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Estimation and Correction of Visibility Bias in Aerial Surveys of Wintering Ducks

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ABSTRACT Incomplete detection of all individuals leading to negative bias in abundance estimates is a pervasive source of error in aerial surveys of wildlife, and correcting that bias is a critical step in improving surveys. We conducted experiments using duck decoys as surrogates for live ducks to estimate bias associated with surveys of wintering ducks in Mississippi, USA. We found detection of decoy groups was related to wetland cover type (open vs. forested), group size (1–100 decoys), and interaction of these variables. Observers who detected decoy groups reported counts that averaged 78% of the decoys actually present, and this counting bias was not influenced by either covariate cited above. We integrated this sightability model into estimation procedures for our sample surveys with weight adjustments derived from probabilities of group detection (estimated by logistic regression) and count bias. To estimate variances of abundance estimates, we used bootstrap resampling of transects included in aerial surveys and data from the bias-correction experiment. When we implemented bias correction procedures on data from a field survey conducted in January 2004, we found bias-corrected estimates of abundance increased 36–42%, and associated standard errors increased 38–55%, depending on species or group estimated. We deemed our method successful for integrating correction of visibility bias in an existing sample survey design for wintering ducks in Mississippi, and we believe this procedure could be implemented in a variety of sampling problems for other locations and species. (JOURNAL OF WILDLIFE MANAGEMENT 72(3):808–813; 2008)

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Estimating animal abundance by aerial survey has a long history and prominent role in wildlife science and management, yet a fundamental concern when surveying is that some animals are not seen by observers (Caughley 1974, 1977; Norton-Griffins 1975). Failure to detect all animals within a sampled area is termed visibility bias, a primary source of error in aerial surveys (Pollock and Kendall 1987). Ignoring visibility bias leads to underestimates of abundance; therefore, survey practitioners should acknowledge the existence and influence of visibility bias when designing aerial surveys and attempt to adjust estimates accordingly.

Numerous methods exist to correct visibility bias, although no method is best for all situations (Pollock and Kendall 1987). A simultaneous air and ground survey is a well-established method to correct for visibility bias in breeding-ground surveys of North American waterfowl, but this method is expensive and assumes ground surveys detect all individuals without error (Martinson and Kaczynski 1967, Martin et al. 1979, Smith 1995). A multiple-observer or removal method uses mark–recapture models to estimate the proportion of individuals missed by observers (Cook and Jacobson 1979). The multiple-observer method has undergone logistical and analytical refinements (Pollock et al. 2006), but its implementation is difficult when large numbers of animals are present (Pollock and Kendall 1987). Distance sampling uses the distance from an individual or group and the observer as the primary means of correcting bias via estimation of a detection function (Buckland et al. 1993). Use of distance sampling has been tested for fixed-wing aerial surveys of large mammals and helicopter surveys of waterfowl (Johnson et al. 1989, Trenkel et al. 1997). Finally, sightability models apply correction factors to observed groups of individuals based on estimated relationships between probabilities of detection and group-specific covariates. Researchers have developed these models for ungulate and waterfowl surveys (e.g., Samuel et al. 1987, Giudice 2001). Sightability models can be less expensive to apply than other methods, but their use requires several assumptions (e.g., closed population, independence of group detections, groups are counted without error; Steinhorst and Samuel 1989, Giudice 2001).

We developed a sightability model to correct for visibility bias associated with aerial surveys of wintering ducks. Local, regional, and continental estimates of waterfowl abundance are critical for population and habitat conservation, yet rigorous surveys to estimate abundance of wintering waterfowl generally have not become operational (Conroy et al. 1988, Reinecke et al. 1992). Previous researchers have suggested heterogeneous visibility bias existed in aerial surveys of wintering ducks (Johnson et al. 1989, Smith et al.

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1995), and researchers attempting to derive bias-corrected estimates have encountered logistical and analytical constraints, specifically incorporation of undercounting individuals within detected groups (Smith 1993, Cogan and Diefenbach 1998). Therefore, our objectives were to estimate visibility bias of ducks during aerial surveys conducted in Mississippi, USA, winters 2002–2004, and to develop a method that incorporates detection rates and count bias of groups into analytical procedures that estimate abundance of wintering duck corrected for visibility bias.

STUDY AREA

Our study sites were located within the Mississippi Alluvial Valley (MAV) physiographic region, a continentally important region for migrating and wintering waterfowl in North America covering 10 million ha and portions of 7 states (Reinecke et al. 1989). Historically, the MAV was an extensive bottomland-hardwood ecosystem composed of various hard- and soft-mast–producing trees that provided important forage and other habitat resources for waterfowl and other wildlife (Fredrickson et al. 2005). Extensive landscape changes occurred during the 20th Century, and large portions of the MAV were cleared of trees and cultivated for agricultural production. We conducted our experiment on 3 privately owned sites in northwestern Mississippi: 1) Wild Wings near Holcomb, Mississippi in Grenada County; 2) Gumbo Flats near Lambert, Mississippi in Quitman County; and 3) York Woods near Charleston, Mississippi in Tallahatchie County. All 3 areas included habitats typically used by ducks during winter in the MAV (i.e., forested wetlands, emergent herbaceous wetlands, and flooded croplands; Reinecke et al. 1989).

METHODS

Visibility-Bias Experiment

Smith et al. (1995) investigated covariates influencing visibility bias of wintering ducks using decoys as surrogates for live ducks, and we used the same approach because it allowed control over experimental variables of interest. We investigated the 2 primary covariates we believed had a considerable influence on visibility bias (i.e., group size and wetland type) and randomly assigned treatments to decoy groups. We defined group size as a continuous variable ranging from 1 to 100 and did not include group sizes >100 because they occurred rarely in field surveys (e.g., represented 6% of approx. 2,000 groups observed in winter 2003; Pearse 2007) and were difficult logistically to replicate. To construct a realistic distribution of group sizes, we partitioned group size into quartiles for all groups of 1–100 individuals observed during surveys in winters 2002 and 2003 (i.e., 1–8, 9–20, 21–40, and 41–100; Pearse 2007) and selected the size of experimental decoy groups from a uniform distribution between the minimum and maximum values of the 4 categories. We included 2 wetland types based on degree of openness of vegetation structure. We defined open wetlands as those without woody vegetation above the water surface and included flooded crop fields, seasonal emergent wetlands, and permanent wetlands (e.g., rivers, oxbow lakes, aquaculture ponds). We defined forested wetlands as those with woody cover above the surface of the water (e.g., scrub shrub, bottomland hardwoods).

To simulate field surveys, we placed decoy groups within experimental transects and ensured the observer had no prior knowledge of the location or configuration of decoy groups. Transects were 250 m wide, arranged in an east–west direction similar to field surveys (Pearse 2007), and they varied in length from 2.3 km to 10.7 km, but they were not located randomly because they had to contain the experimental wetland types. We placed 1–5 decoy groups within each transect at predetermined perpendicular distances from the edge of transects but within the 250-m strip. We determined the number of decoy groups within a transect based on transect length and availability of wetland types for decoy placement. We calculated perpendicular distance of decoy groups from the flight path using a uniform distribution because the true distribution of ducks within transects was unknown.

We conducted experimental surveys on 12, 19, and 26 February 2005 in a Cessna 172 aircraft, flying at approximately 150 km per hour and at a distance of 150 m above ground. Weather conditions varied among surveys but were within parameters acceptable for field surveys. During flights, one of the project staff who participated in decoy placement assisted the pilot in navigating transects. The observer recorded all decoy groups detected, numbers of decoys in each group, and wetland type. During flights, the observer did not receive any communications from the pilot or navigator other than signals indicating the beginning and end of transects.

To reduce potential bias in estimates of detection probabilities, we ensured each decoy group was available for observation (i.e., decoy group was located within the strip transect during the experimental survey). We used a Global Positioning System (GPS) receiver to record the flight path during all surveys and entered these data into a Geographic Information System that included the flight path and GPS location of decoy groups. From these data, we verified that decoy groups were within transects during surveys. Additionally, the navigator reported detection of decoy groups during experimental flights.

During surveillance preceding data collection, we observed live ducks on study sites near decoy groups. Presence of these ducks near or in decoy groups during experimental surveys would have inflated group size and potentially introduced bias by increasing visibility of the group. Thus, we positioned project personnel in locations near decoy groups to disperse any ducks before surveys commenced.

Source of Aerial Survey Data

We used data from an aerial waterfowl survey conducted 26–30 January 2004 to demonstrate application of our bias-correction procedure, although the same procedure could be applied to any survey data set with the same observer. The basic survey method was a stratified random sample design (Pearse 2007). We designated strip transects as sample units, randomly selected them with replacement and probability proportional to length, and allocated sample effort among strata using the Neyman method (Caughley 1977, Cochran 1977). We conducted aerial surveys using methods similar to Reinecke et al. (1992). We recorded number of mallards (*Anas platyrhynchos*), other dabbling ducks (Anatini), and diving ducks (Aythyini, Mergini, and Oxyurini) observed within each transect and used the SAS procedure SURVEYMEANS (SAS Institute, Inc., Cary, NC) to estimate population indices ($\hat{I}$) of these groups and total ducks from sums of individuals counted within transects and transect-specific sample weights (Lohr 1999).

Data Analysis and Estimation

We decomposed visibility bias into 2 response variables for analysis. Group-detection rate was the probability that the observer detected a group of decoys. We modeled group detection rate using logistic regression, wherein the dependent variable was a binomial response (i.e., detected or missed) and independent variables were group size (continuous) and wetland type (categorical). We performed analyses using the GENMOD procedure in SAS with the binomial probability distribution and logit link function. The observer could incorrectly estimate the size of decoy groups that were detected and introduce counting error. We assumed counting error included systematic bias and random error; thus, we referred to this systematic bias as count bias and estimated it by comparing observer counts of groups with known group sizes (Krebs 1999). To model count bias, we performed an analysis of covariance (ANCOVA) on the subset of observations where groups were detected (PROC MIXED). In this ANCOVA, the proportion of ducks counted was the dependent variable and group size and wetland type were independent variables. We used backwards elimination with a criterion of $P > 0.10$ for variable exclusion to select final models in analyses of detection and counting bias.

We developed a method to estimate abundance of ducks ($\hat{N}$) by correcting population indices ($\hat{I}$) for visibility bias. We corrected for group-detection and count biases simultaneously via a series of weight adjustments. We based this procedure on the concept of sampling weights, where a sample unit's weight is the inverse of its probability of selection (Lohr 1999). In the same manner that a sample weight corresponds to the number of units in the population represented by the selected unit, group-detection and count weights represented number of groups and ducks in the sample unit missed by the observer. For example, if probability of detection of a group with a certain set of characteristics was 0.50 (wt = 1/0.5 = 2), a second group with the same characteristics must be accounted for because it was not detected, which we accomplished by multiplying the group's size by the weighting factor (e.g., 5 ducks obs × wt of 2 = 10 ducks). We accounted for count bias in the same manner. If we estimated count bias at 0.80 given a group was detected, then the reciprocal of that estimate could be used as a correction factor or weight to adjust counts (1/0.8 = 1.25). To complete the example, this

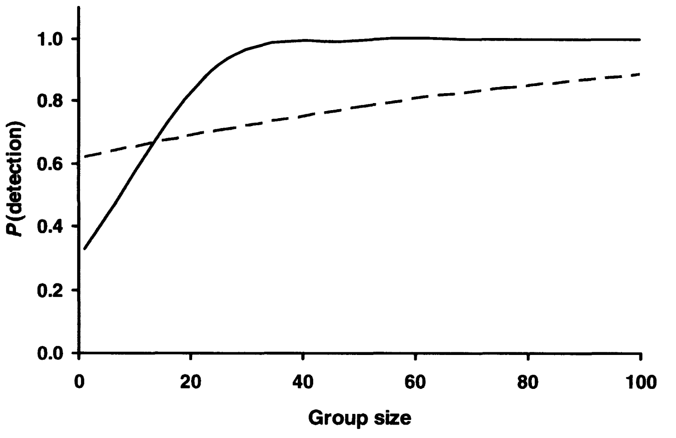

Figure 1. Predicted relationship between probability of detecting decoy groups ($n = 81$) and group size (1–100) for groups placed in open (solid line) and forested (dashed line) wetlands on 28 experimental strip transects in western Mississippi, USA, winter 2005. We estimated probability of observing a decoy group in forested wetlands (P[obs_forest]) by $P(\text{obs\_forest}) = e^{0.476 + 0.016(\text{size})} / 1 + e^{0.476 + 0.016(\text{size})}$ and probability of observation in open wetlands (P[obs_open]) by $P(\text{obs\_open}) = e^{-0.837 + 0.129(\text{size})} / 1 + e^{-0.837 + 0.129(\text{size})}$.

hypothetical observation of a group of 5 ducks actually would represent 12.5 ducks (i.e., 5 × 2 × 1.25 = 12.5).

Results of the visibility bias experiment caused us to consider how group detection rates were estimated using logistic regression. We found group size influenced detection rate, but its effect was only apparent in open wetlands (see Results; Fig. 1). Therefore, we estimated group detection rates for open wetlands using the logistic regression equation and, for forested wetlands, we used the proportion of groups detected after pooling observations over group size (i.e., detection rate independent of group size). Additionally, we corrected observed group size for count bias before estimating group detection rates in open wetlands. Adjusting observed group size before estimating group detection is necessary because group sizes in the visibility bias experiment were known, whereas group sizes recorded during field surveys were subject to count bias.

Although point estimation was relatively straightforward, determining a variance estimation method was challenging. Steinhorst and Samuel (1989) presented a procedure that integrated sampling and group detection errors but assumed no count bias. Cogan and Diefenbach (1998) acknowledged the importance of count bias but did not provide an explicit variance estimator. Lacking an analytic solution, we used bootstrap resampling, an accepted procedure for computing variances from complex surveys (Lohr 1999), to account for errors from sampling, group detection, and count bias in estimating the variance of duck abundance. The bootstrap uses multiple independent resamples from an original sample to reproduce properties of a population (Efron and Tibshirani 1993). To calculate bias-corrected estimates, we bootstrapped the sample of transects from the aerial survey and the group detection and count bias data sets 1,000 times. For each 1,000 data sets, we calculated point estimates of abundance as previously explained using weight

Table 1. Population indices ($\hat{I}$; not corrected for visibility bias) and abundances ($\hat{N}$; corrected for visibility bias), standard errors, and coefficients of variation for mallards, other dabbling ducks, diving ducks, and total ducks estimated from an aerial survey conducted in western Mississippi, USA, 26–30 January 2004.

Species or group	Population index			Abundance		
	$\hat{I}$	SE	CV	$\hat{N}$	SE	CV
Mallards	129,652	11,681	0.09	183,998	18,163	0.10
Other dabbling ducks	91,797	11,784	0.13	124,752	16,575	0.13
Diving ducks	43,174	10,021	0.23	59,573	13,853	0.23
Total ducks	264,623	22,656	0.09	368,323	36,269	0.10

adjustments. We used the mean and standard deviation of abundance estimates from all 1,000 resamples as estimates of ($\hat{N}$) and SE($\hat{N}$), respectively.

We imposed certain constraints on the logistic regression analyses when bootstrapping because the maximum likelihood estimator used in the procedure did not always converge to a finite value for ≥ 1 parameters during all resamples. We selected bootstrap samples following the design of the visibility experiment by constraining resampling so that each resample had the same number of sample units within each combination of wetland-type and group-size quartile as the experimental data (e.g., $n = 10$ for groups of 1–8 decoys in open wetlands). If a resampled data set still failed to converge, we used the proportion of group detections pooled over group sizes within habitats to estimate habitat-specific group detection rates. Finally, whether or not the logistic regression converged, we constrained the probability of group detection to be $\geq 1/n_h$, the inverse of the sample size within wetland types (n_h), because logistic regression may not reliably estimate probabilities $< 1/n_h$.

RESULTS

We sampled 125 transects during the aerial survey conducted 26–30 January 2004 and estimated population indices of 129,652 mallards (SE = 11,681; CV = 0.09), 91,797 other dabbling ducks (SE = 11,784; CV = 0.13), 43,174 diving ducks (SE = 10,021; CV = 0.23), and 264,623 total ducks (SE = 22,656; CV = 0.09). We observed the following percentages of ducks in forested wetlands: mallards, 7.0%; other dabbling ducks, 2.9%; diving ducks, 2.3%; and total ducks, 5.8%. Mean group sizes during the survey were 25.4 birds for mallards, 31.7 for other dabbling ducks, 26.0 for diving ducks, and 32.9 for total ducks.

During the visibility-bias experiment, we collected data from 28 experimental transects containing 81 decoy groups. We replicated each wetland type and group-size quartile combination 10 times except the smallest group-size quartile in forested wetlands (n = 11). The observer detected 60 decoy groups (74%) and 1,427 of 2,269 decoys (63%) placed on transects.

We included wetland type ($\chi^2_1 = 1.97$, $P = 0.161$), group size ($\chi^2_1 = 4.89$, $P = 0.027$), and their interaction ($\chi^2_1 = 3.44$, $P = 0.064$) in the final group-detection model ($R^2 = 0.24$). In a 2-intercept parameterization of the logit model, the intercept for forested wetlands was $\hat{\beta} = 0.476$ (SE = 0.534) and the coefficient for group size was $\hat{\beta} = 0.016$ (SE = 0.017). The intercept for open wetlands was less ($\hat{\beta} = -0.837$; SE = 0.770) and the coefficient for group size greater ($\hat{\beta} = 0.129$; SE = 0.058) than forested wetlands. Generally, probability of group detection for small groups in forests was greater than for small groups in open wetlands, whereas probability of detection of groups with >15 decoys was greater in open than in forested wetlands (Fig. 1). We did not include any of the experimental variables ($P > 0.10$) in the final model of count bias for groups that we detected. Overall, the observer counted 78% (SE = 3%, n = 60) of decoys within detected groups.

Abundance estimates exceeded population indices by 42% for mallards, 36% for other dabbling ducks, 38% for diving ducks, and 39% for total ducks (Table 1). Bias correction increased standard errors of abundance relative to those of population indices by 55% for mallards, 41% for other dabbling ducks, 38% for diving ducks, and 60% for total ducks. However, coefficients of variation increased only slightly after correcting for visibility bias (Table 1).

DISCUSSION

Visibility bias in aerial surveys often results from factors that obstruct the view of animal groups or individuals within groups (e.g., Samuel et al. 1987, Anderson et al. 1998). We found the effects of group size and wetland type interacted to affect detection of decoy groups. Specifically, small groups of decoys in open wetlands had the lowest probabilities of detection, groups of >15 decoys in open wetlands had the greatest probabilities of detection, and detection of groups in forested wetlands was relatively independent of group size. Smith et al. (1995) reported the same pattern in a similar experiment; group size influenced detection of decoy groups in open wetlands but detection rates in forested wetlands were independent of group size or decoy density. We suspect small groups were detected with low probabilities in open wetlands because the observer had difficulty scanning large expanses of open water (e.g., flooded croplands) efficiently enough to detect a small number of individuals. In contrast, flooded forests represented a smaller proportion of available habitat during surveys (Pearse 2007) and generally consisted of smaller wetlands, potentially allowing the observer to scan each more completely and detect decoy groups at a more constant rate relative to group size.

We did not detect effects of wetland type or group size on count bias. This result differs from previous work, where both variables explained variation in count bias (Smith et al.

1995). At group sizes >100, we suspect the magnitude of count bias may increase relative to the value we estimated because others have reported counting accuracy tends to be independent of or decrease slightly with increasing group size (Erwin 1982, Frederick et al. 2003). Failing to account for increased count bias for groups >100 may negatively bias estimates of abundance but, because we observed relatively few large groups of ducks during field surveys, the magnitude of this bias would be small.

The variables manipulated in our visibility experiment explained little of the variation in group-detection rates and none of the variation in count bias. Although Steinhorst and Samuel (1989) concluded that using a perfect visibility bias model was unnecessary, unexplained variation in visibility rates increases variance associated with population estimates, and identifying additional covariates explaining variation in visibility may improve precision of estimates. One option would be to expand the number of wetland categories to explain additional variation in group detection. Smith et al. (1995) used 3 categories of forested wetlands (i.e., cypress [*Cupressus* sp.]–tupelo [*Nyssa* sp.] swamp, shrub swamp, and bottomland hardwoods) and found differences in visibility rates among the types. Furthermore, open wetlands included a variety of emergent wetlands with different attributes (e.g., vegetation structure, water turbidity) and could have been grouped into ≥2 classes with separate estimates of visibility. Additionally, we believe other variables that affect observers' abilities to detect animals may significantly influence waterfowl visibility. Short and Bayliss (1985) reported light conditions influenced visibility of red and grey kangaroos (*Macropus rufus*, *M. fuliginosus*, respectively) in Australia. In aerial surveys of wintering ducks, sun glare from surface water can create heterogeneous visibility conditions. We believe some of the factors determining light conditions (e.g., cloud cover, time of day, and direction of flight path) could be recorded as discrete or continuous variables and provide opportunities to develop more precise models of visibility bias. Other covariates potentially influencing observers' performance include turbulence and fatigue (Krebs 1999).

Correction of population indices for visibility bias increased point estimates and associated standard errors. We anticipated decreased precision because we used model-based correction factors rather than constants. However, correcting for visibility bias using our method of weighting observations for detection and counting rates had little influence on precision of abundance estimates of wintering ducks as measured by coefficients of variation. Additional evaluations are needed to ensure that, after correcting for bias, estimates of abundance have increased accuracy (or decreased mean-squared error), which is not always the case with bias-corrected estimates (Little 1986).

An inherent assumption of our study was that parameters estimated in the decoy experiment represented visibility bias associated with live ducks. We acknowledge decoys were not perfect surrogates for live ducks but the direction and magnitude of any bias is not apparent. The larger size of decoys relative to ducks may have increased visibility, whereas lack of motion among decoys potentially decreased visibility. Sightability models for large mammals have been developed using radiotagged individuals (e.g., Samuel et al. 1987) and a similar study could be conducted with ducks to validate visibility rates estimated with decoys. Additionally, we used mainly mallard decoys to estimate visibility of all ducks. We do not believe this biased our results to a great extent, but experimentation with decoys representing other species would assess the validity this assumption. A more fundamental assumption related to the sightability method is that visibility parameters and their variances are constant among observers and through time. Because the same observer conducted experimental and field surveys in our study, we did not need to consider multiple observers. We recommend aerial surveys of wildlife use a minimum number of observers and estimate separate sightability models for each. Regarding temporal variation, we acknowledge an observer's ability to detect animals may change through time (Johnson et al. 1989). Annual experiments to assess visibility bias would be ideal but likely cost prohibitive and impractical for long-term monitoring of wintering waterfowl in relation to population goals of joint ventures of the North American Waterfowl Management Plan or other avian conservation initiatives (U.S. Department of the Interior and Environment Canada 1986).

MANAGEMENT IMPLICATIONS

Wildlife survey practitioners and managers should recognize that nonconstant bias can exist in aerial surveys. Habitat type, group size, and other variables including observer effects influence detection of animals. Accordingly, estimates for bias correction we developed may have most application for this observer and region. Nonetheless, our method of correcting population indices from aerial surveys of wintering ducks for multiple sources of visibility bias has general applicability and illustrates how natural resource managers can use model-based approaches to correct for visibility bias in wildlife surveys. Previous sightability models for other species and habitats included the assumption that counts of individuals within observed groups were unbiased (Smith et al. 1995, Cogan and Diefenbach 1998, Giudice 2001). Our method of correcting for visibility bias is sufficiently general to allow for counting errors and, therefore, is an improvement over earlier work.

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