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*Population Ecology*

# Spotlight Surveys for White-Tailed Deer: Monitoring Panacea or Exercise in Futility?

**BRET A. COLLIER,**[1] *Institute of Renewable Natural Resources, Texas A&M University, College Station, TX 77843, USA*
**STEPHEN S. DITCHKOFF,** *School of Forestry and Wildlife Sciences, Auburn University, Auburn, AL 36849, USA*
**CHARLES R. RUTH, Jr.,** *South Carolina Department of Natural Resources, Columbia, SC 29202, USA*
**JOSHUA B. RAGLIN,** *Norfolk Southern Railway, Brosnan Forest, Dorchester, SC 29437, USA*

**ABSTRACT** Many monitoring programs for white-tailed deer (*Odocoileus virginianus*) on both private and public lands across the United States have long relied on the use of road-based spotlight surveys for monitoring population size and trends. Research has suggested spotlight surveys are ineffective and that road-based surveys for deer are biased because of highly variable detection rates. To evaluate variability in detection rates relative to the assumption that repeated surveys along roads will provide reliable trend data for use in calculating deer density estimates, we collected 5 years of thermal-imager and spotlight survey data using a multiple-observer, closed-capture approach. Using a Huggin's closed capture model, data bootstrapping, and variance components analyses, our results suggest that density estimates for white-tailed deer generated from data collected during road-based spotlight surveys are likely not reflective of the standing deer population. Detection probabilities during individual spotlight surveys ranged from 0.00 to 0.80 (median = 0.45) across all surveys, and differed by observer, survey, management unit, and survey transect replicate. Mean spotlight detection probability (0.41) and process standard deviation (0.12) estimates indicated considerable variability across surveys, observers, transects, and years, which precludes the generation of a correction factor or use of spotlight data to evaluate long-term trends at any scale. Although recommended by many state, federal, and non-governmental agencies, our results suggest that the benefit of spotlight survey data for monitoring deer populations is limited and likely represents a waste of resources with no appreciable management information gained. 

**KEY WORDS** capture-recapture, data bootstrapping, detection probability, monitoring, *Odocoileus virginianus*, spotlight surveys, variance components, white-tailed deer.

One of the primary tenets of population management for harvestable game species is that abundance and monitoring information accurately describe the current population state or trend. However, adequate data, collected under strict sampling protocols, are rarely available for obtaining accurate and unbiased estimates of population size. Limitations associated with the ability to apply appropriate sampling designs and adequately characterize variability in the observation processes has been of considerable focus for long-standing national survey protocols such as the Breeding Bird Survey (BBS; Thomas 1996, Sauer et al. 2005), as well as studies on other wildlife species (Weir et al. 2005, Johnson et al. 2009). As such, from a biological perspective, testing and adoption of methods that provide rigorous, accurate estimates of population size are not only relevant, but requisite for informed population management of many wildlife species (Williams et al. 2002).

No single species has had more work focused on population size estimation and methodological evaluation than the white-tailed deer (*Odocoileus virginianus*). A suite of approaches have been used to look at deer population size, ranging from browse surveys (Aldous 1944, Tremblay et al. 2005), harvest data reconstruction (Roseberry and Woolf 1991, Millspaugh et al. 2009), pellet counts (Eberhardt and Van Etten 1956, Van Etten and Bennet 1965, Fuller 1991), aerial surveys (Potvin et al. 2002, Potvin and Breton 2005), infrared and thermal imaging surveys (Wiggers and Beckerman 1993, Gill et al. 1997, Collier et al. 2007), and camera surveys (Jacobson et al. 1997, Koerth and Kroll 2000) among others. However, the most commonly applied (and often recommended) method for deer population estimation and monitoring at the local and state scale has been the spotlight survey (McCullough 1982, Mitchell 1986, DeYoung 2011). Application and evaluation of spotlight survey procedures for estimation of white-tailed deer population size has been well studied over the last 50 years, primarily focusing on identifying inherent issues associated with bias in locating individuals during surveys (McCullough 1982, O'Connell et al. 1999, Collier et al. 2007). In the situation where bias has been addressed, the relative precision of spotlight survey estimates, either as raw or detection corrected counts, have been assumed to provide

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[1]*E-mail: bret@tamu.edu*

deer managers with reliable data that can be applied to management decisions.

Research on the utility of spotlight surveys has consistently reported variation in observation (detection) rate (McCullough 1982, Fafarman and DeYoung 1986, Focardi et al. 2001, Collier et al. 2007), but managers continue to suggest that survey replication, when combined with assumptions regarding variation in estimated detection rates, will allow spotlight survey data to represent a viable index for monitoring population trends (Fafarman and DeYoung 1986, Whipple et al. 1994, DeYoung 2011). Thus, the question of interest is whether spotlight surveys for white-tailed deer, corrected for imperfect detection, provide a value that approximates or approaches a true (yet nearly always unknown) estimate of population size. The focus of our work has been to evaluate whether variability in detection rates during spotlight surveys for white-tailed deer has caused spotlight surveys to have negligible benefit for monitoring of population trends. Our objectives were to 1) estimate detection probabilities for white-tailed deer spotlight surveys, 2) determine whether the detection process demonstrated any consistency between and among surveyors, and 3) estimate process and sampling variance allowing for generalizations of the detection process, which would support continued use of traditional spotlight surveys for managing white-tailed deer populations.

## METHODS

### Field Methods

We conducted our research on Brosnan Forest in Dorchester County, South Carolina, USA. Brosnan Forest was a 5,830-ha tract of lower coastal plains habitat, approximately 93% forested, and had about 330 km of navigable roads. Vegetation was comprised primarily of interspersed stands of mature longleaf pine (*Pinus* spp.), bottomland hardwood drains and mixed pine–hardwoods managed for timber production. Overstory species included oak (*Quercus* spp.), sweetgum (*Liquidambar styraciflua*), black gum (*Nyssa sylvatica*), and yellow poplar (*Liriodendron tulipifera*), with mixed pine–hardwoods comprised of loblolly (*Pinus taeda*), slash (*Pinus elliottii*), and pond pine (*Pinus serotina*), oak, sweetgum, and red maple (*Acer rubrum*; Jordan 2002).

The deer population on Brosnan Forest was actively hunted (100 days/yr) and managed using a strategy where hunters were discouraged from harvesting young ($\leq$2 years of age) males, and antlerless harvest was encouraged. Deer season extended from 15 August until 1 January each year during our study with approximately 500 hunters on site during each year. Detailed records were collected from all harvested deer, including information on harvest location, sex, age, gross Boone and Crockett score, live weight, and lactation status.

We used standard methods for spotlight surveys (Mitchell 1986), with surveys beginning at approximately 2100 hours (dusk) and lasting between 2 hours and 3.5 hours depending on transect length and deer encounter rate. We conducted surveys between 25 July and 12 August each year with transects consisting of non-overlapping roads on Brosnan Forest ranging from 12.6 km to 14.8 km within each management unit. We used a multiple observer closed capture approach (Collier et al. 2007), wherein 2 observers (1 thermal imager, 1 spotlight) independently surveyed for white-tailed deer on each vehicle side (4 observers per transect). Thermal imaging and spotlight observers were separated by a partition across the center of the truck bed. Thermal imager observers were located at the front of the truck bed and used either a Raytheon PalmIR 250 Digital or a Raytheon PalmIR Analog (Raytheon Commercial Infrared, Dallas, TX), while spotlight observers were located in the rear of the truck bed and used 1-million candlepower handheld spotlights (Lightforce SL240; Lightforce USA, Inc., Orofino, ID) for deer searches. Thermal imager and spotlight observers independently classified deer into classes (AM, AF, fawn, unknown) based on antler and body characteristics. We assigned each observation a unique time-specific identifier using synchronized digital clocks and thermal imager and spotlight observers cross-checked times when spotlight observers located deer.

### Data Analysis

Following Collier et al. (2007), we used a Huggins closed capture model implemented in Program MARK (Huggins 1989, 1991, White and Burnham 1999) via RMark v2.1.1 (Laake and Rexstad 2012). We let $i$ = detection with the thermal imager and $j$ = detection with the spotlight, where $i$ or $j$ = 1 represents captured (e.g., seen by the thermal imager or spotlight) and $i$ or $j$ = 0 as not captured. We treated our capture occasions as temporal replicates with individuals captured by the thermal imager as the first occasion and individuals captured by the spotlight as the second occasion. The resultant data consisted of individuals captured by both the thermal imager and the spotlight by the $k$th observer pair ($x_{11}^{k}$), individuals captured by the thermal imager only ($x_{10}^{k}$), and individuals captured by the spotlight only ($x_{01}^{k}$) for each survey. We ran 2 replicated surveys on each management unit ($n$ = 4) each year ($n$ = 5), except for 1 survey during 2007, wherein we were limited on observers and thus surveyed 1 side of the vehicle only, resulting in 79 unique management unit–observer–year surveys conducted over the 5 years of our study.

Based on previous research on our study site and our understanding of factors that influenced detection rate (Collier et al. 2007), we developed a set of 7 potential candidate models addressing variation in detection of white-tailed deer during spotlight surveys. Our model set ranged from a constant model, wherein detection did not differ across surveys, management unit, or observers (no. parameters = 1), to a group and time dependent model varying across all unit–transect–observer–year combinations (no. parameters = 158). We evaluated fit of each candidate model using Akaike's information criterion (AIC$_c$; Burnham and Anderson 2002) and for those parameters with a detection probability of 1 (e.g., undefined variance; White and Burnham 1999), we used profile likelihood confidence interval coverage to estimate lower confidence bounds on detection estimates. For our road-transect survey data, we treated each deer as an individual unit, regardless of whether it was captured within a group or individually. However, in many cases, sighted deer were in groups when detected (Table 2 in Collier et al. 2007) and as such we likely violated the independence assumption implicit in capture–recapture modeling (e.g., detection of 1 individual does not influence detection of any other individuals), which would cause sampling variance to be underestimated (Schmutz et al. 1995, Bishop et al. 2008). We used the data-bootstrap simulation procedure ($n = 7{,}000$ simulations) in Program MARK to estimate thermal imager and spotlight detection probabilities while addressing potential dependence in detections (Bishop et al. 2008). Additionally, when discussing spotlight surveys for monitoring, replication has often been suggested to assist with monitoring population trends (DeYoung 2011). As we were interested in how variation in spotlight detection rates could influence estimates of population size for replicated surveys, we used a variance components approach (Burnham and White 2002) to estimate the mean and variance of the spotlight detection rates based on our 79 surveys. As an example of the complexities of using a mean detection correction for trend analysis, we conducted a simulation using replicated random draws ($n = 100$) from a normal distribution $N(\mu, \sigma)$ using the estimated mean and process variance for spotlight detections. For each combination, we estimated the proportion of times populations of fixed survey size were expected to predict an increase, decrease, or remain the same (with constancy defined as the resultant prediction being within $\pm 0.2$ of the mean for all simulation iterations; see study data and R code, available online at www.onlinelibrary.wiley.com).

# RESULTS

During our surveys, we identified 4,508 individuals, with thermal imagers detecting 85% ($n = 3{,}861$) of the total deer seen and the spotlights detecting 48% ($n = 2{,}174$). Of the deer we observed, 33% ($n = 1{,}527$) were observed by both the thermal imagers and spotlights, 51% ($n = 2{,}334$) were detected only by thermal imagers, and 14% ($n = 647$) were detected only by spotlights. We ran 39 unique transects over the 5 years of our study, with the 39 transects resulting in 79 surveys (e.g., we had surveyors on both sides of truck for all but 1 survey), which represented our minimum explanatory unit of analysis.

Our model selection results indicated that the most parsimonious model, given the data, was one where detection rates differed by observer, survey, management unit, and replicate ($k = 158$; Table 1). The $\Delta AIC_c$ between this model and the next highest ranked model was 539.56 and had model weight of 1, thus we limit our inferences to interpretation of results from the global model. Detection probabilities were almost always (>98% of surveys) greater for the thermal imager than spotlight observers. As indicated by our selected model, we found little consistency in detection probabilities for spotlight observers with estimated detection ranging from 0 to 0.80 (median = 0.45) across all surveys. For comparative purposes, predictions from our method-specific model indicated that the average estimate of detection probability for the thermal imager was substantially greater (0.79, SE = 0.009, 95% CI = 0.77–0.80) than the spotlight (0.45, SE = 0.008, 95% CI = 0.43–0.47). Bootstrapped estimates of detection probabilities, which accounted for dependence in the detection rates showed considerable variability for spotlight surveys over our 79 survey occasions (Fig. 1). Based on our variance components analysis, mean thermal imager detection probability and associated process standard deviation estimates ($\mu = 0.739$; $\sigma = 0.178$) were slightly less than thermal imager estimates from the method-specific model (0.79). Spotlight detection probability and associated process standard deviation estimates ($\mu = 0.413$; $\sigma = 0.123$) were also slightly less than the predicted value (0.45) from the method-specific model for spotlight detections. Using the variance component estimates from our data, we estimated that the frequency of surveys under which one could expect the data to exhibit constancy in estimated population size was approximately 21%, with roughly 54% of all surveys expected to exhibit decreasing population trends relative to the mean detection corrected estimate and roughly 24% of all surveys expected to exhibit increasing population trends relative to the mean.

# DISCUSSION

## Detection Rates

Our results highlight several issues that should warrant the interest of white-tailed deer managers and researchers. First, the overall probability of detecting a white-tailed deer during spotlight surveys is quite low, and based on our data an

**Table 1.** Candidate models, number of model parameters ($K$), Akaike's information criterion ($AIC_c$) and associated model ranks ($\Delta AIC_c$), and model weights ($w_i$) used to estimate thermal imaging and spotlight detection probabilities based on double-observer road-transect surveys of white-tailed deer conducted on Brosnan Forest, South Carolina, USA between 2005 and 2009.

| Candidate models | $K$ | $AIC_c$ | $\Delta AIC_c$ | $w_i$ |
|---|---|---|---|---|
| $P(t \times$ Survey)—detection probability differs between thermal imager and spotlight observers for each survey replicate | 158 | 8,152.85 | 0 | 1 |
| $P(t \times$ Year + MU)—detection probability differs between thermal imager and spotlight observers by year with an additive effect of management unit | 13 | 8,692.42 | 539.6 | 0 |
| $P(t \times$ Year)—detection probability differs between thermal imager and spotlight observers by year | 10 | 8,715.19 | 562.3 | 0 |
| $P(t \times$ MU)—detection probability differs between thermal imager and spotlight observers by management unit | 8 | 8,859.81 | 706.9 | 0 |
| $P(t)$—detection probability differs between thermal imager and spotlight observers | 2 | 8,894.90 | 742.0 | 0 |
| $P$(MU)—detection probability differs by management unit | 4 | 9,882.04 | 1,729.2 | 0 |
| $P(.)$—constant detection probability | 1 | 9,906.49 | 1,753.6 | 0 |

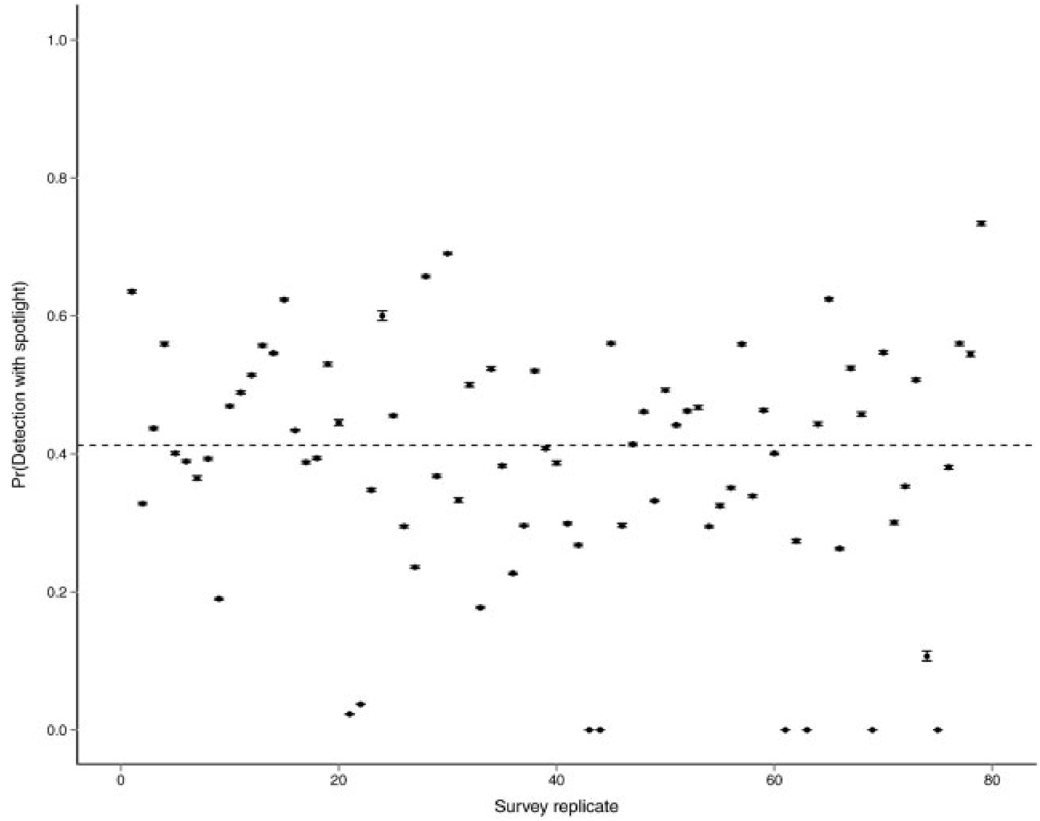


**Figure 1.** Detection probabilities (95% CI) for spotlight observers based on 7,000 bootstrapped replicates for each white-tailed deer survey ($n = 79$) using data collected at Brosnan Forest, South Carolina, USA during 2005–2009. Dashed line represents mean spotlight detection probability ($\mu = 0.413$) estimated from variance component analyses in Program MARK.

average probability of detection falls around 0.41. Next, our best fitting model, given the data, and our variance component analysis supports previous findings (McCullough 1982, Collier et al. 2007) in that detection probabilities, in addition to being low, also exhibit considerable, unstructured variability. The fact that detection rates with spotlights were variable is not a surprising discovery in and of itself, as many authors have lamented the need for addressing detection rates for white-tailed deer (see Collier et al. 2007 and references therein). As observers during our research were consistent both within and between years, and each observer (including all the authors) had at least 5 years of experience (with some having >20 yr) conducting deer spotlight surveys, we are confident that concerns regarding significant differences in observer ability are negligible. Although not quantified, during our work we found that most deer missed by the spotlight were because of either distance from the observer (e.g., outside the bounds at which spotlights could reach) or heavy vegetation obstruction between the deer and the observer. Missing observations by the thermal imager were most always because of vegetation obstruction as heat signatures cannot be seen though vegetation (Ditchkoff et al. 2005). We also found no consistency in detection probability between or among observers, indicating that recommendations to use the same observers during each survey in efforts to increase precision and reduce variability of survey estimates are invalid. Simulations using our variance component analyses indicated that apparent trends in deer density over time are just as likely to be a function of random variability in the observation process as real changes in deer density, and little useful knowledge can be gained by examining or collecting these data. Additionally, our results indicate that use of an average detection probability, as we have provided above, to correct a set of transect surveys for observer variation is also inappropriate as the amount of variation showed no consistent pattern in our data between or among transects over time.

## Why Our Results Are Irrelevant

Regretfully, all the results and effort described in our study are irrelevant from a practical standpoint. Given that spotlight surveys are regularly conducted across the United States on both private and public lands in support of population monitoring and harvest planning, the likelihood of mangers estimating detection rate corrections for each location, observer, and time frame is implausible. However, even though much time and effort has been spent addressing detection heterogeneity, methods for correcting imperfect detection are not the limiting factor (Buckland et al. 2001, Williams et al. 2002, Borchers et al. 2006, Buckland et al. 2010) as the issue driving irrelevancy of white-tailed deer spotlight transects is the inadequacy of the underlying sampling frame, including our study, to meet the most basic sampling assumption; that of random placement of transects (Thompson et al. 1998, Buckland et al. 2001). The inappropriateness and potential bias introduced by road-based sampling for a variety of species has been documented extensively (Anderson et al. 1979, Burnham et al. 1980, Anderson 2001, Pollock et al. 2002, Ellingson and Lukacs 2003, Sauer et al. 2005), has been described as a "distressingly widespread" occurrence (Buckland et al. 2000), and bias from road based transects has been shown to exceed 100% (Marques et al. 2010). Yet, for road-based spotlight surveys, the issue of non-random sampling has been conveniently ignored (Killmaster et al. 2007, Sherrill et al. 2010), or for methods such as distance sampling, statistical assumptions that targets (e.g., deer) are distributed uniform to the transect within the estimated transect strip width (Buckland et al. 2001, Marques et al. 2010) have been misinterpreted in the literature where authors have incorrectly justified their results under assumptions of random or proportional distributions relative to the transect (Butler et al. 2007, Erxleben et al. 2011, McShea et al. 2011). Additionally, arguments that tracking trends based on the same surveys at the same location over time such that index values can be monitored (DeYoung 2011) have been debunked as an appropriate monitoring strategy (Anderson 2001), and thus those suggestions are likely invalid from both a sampling and analytical standpoint as our results have shown. As such, based on our results, we suggest that most estimates of deer population size or trend based on spotlight surveys, regardless of what analytical method correcting for detection is used, exhibit a considerable yet unknown amount of bias which is immeasurable given current sampling limitations.

### What Do We Do Now?

In general, we, as did McCullough (1982), question the usefulness of typical surveys for white-tailed deer that are intended to determine population size or trends, as decades of these surveys have left linkages between deer survey data, population size, or trajectory wanton. As aforementioned, we stated that "adoption of methods which provide rigorous, accurate estimates of population size are not only relevant, but requisite for informed population management of many wildlife species" with emphasis on the "many" in that statement. Based on our experience, few, if any, white-tailed deer populations are managed, or require management, based on truly informed estimates of population size at the state, regional, or even county scale. The lack of informed population size estimates is likely due to the suite of untenable assumptions and significant data limitations associated with monitoring methods such as we have detailed, or other standard population modeling techniques (Millspaugh et al. 2009).

We recognize that our suggestions will be unpopular within many circles as the application of spotlight surveys for population monitoring has been ongoing and continues to be suggested by state and federal natural resource agencies (Naugle et al. 2002, Peitz et al. 2007, Jester and Dillard 2010, McShea et al. 2011) and highlighted for use on private lands (Main 2008, Yarrow 2009, Brown et al. 2010, Jester and Dillard 2010, DeYoung 2011). Although the argument in favor of spotlight surveys is that alternative methods are not available or would be cost ineffective, we suggest that the decades of effort and the immeasurable financial resources directed to gathering deer spotlight data has provided little defensible management information for what is likely the most important game animal in the United States. Finally, considering their shortcomings, we believe that the relative value of deer density estimates for aiding in management decisions has been grossly overestimated. Rather, we suggest that the perceived need to generate estimates of deer density has arisen from external pressure from non-professionals. In short, we as professional biologists are expected to know how many deer exist, because that is perceived to be what we do. Regardless of the accuracy, precision, or intrinsic value of these estimates, the perception of the general public is that density estimates are a requisite for good deer management, and many biologists and agencies both knowingly and unknowingly perpetuate this fallacy. As such, we encourage managers and agencies to evaluate the necessity of conducting or recommending annual spotlight surveys for determining size or trend of white-tailed deer populations. Not only do these techniques likely provide erroneous and misleading data, but the continued affirmation to the general public that these techniques are of value through their sustained use undermines the science, or art, of deer management.

## MANAGEMENT IMPLICATIONS

We suggest that resources designated to monitoring white-tailed deer population size via road-based surveys be reallocated to development and application of alternative methods for population monitoring. Biologically, the continued use of spotlight survey data to monitor deer and base management decisions represents a waste of resources and provides, at best, nothing more than a detection corrected estimate of the minimum number of white-tailed deer seen alive and near the road at the time of the survey. The vagueness of the data collected and the relative ambiguity in how those data are to be interpreted in harvest planning and population monitoring will continue to limit the usefulness of white-tailed deer spotlight surveys for supporting viable management actions. Additionally, we encourage managers to reconsider the necessity and usefulness of deer density estimates for management prescriptions at any scale.


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