Wildlife Society Bulletin 38(1):188–195; 2014; DOI: 10.1002/wsb.374

Tools and Technology

Monitoring Whooping Crane Abundance Using Aerial Surveys: Influences on Detectability

BRADLEY N. STROBEL,[1] *Aransas National Wildlife Refuge, United States Fish and Wildlife Service, 1 Wildlife Circle, Austwell, TX 77950, USA*
MATTHEW J. BUTLER,[2] *National Wildlife Refuge System, United States Fish and Wildlife Service, P.O. Box 1306, Albuquerque, NM 87103-1306, USA*

ABSTRACT The whooping crane (*Grus americana*), an endangered species, has been counted on its winter grounds in Texas, USA, since 1950 using fixed-wing aircraft. Many shortcomings of the traditional survey technique have been identified, calling into question its efficacy, defensibility, repeatability, and usefulness into the future. To improve and standardize monitoring effort, we began investigating new survey techniques. Here we focus on efficacy of line transect-based distance sampling during aerial surveys. We conducted a preliminary test of distance sampling during winter 2010–2011 while flying the traditional survey, which indicated that detectability within 500 m of transects was 0.558 (SE = 0.031). We then used an experimental decoy survey to evaluate impacts of observer experience, sun position, distance from transect, and group size on detectability. Our results indicated decoy detectability increased with group size and exhibited a quadratic relationship with distance likely due to pontoons on the aircraft. We found that detectability was 2.704 times greater when the sun was overhead and 3.912 times greater when the sun was at the observer's back than when it was in the observer's eyes. We found that an inexperienced observer misclassified non-target objects more often than an experienced observer. During the decoy experiment we used marks on the struts to categorize distances into intervals, but we found that observers misclassified distances 46.7% of the time (95% CI = 37.0–56.6%). Also, we found that detectability of individuals within detected groups was affected by group size and distance from transect. We discuss how these results inform design and implementation of future whooping crane monitoring efforts. Published 2013. This article is a U.S. Government work and is in the public domain in the USA.

KEY WORDS aircraft, decoy, distance sampling, endangered species, *Grus americana*, monitoring, sandhill crane, survey techniques, Texas, wintering grounds.

The whooping crane (*Grus americana*) is an endangered species. Its only wild, migratory population breeds in Wood Buffalo National Park, Alberta and Northwest Territories, Canada, and overwinters along the Texas gulf coast centered on Aransas National Wildlife Refuge (NWR), Texas, USA (Canadian Wildlife Service [CWS] and U.S. Fish and Wildlife Service [USFWS] 2007). Since 1938, the whooping crane population has been counted on its wintering grounds (Stehn and Taylor 2008). Starting in 1950, fixed-wing aircraft have been used to implement a technique similar to a cruise survey for waterfowl (Stehn and Taylor 2008). Recently, however, biologists and managers have become concerned about the efficacy, defensibility, and repeatability of the traditional survey technique used to monitor this population (Strobel et al. 2012).

Received: 14 December 2012; Accepted: 30 June 2013
Published: 19 November 2013

[1]*Present address: Necedah National Wildlife Refuge, United States Fish and Wildlife Service, N11385 Headquarters Road, Necedah, WI 54646-7531, USA*
[2]*E-mail: matthew_butler@fws.gov*

The traditional technique was assumed to be a census that documented all individuals in the population (i.e., complete enumeration; Stehn and Taylor 2008). For natural free-ranging wildlife populations, true censuses are exceptionally difficult to achieve for 2 primary reasons. First, most study areas are too large to sample completely within a short enough time frame to ensure geographic closure (Morrison et al. 2008, Conroy and Carroll 2009). Second, the probability of detecting individuals is usually <1 and detectability can be influenced by various circumstances including the behavior of individuals, vegetation density, observer fatigue, and field methodology (Krebs 1999, Buckland et al. 2001, Williams et al. 2002, Morrison et al. 2008, Conroy and Carroll 2009). Stehn and Taylor (2008) recognized that these conditions may bias the results of their survey attempts but they did not provide recommendations to address them.

Many shortcomings of the traditional survey technique have been identified. Primary concerns included lack of a standardized protocol, undefined sampling frame, inconsistent and unrecorded search effort, temporary emigration from the survey area, difficulty repeating surveys without expert knowledge of whooping crane space-use on the wintering grounds, undefined or unquantifiable precision, and no consideration of imperfect detectability (Strobel et al. 2012). With this research, we explore the use of line transect-based distance sampling to remedy the problem of imperfect detection. Imperfect detection of individuals present in the survey area will result in inaccurate estimates of abundance unless the resulting bias is corrected Anderson (2001). Distance sampling is a tractable, widespread approach used to correct for the bias that results from imperfect detection (Burnham et al. 1980; Buckland et al. 2001, 2004; Thomas et al. 2010). Distance sampling has been used in the application of aerial survey techniques to estimate density of many bird species (e.g., Shupe et al. 1987, Johnson et al. 1989, Smith et al. 1995, Ridgeway 2010, McRoberts et al. 2011) and mammal species (e.g., White et al. 1989, Johnson et al. 1991, Jackmann 2002, Fewster and Pople 2008, Schmidt et al. 2012).

Our objective was to test the efficacy of line-transect-based distance sampling during aerial surveys for whooping cranes. We paired distance sampling with the traditional survey technique. The past technique lacked a spatially defined sampling frame and relied on expert judgment over repeated surveys of unstandardized transects; therefore, we were unable to estimate abundance using distance sampling. Instead, we used the traditional survey as a test case to evaluate the possibility of imperfect detection during whooping crane surveys. We also used an experimental decoy survey to evaluate the impacts of observer experience, sun position, distance from transect, and group size on the detection process. Our results inform design and implementation of future whooping crane population monitoring efforts.

STUDY AREA

Our research was conducted on the whooping crane's wintering grounds, which are found on and around Aransas NWR along the Texas gulf coast. Whooping cranes arrive on their wintering grounds in October and depart by late-April (Johnsgard 1983). On the wintering grounds, birds were distributed in coastal salt marsh, shallow bay edges, and tidal flats with some use of upland areas. Wintering whooping cranes were primarily found on Aransas NWR, Matagorda Island, San Jose Island, Lamar Peninsula, and Welder Flats (CWS and USFWS 2007). The marshes and flats were dominated by salt grass (*Distichlis spicata*), smooth cordgrass (*Spartina alterniflora*), and gulf cordgrass (*S. spartinae*; CWS and USFWS 2007). The dominant vegetation types in upland areas included live oak (*Quercus virginiana*) savannah and coastal grasslands.

METHODS

Winter 2010–2011 Surveys

We conducted aerial surveys of whooping cranes along the Texas gulf coast during winter 2010–2011. Surveys were conducted with 2 observers (typically only 1 observer was used in the past) in a Cessna Centurion 210-RG (Cessna Aircraft Company, Wichita, KS). We followed survey procedures used by Stehn and Taylor (2008), during which T. Stehn recorded the locations of observed whooping cranes on hard-copy maps. In addition, we collected the aircraft's flight path with a Global Positioning System (GPS). After each flight, we digitized the locations of observed whooping crane groups and measured distance from detected groups to the transect in a geographic information system. We used those detections and distances in a conventional distance-sampling analysis (Thomas et al. 2010) to estimate encounter rates and model detection probabilities. Transect locations varied between surveys, so we treated each transect as independent samples and each survey as replicates.

We pooled all detections and modeled the detection function using the key function + series expansion approach (Buckland et al. 2001). We used Akaike's Information Criterion corrected for small sample size (AIC_c) to select among the models (Burnham and Anderson 2001, 2002; Anderson and Burnham 2002). We used AIC_c weights (w) to evaluate evidence for each model and model-averaged results (Burnham and Anderson 2002). We used each key function only once to avoid model redundancy (Buckland et al. 1997, Burnham and Anderson 2002). Further, we evaluated evidence for group-size-biased detection by regressing the natural log of group size ($\ln(s)$) against detection probability ($g(x)$; Buckland et al. 2001). We assumed significance at $\alpha < 0.15$ for size-biased regression (Buckland et al. 2001).

We estimated needed statistics to help design future survey efforts (Buckland et al. 2001) and used them to estimate the number of surveys needed to obtain target levels of precision for abundance estimates (i.e., 5–25% coeff. of variation [CV]). To determine levels of precision needed to detect change (i.e., 5–20% decline) from 1 year to the next, we conducted a power analysis based on a z-test (Buckland et al. 2001). We assumed the coefficient of variation of abundance ($CV(\hat{N})$) was constant across estimates of abundance for this power analysis (Gerrodette 1987). Though changes in abundance over 2-year periods do occur, wildlife managers are typically more interested in determining population trends (Thompson et al. 1998). A simple change from 1 year to the next is part of normal population dynamics, but longer-term trends are more important for conservation planning and population management (Thomas et al. 2004). We used Program TRENDS (Gerrodette 1987, 1991, 1993; Link and Hatfield 1990) to estimate the $CV(\hat{N})$ needed to detect a population change given power $(1 - \beta) = 0.8$ and $\alpha = 0.1$ (based on a 1-tailed t-test).

Decoy Surveys

We painted sandhill crane (*G. canadensis*) decoys (Carry-Lite Decoys, Alabaster, AL) to resemble whooping cranes. We painted some decoys white to resemble adults and some tawny to represent hatch year birds. Though sandhill cranes are smaller than whooping cranes, their body form is similar. We used the decoys to simulate whooping crane populations to further test distance-sampling assumptions and evaluate the effects of additional covariates on detectability (Smith et al. 1995, Butler et al. 2007, Pearse et al. 2007, Howlin et al. 2008). We conducted aerial surveys of the decoys during September 2011 from an amphibious Kodiak (Quest Aircraft Company, Sandpoint, ID) fixed-wing airplane. We flew transects at approximately 60 m above ground level at 90 knots (approx. 104 miles/hr, 167 km/hr) of ground speed. We spaced survey transects 1,000 m apart. We deployed the decoys in a different set of randomly generated locations on the Blackjack Peninsula at Aransas NWR on each day of the study. We surveyed each deployment of decoys twice. Observers were positioned on different sides of the aircraft (i.e., front right seat and back left seat); therefore, we flew each transect once in each direction so observers were exposed to different sides of the transects on each pass. Observers were naïve to the location and arrangement of crane decoys each day. Decoys were deployed in groups of 1, 2, 3, or 4 individuals. Groups of 3 or 4 decoys included 1 or 2 tawny-colored decoys, respectively, that represented young of the year. We placed decoy groups in randomly generated locations >1,000 m apart. Decoys within the same group were placed haphazardly within 50 m of the random location.

One observer was experienced with whooping crane aerial surveys and the other was not; we hypothesized that the novice observer would have lower detection probability than the experienced observer and misidentify non-target species more than the experienced observer. We expected sun position (i.e., at back, overhead, or in face) to impact detection probability. Specifically, we hypothesized that detection probability would be lowest when the observer was facing the sun, medium when sun was overhead, and highest when the observer had the sun at their back. Further, we expected group-size-biased detection to occur (i.e., expected larger groups to be more detectable than smaller ones).

The aircraft used during the decoy surveys had pontoons, which can impede detection near the transect and reduced maneuverability of the aircraft. Therefore, we used marks on the struts to categorize distance into 6 intervals (53–90 m, 90 –180 m, 180–330 m, 330–540 m, >540 m; Guenzel 1997). We would have preferred to use a different aircraft, but the amphibious Kodiak was the only one available with proper certification at the time. Because decoy locations were known and flight paths were tracked with GPS, we were also able to measure actual distance to each decoy group using a geographic information system. We used χ^2 tests to determine whether misclassification of distance intervals differed by observer and sun position (PROC FREQ; Conover 1999, SAS Institute 2004). We also used χ^2 tests to determine whether detection of false positives (i.e., misidentification of other white water birds or white objects as whooping cranes) differed by observer, sun position, and distance interval.

We developed *a priori* models to evaluate whether detectability of whooping crane decoy groups was a function of distance from transect (quadratic relationship), observer experience, sun position, and group size. We categorized sun position into 3 groups: sun at observer's back, sun in observer's face, or sun overhead. We used logistic regression to model detectability (Hosmer and Lemeshow 2000) and AIC_c weights to evaluate the relative importance of the models (Burnham and Anderson 2002). For the logistic regression models, the response variable for group detectability was a binary variable where 1 was group detected and 0 was group not detected. We evaluated the goodness-of-fit of the most parameterized model using the Hosmer–Lemeshow test (Hosmer and Lemeshow 2000, Anderson and Burnham 2002).

We developed *a priori* models to evaluate the impact of distance from the transect, group size, observer experience, and sun position on the accuracy of estimates of group size for detected groups. We used logistic regression to model individual detectability within detected decoy groups (event/trials syntax of PROC LOGISTIC; SAS Institute 2004). We evaluated the relative importance of the models using AIC_c weights and evaluated goodness-of-fit of the most parameterized model with the Hosmer–Lemeshow test (Hosmer and Lemeshow 2000, Burnham and Anderson 2002).

RESULTS

Winter 2010–2011 Surveys

We conducted surveys on 2 December 2010, 9 December 2010, 11 February 2011, and 1 March 2011 (Table 1). We found that ≈95% of detected whooping crane groups were within 500 m of transects (Fig. 1). Therefore, we truncated the data >500 m from transects. We observed a whooping crane group encounter rate of 0.211/km (SE = 0.02) and an average group size of 2.502 (SE = 0.048; Table 1). We found no evidence of size-biased detection ($r \leq 0.129$, $P \geq 0.982$). The most parameterized detection-function model fit the data ($\chi^2 = 14.266$, df = 21, $P = 0.858$). Our best detection-function model ($w = 0.470$) was the half-normal key with no series expansion adjustment (Table 2). However, the uniform and hazard-rate models were competitive, so we model averaged our results (Burnham and Anderson 2002). Conventional distance sampling indicated detection probability of a whooping crane group within 500 m of the survey line was 0.558 (SE = 0.031). Many have believed the historical survey techniques of Stehn and Taylor (2008) resulted in a complete census of whooping cranes overwintering around Aransas NWR but these results clearly show detectability was <1.

Assuming a sampling frame composed of 600 km of transects, we estimated that 2 surveys/year would likely result in an abundance estimate with a 12% CV. We estimated 3 surveys of the sampling frame per year would improve precision of abundance estimates to 10% CV, 6 surveys to 7% CV, and 12 surveys to 5% CV. A survey designed to achieve a $CV(\hat{N})$ of approximately 6% would be able to detect a 15% decline from one year to the next (Fig. 2); we estimated that would require approximately 8 surveys/year. A 15% decline/year over 3 years would require a $CV(\hat{N})$ of 6% and over 4 years a $CV(\hat{N})$ of 15% (Table 3).

Decoy Surveys

We conducted 4 surveys of whooping crane decoys with an average of 104 decoy groups within 500 m of transects. For the first survey, we established 103 decoys in 41 groups; for the second survey, 110 decoys in 46 groups; for the third survey, 109 decoys in 43 groups; and for the fourth survey, 94 decoys in 39 groups. Though we expected few decoy groups would be detected within 53 m of transect lines because of

Table 1. Summary of whooping crane distance-sampling-based aerial surveys along the Texas gulf coast, USA, conducted during the traditional survey flights, winter 2010–2011.

Date[a]	k	L	n	n/L	CV(n/L)	b
2 Dec 2010	40	143.47	70	0.488	0.218	3.520
9 Dec 2010	69	265.56	86	0.324	0.163	2.536
11 Feb 2011	72	270.95	73	0.269	0.175	2.459
1 Mar 2011	63	681.96	58	0.085	0.180	2.057
Pooled	244	1,361.94	287	0.211	0.095	3.442

[a] For each survey date, we report no. of transects (k), total transect length in km (L), number of whooping crane groups detected (n), encounter rate (n/L) and its coeff. of variation (CV(n/L)), and the dispersion parameter (b; Buckland et al. 2001:242).

the large pontoons on the aircraft, we detected 8 of 9 groups (88.9%; 95% CI = 51.8–99.7%). We only detected 50.0% ($n = 22$; 95% CI = 28.2–71.8%) of decoy groups placed in the 53–90-m distance interval.

The most parameterized logistic regression model fit the data ($\chi^2 = 9.048$, df = 8, $P = 0.338$). Of the 16 candidate models (Table 4), 2 models appeared competitive. Our best model ($w = 0.607$) indicated that detectability was influenced by group size, distance, and sun position. This model indicated that detectability increased with group size (odds ratio = 1.361; $\hat{\beta} = 0.308$, SE = 0.151; Wald statistic [W] = 4.137, df = 1, $P = 0.042$). It indicated that detectability was 2.704 times greater when the sun was overhead ($\hat{\beta} = 0.995$, SE = 0.381; $W = 6.812$, df = 1, $P = 0.009$) and 3.912 times greater when the sun was at the observer's back ($\hat{\beta} = 1.364$, SE = 0.492; $W = 7.696$, df = 1, $P = 0.006$) than when it was in the observer's eyes. We modeled distance as a quadratic relationship (distance, $W = 0.954$, df = 1, $P = 0.329$; distance^2, $W = 2.300$, df = 1, $P = 0.129$), which indicated that detectability was maximized at approximately 162 m from the transect and predicted that detectability was ≤ 0.843 at any given distance (Fig. 3). Our second-best model (Table 4) appeared competitive ($w = 0.285$) but the effect of observer experience was likely spurious (odds ratio = 0.760; $\hat{\beta} = -0.274$, SE = 0.338; $W = 0.660$, df = 1, $P = 0.416$; Arnold 2010).

During the surveys, observers used marks on the struts to categorize distance into intervals. We compared observer's classifications to actual distances and found that observers misclassified distance categories 46.7% of the time ($n = 169$; 95% CI = 37.0–56.6%). The experienced observer misclassified distance ($P = 57.4\%$; 95% CI = 43.2–70.7%) more than the inexperienced observer ($P = 35.9\%$; 95% CI = 23.1–50.2%; $\chi^2 = 4.994$, df = 1, $P = 0.025$). Misclassification was similar between sun positions ($\chi^2 = 3.831$, df = 2, $P = 0.1473$). Observers mistakenly identified other white objects as whooping cranes on 13 occasions; 12 of those were by the inexperienced observer ($\chi^2 = 8.543$, df = 1, $P = 0.004$). We found no evidence that distance ($\chi^2 = 4.012$, df = 3, $P = 0.260$) or sun position ($\chi^2 = 4.361$, df = 2, $P = 0.113$) influenced the detection of false positives.

We accurately estimated decoy group size 86.9% of the time ($n = 107$; 95% CI = 79.0–92.7%). In 14 instances, we underestimated decoy group size and during 8 of those instances, group size was only underestimated by 1 individual. On average, we underestimated decoy group size by 5.8% (SE = 0.016). Of the 16 candidate models (Table 5), 2 models appeared competitive and the most parameterized mode fit the data ($\chi^2 = 8.618$, df = 8, $P = 0.376$). Our best model ($w = 0.434$) indicated that individual detectability within a detected group was influenced by group size and distance (Table 5). This model indicated that individual detectability decreased with group size (odds ratio = 0.200; $\hat{\beta} = -1.611$, SE = 0.474; $W = 11.573$, df = 1, $P < 0.001$) and distance (odds ratio = 0.996; $\hat{\beta} = -0.004$, SE = 0.001; $W = 7.726$, df = 1, $P = 0.005$). Our second-best model (Table 5) appeared competitive ($w = 0.306$) but the effect of observer experience was likely spurious (odds ratio = 1.755; $\hat{\beta} = 0.562$, SE = 0.467; $W = 1.448$, df = 1, $P = 0.229$; Arnold 2010).

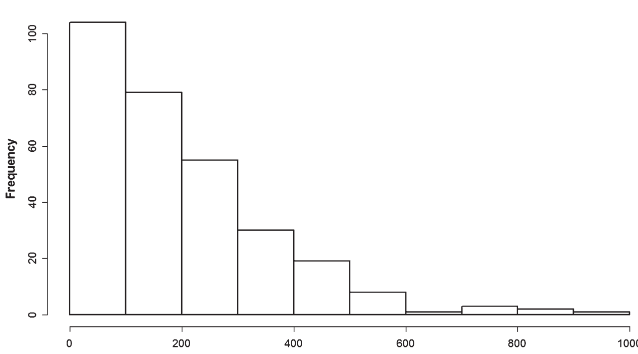

Figure 1. Histogram of whooping crane group distances from transects during aerial surveys along the Texas gulf coast, USA, during the traditional survey flights, winter 2010–2011.

DISCUSSION

Detectability during the traditional survey effort was <1 as indicated by the flights conducted during winter 2010–2011. The previous observer relied on his approximate 30 years of experience of whooping crane space-use on the wintering grounds to account for missed groups over repeated survey effort. However, a well-designed, repeatable survey technique cannot rely on presumed knowledge of, and ability to, identify unmarked individuals in the population. Distance sampling would provide a framework for providing a defined sampling frame, standardizing search effort, and correcting for the bias from imperfect detection.

Previous studies of other wildlife species have suggested many factors can affect detection probability (e.g., Bodie

Table 2. Detection-function models from distance-sampling-based aerial surveys of whooping cranes along the Texas gulf coast, USA, from the traditional survey flights, winter 2010–2011.

Model[a]	−2LL	K	AIC$_c$	ΔAIC$_c$	w
Half normal	3473.218	1	3475.232	0.000	0.470
Uniform + cosine	3473.662	1	3475.676	0.444	0.376
Hazard rate + cosine	3471.386	3	3477.471	2.239	0.153

[a] Models are a key function or key function + series expansion (Buckland et al. 2001). For each detection-function model, we give $-2 \times$ log-likelihood (−2LL), no. of parameters (K), second-order Akaike's Information Criterion (AIC$_c$), difference in AIC$_c$ compared with lowest AIC$_c$ of the model set (ΔAIC$_c$), and AIC$_c$ wt (w).

et al. 1995, Smith et al. 1995, Butler et al. 2007, Marques et al. 2007, McRoberts et al. 2011). Although magnitudes of effects from decoy-based detection studies are often not directly analogous to surveys of live birds, decoy experiments can provide insight into the primary mechanisms that influence the detection process. Our results revealed that distance from transect, sun position, and group size all influenced detection probability. We found, just as Stehn and Taylor (2008) hypothesized, that detection probability would be lowest when the observer was facing the sun, medium when sun was overhead, and highest when the observer had the sun at their back. However, there was little difference between detection probability when the sun was overhead and when the sun was at the observer's back (Fig. 3). The traditional survey was conducted during the morning and afternoon with a break for lunch (Stehn and Taylor 2008). Therefore, much of the survey effort was accomplished when the sun was at low angles, resulting in high detectability on one side of the aircraft but low detectability on the other. Therefore, survey efficiency could be improved by using 2 observers (one on each side of the aircraft) when the sun is overhead (i.e., midday surveys). This would result in little decline in detectability but allow transects to be spaced further apart.

We observed sized-biased detection during the experimental decoy surveys; for each increase in group size, group detection probability increased 1.361 times. Two methodologies exist for dealing with sized-biased detection in distance sampling. The first method uses regression of detection probability against group size to adjust expected group size to account for the size-biased detection (Buckland et al. 2001). A second approach involves using group size as a covariate in the detection function (Marques and Buckland 2003, 2004; Marques et al. 2007). However, the regression method corrects for both size-biased detection and underestimation of group size, assuming that group sizes are estimated accurately on or near the transect (Buckland et al. 2001). Our analysis shows that the magnitude by which group size was underestimated increased with distance (i.e., detectability of individuals within detected groups decreased as distance increased). During the decoy experiment, the group size of all detections within 100 m of transects were correctly counted. However, observers should attempt to minimize inaccurate counts of group size.

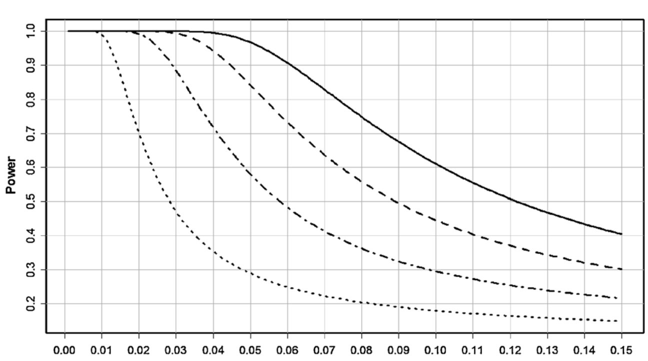

Figure 2. Power curves for determining the coefficient of variation (CV) of whooping crane abundance estimates required to detect a given change in abundance from one year to the next; based on 1-tailed z-test ($\alpha = 0.1$). The solid line represents a 20% decline, the dashed line is a 15% decline, the dot-dashed line is a 10% decline, and the dotted line is a 5% decline.

There are 3 essential assumptions of distance sampling (Buckland et al. 2001). First, detection probability is 1.0 on the transect line. This is usually a problem for fixed-winged aircraft because it is often difficult to see directly below the aircraft (e.g., Buckland et al. 2001, Butler et al. 2007, McRoberts et al. 2011). However, despite the pontoons on the aircraft we used during the experimental decoy survey, the shortest distance to an undetected decoy group was 37 m; 5 other decoy groups had shorter distances and they were detected. When we used the Cessna Centurion 210-RG during winter 2010–2011, all indications were 100% detection on the transect line (Fig. 1). A low instrument panel in the survey platform allowed forward observation of the transect, reducing the probability of missing groups on or near the transect. If aircraft with poor visibility (i.e., pontoons or high instrument panels) cannot be avoided, other distance-sampling-based techniques, such as a double-

Table 3. Estimated precision of abundance estimates (CV($\hat{N}$)) required to detect a population trend from distance-sampling-based aerial surveys for whooping cranes along the Texas gulf coast, USA.

	CV($\hat{N}$)[a]		
Decline/year	3-yr period	4-yr period	5-yr period
5%	0.02	0.04	0.07
10%	0.04	0.09	0.16
15%	0.06	0.15	0.26
20%	0.08	0.22	0.38

[a] We used Program TRENDS (Gerrodette 1987, 1991, 1993) to estimate the CV($\hat{N}$) required to detect a population change given power $(1 - \beta) = 0.8$ and $\alpha = 0.1$ (based on a 1-tailed t-test).

Table 4. Candidate logistic-regression models of whooping crane decoy detectability ($n = 169$) on Aransas National Wildlife Refuge, Texas, USA, during September 2011.

Model[a]	−2LL	K	AIC$_c$	ΔAIC$_c$	w
SIZE + DIST + SUN	211.231	6	223.750	0.000	0.607
SIZE + EXPER + DIST + SUN	210.569	7	225.265	1.515	0.285
DIST + SUN	215.466	5	225.834	2.084	0.214
SIZE + SUN	218.194	4	226.438	2.688	0.158
SIZE + EXPER + SUN	216.771	5	227.139	3.389	0.112
EXPER + DIST + SUN	215.095	6	227.614	3.864	0.088
SUN	223.473	3	229.619	5.869	0.032
SIZE + DIST	221.563	4	229.807	6.057	0.029
EXPER + SUN	222.506	4	230.750	7.000	0.018
DIST	224.918	3	231.064	7.314	0.016
SIZE + EXPER + DIST	220.831	5	231.200	7.450	0.015
SIZE	227.490	2	231.563	7.813	0.012
SIZE + EXPER	226.101	3	232.246	8.496	0.009
EXPER + DIST	224.470	4	232.714	8.964	0.007
CONSTANT	232.143	1	234.167	10.417	0.003
EXPER	231.169	2	235.241	11.491	0.002

[a] The covariate SUN was categorized into 3 groups: sun at observer's back, sun in observer's face, or sun overhead. We used 2 observers during these surveys, one experienced and one inexperienced (EXPER). We modeled the effect of distance (DIST) as a quadratic relationship in each model. The covariate SIZE was the decoy group size. For each detection-function model, we give $-2 \times$ log-likelihood (−2LL), no. of parameters (K), second-order Akaike's Information Criterion (AIC$_c$), difference in AIC$_c$ compared with lowest AIC$_c$ of the model set (ΔAIC$_c$), and AIC$_c$ wt (w).

Table 5. Candidate logistic-regression models of the accuracy of group size estimates of detected whooping crane decoy groups ($n = 107$) on Aransas National Wildlife Refuge, Texas, USA, during September 2011.

Model[a]	−2LL	K	AIC$_c$	ΔAIC$_c$	w
DIST + SIZE	132.737	3	138.970	0.000	0.434
DIST + SIZE + EXPER	131.279	4	139.671	0.701	0.306
DIST + SIZE + SUN	130.969	5	141.563	2.593	0.119
DIST + SIZE + EXPER + SUN	129.910	6	142.750	3.780	0.066
SIZE	140.221	2	144.336	5.366	0.030
SIZE + EXPER	138.664	3	144.897	5.927	0.022
SIZE + SUN	137.584	4	145.976	7.006	0.013
SIZE + EXPER + SUN	135.789	5	146.383	7.413	0.011
CONSTANT	153.821	1	155.859	16.889	0.000
DIST	152.001	2	156.116	17.146	0.000
EXPER	153.068	2	157.183	18.213	0.000
SUN	151.127	3	157.360	18.390	0.000
DIST + SUN	149.046	4	157.438	18.468	0.000
EXPER + DIST	151.407	3	157.640	18.670	0.000
EXPER + SUN	150.570	4	158.962	19.992	0.000
EXPER + DIST + SUN	148.810	5	159.404	20.434	0.000

[a] The covariate SUN was categorized into 3 groups: sun at observer's back, sun in observer's face, or sun overhead. We used 2 observers during these surveys, one experienced and one inexperienced (EXPER). Covariate SIZE was group size and DIST was distance from transect. For each detection-function model, we give $-2 \times$ log-likelihood (−2LL), no. of parameters (K), second-order Akaike's Information Criterion (AIC$_c$), difference in AIC$_c$ compared with lowest AIC$_c$ of the model set (ΔAIC$_c$), and AIC$_c$ wt (w).

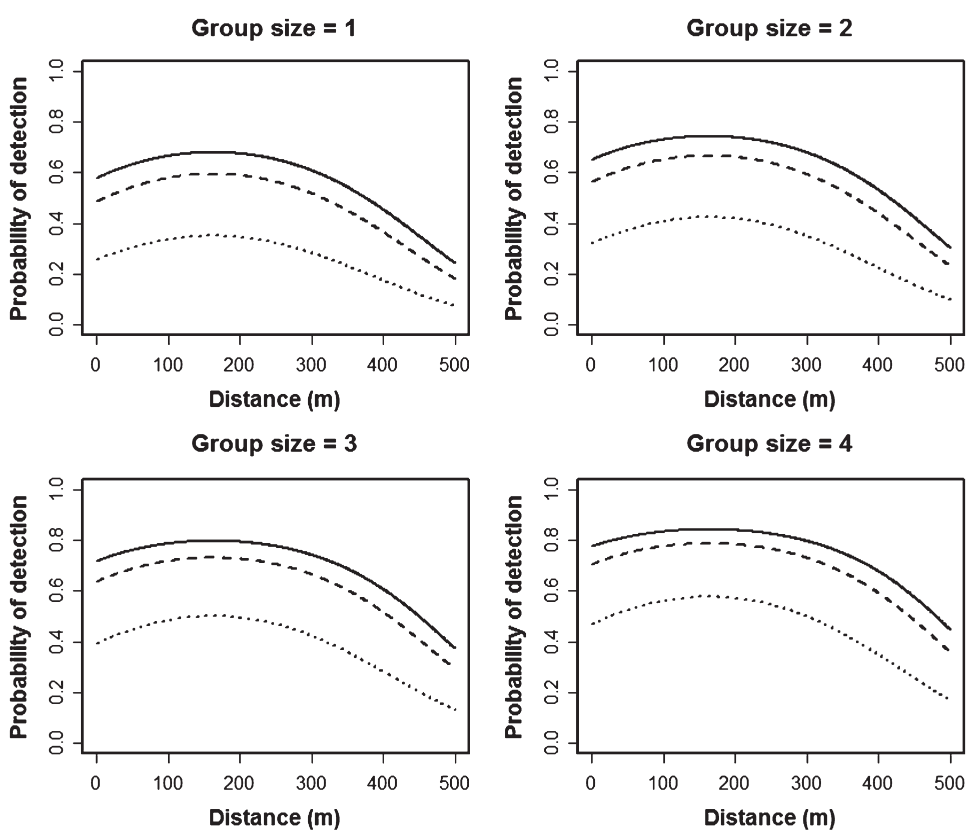

Figure 3. Predicted probability of detection for whooping crane decoy groups on Aransas National Wildlife Refuge, Texas, USA. Predictions based on logistic regression of detection with covariates of group size, distance from transect (quadratic effect), and sun position. Solid line is sun at observer's back, dashed line is sun overhead, and dotted line is sun in observer's face.

observer approach, could be employed to estimate detection probability at the line (Laake and Borchers 2004).

The second assumption that birds are not attracted to, or avoiding, the transect is typically not a problem for aerial surveys. However, the third assumption that distances are measured accurately or birds are correctly placed in the proper distance interval can present hurdles to implementation in the field. Many monitoring efforts have used marks on the struts to categorize distances into intervals (e.g., Caughley et al. 1976, Guenzel 1997, Butler et al. 2007). However, we found that observers misclassified distances 46.7% of the time (95% CI = 37.0–56.6%). It is important that distances be measured accurately because positive bias in distance measurements can bias density estimates low and vice versa (Burnham et al. 1980, Chen 1998, Buckland et al. 2001). The locations of detected whooping crane groups could be marked with a GPS unit by deviating from transects and flying over each detected group. This technique was tested by Marques et al. (2006) from a helicopter and they determined it was accurate. However, this technique can be cumbersome and create safety concerns when using fixed-wing aircraft. Perhaps a feasible alternative would be the use of real-time GPS in conjunction with a tablet computer displaying aerial imagery. This technology would allow observers to accurately mark detected groups' locations without increasing safety risks associated with the multiple turns required to deviate from transect.

The traditional survey technique provided no known methodology for estimating the precision of abundance estimates. This promulgated a belief by some that estimates obtained from the traditional technique were absolute enumeration without error. However, that was clearly not the case. The establishment of a technique that can correct for bias from imperfect detection, such as distance sampling, would allow wildlife biologists to estimate precision of their abundance estimates. Further, it would allow understanding of the limits of inference (i.e., statistical power) that can be drawn from whooping crane population-monitoring data (Anderson 2001).

MANAGEMENT IMPLICATIONS

Our results provide useful insights into improving whooping crane monitoring efforts. We recommend using 2 observers during midday flights to take advantage of relatively high detectability on both sides of the aircraft. Our results emphasize that observer training is important to reducing misidentification of non-targets. Although apparently useful in other aerial surveys (potentially with larger distance intervals and less turbulence), sighting marks placed upon the aircraft's struts did not provide accurate measurements of distances. Future research should examine other techniques that might improve distance measurements. We also recommend avoiding the use of aircraft with pontoons or high instrument panels to maintain complete detection on the transect line. The traditional technique provided no measure of precision but a technique such as line-transect-based distance sampling could account for imperfect detectability and allow for measurement of the precision of abundance estimates. The amount of survey effort we estimated was needed to detect meaningful change will be useful for wildlife biologist who undertake design and implementation of a renewed whooping crane population-monitoring effort. Finally, lessons learned here can also be used to inform and improve monitoring efforts for other large birds, such as swans (*Cygnus* spp.) or other crane species.

ACKNOWLEDGMENTS

We thank Aransas NWR staff and volunteers for helping to set up the decoys across the Blackjack Peninsula; without their hard work, we could not have completed this effort. We thank U.S. Fish and Wildlife Service (USFWS) pilot F. Roetkger. T. Stehn and the authors served as observers during the winter 2010–2011 surveys. D. Iriarte and B. Strobel served as observers during the decoys surveys. The USFWS provided financial support for this work. The findings and conclusions in this manuscript are those of the authors and do not necessarily represent the views of the USFWS. The use of trade, firm, or product names is for descriptive purposes only and does not imply endorsement by the U.S. Government.

LITERATURE CITED

Anderson, D. R. 2001. The need to get the basics right in wildlife field studies. Wildlife Society Bulletin 29:1294–1297.

Anderson, D. R., and K. P. Burnham. 2002. Avoiding pitfalls when using information-theoretic methods. Journal of Wildlife Management 66: 912–918.

Arnold, T. W. 2010. Uninformative parameters and model selection using Akaike's Information Criterion. Journal of Wildlife Management 74: 1175–1178.

Bodie, W. L., E. O. Garton, E. R. Taylor, and M. McCoy. 1995. A sightability model for bighorn sheep in canyon habitats. Journal of Wildlife Management 59:832–840.

Buckland, S. T., D. R. Anderson, K. P. Burnham, J. L. Laake, D. L. Borchers, and L. Thomas. 2001. Introduction to distance sampling: estimating abundance of biological populations. Oxford University Press, Oxford, England, United Kingdom.

Buckland, S. T., D. R. Anderson, K. P. Burnham, J. L. Laake, D. L. Borchers, and L. Thomas. 2004. Advanced distance sampling: estimating abundance of biological populations. Oxford University Press, Oxford, England, United Kingdom.

Buckland, S. T., K. P. Burnham, and N. H. Augustin. 1997. Model selection: an integral part of inference. Biometrics 53:603–618.

Burnham, K. P., and D. R. Anderson. 2001. Kullback–Leibler information as a basis for strong inference in ecological studies. Wildlife Research 28:111–119.

Burnham, K. P., and D. R. Anderson. 2002. Model selection and multimodel inference: a practical information-theoretic approach. Second edition. Springer, New York, New York, USA.

Burnham, K. P., D. R. Anderson, and J. L. Laake. 1980. Estimation of density from line transect sampling of biological populations. Wildlife Monographs 72.

Butler, M. J., W. B. Ballard, M. C. Wallace, S. J. DeMaso, and B. K. McGee. 2007. Aerial surveys for estimating wild turkey abundance in the Texas Rolling Plains. Journal of Wildlife Management 71:1639–1645.

Canadian Wildlife Service and U.S. Fish and Wildlife Service. 2007. International recovery plan for the whooping crane (*Grus americana*). Third revision. Recovery of nationally endangered wildlife. Environment Canada, Ottawa, Canada; and U.S. Fish and Wildlife Service, Albuquerque, New Mexico, USA.

Caughley, G., R. Sinclair, and D. Scott-Kemmis. 1976. Experiments in aerial survey. Journal of Wildlife Management 40:290–300.

Chen, S. X. 1998. Measurement errors in line transect surveys. Biometrics 54:899–908.
Conover, W. J. 1999. Practical nonparametric statistics. Third edition. John Wiley & Sons, New York, New York, USA.
Conroy, M. J., and J. P. Carroll. 2009. Quantitative conservation of vertebrates. John Wiley & Sons, New York, New York, USA.
Fewster, R. M., and A. R. Pople. 2008. A comparison of mark–recapture distance-sampling methods applied to aerial surveys of eastern grey kangaroos. Wildlife Research 35:320–330.
Gerrodette, T. 1987. A power analysis for detecting trends. Ecology 68: 1364–1372.
Gerrodette, T. 1991. Models of power of detecting trends: a reply to Link and Hatfield. Ecology 72:1889–1892.
Gerrodette, T. 1993. Program TRENDS: user's guide. Southwest Fisheries Science Center, La Jolla, California, USA.
Guenzel, R. J. 1997. Estimating pronghorn abundance using aerial line transect sampling. Wyoming Game and Fish Department, Cheyenne, USA.
Hosmer, D. W., and S. Lemeshow. 2000. Applied logistic regression. Second edition. John Wiley & Sons, New York, New York, USA.
Howlin, S., C. Derby, and D. Strickland. 2008. Whooping crane migrational habitat use in the central Platte River during the cooperative agreement period, 2001–2006. Unpublished report. West Inc., Cheyenne, Wyoming, USA.
Jackmann, H. 2002. Comparison of aerial counts with ground counts for large African herbivores. Journal of Applied Ecology 39:841–852.
Johnsgard, P. A. 1983. Cranes of the world. Indiana University Press, Bloomington, USA.
Johnson, B. K., F. G. Lindzey, and R. J. Guenzel. 1991. Use of aerial line transect surveys to estimate pronghorn populations in Wyoming. Wildlife Society Bulletin 19:315–321.
Johnson, F. A., K. H. Pollock, and F. Montalbano, III. 1989. Visibility bias in aerial surveys of mottled ducks. Wildlife Society Bulletin 17:222–227.
Krebs, C. J. 1999. Ecological methodologies. Second edition. Addison-Welsey Longman, Menlo Park, California, USA.
Laake, J. L., and D. L. Borchers. 2004. Methods for incomplete detection at distance zero. Pages 108–189 *in* S. T. Buckland, D. R. Anderson, K. P. Burnham, J. L. Laake, D. L. Borchers, and L. Thomas, editors. Advanced distance sampling: estimating abundance of biological populations. Oxford University Press, New York, New York, USA.
Link, W. A., and J. S. Hatfield. 1990. Power calculations and model selection for trend analysis: a comment. Ecology 71:1217–1220.
Marques, F. F. C., and S. T. Buckland. 2003. Incorporating covariates into standard line transect analyses. Biometrics 59:924–935.
Marques, F. F. C., and S. T. Buckland. 2004. Covariate models for the detection function. Pages 31–47 *in* S. T. Buckland, D. R. Anderson, K. P. Burnham, J. L. Laake, D. L. Borchers, and L. Thomas, editors. Advanced distance sampling: estimating abundance of biological populations. Oxford University Press, New York, New York, USA.
Marques, T. A., M. Andersen, S. Christensen-Dalsgaard, S. Belikov, A. Boltunov, Ø. Wiig, S. T. Buckland, and J. Aars. 2006. The use of global positioning systems to record distances in a helicopter line-transect survey. Wildlife Society Bulletin 34:759–763.
Marques, T. A., L. Thomas, S. G. Fancy, and S. T. Buckland. 2007. Improving estimates of bird density using multiple-covariate distance sampling. Auk 124:1229–1243.
McRoberts, J. T., M. J. Butler, W. B. Ballard, H. A. Whitlaw, D. A. Haukos, and M. C. Wallace. 2011. Detectability of lesser prairie-chicken leks: a comparison of surveys from aircraft. Journal of Wildlife Management 75:771–778.
Morrison, M. L., W. M. Block, M. D. Strickland, B. A. Collier, and M. J. Peterson. 2008. Wildlife study design. Second edition. Springer, New York, New York, USA.
Pearse, A. T., P. D. Gerard, S. J. Dinsmore, R. M. Kaminski, and K. J. Reinecke. 2007. Estimation and correction of visibility bias in aerial surveys of wintering ducks. Journal of Wildlife Management 72:808–813.
Ridgeway, M. S. 2010. Line transect distance sampling in aerial surveys for double-crested cormorants in coastal regions of Lake Huron. Journal of Great Lakes Research 36:403–410.
SAS Institute. 2004. SAS OnlineDoc®, Version 9. SAS Institute, Cary, North Carolina, USA.
Schmidt, J. H., K. L. Rattenbury, J. P. Lawler, and M. C. Maccluskie. 2012. Using distance sampling and hierarchical models to improve estimates of Dall's sheep abundance. Journal of Wildlife Management 76:317–327.
Shupe, T. E., F. S. Guthery, and S. L. Beasom. 1987. Use of helicopters to survey northern bobwhite populations on rangeland. Wildlife Society Bulletin 15:458–462.
Smith, D. R., K. J. Reinecke, M. J. Conroy, M. W. Brown, and J. R. Nassar. 1995. Factors affecting visibility rate of waterfowl surveys in the Mississippi Alluvial Valley. Journal of Wildlife Management 59:515–527.
Stehn, T. V., and T. E. Taylor. 2008. Aerial census techniques for whooping cranes on the Texas coast. Proceedings of the North American Crane Workshop 10:146–151.
Strobel, B., M. J. Butler, and G. Harris. 2012. Aransas-Wood Buffalo whooping crane abundance survey (2011–2012). U.S. Fish and Wildlife Service, Austwell, Texas, USA. <http://www.fws.gov/southwest/refuges/texas/aransas/pdf/FY12_ANWR_WWCAS_Review_01OCT12.pdf>. Accessed 25 Oct 2012.
Thomas, L., S. T. Buckland, E. A. Rexsted, J. L. Laake, S. Strindberg, S. L. Headley, J. R. B. Bishop, T. A. Marques, and K. P. Burnham. 2010. Distance software: design and analysis of distance sampling surveys for estimating population size. Journal of Applied Ecology 47:5–14.
Thomas, L., K. P. Burnham, and S. T. Buckland. 2004. Temporal inferences from distance sampling surveys. Pages 71–107 *in* S. T. Buckland, D. R. Anderson, K. P. Burnham, J. L. Laake, D. L. Borchers, and L. Thomas, editors. Advanced distance sampling: estimating abundance of biological populations. Oxford University Press, New York, New York, USA.
Thompson, W. L., G. C. White, and C. Gowan. 1998. Monitoring vertebrate populations. Academic Press, San Diego, California, USA.
White, G. C., R. M. Bartmann, L. H. Carpenter, and R. A. Garrott. 1989. Evaluation of aerial line transects for estimating mule deer densities. Journal of Wildlife Management 53:625–635.
Williams, B. K., J. N. Nichols, and M. J. Conroy. 2002. Analysis and management of animal populations. Academic Press, San Diego, California, USA.

Associate Editor: White