Detection Probability and Sources of Variation in White-Tailed Deer Spotlight Surveys

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ABSTRACT As a first step in understanding structure and dynamics of white-tailed deer (*Odocoileus virginianus*) populations, managers require knowledge of population size. Spotlight counts are widely used to index deer abundance; however, detection probabilities using spotlights have not been formally estimated. Using a closed mark–recapture design, we explored the efficiency of spotlights for detecting deer by operating thermal imagers and spotlights simultaneously. Spotlights detected only 50.6% of the deer detected by thermal imagers. Relative to the thermal imager, spotlights failed to detect 44.2% of deer groups ($\geq$1 deer). Detection probabilities for spotlight observers varied between and within observers, ranging from 0.30 (SE = 0.053) to 0.66 (SE = 0.058). Managers commonly assume that although road counts based on convenience sampling designs are imperfect, observers can gather population-trend information from repeated counts along the same survey route. Our results indicate detection rate varied between and within observers and surveyed transects. If detection probabilities are substantially affected by many variables, and if transect selection is not based on appropriate sampling designs, it may be impractical to correct road spotlight counts for detection probabilities to garner unbiased estimates of population size. (JOURNAL OF WILDLIFE MANAGEMENT 71(1):277–281; 2007)

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As a first step in understanding structure and dynamics of populations, it is essential that managers estimate population size (Seber 1982). As the goal of most abundance studies is to obtain cost-effective, unbiased, precise estimates (Thompson 2002, Williams et al. 2002), monitoring methods should be critically evaluated before recommendation or application (Anderson 2001). One of the most common tools for estimating relative white-tailed deer (*Odocoileus virginianus*) population size and trajectory has been the road spotlight survey (McCullough 1982, Fafarman and DeYoung 1986, Whipple et al. 1994) because of its ease of use and low cost (Garton et al. 2005). However, data collected from spotlight counts are indices (Thompson et al. 1998, Anderson 2001, Thompson 2002), and they may not accurately represent population size because the ratio of the count to the true population is unknown (Anderson 2003). Although the assumption of count proportionality (e.g., changes in counts between temporally separated surveys indicate changes in population status [Thompson 2002]) is difficult to justify (Burnham 1981, Thompson et al. 1998, Anderson 2001), deer biologists have continued to use spotlight counts for abundance and trend information.

Unlike spatially restricted or temporally predictable species (e.g., waterfowl; United States Fish and Wildlife Service and Canadian Wildlife Service 1987), white-tailed deer are wide-ranging, broadly distributed habitat generalists that have no consistent seasonal phenology that would simplify population surveys. Previous studies (McCullough 1982, Fafarman and DeYoung 1986, Cypher 1991, Whipple et al. 1994, Focardi et al. 2001) have attempted to evaluate the relative utility of spotlight surveys for documenting abundance of white-tailed deer. The consensus was that observers missed deer during spotlight surveys because of a variety of reasons, but by replicating transects, spotlight surveys have management value. However, researchers have not formally estimated the magnitude of bias in detection to date (Lancia et al. 1994). While these studies all contributed to our knowledge of spotlight accuracy and provided data researchers could use to account for non-detection of deer during surveys, they were unable to simultaneously conduct a spotlight survey and evaluate the accuracy of that survey for detecting living animals.

We describe an evaluation of spotlight surveys for detecting and accurately estimating white-tailed deer population size along a road transect. Our primary objective was to estimate detection probabilities for white-tailed deer spotlight surveys. We also sought to evaluate factors that contributed to variation in detection probabilities for spotlight surveys by evaluating historical assumptions regarding variation in detection due to observer variability, management unit, and survey technique.

STUDY AREA

We conducted research at Brosnan Forest, a 5,830-ha tract (33.08591°N, 80.25726°W) of lower coastal plains habitat in Dorchester County, South Carolina, USA. Brosnan Forest was 93% forested and contained 330 km of navigable roads. Vegetation was comprised primarily of interspersed stands of mature longleaf pine (*Pinus palustris*), bottomland hardwood drains, and mixed pine–hardwoods, and the

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forest was actively managed for timber production. Overstory species in hardwood drains were oak (*Quercus* spp.), sweetgum (*Liquidambar styraciflua*), black gum (*Nyssa sylvatica*), and yellow poplar (*Liriodendron tulipifera*), whereas mixed pine–hardwoods comprised loblolly (*P. taeda*), slash (*P. elliottii*), and pond (*P. serotina*) pine, oak, sweetgum, and red maple (*Acer rubrum*; Sanders 2000, Jordan 2002). Controlled burning occurred on about 1,000 to 1,400 ha annually, with mature pine sites on a 2–3-year burning rotation. Managers controlled understory vegetation with mechanical techniques and chemical application, especially on roadsides.

METHODS

Field Methods

We conducted this study following standard protocols for road spotlight surveys of white-tailed deer (Mitchell 1986). Within Brosnan Forest, we selected 4 transects consisting of a set of nonoverlapping roads (survey transects), which was the historic route surveyed by Brosnan Forest employees in 4 management units. The size of the management units ranged from 1,134 ha to 1,316 ha, and survey transect lengths were between 12.6 km and 14.8 km. We conducted road spotlight surveys from 1 August to 10 August 2005, and we surveyed each transect twice during the study. Surveys began at 2100 hours and lasted between 2 hours and 3.5 hours, depending on transect length and deer encounter rate. We used a multiple observer approach to test the efficiency of spotlight surveys to detect white-tailed deer along the roads. Two observers surveyed from each side of the vehicle; each pair had one observer with a thermal imaging camera (thermal imager observer) and one observer using a spotlight (spotlight observer). The thermal imager observer served as the standard to test the efficiency of the spotlight observer. Thus, 4 observers actively searched for white-tailed deer along each survey transect.

The thermal imager observers were located at the front of the truck bed and identified all white-tailed deer located with thermal imagers (Raytheon PalmIR 250 Digital and a Raytheon PalmIR 250 Analog; Raytheon Commercial Infrared, Dallas, TX). Spotlight observers were located at the rear of the truck bed using 1-million-candlepower handheld spotlights (Lightforce SL240; Lightforce USA, Inc., Orofino, ID) for deer searches. Observers counted and delineated captured deer seen by the thermal imager or by the spotlight into classes (M, F, fawn, unknown) based on antler and body size characteristics. As misclassification of marked individuals or groups could bias estimates of detection (e.g., tag loss; Williams et al. 2002), we labeled each observation with a unique, time-specific identifier using synchronized digital clocks, and we cross-checked these times between thermal imager and spotlight observers when spotlight observers located deer.

We assumed that capture events were independent (i.e., detection by thermal imagers did not influence detection by spotlights [Nichols et al. 2000, Williams et al. 2002]) and that it was a closed population (Williams et al. 2002). To ensure observer independence, we applied several protocols to our survey design. We separated thermal imager and spotlight observers by an opaque partition in the middle of the vehicle, ensuring each observer acted independently. Because we broadcast the image from each thermal camera to a 24-cm television, the vehicle would only stop once the spotlight captured an individual, not when thermal imagers located individuals. This ensured thermal imager detections would not influence spotlight detections. We did not allow thermal imager observers to comment on counts or assist with classification of white-tailed deer located by spotlight observers, but they independently noted the accuracy of spotlight counts when possible.

Data Analysis

We treated each deer as an individual unit within the analysis, whether we captured it within a group or individually, based on our assumption of equal detection between methods. We computed detection probabilities using a Huggins closed capture model implemented in Program MARK (Huggins 1989, 1991; White and Burnham 1999). Huggins closed capture models are conditional on an individual being captured at least once during the sampling period, and the models estimate abundance as a derived parameter rather than within the model likelihood (Huggins 1989, 1991; Williams et al. 2002). For data collection, we let $i =$ detection with the thermal imager, $j =$ detection with the spotlight, and we defined i or $j = 1$ as captured (e.g., seen by the thermal imager or spotlight) and i or $j = 0$ as not captured (e.g., not seen with the thermal imager or spotlight). We viewed our capture occasions temporally, with individuals captured by the thermal imager as the first occasion and individuals captured by the spotlight as the second occasion. Thus, data consisted of individuals captured both with the thermal imager and spotlight by the k^{th} observer pair ($x_{11}{}^{k}$), individuals captured with the thermal imager and not recaptured with the spotlight ($x_{10}{}^{k}$), and individuals captured only with the spotlight ($x_{01}{}^{k}$) for each of 2 replicated surveys on each management unit.

Before implementing our study, we developed a set of 9 candidate models of factors we felt could contribute to variation in detection probabilities of white-tailed deer. In general, we developed our candidate model set to address specific hypotheses on differences between thermal imagers and spotlight detection probabilities, differences between and among observers for each method, and differences between transects surveyed. Our model set ranged from a model for which detection probability was constant across all management units, survey transects, observers, and methods (no. parameters = 1) to one for which detection probability varied between all management units, survey transects, observers, and methods (no. parameters = 32). We evaluated the fit of each candidate model relative to other models in the set using the small-sample-size adjustment of Akaike's Information Criterion (AIC_c; Burnham and Anderson 2002) as computed by MARK (White and Burnham 1999). Estimates with a detection probability of 1 produced

Table 1. Numbers of white-tailed deer individuals per detection history and survey transect designation (management unit, survey replicate [1, 2], and observer pair [1, 2]) during simultaneous observations on Brosnan Forest, South Carolina, USA, during August 2005.

Encounter history[a]	Missy Lane				Hugh Camp				Big Bay				Powderhorn				Total
	Survey 1		Survey 2		Survey 1		Survey 2		Survey 1		Survey 2		Survey 1		Survey 2		
	1	2	1	2	1	2	1	2	1	2	1	2	1	2	1	2	
11	32	36	21	37	9	16	17	16	19	21	44	25	39	33	23	24	412
10	30	25	36	24	17	18	13	20	12	30	23	14	30	29	52	30	403
01	4	3	1	10	6	5	0	1	1	7	5	5	15	5	0	0	68
Total	66	64	58	71	32	39	30	37	32	58	72	44	84	67	75	54	883

[a] The first numeral in the encounter history refers to detection (1) or non-detection (0) by the capture observer (thermal imager), and the second numeral refers to detection (1) or non-detection (0) by the recapture observer (spotlight).

an undefined variance estimate (SE = 0); thus, we used profile likelihood confidence interval coverage to estimate the lower confidence bounds.

RESULTS

We identified 883 individuals during the surveys (Table 1). The thermal imager (TI) detected 92.3% of the total white-tailed deer seen, whereas the spotlight (SL) detected 54.4%. Of the total deer seen, the TI and SL located 46.7%, the TI located 45.6%, and the SL located 7.7%. Detections within groups varied with group size, as spotlight observers were more likely to either completely count or completely miss smaller groups (1 or 2 deer), while they were more likely to miss entirely or only partially count larger groups ($\geq$3 deer; Table 2).

Spotlight observers classified fewer deer as unknown (45.7%) than did thermal imager observers (50.8%). Classification of animals by age and sex varied between the 2 survey methods. Of those classified individuals, spotlights classified 28.5% as males, 38.0% as females, and 33.5% as fawns, whereas thermal imagers classified 36.7% as adult males, 31.4% as adult females, and 31.9% as fawns. We estimated survey adult sex ratio (F:M) for these data as 1.34:1.00 and 0.86:1.00 for spotlights and thermal imagers, respectively.

Based on the data collected during this study, the most parsimonious model was one in which thermal imager capture probabilities differed between observers for each survey transect, spotlight capture probabilities differed between observers for each survey transect, and capture probabilities varied between surveys. This 32-parameter model had the lowest AIC_c value (1,581.63) with a model weight of 0.989. The evidence ratio (w_1/w_2) between this model and the subsequent model in the candidate set was 94.72, implying this was the only plausible model given the data, and we limit our interpretation to this model.

Based on our selected model, we found evidence of variation in detection probabilities between the 2 observation techniques used. Observers using the thermal imagers had a greater detection probability than observers using spotlights (Fig. 1). Across surveys, detection probabilities for thermal imagers ranged from 0.60 (SE = 0.126) to 1.00. Detection probabilities by spotlight observers for previously captured individuals varied between and within observers, with detection ranging from 0.31 (SE = 0.053) to 0.66 (SE = 0.058). Detection probabilities were different among thermal imager and spotlight observers, and variation in detection probabilities existed both between management units and observers (Fig. 1). Spotlight counts were less than thermal imager counts for all surveys, detecting 30–78% of the deer counted by the thermal imager (Fig. 2). Confidence intervals for the derived abundance estimates indicated spotlight counts underestimated the number of deer located along survey transects (Fig. 2).

DISCUSSION

Applying a Huggins closed capture model (Huggins 1989, 1991) to our study enabled us to estimate detection probabilities for white-tailed deer spotlight surveys. We found considerable evidence of low detection probabilities for spotlight surveys relative to thermal imager surveys. Our spotlight detection probabilities were $\leq$0.66, lower than

Table 2. Percentage of individual white-tailed deer detected with a spotlight relative to group size of deer as determined with a thermal imaging system during simultaneous observations on Brosnan Forest, South Carolina, USA, during August 2005.

Thermal imager group size	Spotlight group size											
	0		1		2		3		4		5+	
	%	*n*	%	*n*	%	*n*	%	*n*	%	*n*	%	*n*
1	58.9	109	41.1	83								
2	37.6	38	17.8	18	44.6	45						
3	31.3	15	10.4	5	25.0	12	33.3	16				
4	25.0	7	7.1	2	25.0	7	25.0	7	17.9	5		
5+	38.9	7	5.6	1	16.7	3	16.7	3	5.6	1	16.7	3

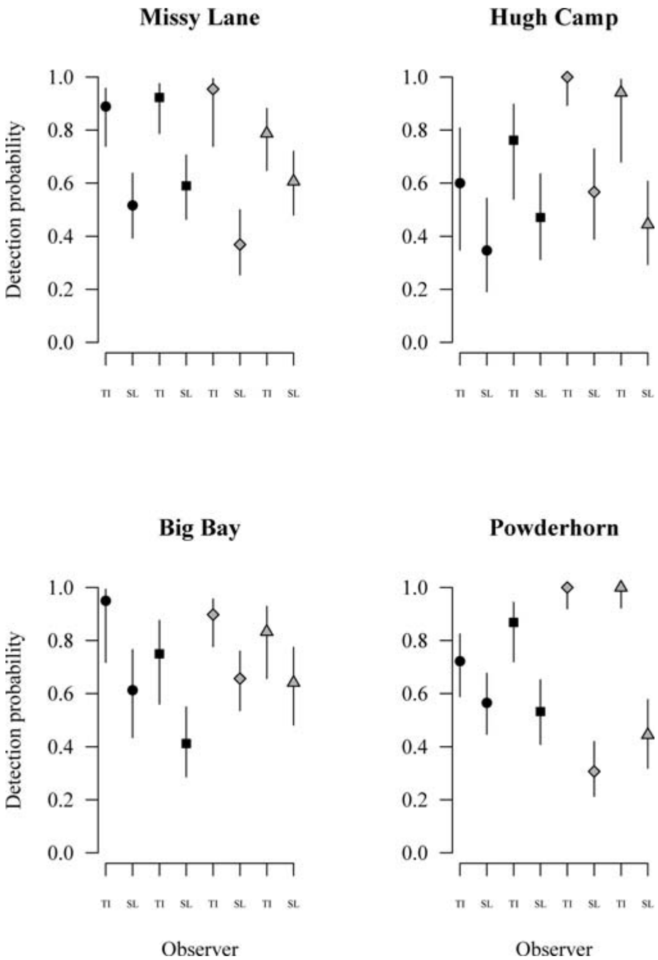

Figure 1. Detection probabilities for thermal imager (TI) and spotlight (SL) white-tailed deer surveys conducted at Brosnan Forest, South Carolina, USA, during August 2005. We specified survey methods at the management unit level as either first survey transect replicate (black) or second (gray), paired at the level of observer shown by the character styles in each plot (circle, square, diamond, or triangle).

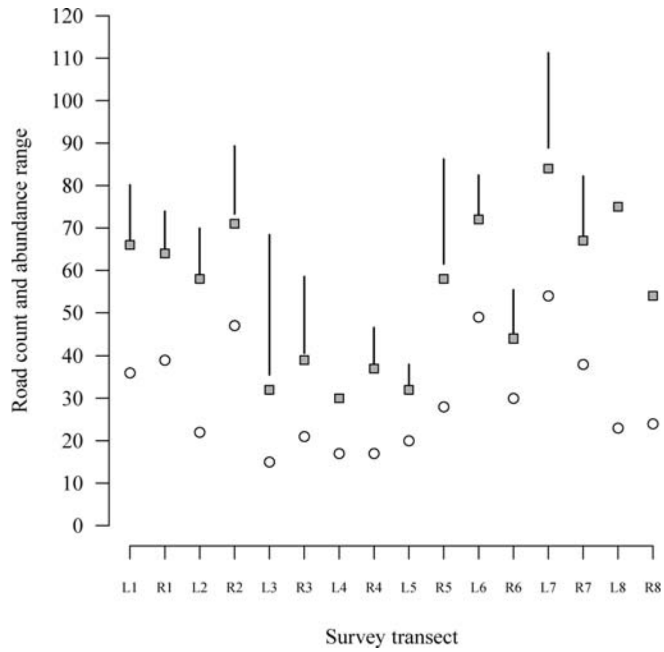

Figure 2. Counts of white-tailed deer seen for different observer pairs (L = left observer pair, R = right observer pair) for each survey transect (1–8) on Brosnan Forest, South Carolina, USA, during August 2005. Spotlight counts are shown as circles, total (spotlight and thermal imager) counts as squares, with the 95% confidence interval of the derived abundance estimates from a Huggins closed capture model corrected for differential detection probability shown as segments.

estimates (67–72%) shown by Whipple et al. (1994). Our detection probability estimates suggest that for every 2 deer detected by spotlight observers, they would fail to detect one additional deer. However, our estimated detection rates indicate spotlight detections may be so low that 2 deer may be missed for every deer observed (detection probability = 0.31). Based on our estimated detection probabilities, conditional on our encounter technique, simple changes in methodology, such as using different observers, can influence detection probabilities by 26%. Our data suggest intra-observer variability can approach 30%.

Variability in detection among survey routes highlights the importance for probabilistic-based sampling schemes (Thompson et al. 1998, Buckland et al. 2001, Williams et al. 2002) when designing surveys. Our objective was to evaluate bias in detection using the most common approach to evaluating deer population size; thus, we readily acknowledge our convenience sampling design (e.g., survey from the road) would be inappropriate for making inferences to the entire Brosnan Forest (Anderson 2001, Thompson 2002). Although researchers often suggest distance sampling (Buckland et al. 2001) as a technique that could provide deer density estimates (Lancia et al. 1994, Drake et al. 2005), design requirements for distance-based sampling would suffer the same restriction left unaddressed in road spotlight surveys: the assumption that transects are located according to some probabilistic scheme across the study area of interest (Buckland et al. 2001, Williams et al. 2002).

Our assumption that detection with the thermal imager and spotlight was equivalent is a concern as there could have been heterogeneity in detection based on factors such as distance or habitat type causing positive covariance between observers, biasing detection high, and subsequently underestimating abundance (Williams et al. 2002). If transects could be placed in a probabilistic fashion, perhaps a combined double-observer distance sampling approach would be appropriate to adjust for heterogeneous sighting probabilities due to variables such as group size, habitat type, and distance (Manly et al. 1996).

Although our results suggest non-detection with thermal imagers was less than with spotlights, we found counts made with thermal imagers cannot be considered a census, as thermal imager surveys also exhibited bias due to incomplete detection (Potvin and Breton 2005). Detection probability for thermal imager observers was $\leq$1 for 13 of 16 observers, with the lowest mean detection probability of 0.59, indicating counts using a thermal imager also should be considered indices.

Originally, we had hypothesized thermal imagers would provide a much stronger classification than spotlights. However, once we began the experiment, we realized our thermal cameras could not reproduce the quality of image we could obtain simply by using a pair of binoculars to identify a deer in a spotlight. While we easily classified large-antlered adult males with the thermal imagers (Focardi et al. 2001), classification of adult females, fawns, and small-antlered adult males was more difficult because only size and physical proportions could be used for classification. Thus, we classified about 11% more deer as unknown with the thermal imagers than with spotlights, which biased our estimated sex ratio toward adult males.

MANAGEMENT IMPLICATIONS

Our results suggest that uncorrected road spotlight surveys have limited value to managers for accurately assessing abundance or trajectory of white-tailed deer populations, unless population changes are considerable (Rakestraw et al. 1998). However, if road-based surveys are going to be used to derive indices of deer abundance, regardless of their inherent flaws, then use of thermal imaging technology may be advantageous to use of spotlights. Our concern is that as road-based spotlight surveys are deemed unsuitable for assessing trends in white-tailed deer population densities, managers are left with few viable, proven options for assessing population size and will continue to rely upon collection and interpretation of data that may not accurately reflect reality.

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