Using Distance-sampling to Estimate Density of White-tailed Deer in Forested, Mountainous Landscapes in Virginia

David M. Montague[1, 2,*], Roxzanna D. Montague[1], Michael L. Fies[3], and Marcella J. Kelly[1]

Abstract - Although *Odocoileus virginianus* (White-tailed Deer, hereafter, Deer) are abundant on private lands throughout much of the western Virginia mountain region, populations are comparatively low on publicly owned lands in this area. Concerns voiced by sportsmen regarding declining numbers of Deer on public lands in western Virginia prompted research to estimate the population density in selected areas within this region. From January 2012 through April 2013, we used ground-based transect sampling with forward-looking infrared (FLIR) techniques in a distance-sampling framework to estimate seasonal Deer density in mountainous western Virginia. We included habitat variables and abiotic factors thought to influence detection and ranked models using AIC_c model selection in the program DISTANCE. We observed 430 groups of Deer (mean group size = 2.9) during 5 sampling sessions conducted along 562.5 km traveled in Bath County, versus 102 groups (mean group size = 2.6) along 643.6 km in Rockingham County. Wind speed negatively affected detection, and minimum temperature positively influenced detection. Detection rates were higher in open areas and forest edges, and higher closer to a full moon. Overall, we found Deer densities to be lower in the mountainous areas we sampled compared to the few studies using similar sampling techniques in other nearby areas of the state. Additionally, we found that while density did not vary seasonally, Deer densities were higher in Bath County (4.75–16.06 Deer/km^2) than in Rockingham County (0.17–3.55 Deer/km^2), likely due to the presence of more edge and open habitat in Bath County. We suggest that distance estimation is a viable technique to survey Deer, but caution that our sample sizes were small for some surveys and suggest that future research should seek to account for low detection rates on national forest lands by increasing effort.

Introduction

Odocoileus virginianus Zimmermann (White-tailed Deer, hereafter, Deer) are abundant throughout many areas of Virginia; however, Deer populations in parts of western Virginia, especially on publicly owned lands in the Allegheny Mountains, are comparatively lower than most other areas of the state (VDGIF 2015). Since the mid-1990s, Deer population indices on public lands in counties within this region have declined by 58–71% (VDGIF 2015). During this same time period, the Deer harvest on public land in western Virginia trended downward by 64% (VDGIF 2015). Long-term declines in Deer herds on private land have also been documented in the Alleghany Highland counties (Alleghany, Bath, and Highland) and in the northern

[1]Department of Fish and Wildlife Conservation, Virginia Tech, Blacksburg, VA 24061. [2]Downeast Lakes Land Trust, Grand Lake Stream, ME 04668. [3]Virginia Department of Game and Inland Fisheries, Verona, VA 24482. [*]Corresponding author - dmontague@downeastlakes.org.

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Shenandoah Valley (VDGIF 2015). Possible reasons for reduced Deer harvests in this region could include decreasing numbers due to a reduction in habitat quality, increased mortality due to predation, or alternatively, the harvest decreases could be due simply to decreases in the number of Deer hunters (Knox 2011).

In the mid-20th century, Deer hunters traveled long distances to the counties west of the Shenandoah Valley during Deer season, setting up temporary camps and spending a week or more hunting the large tracts of public land in these areas (Knox 2011). However, in recent decades, relatively few Deer hunters have traveled to public lands in these counties, and those that did, reported seeing fewer Deer and experiencing reduced hunter success (Knox 2011). To some degree, the reduction in hunters on public lands in western counties corresponds with the decline in the overall number of hunters in the state. Based on license sales, the number of hunters in national forests in Virginia has declined by 30% since the mid-1990s (Knox 2011). This decrease in the number of sportsmen utilizing these historically popular hunting areas was likely influenced by the increased availability of alternative Deer hunting opportunities in other parts of the state. When hunter numbers were higher on public lands west of the Shenandoah Valley, Deer populations in many other parts of the state, such as in southwestern Virginia, were relatively or extremely low, which is no longer the case (Knox 2011).

Alternatively, the reduced number of Deer hunters on public lands could be in response to lower Deer densities associated with declining habitat quality. Decreased timber harvest during the past 30+ years on national forests has resulted in a dominant habitat type that is of poor quality for Deer: even-aged intermediate and mature hardwood forests with very little disturbance, few stands of young forest, and less edge-habitat (VDGIF 2015). The positive association between robust White-tailed Deer populations and young, disturbed forests and edges is well-established (Roseberry and Woolf 1998, Vreeland et al. 2004, Williamson and Hirth 1985). As forests age and habitat structure becomes increasingly homogeneous, carrying capacity for Deer declines (Sinclair 1997).

In Virginia, hunter-harvest data (antlered Deer per square mile of forested range) is used as an index of relative population abundance (VDGIF 2015). This metric is commonly used to monitor trends in hunted Deer populations with minimal expense and sampling effort. However, such data have limited utility for estimating actual Deer population density because hunter harvest fluctuations can result from numerous variables unrelated to Deer abundance. Deer harvest data can be influenced by changes in hunter numbers, hunter effort (number of days hunted), variability in hunter reporting, or hunter success rate due to other variables (i.e., weather, mast abundance) (Roseberry and Woolf 1991, Rosenberry et al. 2004). To investigate the current status of Deer populations in areas west of the Shenandoah Valley (Bath County and western Rockingham County), we employed ground-based distance sampling (Buckland et al. 2001), with forward-looking infrared (FLIR) techniques, to estimate seasonal Deer density. This survey method allowed us to directly model and account for biotic and abiotic factors that might influence Deer detection on transects. Our objectives were to determine and compare Deer population densities between

Rockingham County, which is comprised predominantly of public national forest lands, and Bath County, which contains a mosaic of public national forest land and small, private inholdings of open and edge habitat. We expected public forest lands to have lower Deer density because Deer prefer younger, disturbed forests and edges. We also compared our Deer densities to reported densities in other nearby areas of the state that used similar sampling techniques. Finally, we offer suggestions for improving precision of distance sampling for deer in forested habitat.

Field-site Description

Our study areas in Bath and western Rockingham Counties were identified by the Virginia Department of Game and Inland Fisheries (VDGIF) as priorities for this research based, in part, on the perception of lower Deer population densities relative to many other parts of the state (Fig. 1). Land ownership in both areas includes state, federal, and private holdings.

In Bath County, the study area comprised ~1300 km^2 of mosaic landscape that included forested mountain land under predominately public ownership heavily interspersed with small, privately owned open land used primarily for pasture and silage production. Public lands included the George Washington National Forest (federal), T.M. Gathright Wildlife Management Area (state), and Douthat State

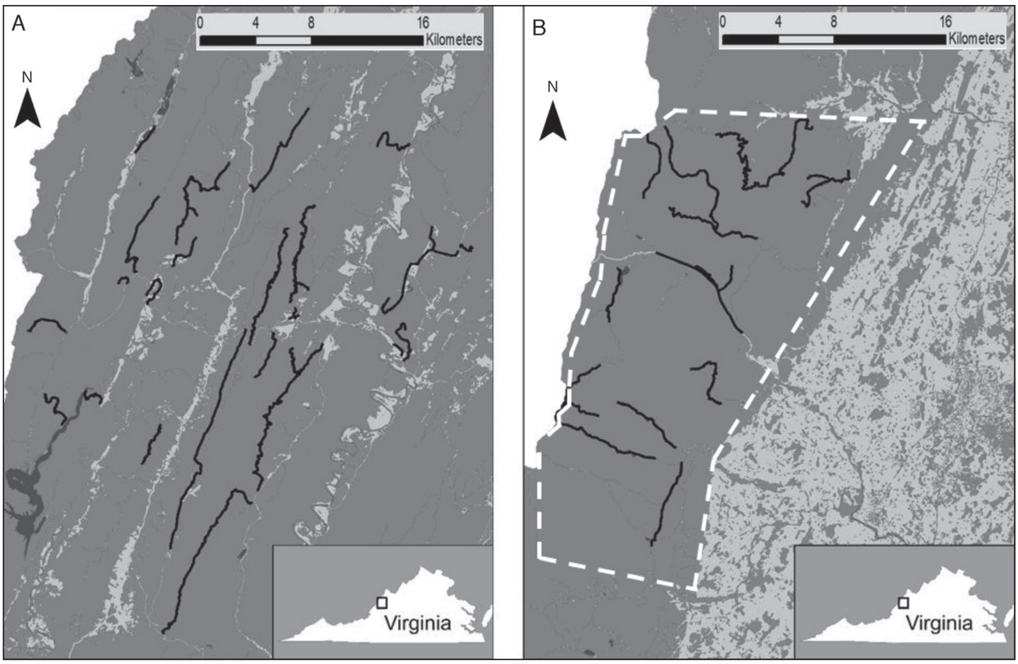

Figure 1. Study areas in 2012 and 2013 for (A) Bath and (B) Rockingham Counties, VA. Forest is dark gray, open space is light gray, and transects are black lines. Bath County (89% forested) has more open, private land in the valley bottoms with national forest lands interspersed along the ridges, whereas Rockingham County (95% forested) has more contiguous forest habitat with a hard edge to the east formed by agricultural and developed lands. Rockingham study area depicted within white-dashed polygon.

Park (state). Public lands are mostly higher-elevation areas consisting mainly of contiguous, even-aged (≥70 y old), mixed-oak forest, with a few widely dispersed, small clearings dominated by cool-season grasses and planted *Trifolium* spp. (clover). Some modified shelterwood harvesting and prescribed fire is used in land management.

The Warm Springs Mountain Preserve, a large area of private ownership managed by The Nature Conservancy (TNC), in Bath County, covers ~37 km^2 and adjoins national forest lands to create an area of roughly 311 km^2 (77,000 ac) of largely unfragmented forest (TNC 2011). There is no timber management within the TNC preserve, but prescribed fire is used to restore the historic disturbance regime.

With the exception of the Warm Springs Mountain Preserve, private land in Bath County is concentrated at lower elevations along roadways in the valleys. Private lands are primarily open and edge habitats or riparian corridors. Much of this area is managed as farmland or former farmland in various stages of post-agricultural succession.

The 625-km^2 study site in Rockingham County was restricted to the western third of the county, which is primarily national forest with very few private inholdings, nearly contiguous forested habitat, and little open land. At the eastern edge of the Rockingham study site, the forest ends abruptly and transitions into a large-scale agricultural area with livestock pastures, hayfields, and row crops such as corn and alfalfa (Fig. 1). We did not include this agricultural area in the study; transects were located at least 1.6 km (1 mi) from the abrupt edge to reduce the influence of these areas on Deer density estimates.

Methods

We adapted our methodology from those of other distance-sampling studies in Virginia (Lovely et al. 2013, McShea et al. 2012) except that we also incorporated forward-looking infrared (FLIR) technology to increase detection probability and account for mountainous terrain and low Deer detections. FLIR technology detects body heat, and during our surveys, Deer appeared as bright white objects against a black background, even when sparse vegetation obscured the outline of the Deer seen with the naked eye (Fig. 2). We sampled Deer populations during 5 survey sessions: January, April, and October 2012 and January and April 2013 in both Bath and Rockingham counties. During the first 2 sessions, we sampled Deer for 4 nights per county in each session (53–74 km). However, due to low numbers of Deer observed, we increased sampling effort in the next 3 sessions (Table 1) to include as many nights of sampling as needed to reach a target number of detections. In the mosaic landscape of Bath County, we targeted 40 detections on public (closed forest) and private (open and edge) land, while in Rockingham County we targeted a total of 40 detections on national forest land. Originally, we had planned to obtain 80 detections per habitat type (as suggested by Buckland et al. 2001), but we were unable to obtain that goal, even with extensive survey effort. Thus, we note that our results may not adequately capture variance in detection rates, potentially leading to imprecise estimates. Although our sampling sessions straddled the 2012–2013 Deer

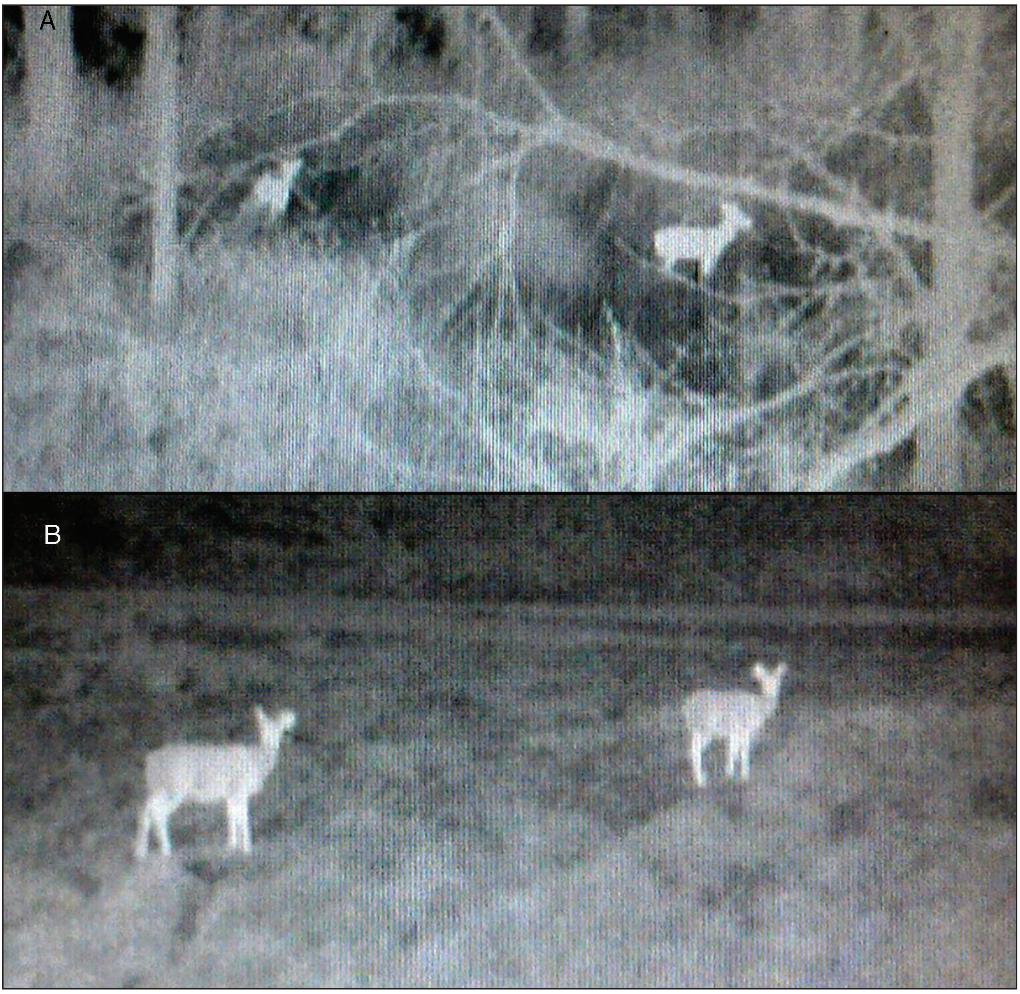

Figure 2. Thermal images of White-tailed Deer as seen through forward-looking infrared (FLIR) imagery in April 2013 in Bath County, VA.

Table 1. Seasonal sampling-effort in Bath and Rockingham counties, VA, from January 2012 to April 2013, including distance surveyed (km), the number of Deer groups, and total number of Deer observed. Average prop. surveyed = average proportion of open habitats surveys Asterisks (*) indicate sampling sessions with sufficiently large sample sizes to obtain reliable Deer density estimates in Rockingham County.

	Bath County					Rockingham County				
Session	Distance (km)	# of groups	# of deer	Average prop. surveyed	# of sampling nights	Distance (km)	# of groups	# of deer	Average prop. surveyed	# of sampling nights
Jan 2012	53.17	43	133	0.43	4	56.6	2	3	0.04	4
Apr 2012	74.56	91	289	0.38	4	64.82	14	39	0.18	4
Oct 2012	154.99	96	160	0.26	7	183.98*	50	85	0.17	10
Jan 2013	215.77	105	356	0.20	10	158.16	6	10	0.17	10
Apr 2013	83.7	95	401	0.27	6	152.13*	30	63	0.27	6

hunting season, hunter harvest of antlered bucks per unit area (the statistic used as a population index by Deer biologists in Virginia; VDGIF 2015) was lower in our study areas than the average for all counties west of the Blue Ridge Mountains (i.e., in mountainous Virginia) during this period (Bath: 0.79 antlered bucks/km^2, Rockingham public land: 0.54 antlered bucks/km^2, West of the Blue Ridge: 1.01 antlered bucks/km^2; VDGIF unpubl. data). Thus, we stratified our results by season to account for differences in density among seasons due to any factor, including hunter harvest.

We considered all existing roads within each study area (except major highways and other high-use paved roads) as transects (Bath: n = 28, Rockingham: n = 18), and surveyed transects randomly using assigned numbers and a random-number generator. The majority of roads (98%) were low-use, unpaved forested roads with complete canopy closure, no cleared median or right-of-way, and no houses, yards, fields, or other structures that would render them distinct from the surrounding natural habitat or that would cause Deer to cluster around the road. When necessary, we repeated sampling of transects, but only after all available transects had been visited once and only after several days of sampling; thus, no transects were sampled more than once per night.

We sampled between the hours of 20:00 and 03:00 using 4 x 4 vehicles traveling at speeds ≤10 km/h. Two observers stood in the bed of the pickup truck searching opposite sides of the road using the handheld FLIR units (First Mate HM-224, FLIR Systems, Wilsonville, OR) to detect Deer. To mitigate potential bias that might arise from movement of Deer from the transect in response to the observer, we used 2 spotters at all times, avoided unnecessary noise or light, and measured distance to the location of the first sighting of the Deer if obvious movement away from the observers occurred. Upon detection, we recorded the vehicle's location with a handheld GPS unit, time, weather conditions, air temperature, broadly-classified habitat type, and the number of Deer detected. We followed Lovely et al. (2013:3) to define a group of Deer as "deer at rest within 6 m of one another, deer grazing within 6 m of one another, or deer in motion traveling the same direction and within 6 m of one another". We used a handheld spotlight, laser rangefinder, and a large protractor mounted on the roof of the truck to obtain the sighting angle from the transect to the Deer. We used the distance to the Deer or the center point of a group of Deer along the sighting angle to calculate a perpendicular distance measurement from the transect to the Deer.

To estimate Deer density for both counties and include covariates influencing detection, we used the multiple-covariates distance-sampling (MCDS) platform program DISTANCE (Thomas et al. 2009). Covariates of detection included wind speed (mph), minimum daily temperature (°C), habitat type (forest, pasture, crop field, edge, riparian), and lunar phase (full, waning gibbous, waning crescent, new, waxing crescent, waxing gibbous). MCDS uses observation-specific data to estimate a detection probability; thus, habitat type was the categorical variable assigned individually to each observation. We tested all covariates singly and in combination, resulting in more 30 a priori models. Group size was treated using DISTANCE's default regression analysis, which reduces the potential bias caused by larger groups being detected more frequently at longer distances by plotting observed cluster-size against distance to estimate average group size. Wind speed, temperature, and lunar phase were based on archived NOAA weather data collected at stations located within the study sites (NOAA 2014). If there were too few detections to warrant covariate testing, we calculated basic density estimates using the half-normal detection function without covariates. We used a 5% right truncation of the data to remove outliers according to conventions for analyzing ground-based linear-survey data (Buckland et al. 2001). We added covariates in DISTANCE using forward stepwise model-building techniques, and we used various combinations of key functions, adjustment terms, and bin sizes to achieve model fit. We had several covariates and a relatively small sample size in some cases; thus, we made sure to always compare models with covariates to those without. We ranked models using Akaike's information criterion corrected for small sample size (AIC_c), and competing models were denoted as those within 2 ΔAICs of the top model (Burnham and Anderson 2002). If 95% confidence intervals on density estimates did not overlap, we assumed that there was a difference in Deer density between the 2 counties.

To avoid potential habitat sampling bias associated with the use of roads as transects, we buffered each transect in ESRI ArcMap 10.2.2 with the effective strip width (ESW) estimated by DISTANCE, averaged among seasons and stratified by county. We employed the Reclassify tool in ArcMap (ESRI 2014) to combine landcover types from the 2011 National Land Cover Database (NLCD; Homer et al. 2015) to calculate the percentages of open and forested habitats within each transect buffer; these were multiplied by the number of times each transect was visited in each sampling session to estimate the proportion of open and forested habitat sampled in each session. We compared these mean proportions among the transects to the proportion of available habitats within each study area using 95% confidence intervals.

Results

In all 5 sessions, we detected an adequate number of Deer clusters (n = 43–105; Table 1) to produce estimates of Deer density in the 130-km^2 Bath County study area. Despite extensive surveying in the 625-km^2 Rockingham County study site, we obtained too few detections in January 2012 (n = 2), April 2012 (n = 14), and January 2013 (n = 6) to obtain reliable density estimates (i.e., failed chi-square goodness-of-fit tests for all models). Based on chi-squared goodness-of-fit tests, we did accumulate enough detections to obtain reliable estimates for Rockingham County in October 2012 (n = 50) and April 2013 (n = 30).

The mean effective strip width (ESW) was 78.1 m in Bath County (SD = 21.4 m) and 53.6 m in Rockingham County (SD = 8.7 m). The mean proportions of open habitats sampled within the ESW were 0.31 (SD = 0.09) in Bath County and 0.17 (SD = 0.08) in Rockingham County. The proportion of open habitat available in each study area is 0.21 in Bath County and 0.14 in Rockingham County, both of which fall within the 95% confidence intervals of the proportions sampled.

In all seasons for both study sites, the half-normal detection function (with no adjustments) was highest ranked by AIC compared to other detection functions (Table 2). Using the default bin sizes led to failure of DISTANCE's goodness-of-fit test; thus, we manually adjusted bin sizes to achieve model fit. In the 5 surveys in Bath County the half-normal cosine with no adjustments was always the best detection model as ranked by AIC_c, but models incorporating habitat, temperature, wind, and lunar phase were competing, thus demonstrating model uncertainty. In Rockingham County the half-normal cosine without adjustments was always the best model, and in 3 of the 5 surveys, no covariates were included in the top-ranked model with no competing models. In the other 2 surveys, models incorporating habitat, temperature, and wind were competing (Table 2). In both study areas, covariates that improved model fit in some seasons included average wind speed and minimum temperatures. Detection was always negatively related to average wind speed and positively related to minimum temperature. Detection rate was higher in open habitats (fields, forest edges, etc.) and higher closer to the full moon.

Density estimates varied from 4.75 to 16.06 Deer/km^2 in Bath County and from 0.17 to 4.96 Deer/km^2 in Rockingham County (Table 2). Based on the overlap in the 95% confidence intervals, Deer density did not vary among seasons within each site, but density estimates were higher in Bath County in 4 of the 5 sessions. Bath County Deer density varied from 4.3 to 91.3 times higher than in Rockingham County across seasons (Fig. 3).

Discussion

White-tailed Deer density estimates in our study areas are relatively low compared to several nearby counties farther east that estimated Deer density using distance-estimation techniques. Those studies estimated Deer densities of

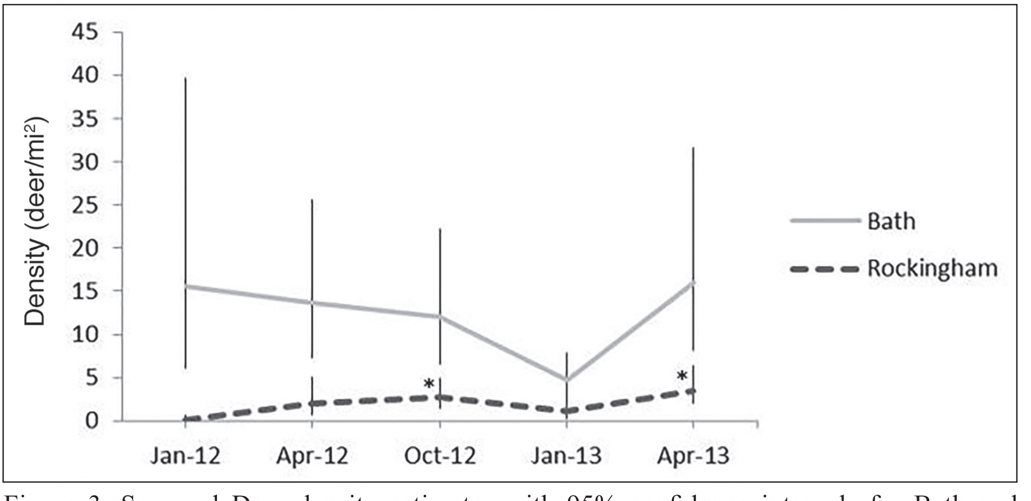

Figure 3. Seasonal Deer density estimates with 95% confidence intervals for Bath and Rockingham Counties, VA, from January 2012 to April 2013 as determined by distance estimation in the program DISTANCE. Asterisks (*)indicate sessions from which reliable estimates (based on goodness-of-fit tests) were obtained in the Rockingham study area.

Table 2. Models of White-tailed Deer density (Deer/km^2; D), including the lower and upper confidence limits (DLCL and DUCL, respectively) and the coefficient of variation (DCV) in Bath (BA) and Rockingham (RO) counties, VA, analyzed in the program DISTANCE. Models with ΔAIC > 6 are not shown. K = the number of parameters, ESW/EDR = the effective strip width (m), P = detection probability, HN = half-normal key function, Cos = cosine (in all cases no adjustment term was needed), Hab = habitat type, Wind = average wind speed, Temp = minimum temperature, Moon = lunar phase, and None = no covariates. [Table continued on following page.]

Session/ County	Model	Covariates	K	ΔAIC_c	ESW/EDR	D	DLCL	DUCL	DCV	P	Var-P
January 2012											
BA	HN_Cos	Temp	2	0.000	93.755	15.525	6.074	39.682	0.451	0.66968	0.0721
RO	HN_Cos	None	1	0.000	56.191	0.170	0.000	0.690	0.302	0.45140	0.5402
April 2012											
BA	HN_Cos	Hab	3	0.000	72.562	13.740	7.369	25.619	0.311	0.36281	0.0353
	HN_Cos	Hab + Temp	5	0.330	67.890	15.024	7.999	28.221	0.316	0.33945	0.0377
	HN_Cos	Hab + Wind + Moon	5	0.730	69.653	14.483	7.730	27.137	0.314	0.34826	0.0371
	HN_Cos	Hab + Temp + Wind	5	0.980	70.236	14.104	7.532	26.411	0.314	0.35118	0.0372
	HN_Cos	Hab + Temp	4	1.126	72.229	13.534	7.256	25.244	0.311	0.36114	0.0355
	HN_Cos	Wind + Hab	4	1.653	72.565	13.537	7.258	25.246	0.311	0.36282	0.0356
	HN_Cos	Hab + Moon	4	1.975	72.444	13.836	7.414	25.821	0.312	0.36222	0.0359
	HN_Cos	Hab + Temp + Wind + Moon	6	2.403	69.375	14.441	7.697	27.095	0.315	0.34687	0.0379
	HN_Cos	Wind + Moon	3	4.434	75.900	12.120	6.515	22.549	0.310	0.37950	0.0360
RO	HN_Cos	None	1	0.000	56.373	1.960	0.760	5.050	0.419	0.22689	0.0517
October 2012											
BA	HN_Cos	Wind + Moon + Temp	5	0.000	43.953	12.090	6.593	22.171	0.305	0.35163	0.0387
	HN_Cos	Wind + Moon	4	4.318	46.648	10.742	5.894	19.578	0.301	0.37319	0.0370
	HN_Cos	Wind	2	5.611	49.352	9.709	5.358	17.591	0.298	0.39482	0.0346
	HN_Cos	Wind + Temp	3	5.794	48.238	9.859	5.436	17.882	0.298	0.38591	0.0347
RO	HN_Cos	None	1	0.000	58.971	2.707	1.502	4.880	0.301	0.53610	0.0678
	HN_Cos	Hab	3	0.347	57.101	3.161	1.774	5.633	0.294	0.51910	0.0557
	HN_Cos	Temp	2	1.699	58.731	2.658	1.498	4.717	0.292	0.53392	0.0554
	HN_Cos	Wind	2	1.928	58.912	2.720	1.534	4.822	0.291	0.53556	0.0544
	HN_Cos	Wind Hab	4	2.258	57.048	3.161	1.747	5.717	0.303	0.51862	0.0669
	HN_Cos	Wind + Temp	3	3.647	58.663	2.673	1.504	4.750	0.292	0.53330	0.0566

Table 2, continued.

Session/ County	Model	Covariates	K	ΔAIC_c	ESW/EDR	D	DLCL	DUCL	DCV	*P*	Var-*P*
January 2013											
BA	HN_Cos	Wind	2	0.000	98.340	4.749	2.871	7.856	0.257	0.54633	0.0471
	HN_Cos	Wind + Temp	3	1.952	98.396	4.833	2.911	8.023	0.259	0.54664	0.0502
	HN_Cos	Wind + Moon	5	5.134	95.202	5.049	1.166	21.858	0.851	0.52890	0.4317
RO	HN_Cos	None	1	0.000	58.369	1.100	0.21	5.77	0.328	0.42623	0.0359
April 2013											
BA	HN_Cos	Wind	2	0.000	78.853	16.063	8.150	31.660	0.342	0.16702	0.0738
RO	HN_Cos	Hab	3	0.000	38.238	4.126	1.837	9.267	0.420	0.47797	0.1530
	HN_Cos	Wind + Hab	4	2.000	37.354	4.313	1.794	10.370	0.458	0.46692	0.1717
	HN_Cos	Hab + Temp	4	2.000	36.369	4.463	1.627	12.239	0.533	0.45461	0.2079
	HN_Cos	Hab + Temp + Wind	5	4.000	34.515	4.960	1.705	14.434	0.567	0.43144	0.2140

9.4–30.1 Deer/km^2 (Lovely et al. 2013), 5–47 Deer/km^2 (McShea et al. 2008), and 5.8–33.4 Deer/km^2 (McShea et al. 2012). Interestingly, the authors of these studies did not report difficulty in obtaining adequate sample sizes for distance estimation and achieved minimum sample sizes in far less time than we did. However, these studies occurred in parts of northern Virginia where the availability of suburban and open habitats is greater. VDGIF Deer density indices based on harvest data (antlered Deer killed per km^2 forested range) varied from 1.4 to 1.7 in these counties, compared to 0.5 on public lands in Bath and western Rockingham counties (VDGIF 2015).

The positive relationship between Deer abundance and young forests created by fire or timber harvest, edge habitats, and open agricultural landscapes is well documented (Beier and McCullough 1990, Roseberry and Woolf 1998, Vreeland et al. 2004). Given this established habitat association for Deer, we were not surprised to find that Bath County, with a higher proportion of these habitats, had a substantially higher Deer density than national forest land in Rockingham County. In our first 2 surveys on the Rockingham County land, we had so few Deer detections that we were only able to fit models with constant detection and no covariates (thus, the reliability of these estimates should be treated with caution). Hence, we increased survey effort in Rockingham County in the next 3 sessions (doubling and/or tripling our effort), yet were only able to include covariates in 2 of these 3 sessions. In the 2 sessions with sufficient detections to incorporate covariates, Deer density was still significantly lower (95% CIs did not overlap) in Rockingham County than in Bath County. In fact, of all 5 sessions, only in January 2013 did density CIs overlap between counties, likely due to low detection of Deer at both sites (relative to survey effort) and subsequent high model-uncertainty in that winter. Anecdotally, in Rockingham, Deer were most commonly observed in the few areas that were close to fields, timber harvests, and agricultural edges—habitats that are uncommon on the national forest lands. Our study also highlights the need for high expenditure in sampling effort in future studies in this region to achieve adequate detections for density estimation in winter.

Detection was often negatively related to average wind speed and positively related to minimum temperature in our models; thus, our inability to achieve an adequate number of detections in mid-winter may have been due to abiotic factors. It is possible that cold, windy weather reduced Deer movements, as observed by Schmitz (1991). Such a reduction in movement could affect the detectability of Deer during distance sampling. Alternatively, Deer in western Rockingham County may have reduced their use of forested habitats during the winter months in favor of nearby open habitats with higher food availability. Winter movement toward agricultural row crops was observed by Brinkman et al. (2005) in Minnesota, and both Storm et al. (2007) and Kilpatrick and Spohr (2000) documented Deer movement toward human dwellings in winter. These more open or early-successional habitats were typically found on private lands adjacent to the national forest lands we sampled, and if such a habitat shift occurred, our low estimates accurately reflect deer densities in western Rockingham County in winter. Interestingly, our

Deer-detection rate increased close to the full moon, which may indicate higher Deer activity levels at this time due to enhanced visual detection of predators.

We note that the use of roads as transects can bias density estimates if Deer are attracted to or avoid roads (Buckland et al. 2001). For example, if open or agricultural habitats are disproportionately located in close proximity to roads, deer may be drawn to these habitats, resulting in inflated estimates of density. This bias is unlikely in our Rockingham County study area because the available roads used as transects were almost exclusively narrow, dirt roads used for recreational access within the national forest that were not associated with agriculture, houses, or associated open areas. Rights of way seeded with vegetation occurred rarely, and we did not observe Deer using these areas when they were available. Given the low intensity of human use of these roads, it is also unlikely that bias was introduced by Deer avoiding roads. Thus, sampling on such low-use roads was the best option to effectively cover the 2 study areas.

Our estimates of Deer density in Bath County (4.75–16.06 deer/km^2) are consistent with crude density estimates inferred from harvest data (calculated as roughly 10 times the number of antlered bucks killed per square mile) reported by VDGIF in Bath County (density estimate of ~10.0 deer/km^2; VDGIF 2015). The lack of seasonal differences in population density may be due to the relatively short duration of the study and a corresponding low sample size for comparisons. Comparisons of Deer density among years may reveal differences over longer time periods, particularly when comparing years during which food availability varied (i.e., years with high abundance of acorns versus years with acorn crop failure. Our estimates are also consistent with VDGIF observations that Deer density indices in Bath County (public and private lands combined) were higher than on public lands in western Rockingham County. Despite low Deer densities, particularly for Rockingham County, we were able to document significantly lower density estimates in Rockingham County via distance sampling, especially once we increased sampling effort.

In addition to being consistent with Deer density-index data (VDGIF 2015), our data also support anecdotal hunter reports of very low Deer density on public lands in the areas we studied. The cause of these low densities remains unclear; however, the higher density that we observed in Bath County likely correlates with greater availability of open and disturbed habitats that Deer are known to favor (Johnson et al. 1995, Nixon et al. 1991). This conclusion is supported further by our observation that a majority of Deer were detected in open and disturbed habitats in all seasons in both study sites.

Although distance sampling is widely used to study ungulates in other parts of the US (Koenen et al. 2002, LaRue et al. 2007, Ward et al. 2004), it has not been used often for White-tailed Deer in Virginia. Aerial distance-sampling with infrared imagery can be cost prohibitive, and may be limited primarily to sampling in deciduous forests with low topographical relief during the winter months (Beaver et al. 2014, Kissell and Nimmo 2011, Storm et al. 2011). Ground-based distance sampling with FLIR has been used successfully for multi-species sampling in mixed habitats (Morrelle et al. 2012) and in areas where precise estimates are needed for focused management plans (Techentin et al. 2012). Our study demonstrates the utility of ground-based distance sampling with FLIR in a mountainous area with mixed coniferous and deciduous forest during non-winter seasons. Distance sampling at a county scale avoids issues surrounding the prevailing use of harvest data to estimate trends in Deer numbers, and while distance sampling has its own assumptions and limitations, we have shown that it can be a viable alternative tool for estimating and comparing densities across habitats. We caution however, that low-density Deer populations require extensive effort to obtain enough detections to reliably estimate density, and researchers should plan accordingly.

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