2018 ROADSIDE DISTANCE-SAMPLING SURVEYS OF WHITE-TAILED DEER IN SOUTHERN MINNESOTA

John H. Giudice, Brian S. Haroldson, Tyler R. Obermoller, and Andrew S. Norton

SUMMARY OF FINDINGS

This project was the first year of a 2-year pilot study designed to evaluate the feasibility of using roadside distance-sampling (DS) surveys to generate a reliable and cost-effective population monitoring metric for white-tailed deer (*Odocoileus virginianus*) in Minnesota's farmland and transition zones. In spring 2018, we surveyed 15 primary sampling units (PSUs) ≥3 times to assess temporal variation in deer population estimates; we observed a similar number of deer across replicates 1–3 (total deer/replicate for all PSUs = 1,038, 1,002, and 1,082, respectively). PSUs included high- and low-density road segments based upon juxtaposition to deer cover. Mean perpendicular sighting distance was greater in the low-density stratum (135 m) compared to the high-density stratum (108 m). As expected in convenience sampling from roadways, deer detections spiked away from the road, which likely reflected road avoidance rather than animal movement. Among-plot variation accounted for approximately 89% of total variation in raw deer counts. Thus, variation due to survey day (run) was relatively small compared to variation in counts among PSUs. Among the 8 DS models fit to the survey data, the 2 best-supported models included a covariate for relative visual obstruction (RVO). Models with strata as a covariate did not fit the data well, which suggests that the detection function [g(x)] did not vary significantly among the 2 strata. The deer density estimate from the top model was 8.6 deer/mi^2 (95% CI = 6.1–12.2). Estimates from the other models were similar. Likewise, the density estimate when data from each stratum were analyzed separately was nearly identical ($\widehat{D}$ = 8.5, ~95% CI = 5.5–11.3), which supports the decision to use a stratified DS estimator where data are pooled across strata to estimate g(x). The density estimate from a winter aerial survey ($\bar{x}$ = 6.4, 95% CI = 5.1–7.7) was comparable. Precision of the density estimate from our top model was reasonable (CV = 17.1%), but likely optimistic because it may not adequately reflect variation due to survey date. Precision was much lower (mean CV = 24.8%) when we bootstrapped distance data using PSU and run (surrogate for survey date). Overall, density estimates seem reasonable and precision was better than expected. We have identified and resolved several data collection and survey-design challenges and have developed detailed field protocols to ensure consistency in data collection. Another year of data collection will be helpful for evaluating the ultimate question of whether a DS metric can be effectively and reliably used to help monitor white-tailed deer populations in Minnesota's farmland and transition areas.

INTRODUCTION

White-tailed deer (*Odocoileus virginianus*) hunting season recommendations should use the most reliable information available to determine the status of the deer population relative to goal, while prioritizing objectivity. Because hunting season recommendations are made annually, this information needs to be collected on an annual basis. Currently, the only objective annual data the Minnesota Department of Natural Resources (MNDNR) collects at the deer permit area (DPA) scale is winter severity, hunter-reported harvest, and hunter effort. Although these data can provide inference about population trends, they require subjective user inputs that can result in incorrect inference. Objectivity and reliability of harvest-based models can be improved by collecting annual information to model variation of non-harvest vital rate parameters or any other model parameters that vary annually (e.g., harvest reporting rates). A potentially more cost-efficient and alternative approach would be to collect annually recurrent information to independently estimate population trends. Winter aerial surveys can provide this index, but financial and environmental (e.g., snow cover, conifer cover) constraints limit their use to every 5- to 10-years for each DPA; moreover, they are not considered reliable across western Minnesota where seasonal migration is suspected to violate DPA closure assumptions between winter surveys and fall hunting seasons. Several Midwestern states have explored the use of recurrent roadside observation surveys for monitoring deer population trends (Rolley et al. 2016). Variation in the observation process, possibly as a function of annual variation in deer distribution and resource use, has limited the reliability of these indices. DS methods can be used to statistically model the detection probability and calibrate annual variation in the observation process. However, problems have been identified with sampling deer from roadside surveys. Further research is needed to identify an optimal sampling design and evaluate robustness of roadside observation surveys to assumption violations.

Our objective was to evaluate the feasibility of using roadside DS surveys to generate a reliable (potentially biased but reasonably precise and repeatable) and cost-effective population monitoring metric for white-tailed deer in Minnesota's farmland and transition zones.

METHODS

Sampling Design

The 2,787-mi^2 sampling frame consisted of 4 DPAs (252, 253, 296, and 299) in southern Minnesota (Figure 1). We used a geographic information system (GIS; ArcGIS v. 10.4, Environmental Systems Research Institute, Inc., Redlands, CA) to stratify land-cover within the sampling frame into "high" and "low" strata based upon expected deer density. We defined high-density polygons as being within a 250-m buffer of woodland, grassland (permanent to semi-permanent, excluding pasture), and wetland cover classes. Low-density polygons were the remaining areas (e.g., agricultural land, open water, and urban/developed areas). Data sources for deer-density polygons included Minnesota Land Cover Classification and Impervious Surface Area by Landsat and Lidar: 2013 update – Version 2 (woodlands), a compilation of public/private grassland layers (e.g., Waterfowl Production Areas, Wildlife Management Areas, conservation easements, etc.), and the National Wetlands Inventory for Minnesota (wetlands). We then overlaid the sampling frame with a hexagonal grid, with township-sized hexagons (size = 36.1 mi^2) having >50% of their area inside the sampling frame serving as PSUs. We chose this size because it represented the approximate area that could be surveyed within a 4–6 hr period each night. We randomly selected a spatially balanced sample (Stevens and Olson 2004) of 16 PSUs, but discarded 1 PSU that was on the edge of the sampling frame and contained the city of Mankato. We then used a GIS to identify all secondary (e.g., county and township) roads within each PSU, defined by juxtaposition to deer-density strata (high, low). Finally, we randomly selected road segments (pooling roads $\geq$0.25 mi from all PSUs) using an equal allocation of effort by stratum (~200 mi per stratum). Thus, each PSU contained a combination of high- and low-strata road segments. We derived road data from the Roads of Minnesota, 2012 database. For the purposes of the pilot study, we were interested in obtaining sufficient observations in the low stratum to make informed decisions about the detection process and the potential to modify the stratification and allocation scheme; however, we envision putting more sampling effort into the high-density stratum in an operational survey.

Field Protocols

We surveyed each PSU 3–4 times, with repeated survey dates being close in time within a PSU (i.e., variation in survey dates was greater among than within PSUs). We did this to evaluate daily variation in counts while minimizing the confounding effect of among-PSU differences in counts. We based the start of the survey season on anecdotal information on spring dispersal of deer (from wintering areas to spring-summer-fall range). To be consistent among years and to match the "modeled population", it was important that deer were on their spring-summer-fall range. We began surveys approximately 1 hr after sunset and we surveyed 1–2 PSUs per night. We conducted surveys with 2-member crews (driver and observer) using extended-cab pickup trucks. We detected deer using FLIR Scout III (FLIR Systems, Inc., Wilsonville, OR) hand-held infrared (IR) sensors attached to the rear windows of the vehicle with window mounts. We viewed images on dual computer monitors attached to the front passenger seat using customized mounts. Monitor power was supplied via the vehicle's electrical system. The observer searched for deer along the survey route within each PSU. We initially oriented sensors at 45- and 315-degree angles from the direction of travel, but we adjusted them as needed to account for visual obstruction due to variable terrain, woody cover, buildings, etc. Survey speed ranged from 5–30 mph depending upon vegetative cover density. When a deer group (≥1 animal) was identified, the observer directed the driver to an approximate perpendicular angle (i.e., 90 or 270 degrees) from the group to minimize sighting distance and counted group size. Then, while the observer shined the animal(s) with a spotlight, the driver measured distance and angle to the group using a laser rangefinder and digital protractor, respectively. We used a real-time, moving-map software program (DNRSurvey; Haroldson et al. 2015), coupled to a global positioning system receiver and convertible tablet computer, to guide route navigation and record survey metrics (e.g., PSU, run [replicate], deer and vehicle location, distance, bearing, count, cover type) to GIS shapefiles. Cover type designations included woodland, wetland, grassland, pasture, standing crop, harvested crop, other, and unknown classes. We recorded weather data (temperature, wind speed, cloud cover, precipitation) at the beginning, middle, and end of each survey route.

We also conducted a winter helicopter survey of the DS study area using a quadrat-based design, where quadrats were delineated by Public Land Survey section (640 ac) boundaries. We stratified quadrats into 3 density categories (high, medium, low) using the local wildlife manager's knowledge of deer abundance and distribution. Using optimal allocation, we randomly selected a spatially balanced sample (Stevens and Olson 2004) of 162 plots to survey. Within each plot, a pilot and 2 observers searched for deer along transects spaced at 270-m intervals until they were confident all "available" deer were observed. To maximize sightability, we completed surveys when snow cover measured ≥6 in and we varied survey intensity as a function of cover and deer numbers (Gasaway et al. 1986).

Data Analysis Objectives

1. Perform an exploratory data analysis (EDA) on the 2018 survey dataset (year 1).
2. Fit, evaluate, and compare DS models for estimating deer abundance and density in the sampling frame.
3. Decompose variation in counts due to among-plot (PSU) and within-plot (run or survey date) sources of variation. Also, compare DS models and population estimates from different runs (replicated surveys within PSUs). Temporal variation is especially important in this application because if counts and resulting population estimates are highly variable over time, then a single-effort operational survey (non-replicated counts) may not be reliable.
4. Conduct a power analysis to help evaluate the feasibility of using roadside DS surveys to estimate deer density in Minnesota's farmland and transition zones. More

specifically, determine how many PSUs would be required to obtain a target level of precision given the current stratification and allocation scheme and observed among-plot (PSU) and within-plot (survey date) sources of variation in roadside counts.

5. Evaluate an alternative stratification scheme (using a 500-m buffer vs. the current 250-m buffer around deer-cover polygons) by re-stratifying road segments (sample only) and deer observations. This is an exploratory post-stratification analysis to determine whether the precision of the population estimate might be improved by modifying the stratification scheme to identify more uniform strata (both in terms of the detection process and relative deer densities).

RESULTS AND DISCUSSION

Summary Statistics and EDA

We completed 48 surveys during 23 nights from 1 April to 6 May 2018. Mean start time was 2055 hours (0.8 hr post-sunset) and mean survey duration was 4.1 hours. All 15 PSU were surveyed 3 times and 3 PSU were surveyed 4 times. Within each PSU, we completed 3 replicates within 8 days and all replicates within 35 days. In total, we detected 931 deer groups (clusters) consisting of 3,194 individual deer (596 deer along low-density road segments and 2,598 deer along high-density road segments). We observed a similar number of deer in replicate surveys 1–3 (total deer/replicate for all PSUs = 1,038, 1,002, and 1,082, respectively). Mean group size (observed) was 4.1 in the low-density stratum (range = 1–41, median = 3), 3.3 in the high-density stratum (range =1–42, median = 2), and 3.4 overall. Group size was not correlated with distance (r = 0.025, 95% CI = -0.039–0.089), which suggests we may not need an adjustment for group-size bias in our DS estimator (a common issue in DS). In the low stratum, 62% of group detections were located in harvested crop fields. Conversely, only 42% of detections were in harvested crop fields in the high stratum, with relatively more detections in grasslands (24% vs. 13%) and woodlands (12% vs. 8%). As expected, mean perpendicular sighting distance was greater in the low stratum (135 m; range = 0–679) compared to the high stratum (108 m; range = 0–503). Additionally, there was a spike in deer detections away from the road (Figure 2). We observed a similar pattern in both strata, although the peak was shifted right in the low stratum, likely because road segments in the low stratum had less deer cover adjacent to roads. As Stainbrook (2001) noted, this could result in a negatively biased population estimate in DS because the mean probability of detection will be overestimated based on the assumptions that g(0) = 1 and objects are distributed randomly with respect to transect lines. This is a common and valid criticism of convenience sampling from roadways. However, if the bias is consistent over space and time, then the DS estimator might still generate a useful long-term and large-scale monitoring metric.

Fit and Evaluate DS Models

Data truncation

A useful rule of thumb in DS is to right truncate at least 5% of the data for robust estimation of the detection function (Buckland et al. 1993:106). The 95th percentile of our distance data was 289 m; therefore, we set w = 300 m which resulted in 4.3% of the data being truncated. We also considered left truncation because the peak in observations was away from the road (Figure 2). However, the peak likely reflects road avoidance rather than animal movement (e.g., due to disturbance, which is unlikely in this case because crews used IR cameras for initial detection). Thus, left-truncation methods would not resolve the underlying issue that animals are not randomly distributed with respect to the transect line. Left-truncation with rescaling would (and did) improve the fit of the model(s) to the data because we now have a shoulder at g(0). However, one would then need to generate a separate ad hoc estimate of abundance for the sampling space that is within some distance *x* of the road transect. Thus, for this pilot-study application, it seemed prudent to set left truncation = 0 and focus on evaluating the consistency of the detection function (i.e., recognizing that the resulting density estimate is likely biased [Stainbrook 2001, Marques et al. 2013], but it may still serve as a useful monitoring index if the bias is reasonably consistent over space and time).

Model structure

The half-normal and hazard-rate key functions are robust estimating functions and allow the inclusion of covariates (Buckland et al. 1993, 2004). Therefore, we focused on these 2 key functions for this analysis. Our base models included no adjustments or covariates. We then added a cosine adjustment to each base model. Finally, we evaluated 2 covariates (with adjustment = NULL). The first covariate, strata, was used to test whether the detection function varied by strata. The second covariate, RVO, was a surrogate for relative visual obstruction (low vs. high) based on mean detection distance by cover type. The "high" visual-obstruction category included woodland, grassland, standing crop, and "other" cover types and contained 487 deer clusters with a mean detection distance of 90 m (range = 0–412). The "low" visual-obstruction category included harvested crop, pasture, wetland, and "unknown" cover types and contained 444 deer clusters with a mean detection distance of 136 m (range = 14–679). The goal here was to determine if RVO could help explain some uncertainty in the detection function, including why g(x) might vary among strata. If RVO could accomplish the latter, then distance data could be pooled over strata to generate a more precise detection function while still generating separate density estimates for each stratum (i.e., a stratified DS estimator; Buckland et al. 2013:99–103, Miller et al. 2016). Conversely, if g(x) varied significantly by stratum (after accounting for RVO), then we would need stratum-specific distance functions. We tested this by comparing density estimates from our top model (where distance data were pooled to compute one detection function) to estimates from a similar model structure but where strata were analyzed separately.

Among-plot and within-plot variation

We decomposed the sampling variance of raw deer counts by PSU and run to determine if "run" (survey date) was a significant source of variation. This is an important consideration because large variation or uncertainty due to "run" would be difficult to control statistically or through survey design, whereas variation due to PSUs could, in theory, be reduced by increasing the sample size. Among-plot variation accounted for approximately 89% of total variation in raw deer counts. Thus, variation by survey day was relatively small compared to variation in counts among PSUs. Consequently, we restricted subsequent DS analyses, including model comparisons, to run #1. Next, we used a bootstrap procedure (with replacement where samples were drawn from both PSU and run) to obtain a more realistic estimate of Var(D) that included among-plot (PSUs) and within-plot (survey date or runs) sources of variation. This should be more reflective of how an operational survey would likely be conducted (i.e., using a single, non-replicated survey). We also used the bootstrap routine to examine precision of the population estimate as a function of sample size (PSUs | allocation is approximately 50:50). This will be useful for evaluating the "feasibility" of conducting an operational survey given some target level of precision. The true expected precision of the estimate is likely somewhere between our top DS model and the bootstrap routine because we cannot completely separate allocation from stratification in either case. To properly estimate total sampling uncertainty, we would need to replicate the entire sampling process, which includes selection of PSUs, road segments within PSUs, and survey dates.

Model comparisons and parameter estimates

We fit 8 DS models to survey data from both strata but restricted to run #1, which provided 281 deer-cluster observations after right truncation (Table 1). We fit all models using the "ds" function in the R library “Distance” (Miller et al. 2016, Miller 2017; R Core Team 2018). The top-supported model (lowest AIC; model 7), was based on the hazard-rate key function and included the RVO covariate. The next-best model (ΔAIC= 9.5; model 3) also included the RVO covariate but was based on the half-normal key function. Models with strata as a covariate did not fit the data well, which suggests that g(x) did not vary significantly among the 2 strata. On the other hand, RVO was useful for describing variation in g(x) associated with cover type (Figure 3), with the underlying mechanism likely being the relative amount of visual obstruction between the observer and the first deer detected. Because relatively more deer were located in harvested cropland in the “low” stratum, RVO also described differences in g(x) between the 2 strata (i.e., 64% of deer groups in the “low” stratum were located in the “low” RVO class, whereas 55% of deer in the “high” stratum were located in the “high” RVO class). The hazard-rate detection function is described by the following equation:

$$g(x) = 1 - \exp[-(x/\sigma)^{-b}]$$

where the parameter *b* is a shape parameter, σ is a scale parameter, and *x* is the perpendicular sighting distance (which may be standardized). Covariates enter the detection function via the scale parameter (e.g., $\sigma = \beta_0 + \beta_1 RVO$). The detection function parameters from our top model were $\hat{b}$ = 1.154 (SE = 0.174), $\hat{\beta}_0$ = 5.302 (SE = 0.100), and $\hat{\beta}_1$ = -0.544 (SE = 0.128). Given these parameters, mean detection probability was 0.594 (SE = 0.033, CV = 5.6%), which describes the area under the detection curve. When adjusted for the covariate RVO, the predicted mean probability of detection was 0.491 for deer located in cover types with relatively “high” levels of visual obstruction versus 0.764 for animals with relatively “low” levels of visual obstruction.

The density estimate from model 7 was 8.6 deer/mi^2 (95% CI = 6.1–12.2). Estimates from the other models were similar (Table 1). Likewise, the density estimate when data from each stratum were analyzed separately was nearly identical ($\widehat{D}$ = 8.5, ~95% CI = 5.5–11.3), which supports the decision to use a stratified DS estimator where data are pooled across strata to estimate g(x). Finally, the deer density estimate from the Jan 2019 aerial survey was 6.4 deer/mi^2 (95% CI = 5.1–7.7; MNDNR, unpublished data), which is reasonably similar to the DS estimates given the time lag (spring vs. winter) in surveys.

Precision vs. Sample Size

Precision of the density estimate from our top model was reasonably good (CV = 17.1%), but this is likely optimistic because it may not adequately reflect variation due to survey date. Not surprisingly, precision was much lower (mean CV = 24.8%) when we bootstrapped distance data using PSU and run (surrogate for survey date). This is probably a more realistic expectation of precision for an operational survey with *n* = 15 PSUs and approximately equal allocation of survey effort in each stratum. A common target level of desired precision for management surveys is CV ≈ 15%. To achieve this level of precision with our current design (stratification scheme and allocation) and assuming a single non-replicated operational survey would likely require increasing the number of PSUs from 15 to approximately 30 (Figure 4). Whether this is a feasible option is unknown at this point in time, and an additional year of data is needed to better inform these types of questions.

Post-Stratification Analysis

The above estimates of precision are based on the current stratification and allocation scheme. We anticipate putting more effort into the high-density stratum in an operational survey, which is consistent with DS design recommendations (Buckland et al. 1993). We elected to use an equal allocation of effort in the pilot study to ensure we collected sufficient distance data to evaluate g(x) in the low-density stratum. Finally, our initial stratification scheme, based on a

250-m buffer around deer-cover patches $\geq$2 ac, was exploratory and we have since developed some alternative stratification schemes based on modifying minimum patch size and buffer distance. Unfortunately, it is challenging to evaluate these new schemes using existing distance data (i.e., post-stratification analysis). For example, reclassifying the 2018 distance data using a minimum patch size of 2 ac but with a larger buffer (500 m) did not appreciably change relative precision (17.6%), although it unexplainably generated a larger density estimate (9.2 deer/mi^2; 95% CI = 6.4–13.2). In theory, stratification should improve precision if the stratification scheme is effective, whereas the point estimate should be similar among sampling designs (i.e., it should be design unbiased). However, it is more complicated in DS because we are also dealing with the detection function. And in a post-stratification analysis, the number of observations for estimating g(x) is fixed and sample allocation is confounded with the stratification scheme. Thus, a post-stratification analysis has limited utility for answering the primary question of interest: “which stratification scheme and allocation of effort will produce the most precise estimate?” Obtaining a reliable answer to this question will require a more sophisticated analysis that will likely involve simulating the distribution and DS of deer in a computer-generated landscape (*sensu* Buckland et al. 2004:226–228). Again, another year of data collection would be helpful for constructing such an analysis/simulation.

CONCLUSIONS

The results from the first year of the pilot study are encouraging. Density estimates seem reasonable and precision was better than expected. We identified and resolved several data collection and survey-design challenges and developed detailed field protocols to ensure consistency in data collection. Another year of data collection will be helpful for evaluating the ultimate question of whether a DS metric can be effectively and reliably used to help monitor white-tailed deer populations in Minnesota’s farmland and transition areas. More specifically, we will be evaluating whether: (1) g(x) and the distribution of deer relative to roads and cover is relatively consistent over time and space; (2) the effect of variation in spring dispersal can be minimized by using observational cues to inform the start of the survey; and (3) can we afford (staff time and cost) to collect a sufficient sample of distance data in an operational survey to generate a reasonably precise density index for monitoring purposes.

ACKNOWLEDGMENTS

We thank G. Gehring, M. Diamond, J. Westfield, T. Klinkner, M. Orr, and R. Tebo for conducting the surveys. E. Michel and N. Davros reviewed an earlier draft of this report. This project was funded in part by the Wildlife Restoration (Pittman-Robinson) Program.

LITERATURE CITED

Buckland, S. T., D. R. Anderson, K. P. Burnham, and J. L. Lake. 1993. Distance sampling: estimating abundance of biological populations. Chapman and Hall, London, reprinted 1999 by RUWPA, University of St. Andrews, Scotland.

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

Gasaway, W. C., S. D. Dubois, D. J. Reed, and S. J. Harbo. 1986. Estimating moose population parameters from aerial surveys. Biological Papers of the University of Alaska 22, Fairbanks, Alaska, USA.

Haroldson, B. S., R. G. Wright, and C. Pouliot. 2015. DNRSurvey User Guide 2.30.01. <http://www.dnr.state.mn.us/mis/gis/DNRSurvey/DNRSurvey.html>.

Marques, T. A., S. T. Buckland, R. Bispo, and B. A. Howland. 2013. Accounting for animal density gradients using independent information in distance sampling surveys. Statistical Methods and Applications 22:67–80.

Miller, D. L. 2017. Distance: distance sampling detection function and abundance estimation. R package version 0.9.7. <https://CRAN.R-project.org/package=Distance>, accessed 14 Nov 2018.

Miller, D. L., E. Rexstad, L. Tomas, L. Marshall, and J. L. Lake. 2016. Distance sampling in R. 2016. bioRxiv reprint <http://dx.doi.org/10.1101/063891>, accessed 14 Nov 2018.

R Core Team. 2018. R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. <https://www.R-project.org/>, accessed 14 Nov 2018.

Rolley, R. E., D. J. Storm, K. B. Wallenfang, and M. J. Tonkovich. 2016. Midwest deer metrics: what, how, and why we measure. Unpublished report. Wisconsin Department of Natural Resources, Madison, USA.

Stainbrook, D. P. 2001. Methods of estimating white-tailed deer abundance at Gettysburg National Military Park: testing assumptions of distance sampling. Thesis, School of Forest Resources, Pennsylvania State University, University Park, USA.

Stevens, D. L. Jr., and A. R. Olsen. 2004. Spatially balanced sampling of natural resources. Journal of the American Statistical Association 99:262–278.

Table 1. Distance sampling models based on Akaike's Information Criterion (AIC) used to evaluate roadside surveys of white-tailed deer (*Odocoileus virginianus*) in southern Minnesota, spring 2018. For all models, we restricted survey data to the initial run (replicate) of the 15 primary sampling units, after right truncation. Analysis was restricted to the half-normal and hazard-rate key functions. Covariates included deer density strata (Strata) and a relative measure of visual obstruction (RVO). Mean detection probability, deer density estimates, and summary statistics (CI, CV) are also presented. Confidence intervals for deer density estimates were based on α = 0.05.

Model	Key function	Covariates	AIC	ΔAIC	Detection probability ($\bar{x}$)	Density (deer/mi^2)	95% CI	CV (%)
7	Hazard-rate	RVO	3097	0.0	0.594	8.6	6.1–12.2	17.1
3	Half-normal	RVO	3107	9.5	0.555	9.2	6.5–13.0	17.1
8	Hazard-rate	Strata	3116	18.4	0.606	8.5	5.9–12.1	17.6
5	Hazard-rate	Null	3117	20.2	0.614	8.6	6.0–12.5	18.3
6	Hazard-rate + cosine	Null	3117	20.2	0.614	8.6	6.0–12.5	18.3
2	Half-normal + cosine	Null	3123	25.5	0.630	8.4	5.6–12.7	20.6
1	Half-normal	Null	3124	26.8	0.575	9.2	6.4–13.3	18.0
4	Half-normal	Strata	3124	26.8	0.573	9.0	6.3–12.8	17.7

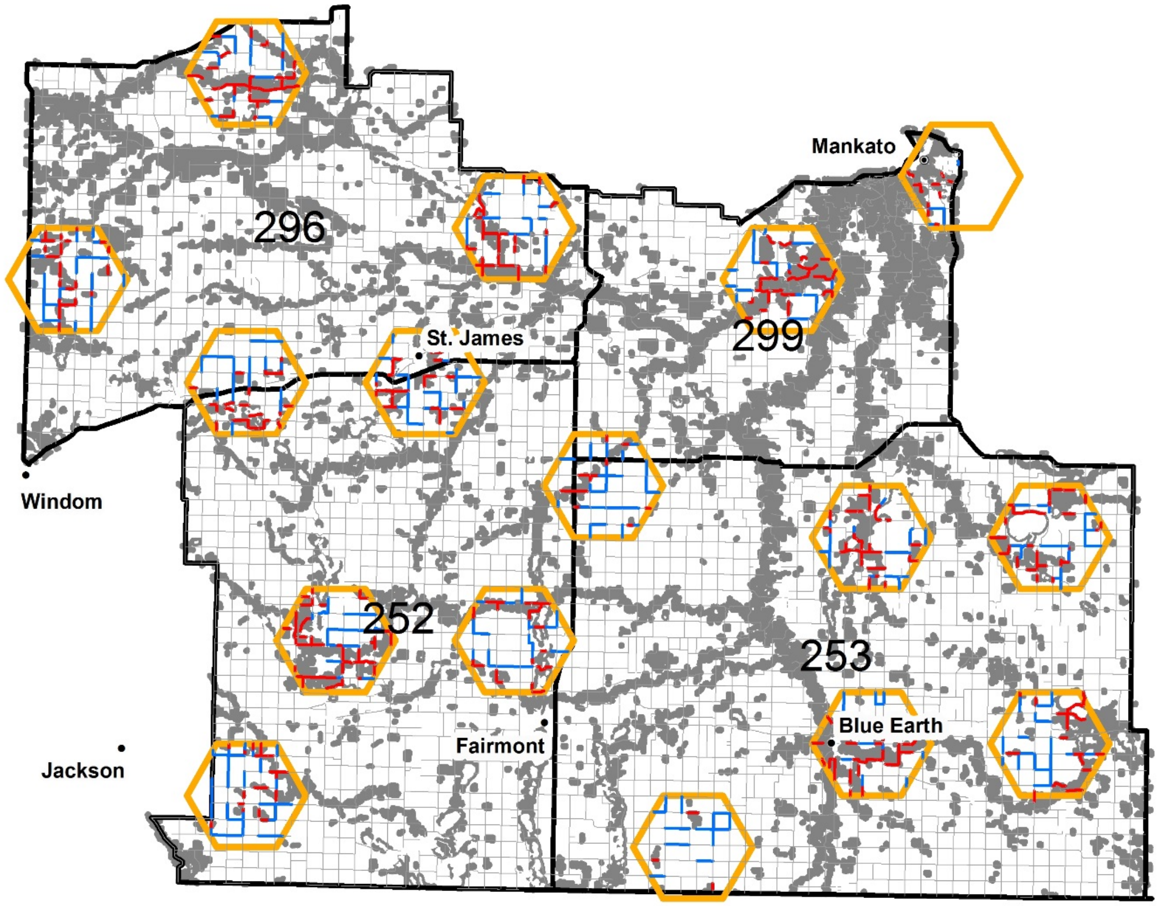

Figure 1. Sampling frame (deer permit areas 252, 253, 296, 299), primary sampling units (PSU; hexagons), and secondary sampling units (road segments; red = high-density stratum, blue = low-density stratum) for roadside distance-sampling surveys of white-tailed deer (*Odocoileus virginianus*) in southern Minnesota, spring 2018. Grey areas denote deer-cover polygons ($\geq$2 ac) consisting of woodland, grassland, and wetland cover types with a 250-m buffer. The northeast PSU was dropped prior to beginning surveys because it was on the edge of the sampling frame, contained the city of Mankato, and included few rural roads.

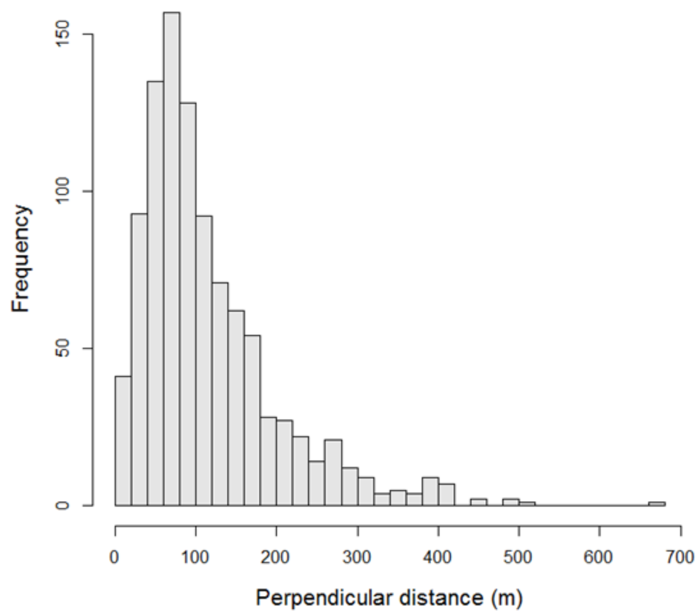

Figure 2. Histogram of deer-cluster observations as a function of perpendicular sighting distance from roadside distance-sampling surveys of white-tailed deer (*Odocoileus virginianus*) in southern Minnesota, spring 2018. Data include distance measurements collected during replicate surveys of 15 primary sampling units.

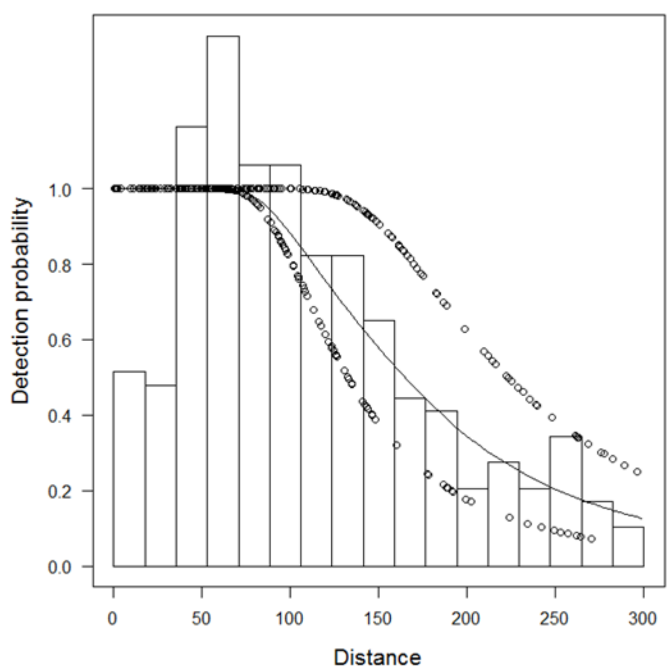

Figure 3. Estimated detection function g(x) from the best-fit model (model 7; based on Akaike's Information Criterion) overlaid on a histogram of deer-cluster observations as a function of perpendicular sighting distance from roadside distance-sampling surveys of white-tailed deer (*Odocoileus virginianus*) in southern Minnesota, spring 2018. We restricted survey data to the initial replicate of the 15 primary sampling units, after right truncation. The solid curved line

denotes the average detection function. The open circles describe the effect of the covariate RVO, which was a binary indicator variable for cover classes where visual obstruction was relatively high (lower line of circles; e.g., woodland and grassland cover) versus where visual obstruction was relatively low (upper line of circles; e.g., harvested cropland and pasture).

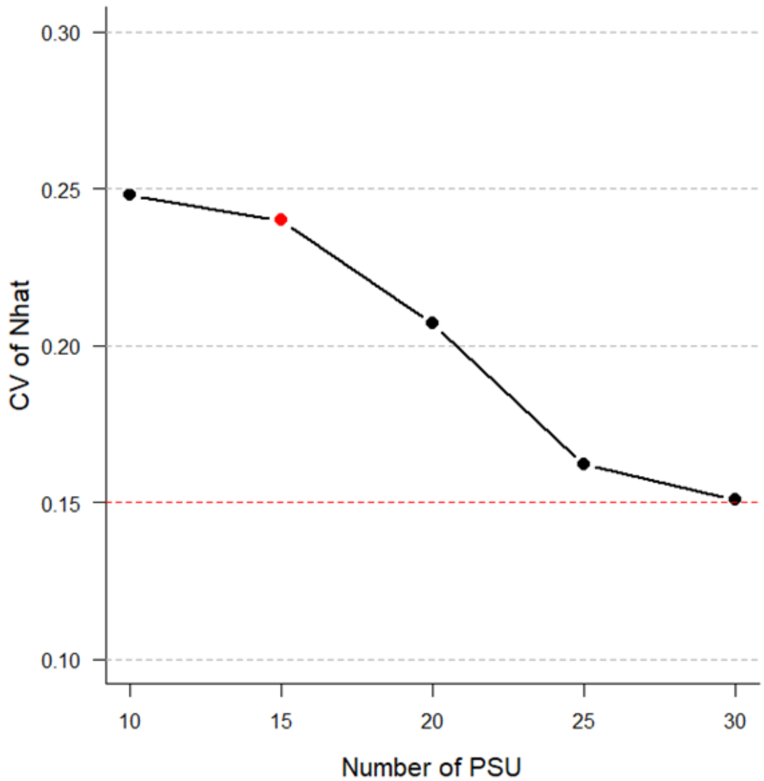

Figure 4. Precision of population estimates as a function of sample size (number of primary sampling units; PSU) from roadside distance-sampling surveys of white-tailed deer (*Odocoileus virginianus*) in southern Minnesota, spring 2018. Estimates are based on bootstrapping of PSUs and replicate surveys (survey date) where land cover was stratified (high, low) according to expected deer density and survey effort was allocated approximately equally within each stratum. The red circle denotes the current sample size. The red dashed horizontal line denotes a common target level of precision for management surveys.