–2001 land-use change analysis using NLCD data, associations of CCS trends with change in land use showed positive associations of nonurban open land-use changes and trends in both CCS-heard (slope = 1.26 [CI = 0.25, 2.27]) and CCS-seen (slope 1.52 [CI = 0.03, 3.02]); slopes were similar for the indices. Slopes of the associations of change in urban land uses were weakly negatively associated with both CCS-heard (slope = −1.03 [CI = −2.78, 0.72]) and CCS-seen (slope −0.98 [CI = −3.58, 1.62]) indices. There were no apparent differential effects of changes in either land-use type on the CCS indices.

BBS

The BBS showed a more optimistic view of dove populations than did the CCS-heard. We note that, due to variation in the starting year of the BBS by region, the CMU results represent the interval 1967–2007 and the WMU results are for 1968–2007. In the EMU, the 1966–2007 trend was 0.77 (CrI = 0.63, 0.90) based on BBS, similar to CCS-seen results (0.70) but larger than the −0.31 based on CCS-heard data. Trends differed between BBS and CCS-heard in Florida, Indiana, Ohio, Pennsylvania, Tennessee, Virginia, Wisconsin, and New Jersey, and magnitudes of trends differed by >1.5% between indices in several other states (Table 1). Trends based on CCS-seen were more consistent with BBS results, varying only in New York. Trends based on the BBS were more precise than CCS indices; half-widths of the credible intervals of trends based on the CCS-heard indices were 0.36 (CI = 0.21, 0.50) larger, and CCS-seen indices were 0.63 (CI = 0.49, 0.77) larger, than those based on BBS indices.

Patterns of change among CCS and BBS indices were not consistent among regions. In the CMU, the 1966–2007 BBS trend was −0.33 (CrI = −0.51, −0.16), more positive

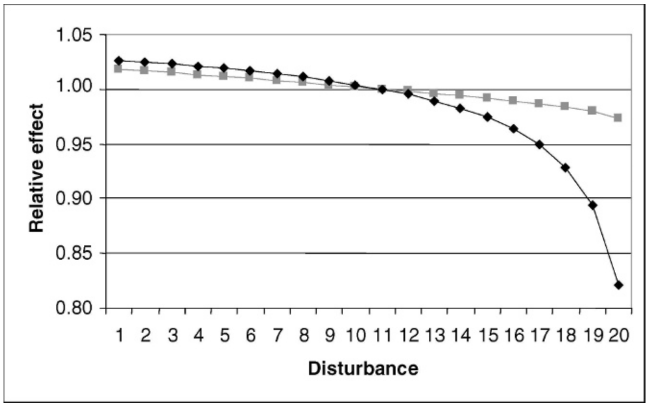

Figure 2. Proportional effect of disturbance (sum of stops with moderate or high disturbance) on Mourning Dove Call-Count Survey (CCS-heard [diamonds] and CCS-seen [boxes]) indices based on data from the contiguous United States, 1968–2007.

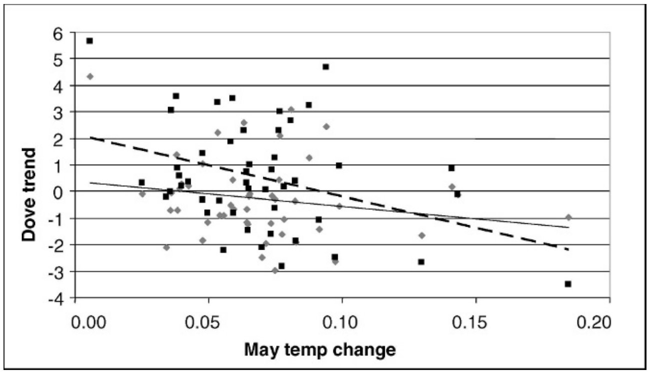

Figure 3. Association of yearly percentage change in average May temperature and Mourning Dove Call-Count Survey (CCS)-heard (diamonds, solid line) and CCS-Seen (boxes, dashed line) trend estimates from the contiguous United States over the interval 1966–2007.

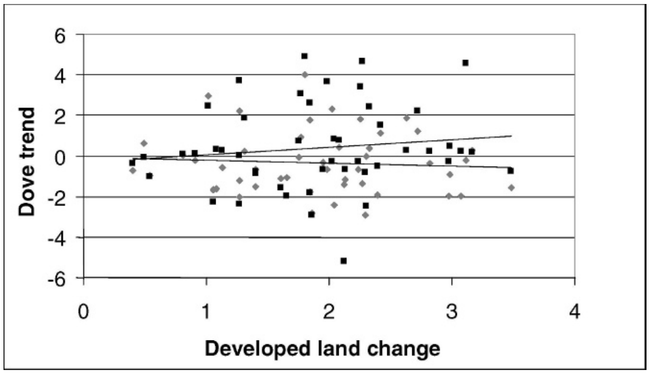

Figure 4. Association of yearly percentage change in developed land and difference in Mourning Dove Call-Count Survey (CCS)-heard (diamonds, solid line) and CCS-seen (boxes, dashed line) trend estimates from the contiguous United States over the interval 1966–2007.

than −0.53 based on CCS-heard data but more negative than 0.11 based on CCS-seen data. Trends were different (as defined by nonoverlapping CrIs) only in the CCS-seen index for Texas (Table 1). Trends based on the BBS were more precise than CCS indices, because half-widths of the credible intervals of trends based on the CCS-heard indices were 0.19 (CI = 0.11, 0.27) larger, and trends based on CCS-seen indices were 0.41 (CI = 0.31, 0.52) larger, than those based on BBS indices.

In the WMU, the 1968–2007 BBS trend was −0.70 (CrI = −1.11, −0.30), more positive than −1.47 based on CCS-heard data and −1.94 from CCS-seen data. Trends were different (as defined by nonoverlapping CrIs) between BBS results and CCS results for both indices for California (Table 1). Trends based on the BBS were not more precise than CCS-heard indices in the WMU; half-widths of the credible intervals of the BBS indices were 0.04 (CI = 0.05, 0.14) larger. However, half-widths of credible intervals of trends from CCS-seen indices were 0.54 (CI = 0.05, 1.03) larger than those based on BBS indices.

Annual Indices of Abundance

We present annual indices of abundance for EMU, CMU, and WMU for CCS-heard, CCS-seen, and BBS results (Fig. 5). The BBS index is larger because it is based on over twice the number of stops as the CCS. In the EMU, fluctuations caused by severe winters in 1976–1977 are evident in the time series, but the CCS-seen and BBS results plot a generally increasing trajectory, whereas the CCS-heard results do not show the increase. As mentioned earlier, trajectories of CCS-seen and CCS-heard indices appear more divergent in recent years. The CCS-heard index adjusted for disturbance is slightly larger than the unadjusted heard index in the early years, but shows similar patterns in later years. In the CMU, BBS results and CCS-heard data show declines, whereas CCS-seen shows a stable population. Adjusting for disturbance does not change the CCS-heard index (Fig. 5). In the WMU, all annual indices are similar.

Florida and Texas are influential states in which indices show differing patterns of population change (Fig. 6). We plotted human census data (United States Census Bureau 2009) to illustrate the association of dove counts and human population. Human population increases with the CCS-seen indices in the states, but phenology (as summarized by mean temp data) has little association with dove indices (Fig. 6).

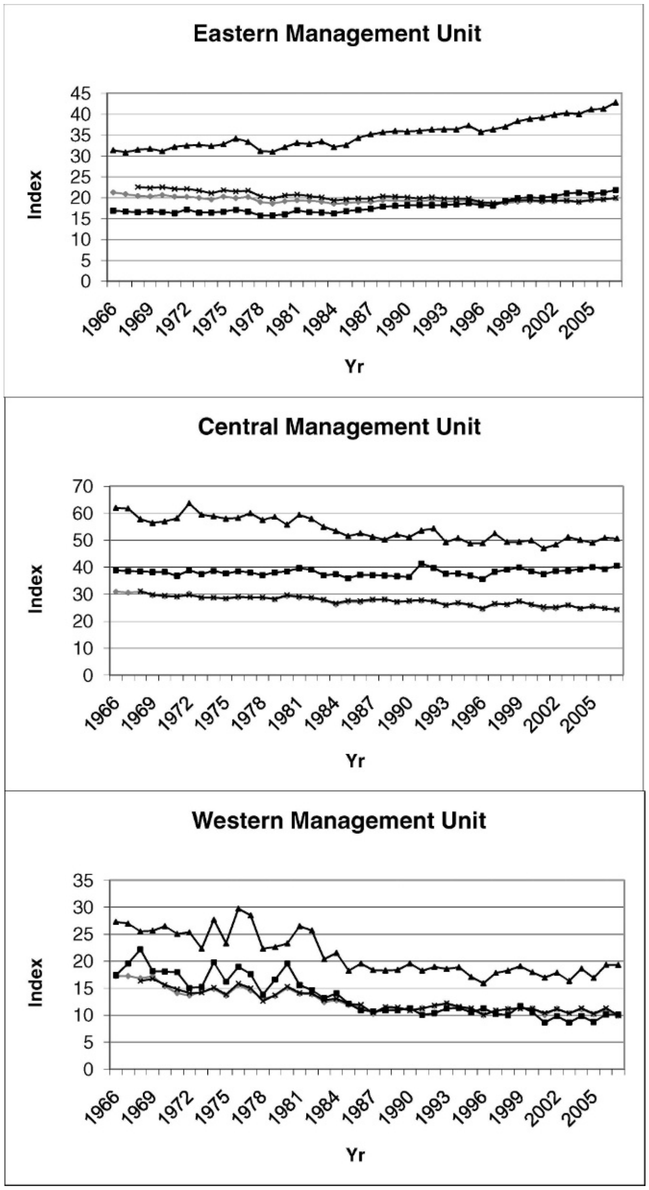

Figure 5. Annual indices of abundance for mourning doves in the Eastern, Central, and Western Management Units, based on Call-Count Survey (CCS)-seen (boxes), CCS-heard (diamonds), indices adjusted for disturbance for the CCS-heard index (x), and North American Breeding Bird Survey data (triangles) over the interval 1966–2007.

DISCUSSION

The log-linear hierarchical model provides a convenient framework for analysis of mourning dove population change from CCS and BBS data. For the first time, we were able to directly include inexperience effects of observers and disturbance effects in the model and calculate credible intervals for the annual indices. The hierarchical model is easily modified to include both additional covariates and

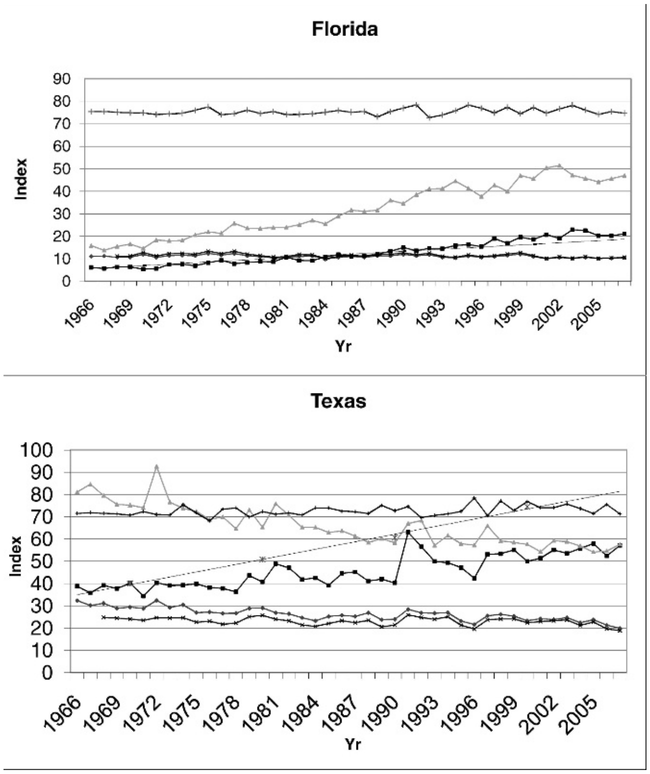

Figure 6. Annual indices of abundance for mourning doves in Florida and Texas, based on Call-Count Survey (CCS)-seen (boxes), CCS-heard (diamonds), North American Breeding Bird Survey data (triangles), and the CCS-heard-disturbance index (x) for the interval 1966–2007. We also present time series of mean May temperatures (+) and a linear description of human population estimates scaled to the dove CCS-seen population index in 1970. We present the 3 data points for human population with dashes.

spatial effects (e.g., Thogmartin et al. 2007). We directly documented effects of disturbance, showed that this effect differed between the CCS-seen and CCS-heard indices, and estimated population change in doves while controlling for disturbance in analysis of count data.

Hierarchical model results also documented differences in trend estimates among the CCS-heard, CCS-seen, and BBS indices in several states (notably TX, FL, and AZ) and in Dove Management Units. Estimates of population change based on the CCS-heard index tended to provide more negative estimates in areas in which they differed from the CCS-seen index. Analyses based on BBS results, which contain information on doves either seen or heard, generally tended to provide estimates either similar to the CCS-seen index or intermediate between results of CCS-heard and CCS-seen analyses.

These inconsistencies complicate our use of dove survey results for management, because it is unclear whether any of the indices accurately reflect actual changes in the dove population. Identification of environmental features that are differentially influencing the indices and appropriate incorporation of these features into analyses to control for these differential effects of counting should be a high priority for survey analysis. Our hierarchical models provide an appropriate framework for incorporating covariates that influence detection of doves.

Factors That Influence Indices

It is likely that disturbance, phenology, and land-use changes all influenced the differences we documented in the CCS indices. All of these influences vary regionally, complicating analysis and interpretation of results. All correlations must be viewed with caution, but they do allow us to evaluate the consistency of hypotheses regarding changes in the indices.

All roadside bird counters understand the limitations on counting imposed by ambient noise and traffic, and we documented that several of the states in which estimated dove trends differed between CCS indices have also experienced increases in disturbance over the survey period. We found that CCS indices were differentially affected by disturbance. Whereas the CCS-seen index was influenced little by disturbance the CCS-heard index declined as amount of disturbance increased. However, disturbance was not consistently increasing over the survey area, and the actual consequences of controlling for disturbance were slight for the CCS indices; controlling for changes in disturbance did not eliminate differences in estimates.

Most noise-based disturbance is human-mediated. Increases in vehicle traffic, lawn mowing, and other domestic aspects of increasing urbanization accompany increasing human population along routes and correlate with development and other land-use changes. Consequently, temporal trends in disturbance and the covariate effects of disturbance may reflect the influence of broader land-use change effects.

Although not presently a critical component of the analysis, there is a clear need to monitor disturbance and retain it as a possible covariate for future analyses. More investigation is also needed into refining the disturbance covariate. As with counts, it is likely that there is much observer interpretation of disturbance, and although our analysis of trends in disturbance controlled for these observer effects, the disturbance covariate did not. There are also many ways to summarize disturbance, and our measure tended to emphasize strong disturbance at stops. Exploration of alternative disturbance metrics may clarify the incremental effects of disturbance on counts.

Although phenology likely affects both CCS-heard and CCS-seen data, the negative association of mean May temperature with indices was stronger for CCS-seen, contrary to our hypothesis. Changes in May temperatures were often slight, and May temperatures have exhibited much year-to-year variation in recent years (e.g., Fig. 6), and changes in May temperature did not explain disagreements between dove indices in Florida and Texas. However, phenology is associated with the seen index, particularly in the central and western United States where more doves are seen than heard along CCS routes. Patterson (2005) noted that National Oceanic and Atmospheric Administration temperature data documented increases in spring temperature in recent decades in the western United States but little change in the southeastern United States. The influence of phenology on dove counting clearly merits further study, as trends in temperature data make it more likely that any temperature-related effects on phenology will become more prevalent in the future (Patterson 2005).

Associations we noted between rates of development and differences in trend estimates suggested that development may lead to increases in numbers of doves seen. However, weak associations (even for 1966–2007 trend estimates, the CrI of the slope estimate still slightly overlapped zero) did not permit definitive statements about relationships between indices and land use. Similarities in rate of human population change and rate of increase in the CCS-seen indices in Florida and Texas are also consistent with the notion that human-related development may be differentially influencing the CCS-seen index. Data were not available for recent years, even though changes between heard and seen indices may be most dramatic in recent years. Further exploration of the association of recent changes in dove indices and land-use changes may provide better insights into relationships between doves seen and land-use changes.

Limitations of Association Analyses

Our evaluation of factors influencing seen and heard dove indices should be viewed as exploratory, because we based it on observational data and it was limited by availability of covariates at appropriate spatial and temporal scales. Disturbance could be convincingly accommodated in the analysis because it was collected as part of the survey; other covariates were available only at the scale of states and for only a few times during the 42-year period in which the CCS has been conducted. States were not a particularly useful replicate for analyses, because they vary in size and many factors also vary spatially and are likely confounded in the analysis. Finally, review of the indices suggests that differences in CCS-seen versus CCS-heard indices may be more pronounced in recent years. A more informative analysis of land-use change may be possible when recent (post-1995) land-use change data become available for comparison with dove indices.

A critical goal of future analyses must be to more effectively use covariate analyses to control for factors that influence detectability of doves. The best way to control for detectability is to collect information (or obtain better information as it becomes available) at the scale of survey routes, allowing for analyses at the scale of the sample units of the survey. Better data collected at the scale of survey routes would facilitate direct incorporation of these covariates into the hierarchical analysis. Texas and Florida are states that merit more intensive analyses of effects of land-use change on dove populations, because those states have large samples of survey routes, notable differences in index results, and are rapidly urbanizing.

MANAGEMENT IMPLICATIONS

Hierarchical models should be used for analysis of CCS data in future Mourning Dove Status Reports (Dolton et al. 2007). Hierarchical models provide a coherent framework for appropriate estimation of estimates and variances, provide efficient estimates of change derived directly from the annual indices, and allow for easy accommodation of covariates. The hierarchical structure is also a natural framework for 2 additional modeling activities needed for management: 1) composite analyses of CCS and BBS data, a topic currently under consideration by managers (National Mourning Dove Planning Committee 2003; D. R. Otis, United States Geological Survey, unpublished data), and 2) development of demographic models that use CCS data and survival and productivity data to make predictions of future populations needed for harvest management (Nichols and Williams 2006). Composite models that integrate surveys and demographic data would facilitate direct use of CCS and BBS data in dove population management.

However, differences in results we documented among analyses based on CCS-seen, CCS-heard, and BBS indices suggest the need for additional studies before implementation of models that integrate surveys. All indices are not equal, in terms of both precision and bias in estimation, and there is a clear need to better understand the limitations of each index. Further evaluations of effects of development and changes in phenology on the indices are needed and will be critical in increasing our understanding of environmental influences on detectability of mourning doves. Opportunities exist to conduct studies at the scale of individual stops to associate changes in CCS-heard and CCS-seen indices with temperature and land-use information, and these site-specific analyses should provide more powerful tests of hypotheses about factors influencing detectability. Hierarchical models provide a coherent analysis framework that will be essential for these multiple-scale analyses of environmental influences on dove indices.

Finally, our results clearly indicate that even well-implemented index surveys may not always be interpretable due to unmodeled changes in detection of doves; reducing uncertainty in survey results must be a priority for managers. The most direct way of reducing this uncertainty is to implement sampling procedures that permit estimation of detection rates during surveys, and we encourage continued investigation of ways to efficiently estimate detectability from both the CCS and BBS.

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