ROADSIDE DISTANCE SAMPLING SURVEYS OF WHITE-TAILED DEER IN SOUTHERN MINNESOTA (2018-2023): A FEASIBILTY STUDY

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SUMMARY OF FINDINGS

We evaluated the feasibility of using roadside distance-sampling surveys to generate a reliable and cost-effective population monitoring metric for white-tailed deer (*Odocoileus virginianus*) in Minnesota's farmland zone. Here we report on surveys conducted in the spring of 2018, 2019, 2022, and 2023 (note: we did not conduct surveys in 2020 or 2021 due to the COVID pandemic). Our study area included 4 deer permit areas (DPAs = 252, 253, 296, and 299) in southern Minnesota's farmland zone. Estimated deer density (deer/mi^2 of land, to be consistent with units used in population modeling) based on spring distance sampling was 8.9 deer/mi^2 in 2018 (85% CI: 7.0-11.4), 7.5 deer/mi^2 in 2019 (85% CI: 6.0-9.5), 10.6 deer/mi^2 in 2022 (85% CI: 8.6-13.0) and 10.6 deer/mi^2 in 2023 (85% CI: 8.6-13.0). Distance sampling estimates were similar (overlapping CIs) but consistently higher than aerial survey estimates in the winters of 2018-19 (6.5 deer/mi^2, 85% CI: 5.1-7.9), 2019-20 (6.5 deer/mi^2, 85% CI: 5.3-7.7), 2021-22 (7.7 deer/mi^2, 85% CI: 6.6-8.9) and 2022-23 (8.3 deer/mi^2, 85% CI: 6.6-10.0). Likewise, precision of our distance-sampling estimates (mean CV = 15%; range: 14-17) was slightly inferior to aerial estimates (mean CV = 13%; range: 11-15). However, 75-80% of the variation in roadside deer counts was due to among-sampling-unit differences rather than day-to-day variation in the observation process. We can address this type of variation, and improve precision, by increasing the number of sampling units in operational surveys. Conversely, the presence of large day-to-day variation in deer observations would require replicate surveys, which would not be feasible in operational surveys due to staff and cost constraints and the spatial scale of our monitoring program. Our analysis suggested we would need a sample of 20-25 primary sampling units (PSU; 36-mi^2 hexagons) to obtain a target CV of 13% given 1 survey/year in operational surveys. This level of sampling effort would require 10-13 survey nights and 216-281 h of staff time (over a 1-month period in spring, excluding survey preparation and analysis/write-up tasks, assuming 2 survey crews with 2 individuals/vehicle capable of surveying 1 PSU/crew/night on average). Thus, although our results suggest that roadside distance sampling has the potential to provide a biologically reasonable and more frequent metric (vs. aerial surveys) for monitoring deer population trends in the farmland zone of Minnesota, it would require a significant investment of time that might be better addressed through seasonal labor contracts (vs. using area managers). Given current seasonal labor costs, the estimated cost to implement roadside distance-sampling surveys is $8K-$10K per survey area/year (including fleet and equipment, but excluding MNDNR staff time devoted to survey preparation, training and supervising contractors, and analyzing/writing-up the data). Contract labor accounts for

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about 70% of this estimate. In comparison, the 2023 aerial survey of the study area cost about $28K (excluding staff time).

INTRODUCTION

Road-based surveys (e.g., spotlight, thermal imaging) are commonly used for deer population monitoring (McCullough 1982, Mitchell 1986, Focardi et al. 2001, Collier et al. 2007, DeYoung 2011, Kaminski et al. 2019). Unfortunately, the counting process can be highly variable in roadside surveys (see Collier et al. 2013), possibly as a function of variation in deer distribution and resource use, which has limited the reliability of roadside indices. Applying distance-sampling methods (Buckland et al. 1993, 2004) to road-based surveys might provide a means to calibrate the counting process and make annual comparisons more reliable. However, some important statistical issues remain (Anderson et al. 1979, Burnham et al. 1980, Marques et al. 2010, McShea et al. 2011, Green et al. 2022). For example, convenience sampling violates the assumption that transects are randomly placed (or that animals are randomly located with respect to transects), which can make it difficult to obtain unbiased estimates of abundance via distance-sampling theory (e.g., Green et al. 2022). However, if that bias is relatively small and constant, then these surveys can provide a reasonable index for population monitoring.

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. In Minnesota, we use estimates of deer abundance and trends to inform annual deer season-setting recommendations for each deer permit area (DPA). The primary source of information used by the Minnesota Department of Natural Resources (MNDNR) to inform decision-making is a harvest-based population model. Currently, the MNDNR collects annual data on winter severity, hunter-reported harvest, and hunter effort (license sales) at the DPA scale. Reliability of harvest-based models can be improved by incorporating annual information on spatial and temporal variation in vital rates and other model parameters. However, collection of such data is generally cost-prohibitive at the DPA scale, especially given the large number of DPAs in Minnesota.

An alternative approach would be to collect independent recurrent information on population abundance or trends, which we could use to calibrate the existing population model or as input into an integrated population model (IPM). For example, the MNDNR has tried to use winter aerial surveys to calibrate harvest model estimates. However, financial, logistical, and environmental (e.g., snow cover, conifer cover) constraints prevent recurrent use of aerial surveys for all DPAs, at least at a frequency that is useful for model calibration. Moreover, comparisons involving aerial surveys may not be reliable in DPAs where seasonal migration is suspected to violate closure assumptions (e.g., when comparing winter surveys to harvest-based population models). Thus, we need alternative, cost-effective, large-scale monitoring methods. One potential approach in the farmland zone is road-based distance-sampling surveys (e.g., LaRue et al. 2007, Stainbrook 2011, Haus et al. 2019).

OBJECTIVES

Our goal was to evaluate the feasibility of using roadside distance-sampling 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 zone. Because we envisioned that area managers and research biologists would be involved with survey preparation, execution, and analysis, we focused on an evaluation of standard distance-sampling methods rather than more complicated theoretical methods (e.g., based on integrating resource selection functions, viewshed analyses, and multiple estimators) that would require high levels of statistical and geographic information system (GIS) expertise. Our specific objectives were:

1. Decompose variation in annual deer counts due to spatial variation (among sampling units) and temporal variation (among survey days within the same sample units). If total variation is mostly due to among-unit variation, then we can potentially address this issue via increased sample sizes. Conversely, if total variation was mostly due to among-day variation, then we would likely need to conduct replicate surveys within each sampling unit, which could be prohibitive in terms of staff time and overall cost.
2. Compare distance-sampling and aerial-survey estimates of deer density. If aerial-survey estimates are the gold standard (on average, closer to the truth), then the difference is an index of bias (albeit confounded by sampling uncertainty in both estimates). The primary questions of interest are the magnitude of bias (index) and the degree to which it varies over time.
3. Identify factors (covariates) that cause the detection function, g(x), to vary over space or time, and determine whether those factors appreciably affect density estimates. Similarly, identify g(x) covariates that we might need to measure in future operational surveys.
4. Investigate the critical distance-sampling assumptions that a) all animals on the line are detected perfectly and b) the g(x) function has a "shoulder" at distance zero (i.e., g(x) has an asymptote at distance zero but eventually declines with increasing distance). Violation of these assumptions (either by animals moving away from the transect centerline or not being randomly distributed around the transect lines) can result in biased estimates of density (see Green et al. 2022). However, if the shape of the g(x) function is reasonably consistent across time (replicate surveys and sampling years), then the resulting density estimates might still serve as a useful monitoring index.
5. Use empirical data and simulation methods to investigate study-design tradeoffs involving buffer sizes around deer-cover polygons, secondary-sample allocation (road segments) among habitat strata, and sample-size requirements (primary sampling units) needed to achieve a target CV of 13%. This information will be used to guide future survey-design recommendations.
6. Summarize survey times, travel times, and equipment and staff needed to complete each survey, which we will use to quantify the feasibility (with respect to dollars and staff time) of implementing operational distance-sampling surveys in the farmland region.

METHODS

Study Area

Our 2,787-mi^2 (7,218-km^2) study area consisted of 4 DPAs (252, 253, 296, and 299) in southern Minnesota (Figure 1) within the North Central Glaciated Plains section of the Ecological Classification System (MNDNR 2019). Topography is level to gently rolling, with the steepest topography along the Minnesota River. Row-crop agriculture (71%), primarily corn (*Zea mays*) and soybeans (*Glycine max*) characterize the region, with remaining areas comprised of grassland (12%), urban/developed (7%), wetland (5%), woodland (3%), and open water (2%) cover types (Rampi et al. 2016). Mean pre-fawn deer density ranged from 9–26 deer/mi^2 (4–10 deer/km^2) across the 4 DPAs (Michel and Giudice 2022).

Sampling Design

This project was iterative in that we used what we learned in one year to guide the sampling design the next year. Part of that process involved evaluating 2 buffer distances (and associated stratification schemes) around deer-cover polygons.

250-m buffer

We used a GIS (ArcGIS v. 10.4, Environmental Systems Research Institute, Inc., Redlands, CA) to stratify land-cover 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 study area with a grid of township-sized hexagons (size = 36 mi^2 [93.5 km^2]). Hexagons with >50% of their area inside the study area served as our primary sampling units (PSU). We chose a township-sized PSU based on the limits of what we could survey in a 4–6 hr period each night. We randomly selected a spatially balanced sample (Stevens and Olsen 2004) of 16 PSUs, but discarded 1 PSU that contained the city of Mankato and few rural roads. Thus, our final design contained 15 PSUs (Figure 2A). We then used a GIS and the 2012 Roads of Minnesota database to identify and classify all secondary (e.g., county and township) roads within each PSU, defined by juxtaposition to deer-density strata (high, low). The final secondary sampling frame consisted of 3,339 mi (70%) of road segments in the low stratum and 1,412 mi (30%) in the high stratum. We then randomly selected road segments (pooled over all PSUs) using an equal allocation of effort by stratum (~200 mi [322 km] per stratum), which resulted in a higher sampling rate in the high stratum (14% vs. 6%). The allocation of 200 mi of road segments/stratum was an arbitrary choice based on the amount and distribution of secondary sampling units available within the 15 PSUs and the need to obtain enough deer observations in the low stratum to make informed decisions about the detection process and the potential to modify our stratification and allocation schemes. Although we randomly selected secondary sampling units from the pooled sampling frame, each of the randomly selected PSUs contained a combination of high- and low-strata road segments (mean high = 12.9 miles, range: 1.5-21.9; mean low = 13.1 miles, range: 8.4-21.2). We surveyed the same sample of PSUs and road segments each year (2018, 2019, 2022, 2023), which is how we envision an operational survey being conducted. Note: we did not conduct roadside surveys in 2020 or 2021 due to the Covid19 pandemic.

500-m buffer

Similar to above, we stratified land cover into 2 classes, except we defined high-density polygons as being within a 500-m buffer of woodland, grassland (permanent to semi-permanent, excluding pasture), and wetland cover classes (Figure 2B). We retained 10 of the original 15 PSUs (due to time constraints) with this new design but selected new secondary road segments. We duplicated all remaining design aspects from the 250-m buffer scheme. The secondary sampling frame for the 500-m buffer consisted of nearly equal miles of low- and high-stratum road segments (52% vs. 48%, respectively), which resulted in similar sampling rates in each stratum (4.3 vs. 5.0%). As with the 250-m sampling scheme, each of the 10 PSUs contained a combination of high- and low-strata road segments (mean high = 14.4 miles, range: 9.3-20.5; mean low = 13.9 miles, range: 6.3-23.1). We only surveyed the 500-m buffer scheme in 2019 (concurrently with the 250-m scheme), which we used to inform a simulation study of design tradeoffs involving buffer distances (250 vs 500 m), PSU sample sizes, and stratified allocation of secondary sampling units (see below).

Field Protocols

During 2018-2022 we surveyed each PSU 2–3 times, with 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 quantify day-to-day variation in counts and to separate this from spatial variation (i.e., among PSUs). Thus, replicate surveys (hereafter, runs) overlapped in terms of start and stop dates, but the survey of PSUs was randomly ordered. By 2023, we had a good handle on design tradeoffs and the primary source of variation in deer counts. Therefore, in 2023 we only conducted a single survey of PSUs (similar to an operational survey).

We based the start of the survey season on anecdotal information on spring dispersal of deer (from wintering areas to spring-summer-fall range). It was important that deer were on their spring-summer-fall range to ensure consistency among years and to match the modeled population. We began surveys approximately 1 hour after sunset and each crew surveyed 1–2 PSUs per night. We conducted surveys with 2-member crews (driver and observer) using extended-cab pickup trucks. We used 1-2 crews/night in 2018 and 2023, and 1-3 crews/night in 2019 and 2022. We detected deer using 2 FLIR Scout III 640 (FLIR Systems, Inc., Wilsonville, OR) hand-held infrared (IR) sensors attached to the rear windows (1 sensor per window) of the vehicle with window mounts. We viewed images on dual computer monitors attached to the front passenger seat using customized mounts. The vehicle's electrical system supplied power to the monitors. The observer searched for deer along both sides of the survey route within each PSU. We initially oriented sensors at 30- and 330-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 mi/hr (8–48 km/hr) depending upon vegetative cover density. When we identified a deer group (≥1 individual), the observer directed the driver to an approximate perpendicular angle (i.e., 90- or 270-degree angle to the transect) from the group to minimize sighting distance and counted group size. Then, while the observer illuminated the animal(s) with a spotlight, the driver measured distance and angle to the approximate center of each 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 (GPS) receiver and convertible tablet computer, to guide route navigation and record survey metrics (e.g., PSU, run, timestamp, deer and vehicle location, distance, bearing, count, cover type) to GIS shapefiles. Cover type designations included woodland, wetland, grassland, pasture, standing crop, harvested crop, roadside, farmstead, and other. We recorded weather data (temperature, wind speed, cloud cover, precipitation) at the beginning, middle, and end of each survey route. Beginning in 2019, we also recorded information on activity (lying, standing, moving) of the first deer detected in each group and relative topography (low, med, high) between the survey vehicle and each deer group.

Aerial Surveys

During the winters of 2018-19, 2019-20, 2021-22 and 2022-23 we also conducted helicopter surveys of the study area using a quadrat-based design (Haroldson and Giudice 2013), where quadrats were delineated by Public Land Survey (PLS) section (1 mi^2 [259 ha]) 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 (based on previous aerial surveys), we randomly selected a spatially balanced sample (Stevens and Olsen 2004) of 160 plots to survey. A pilot and 2 observers searched for deer along transects spaced at 270-m intervals until they were confident all available deer were observed within each plot. To maximize sightability, we completed surveys when snow cover measured ≥6 in (15 cm) and we varied survey intensity as a function of cover and deer numbers (Gasaway et al. 1986). We intensively resurveyed a subset of plots each year to estimate a sightability correction factor (i.e., via a double-sampling estimator). The survey was designed to generate reasonably precise (target CV = 13%) density estimates for the study area, but we were also able to generate less precise estimates at the DPA scale using a domain analysis. The focus here was on comparing winter population estimates (aerial surveys) to distance sampling estimates from the subsequent spring.

Data Analysis

Data cleaning

A variety of quality-control checks were run on the distance datasets to identify questionable observations and computed distances, including visually inspecting deer locations and survey breadcrumb trails in GIS and comparing observed (laser range finder) to computed perpendicular distances (based on snapping a line to the nearest roadside segment). For example, we identified and removed deer observations that were later determined to be off transect or probable duplicate counts. Based on quality-control checks, we removed between 1% (2023) and 10% (2018) of deer-group observations from annual 250-m datasets and 11% from the 2019 500-m dataset. The higher removal rates in 2018 and 2019 reflect the first year of surveys (250 and 500 m, respectively) and adaptive learning about which road segments were unavailable for sampling. We would expect similar issues in the first year of surveys in new areas (i.e., until survey segments are verified and the GIS layer is cleaned and standardized). Furthermore, there is likely to be some annual variation in survey effort (road segments surveyed) due to road closures, impassible road segments, vehicle or equipment issues, etc.

Sources of variation

Temporal variation in the observation process is an especially important concern. If the observation process is highly variable over time (either within or among years), then a single-effort (non-replicated) operational survey may be unreliable. Conversely, if most of the count variation is spatial (among PSUs), we could address this through our sampling design (e.g., by increasing the PSU sample size). We used ANOVA and linear mixed-effects methods to decompose the sampling variance of deer counts by PSU and run (day-to-day variation). We also compared distance sampling density estimates by year. Harvest and population-modeling data suggested the target population was stable to increasing slowly during the study period. Thus, we expected density estimates from distance sampling to be very similar in 2018 and 2019, and slightly increased in 2022 and 2023. Large differences in density estimates would likely reflect annual variation in the observation process, which would raise questions about the reliability of the method.

Data truncation

A useful rule of thumb in distance sampling is to right truncate (i.e., exclude) 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 322 m for the 250-m buffer surveys (pooled over years and runs) and 330 m for the 500-m buffer survey (pooled over runs). We set the truncation distance w = 300 m, which resulted in 6% and 7% of deer-group observations being excluded from the 250- and 500-m datasets, respectively. We also considered left truncation because the peak in observation distances was consistently 60-80 m away from the road. 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 sensors 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 at some distance x from the road (e.g., 100 m), with rescaling, would improve model fit by creating the desired asymptote at distance zero. However, one would then need to generate a separate ad hoc estimate of abundance for the sampling space that is within distance *x* of the road transect. Thus, for this application, it seemed prudent to set left truncation = 0 and focus on evaluating the consistency of the detection function g(x). Although the resulting density estimate is likely biased (Stainbrook 2011, Marques et al. 2013), it may still serve as a useful monitoring index if the bias is reasonably consistent over space and time.

Detection function and density estimates

We used pooled distance data (over years and runs) from our 250-m buffer survey to fit and evaluate various detection functions, g(x). If g(x) did not vary appreciably by run, year, or strata, we could apply the pooled g(x) function to each annual dataset to generate density estimates by year and run (i.e., via a Horvitz-Thompson type estimator). The potential benefit of this approach is our g(x) function would be more precise than if we had to fit a g(x) function to each individual dataset (year and run), which would be based on much smaller sample sizes. We focused on the 250-m buffer surveys for g(x) development because we had data from 15 PSUs and 3 runs each year (excluding 2023) whereas the 500-m buffer survey was based on a subset of PSUs, 2 runs, and only 1 year of data. The latter dataset's primary utility was in examining design-choice tradeoffs via a Monte Carlo simulation (below).

We used a sequential approach to fit and evaluate g(x) models based on the pooled 250-m dataset. We fit our g(x) models with the R (ver. 4.3.2) package Distance (Miller et al. 2019, R Core team 2023) and compared models using AIC (via the aictabCustom function in the AICcmodavg package; Mazerolle 2023) and a crude estimate of density based on dividing the estimated total by the number of years and runs in the pooled data. In step 1, we fit two conventional distance sampling (CDS) models (without covariates or adjustment terms) based on the half-normal (HN) and hazard-rate (HR) key functions. We restricted our analysis to these estimating functions because they are robust (Buckland et al. 1993, 2004) and allow the inclusion of covariates (later modeling steps). We also fit and evaluated a binned-distance model to address the lack of a shoulder in our distance data. We used the following distance bins: 0-100, 101-150, 151-200, 201-250, 251-300 m. Our primary interest here was whether a CDS model based on binned distance data would generate a different or more precise density estimate than a comparable CDS model based on continuous data. In step 2, we evaluated whether our best-supported base model could be improved by adding polynomial or cosine adjustment terms. In step 3, we explored if there was support for multiple covariate distance sampling (MCDS) models that allowed g(x) to vary by year, run, stratum, cover type (pooled into short/open vs. tall/dense types; hereafter open vs. dense), or group size (a common issue in distance sampling). It is in this step that we determined whether using a pooled g(x) estimating function was feasible by looking for evidence that g(x) varied by year, run, or stratum. Step 4 was an exploratory step where we restricted the analysis to 2019, 2022, and 2023 in order to evaluate two additional g(x) covariates: activity (reclassified into stationary vs. moving) and topography (reclassified into low vs. med/high). We did not measure these covariates in 2018.

Our estimates of precision may be optimistic in terms of expectations for single-effort operational surveys in new areas. For example, at least initially, sample sizes for estimating g(x) will likely be smaller in operational surveys. Furthermore, with only 15 PSU, we might be underestimating among-PSU variation. Thus, to get a more realistic estimate of expected precision for future operational surveys, we bootstrapped (with replacement) deer-group observations by year, PSU, and run to better capture both within- and among-PSU sources of variation. We fit a g(x) (HR null model) to each bootstrapped annual dataset rather than using our pooled g(x), which should better reflect sample size and g(x) limitations in the first few years of operational surveys. We computed a population estimate for each annual bootstrap replicate (B = 100/year), and then computed the mean, SD, and CV (SD/mean) for each year.

Monte Carlo simulation

In 2018, we used a post-stratification analysis to examine an alternative stratification scheme based on a 500-m buffer and equal allocation of effort. However, in this application, the number of observations for estimating g(x) is fixed and secondary sample allocation is confounded with the stratification scheme. Thus, a post-stratification analysis has limited utility for answering the question of “which stratification scheme and allocation of effort will produce the most precise estimate?” Obtaining a reliable answer to this question requires a more sophisticated analysis that involves simulating the distribution of deer and detection distances in a computer-generated landscape (*sensu* Buckland et al. 2004:226–228). In 2019, we collected independent survey data from both a 250- and 500-m buffer design, which allowed us to construct simulated distance sampling datasets (deer detections) drawn randomly from all possible PSUs and road segments in the study area. Our focus was on examining the relative precision of the density estimates rather than quantifying bias because we did not know true density. That is, we only had estimates of 1) the distribution of perpendicular sighting distances, 2) mean encounter rate (deer groups per survey mile) and variance by stratum, and 3) mean group size and variance. We simulated the entire sampling and model-fitting process 500 times for both the 250- and 500-m buffer designs using n(PSU) = {15, 20, 25, 30} and allocation of secondary sample units (road segments) to the high stratum = {0.30, 0.50, 0.65}. Proportional allocation would be approximately 0.70:0.30 (L:H) in the 250-m buffer design and 0.50:0.50 in the 500-m buffer design. We summarized the results graphically to illustrate how expected precision varied as a function of sampling-design choices.

RESULTS

Descriptive Statistics

250-m buffer surveys (2018-2023)

We completed 1-3 replicate surveys of 15 PSUs with an average of 26 miles (range: 15–34 mi) of road segments/PSU using 1-3 crews/night, which required an average of 17.8 survey nights/year (range: 10-23). The average time needed to survey a PSU, including travel time, was 5.4 hr (range: 2.8-8.5). Start dates ranged from 28 March to 9 April and end dates ranged from 26 Apr to 6 May (Table 1). Survey effort/run is more difficult to quantify because we conducted replicate surveys concurrently. That is, replicate surveys were designed to be conducted within PSUs within a few days of each other (median = 1 day, mean = 3.8, range: 1-22) to evaluate day-to-day variation in counts. However, based on total unique survey dates divided by number of runs, a single-effort operational survey of 15 PSUs would require 6-8 survey nights to complete using 2 survey crews (see “Days per run” in Table 1). Crews detected an average of 305 deer groups/survey.

Our pooled dataset contained 3,047 deer-group observations (annual range: 329-989), with 84% of the observations from high-stratum road segments (Table 1). Average group size was 3.6 deer/group (range: 1-42) and was similar among years (range: 3.3-3.9). Mean perpendicular detection distance was 116 m (median = 86, range: 0-679) and the distribution of distances was remarkably consistent among years, including a consistent peak at 60-80 m from the road (Figure 3). Deer-group observations were an average of 70 m from deer-habitat polygons (annual range: 66-78 m; Table 1), but as expected, deer observations tended to be closer to cover in the high stratum (mean = 3 m, range = 0-372 m) compared to the low stratum (mean = 422 m, range = 0 m to 2.7 km). We classified 61% of deer groups as being in open cover types (e.g., harvested crops, pasture, farmsteads, roadsides), which was reasonably consistent among years (Table 1) but varied by stratum (e.g., low = 81%, high = 58%). Furthermore, 69% of deer-group observations were in areas with low topographic relief (i.e., flat to gently rolling terrain), which is expected given the location of our study area. Finally, 89% of initial detections (first deer) involved stationary deer (lying or standing). Summary statistics for the 250-m buffer surveys were also reasonably similar among runs (Table 2).

500-m buffer surveys (2019 only)

Survey crews completed 2 replicate surveys of 10 PSUs and 283 miles of road segments over 14 nights during 6 April to 3 May 2019 (Table 3). We observed 318 deer groups, and sample statistics were similar for the 2 runs (Table 2), as well as when compared to 250-m surveys conducted on the same subset of 10 PSUs (Table 3).

Sources of variation in deer counts

Among-plot variation accounted for 75–80% of total variation in deer-group counts. Thus, variation in counts within PSUs (due to survey day) was relatively small compared to variation among PSUs. This is important because large day-to-day variation in the observation process could result in an unreliable estimator (e.g., one that is not highly repeatable). Conversely, we can address large among-plot variation through design choices such as increasing the number of PSUs sampled.

Detection Function and Density Estimates

The HR function fit our pooled distance data considerably better (ΔAIC = 59.7) than a HN function (Table 4: Step 1). Not surprisingly, an HR model with binned distance data fit the data better (Chi-square = 2.455, 2 df, P = 0.293) than a similar model based on continuous data, but this simply reflected the lack of a shoulder in our distance data. Furthermore, the two models generated very similar density estimates (9.4 vs. 9.5 deer/mi^2; Table 4: Step 1). Therefore, rather than being limited to a set of distance bins for exploring density estimation and evaluating covariates, we elected to retain the more general model with continuous distance data for Step 2. In Step 2, we found the base HR model fit the data better than models with either cosine (ΔAIC = 5.8) or polynomial (ΔAIC = 5.9) adjustment terms; thus, we carried the base HR model to Step 3 where we examined multiple g(x) predictor variables (MCDS models). In Step 3, we found that an additive model with cover type (open vs. dense) and group size fit the data better than the base HR model (ΔAIC = 58.9) or MCDS models containing stratum, run, year, or year+run (ΔAIC $\geq$ 49.6; Table 4: Step 3). As predicted, probability of detection was positively associated with group size and was higher in open cover types (predicted mean = 0.598; range: 0.585-0.784) than in dense cover types (predicted mean = 0.462; range: 0.452-0.640; see Figure 4). In Step 4, we had to exclude data from 2018 because we did not measure activity or topographic relief in 2018. Thus, step 4 was exploratory. We found that the top model structure from Step 3 (COVER2 + SIZE) was improved (ΔAIC = 54.7) by adding ACT2 (activity reclassified as stationary vs. moving) and TOPO2 (topographic relief reclassified as low vs. med/high) to the detection function. The model suggested that probability of detection was negatively associated with moving deer and higher for deer in areas with medium-to-high topographic relief. However, only 11% of detections involved moving deer and 69% of detections were in areas of low topographic relief (with 89% of the remainder in areas with medium relief). Because we only had 3 years of data for these covariates and the sample distributions were highly unbalanced, we elected to use our top g(x) model from Step 3 (COVER2 + SIZE) for estimating deer densities. However, we recommend continuing to measure and evaluate activity and topographic relief as potential covariates in future operational surveys.

Deer density estimates from initial runs (similar to an operational survey) averaged 4.4, 21.3, and 9.4 deer/mi^2 in the low stratum, high stratum, and study area, respectively (Table 5). Relative precision was better in the high stratum (mean = 15%) compared to the low stratum (mean = 34%), but this mostly reflects differences in stratum weights (expansion factors) and the unbalanced distribution of deer-group observations (after right truncation) by stratum (189-263 observations/year in the high stratum vs. 46-55 observations/year in low stratum). Overall, precision was reasonably good at the study-area scale (mean = 15%; range: 14-17%; Table 5), although it was slightly above our target level (CV $\leq$13%) for operational surveys. Furthermore, we caution that the precision reported here is likely optimistic because we used a pooled detection function (whereas operational surveys will only have data from one run/year) and future surveys in other parts of the Minnesota farmland could have lower deer densities (which would also affect precision via fewer deer observations). Precision was much lower (CV ≈ 20%) when we bootstrapped distance data using year, PSU, and run (surrogate for survey date). This is probably a more realistic expectation of precision for a single-effort operational survey with a 250-m buffer, *n* = 15 PSUs, and approximately equal allocation of survey effort in each stratum, at least for the first few years.

Density estimates did not vary appreciably by run within years, but they were consistently higher than aerial survey estimates (Figure 5). Unfortunately, due to the COVID-19 pandemic, we only have 3 years (2019, 2022, 2023) of paired distance and aerial survey estimates, which makes it difficult to predict the magnitude of bias in future surveys, especially in new areas.

Expected Precision vs. Design Choices

A common target level of desired precision for management surveys is CV ≈ 13% or a 95% CI bound of ±25% (Robson and Regier 1964 as cited in Krebs 1999:29). To achieve this level of precision with our current design (250-m buffer and 50:50 allocation), and assuming a single-effort operational survey, would require increasing the number of PSUs from 15 to ~25 (Figure 6). However, choices related to the stratification scheme and allocation of secondary sampling units are important too. Our Monte Carlo simulation indicated that the 250-m buffer design with 50:50 allocation (low:high) of secondary units resulted, on average, in similar precision to the 500-m buffer design with 35:65 allocation (Figure 6). Conversely, the 250-m buffer with 35:65 allocation and the 500-m buffer with 50:50 allocation tended to produce more imprecise density estimates. Increasing the buffer distance from 250 m to 500 m resulted in approximately equal stratum weights (0.53 vs. 0.47 in low vs. high stratum, respectively), but the low stratum had significantly fewer deer-group detections (see Table 3) and a very low estimated deer density (1.1 deer/mi^2 in 2019, 85% CI: 0.4-2.9). Thus, for the 500-m buffer design, it makes sense to put more sampling effort into the high stratum to increase precision of the estimate (i.e., you get more “bang for your buck” because >90% of deer are in the high stratum). However, with so few deer observations in the low stratum, it becomes difficult to determine whether g(x) varies by stratum and one must pool data over strata to estimate g(x). Conversely, the low stratum in the 250-m buffer design is relatively large (70% of study area). Deer densities are still relatively low (3.9-4.8 deer/mi^2) in the low stratum, but because of its size, it is important to put relatively more effort into surveying the low stratum. Thus, for the 250-m design the 50:50 allocation generates a more precise estimate and provides more data to evaluate potential variation in g(x). However, it is important to note that we are still putting relatively more effort into the high stratum with 50:50 allocation because the high stratum only comprises 30% of the sampling frame. These tradeoffs are not necessarily straightforward and would be difficult to ascertain without some type of simulation.

Resource Requirements and Estimated Cost of Operational Surveys

Resources needed to implement road-based distance sampling surveys include investments in labor, fleet, and equipment. Based on survey results and simulation analysis, we need to complete 1 survey within 20-25 PSUs/survey area to obtain target precision goals (CV ~13%). Assuming 2 survey crews with 2 individuals/vehicle capable of surveying 1 PSU/crew/night, we would need 10-13 survey nights and 216-281 h of staff time (excluding survey preparation and analysis/write-up tasks) to complete surveys in each area. Because surveys occur over about a 1-month period in spring, managers may be preoccupied with spring burning activities and unavailable to complete survey tasks. An alternative labor source could be temporary technicians (NR Tech). Given projected NR Tech salary rates ($27/h, excluding insurance), the estimated labor cost (excluding MNDNR staff time devoted to survey preparation, training and supervising contractors, and analyzing/writing-up the data) is approximately $6K-$8K per survey area/year. This estimate excludes housing and lodging costs.

This same level of sampling effort would also require driving 2,400-3,000 miles. Given projected fleet rates ($0.77/mi), the estimated fleet cost is approximately $1,850-2,310 per survey area/year (assuming fleet vehicles are centrally located within each survey area).

Purchase of all required equipment (e.g., thermal sensors, monitors, spotlights, camera mounts, power inverters.) would require an investment of approximately $5K/vehicle. However, much of this equipment is already on-hand and, as a result, estimated equipment cost is approximately $250/vehicle.

In total, the estimated cost to implement road-based distance sampling surveys is approximately $8K-$10K per survey area/year. Contract labor accounts for about 70% of this estimate.

Data Collection and Management Challenges: Lessons Learned

We tested 2 types of infrared sensors in 2018 - Nightsight PalmIR 250 (Raytheon Systems Company, Dallas, TX) and FLIR Scout III 640 (FLIR Systems, Inc., Wilsonville, OR). Although deer were detected using both systems, there were important feature differences. With the Nightsight sensor, video gain and level settings could be manually adjusted (overriding auto settings) to improve contrast between deer and background features. This can be important when conditions are such that deer “blend” into the background and are difficult to detect. However, during most surveys, image contrast was not an issue and gain/level setting adjustments were rarely needed. Conversely, detector resolution (i.e., image clarity) of the FLIR sensor was twice that of the Nightsight sensor, where images were grainy and pixilated. Finally, the FLIR sensor was significantly smaller and lighter than the Nightsight sensor. After testing both sensors during multiple surveys, we ultimately discontinued use of the Nightsight sensor in favor of the FLIR sensor.

After detecting deer with IR sensors, we used 12-volt rechargeable (Stanley SL10LEDS, Towson, MD) or corded (Lightforce SL2406, Hindmarsh, South Australia, Australia) spotlights to illuminate deer and measure distance from observer. The rechargeable spotlights worked well only at short distances (<~200 m) and when deer were facing the light. We needed the corded spotlights at longer distances and when deer were facing away from the light.

Perpendicular distance is a measure of the shortest distance between the observer and target animal (deer) and is a required metric in distance sampling analysis. We can measure this value directly using a laser rangefinder or indirectly using target distance and angle metrics. Visual obstruction or animal disturbance can inhibit direct measurement. One of the assumptions associated with distance sampling is that target animals do not move prior to being detected. In 2018, we initially stopped and measured target distance as soon as we detected a deer, regardless of target distance or angle. However, after completing a few surveys, we observed that most deer detected close to the road (e.g., bedded within or adjacent to the road ditch) did not move in response to our presence. Thereafter, we attempted to minimize target distance before stopping. This is important because measurement errors are less significant at shorter distances.

Our sample of road segments consisted of county and township roads within each PSU. Because of classification errors within the road database, some municipal and private roads (e.g., driveways and field roads) were included in the sample. We used a combination of aerial photo inspection and on-site visits to identify misclassified roads. We then subjectively selected new road segments to replace the misidentified segments. Despite these efforts, we discovered additional driveways and field roads while conducting surveys in 2018. These segments were excluded, without replacement, and segment lengths were subsequently deleted from total sample road length during all survey years. Although identification of misclassified roads is time consuming, it should occur during survey setup to allow for road replacement, maintain a consistent sample of road segments, and minimize landowner disturbance on municipal and private roads.

Poor road conditions via spring flooding also negatively affected availability of road segments for sampling. For example, 2 and 9 road segments were impassable due to spring flooding in 2018 and 2019, respectively. These flooded segments (or portions thereof) were not sampled and segment lengths were deleted from total road length, but only during years when they were not surveyed. In addition, although road construction did not occur along sample roads during this study, it certainly could occur during future surveys. Poor road conditions are inevitable during spring roadside surveys in northern latitudes due to melting snow. By documenting changes to annual sampling effort, post-survey adjustments can be made during data analysis.

DISCUSSION

The results from our feasibility study are encouraging. We identified and resolved several data collection and survey design challenges (see above) and developed detailed field protocols to ensure consistency in data collection. Furthermore, we found that variation in deer counts was mostly due to among-PSU variation rather than day-to-day variation. We can address among-PSU variation by increasing the number of PSUs sampled, whereas large day-to-day variation in counts would be difficult to deal with from a design and analysis perspective and could result in an unreliable monitoring metric.

Our distance sampling density estimates were consistently higher but within a reasonable range of the aerial survey estimates (Figure 5). However, we need more than 3 years of paired estimates (2019, 2022, 2023) to confirm this observation and improve our understanding of how it might vary over space and time, and the implications of that bias for our ability to make good management decisions. Past research has shown sampling along roads can result in biased detection rates and density estimates, with the direction of the bias dependent upon whether transects follow landscape features preferred (Anderson et al. 2013, Beaver et al. 2014, Green et al. 2022) or avoided (Ruette et al. 2003, Ward et al. 2004, Stainbrook 2011, Green et al. 2022) by target animals. We observed fewer groups of deer on and immediately adjacent to roads than areas further away, resulting in a “detection trough” near the transect lines (Figures 3 and 4). Fewer detections can occur if animals are missed, animals move in response to observers, or animals avoid areas near roads (Buckland et al. 1993). Regardless of the reason, a lack of observations near roads would lead to biased density estimates (Stainbrook 2011, Green et al. 2022). However, if the shape of the detection function is reasonably consistent across time, then the resulting density estimates might still serve as a useful monitoring index. Our detection function, $g(x)$, did not vary appreciably over sampling years, replicate surveys, or strata. As a result, we were able to use a pooled $g(x)$ to estimate deer densities, which improved precision of density estimates.

In conclusion, the road-based distance sampling survey method has potential to provide a useful and more frequent (vs. aerial surveys) deer-monitoring metric (index) for the farmland zone of Minnesota. However, it will require a significant investment of resources (including staff time) to setup and conduct the survey in each target area, and those areas will need to be larger than individual DPAs in most cases due to sample-size requirements (in terms of both deer observations and number of PSUs). Moreover, the roadside distance-sampling method may be a stopgap approach because eventually crewed or uncrewed aerial vehicles with high-end detection hardware (cameras and thermal sensors) will likely become the standard tool for surveying wildlife over large areas (e.g., Beaver et al. 2020, Delisle et al. 2022). For example, recent research in Indiana (Delisle et al. 2022) suggests that aerial surveys with thermal sensors and cameras might be more cost-effective than labor-intensive ground-based methods (e.g., camera-trap sampling and pellet surveys), especially when replicated over multiple management units such as DPAs. However, this would require careful evaluation in Minnesota's diverse landscapes, including the farmland region. We might be in a position to evaluate the cost-benefit tradeoffs of this alternative because MNDNR will be purchasing a new aircraft with a high-end thermal imaging/camera system in 2024.

RECOMMENDATIONS

If road-based distance sampling surveys are implemented within additional survey areas (e.g., DPA aggregations) throughout Minnesota's farmland zone, we suggest the following:

- Incorporate the 250-m habitat buffer design and 50:50 (low:high) sample allocation of secondary roads to obtain a sufficient sample of deer to estimate density in the low habitat stratum.
- Within each survey area, decrease the number of replicate surveys from 3 to 1/year and increase the number of PSUs from 15 to 20-25 to obtain a target CV of ~13%.
- Continue measuring and evaluating deer activity and topographic relief as potential model covariates.
- Continue flying aerial surveys on a subset of survey areas to improve our understanding of how roadside distance sampling estimates compare to aerial survey estimates over space and time.

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Table 1. Summary statistics for 250-m buffer surveys by year from roadside distance sampling surveys of white-tailed deer in southern Minnesota during spring 2018, 2019, 2022, and 2023. Data incorporate 1–3 replicate surveys (Runs) of 15 primary sampling units (PSU).

Year	Number of PSUs	Total miles/stratum		Runs	Start date	End date	Survey days	Days per run	Deer groups /stratum		Total deer	Mean group size (range)	Mean perpendicular distance (m); (range)	Mean distance (m) to habitat	Prop open cover	Prop low topo relief	Prop stationary
		Low	High						Low	High							
2018	15	589	582	3	1-Apr	6-May	23	7.7	140	759	3,137	3.5 (1-42)	117 (0-679)	71	0.626	---	---
2019	15	589	571	3	2-Apr	2-May	20	6.7	138	692	2,710	3.3 (1-21)	117 (0-617)	66	0.687	0.713	0.880
2022	15	589	586	3	28-Mar	5-May	18	6.0	155	834	3,813	3.9 (1-41)	120 (0-650)	70	0.553	0.650	0.910
2023	15	196	195	1	9-Apr	26-Apr	10	10.0	58	271	1,203	3.7 (1-21)	98 (0-406)	78	0.578	0.729	0.866
Pooled	15	1,963	1,934	10	28-Mar	6-May	71	7.1	491	2,556	10,863	3.6 (1-42)	116 (0-679)	70	0.614	0.687	0.891

Table 2. Summary statistics by year, buffer distance (250-m, 500-m), and run (replicate survey) from roadside distance sampling surveys of white-tailed deer in southern Minnesota during spring 2018, 2019, 2022, and 2023. Data incorporate 1–3 replicate surveys (Run) of 10–15 primary sampling units (PSU).

Year	Buffer-Run	Number of PSUs	Start date	End date	Survey days	Deer groups /stratum		Total deer	Mean group size (range)	Mean perpendicular distance (m); (range)	Mean distance (m) to habitat	Prop open cover	Prop low topo relief	Prop stationary
						Low	High							
2018	250-1	15	1-Apr	4-May	14	49	247	1,045	3.5 (1-30)	128 (0-679)	80	0.635	---	---
2018	250-2	15	2-Apr	5-May	15	39	218	1,003	3.9 (1-42)	107 (0-496)	70	0.619	---	---
2018	250-3	15	4-Apr	6-May	15	52	294	1,089	3.1 (1-25)	115 (0-490)	65	0.624	---	---
2019	250-1	15	2-Apr	22-Apr	10	52	201	864	3.4 (1-18)	115 (1-423)	61	0.743	0.759	0.889
2019	250-2	15	5-Apr	25-Apr	10	47	204	891	3.5 (1-21)	121 (0-547)	69	0.781	0.705	0.853
2019	250-3	15	23-Apr	2-May	8	39	287	955	2.9 (1-20)	116 (0-617)	69	0.571	0.684	0.893
2019	500-1	10	6-Apr	24-Apr	7	12	156	594	3.5 (1-21)	123 (0-610)	42	0.762	0.661	0.893
2019	500-2	10	7-Apr	3-May	7	17	133	482	3.2 (1-20)	119 (0-468)	49	0.673	0.627	0.893
2022	250-1	15	28-Mar	3-May	10	56	270	1,283	3.9 (1-41)	123 (0-551)	61	0.589	0.629	0.902
2022	250-2	15	31-Mar	4-May	11	51	288	1,239	3.7 (1-26)	119 (0-559)	79	0.499	0.646	0.903
2022	250-3	15	1-Apr	5-May	11	48	276	1,291	4.0 (1-28)	117 (0-650)	70	0.574	0.676	0.926
2023	250-1	15	9-Apr	26-Apr	10	58	271	1,203	3.7 (1-21)	98 (0-406)	78	0.578	0.729	0.866

Table 3. Summary statistics for 500-m buffer surveys and comparable data for 250-m buffer surveys of the same 10 primary sampling units (PSU) from roadside distance sampling surveys of white-tailed deer in southern Minnesota during spring 2019.

Year	Buffer	Number of PSUs	Total miles/stratum		Runs	Start date	End date	Survey days	Days per run	Deer groups /stratum		Total deer	Mean group size (range)	Mean perpendicular distance (m); (range)	Mean distance (m) to habitat	Prop open cover	Prop low topo relief	Prop stationary
			Low	High						Low	High							
2019	500	10	278	288	2	6-Apr	3-May	14	7.0	29	289	1,076	3.4 (1-21)	121 (0-610)	45	0.720	0.645	0.893
2019	250	10	269	261	2	2-Apr	22-Apr	12	6.0	75	320	1,402	3.5 (1-21)	120 (0-547)	57	0.777	0.747	0.861

Table 4. Detection function models examined to evaluate roadside distance sampling surveys of white-tailed deer in southern Minnesota, fit to the 2018, 2019, 2022, and 2023 pooled[a] dataset. Number of model parameters (K), log likelihood (LL), Akaike's Information Criterion (AIC) values, change in AIC values relative to the top model (ΔAIC), AIC weights (AICWt), and deer density estimates ($\widehat{D}$) are also presented.

Step Model	Key function	Adj	Dist data	Covariates[b]	K	LL	AIC	ΔAIC	AICWt	$\widehat{D}$[c]
Step 1										
1.1	HR	None	Cont	~1	2	-15678	31359	0.0	1.000	9.4
2.1	HN	None	Cont	~1	1	-15709	31419	59.7	0.000	9.9
3.1	HR	None	Bin	~1	2	-3266	---	---	---	9.5
Step 2										
1.2	HR	None	Cont	~1	2	-15678	31359	0.0	0.903	9.4
2.2	HR	COS	Cont	~1	5	-15678	31365	5.8	0.049	9.4
3.2	HR	POLY	Cont	~1	5	-15678	31365	5.9	0.048	9.4
Step 3										
8.3	HR	None	Cont	~COVER2 + SIZE	4	-15646	31301	0.0	0.726	9.1
6.3	HR	None	Cont	~COVER2	3	-15648	31302	1.9	0.274	9.3
5.3	HR	None	Cont	~STRATUM	3	-15672	31350	49.6	0.000	9.2
4.3	HR	None	Cont	~YEAR + RUN	7	-15669	31352	51.5	0.000	9.4
7.3	HR	None	Cont	~SIZE	3	-15675	31356	55.1	0.000	9.1
2.3	HR	None	Cont	~YEAR	5	-15673	31356	55.4	0.000	9.4
1.3	HR	None	Cont	~1	2	-15678	31359	58.9	0.000	9.4
3.3	HR	None	Cont	~RUN	4	-15676	31361	60.0	0.000	9.4
Step 4										
6.4	HR	None	Cont	~COVER2 + SIZE + ACT2 + TOPO2	6	-10889	21789	0.0	0.998	9.5
5.4	HR	None	Cont	~COVER2 + SIZE + TOPO2	5	-10896	21802	12.4	0.002	9.4
4.4	HR	None	Cont	~COVER2 + SIZE + ACT2	5	-10912	21834	45.0	0.000	9.4
3.4	HR	None	Cont	~COVER2 + SIZE	4	-10918	21844	54.7	0.000	9.3
2.4	HR	None	Cont	~COVER2	3	-10921	21847	57.7	0.000	9.6
1.4	HR	None	Cont	~1	2	-10941	21887	97.5	0.000	9.7

[a]For steps 1-3, we pooled data over 4 years (2018, 2019, 2022, 2023) and 1-3 replicate surveys (runs)/year. For step 4, we pooled data over 3 years (2019, 2022, 2023) and 1-3 runs/year because ACT2 and TOPO2 were not measured in 2018.

[b]Detection function covariates: ~1 (intercept only); COVER2 (cover types: short/open vs. tall/dense); SIZE (group size); STRATUM (deer density: low vs. high); RUN (replicate survey); ACT2 (deer activity: stationary vs. moving); TOPO2 (topographic relief: low vs. med/high).

[c]Approximate deer/mi^2 based on dividing estimated total deer by study-area size.

Table 5. Estimated deer densities (per mi^2) and 85% CIs by density stratum and year derived by applying a multiple covariate detection function (COVER2 + SIZE model) to roadside distance sampling surveys conducted in southern Minnesota during spring 2018, 2019, 2022, and 2023. Estimates are based on the 250-m stratification design (buffer around deer habitat) from the initial replicate (run 1) survey of 15 primary sampling units.

Year	Stratum	Density estimate	LCL85	UCL85	CV
2018	Low	4.0	2.3	7.1	0.383
2018	High	20.5	16.1	26.2	0.162
2018	Total	8.9	7.0	11.4	0.165
2019	Low	3.9	2.5	6.3	0.314
2019	High	16.0	12.4	20.7	0.171
2019	Total	7.5	6.0	9.5	0.159
2022	Low	4.8	2.7	8.3	0.378
2022	High	24.2	20.9	28.0	0.097
2022	Total	10.6	8.6	13.0	0.139
2023	Low	4.7	3.0	7.2	0.291
2023	High	24.6	19.5	30.9	0.152
2023	Total	10.6	8.6	13.0	0.139

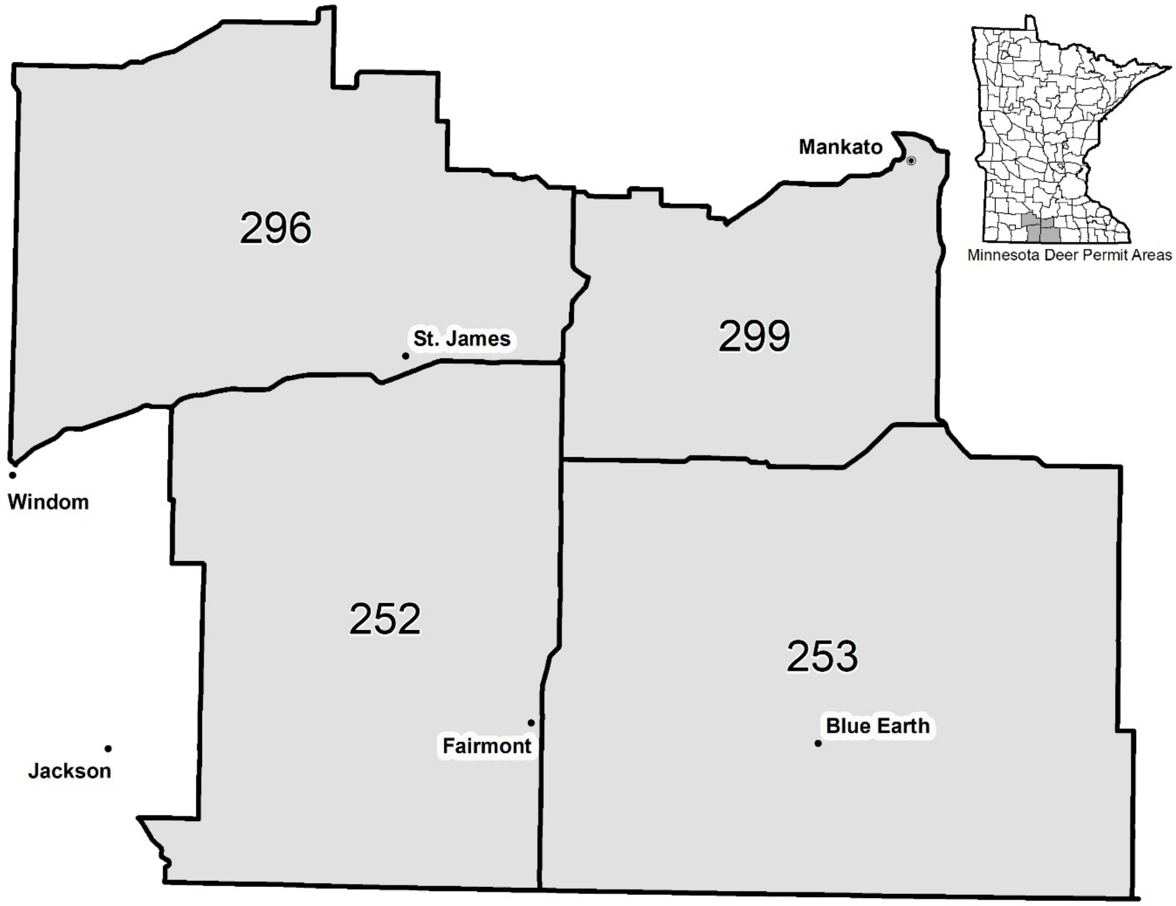

Figure 1. Deer permit area delineation of the study area boundary for roadside distance sampling surveys and aerial quadrat surveys of white-tailed deer in southern Minnesota during 2018, 2019, 2022, and 2023.

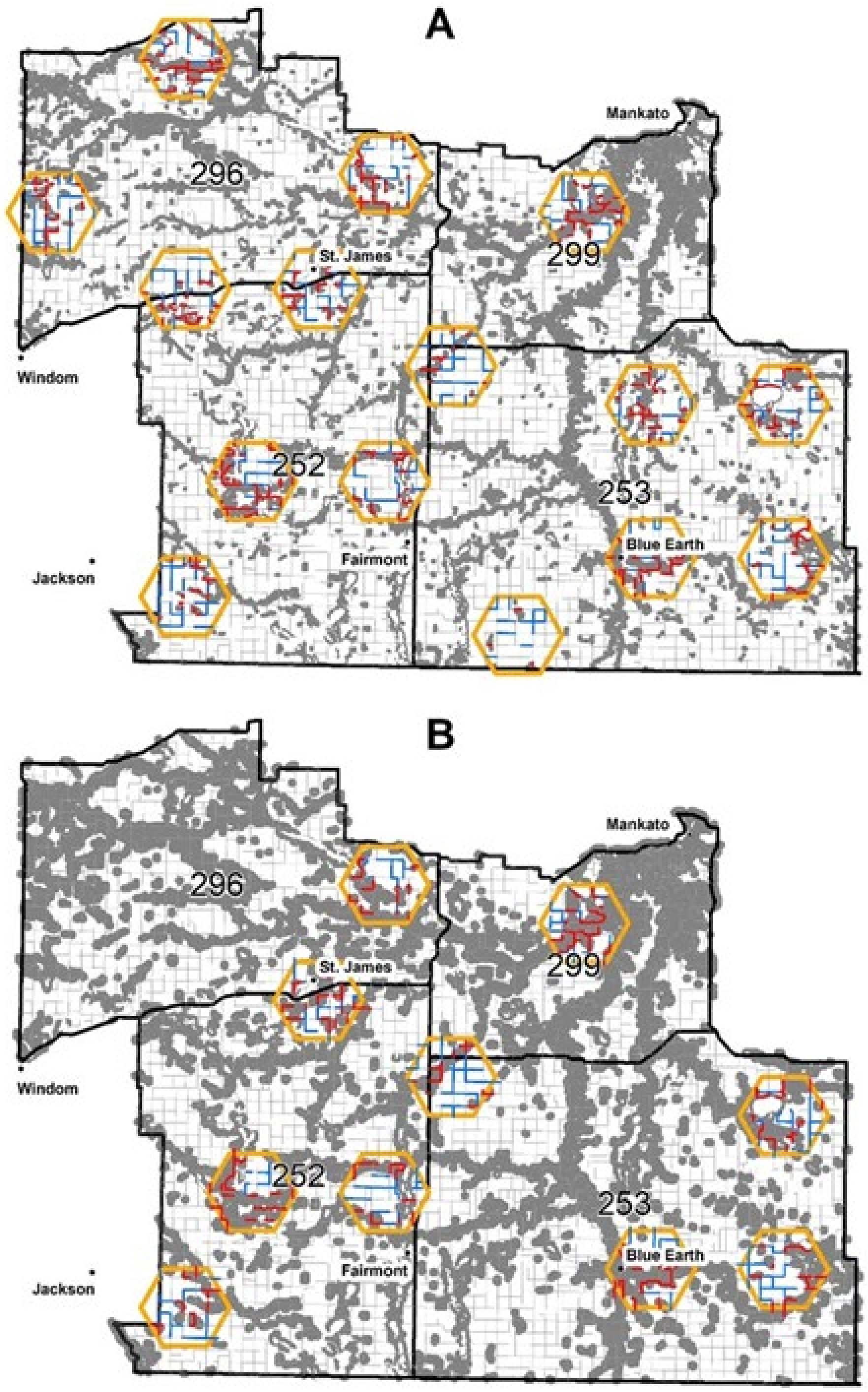

Figure 2. Sampling frame (deer permit areas 252, 253, 296, 299), primary sampling units (PSU; hexagons), and secondary sampling units (road segments; red = high-density stratum, blue = low-density stratum) for roadside distance sampling surveys of white-tailed in southern Minnesota during **A**) spring 2018, 2019, 2022, and 2023 (250-m buffer surveys) and **B**) spring 2019 (500-m buffer surveys). Grey areas denote deer-cover polygons ($\geq$2 ac) consisting of woodland, grassland, and wetland cover types with a 250-m or 500-m buffer.

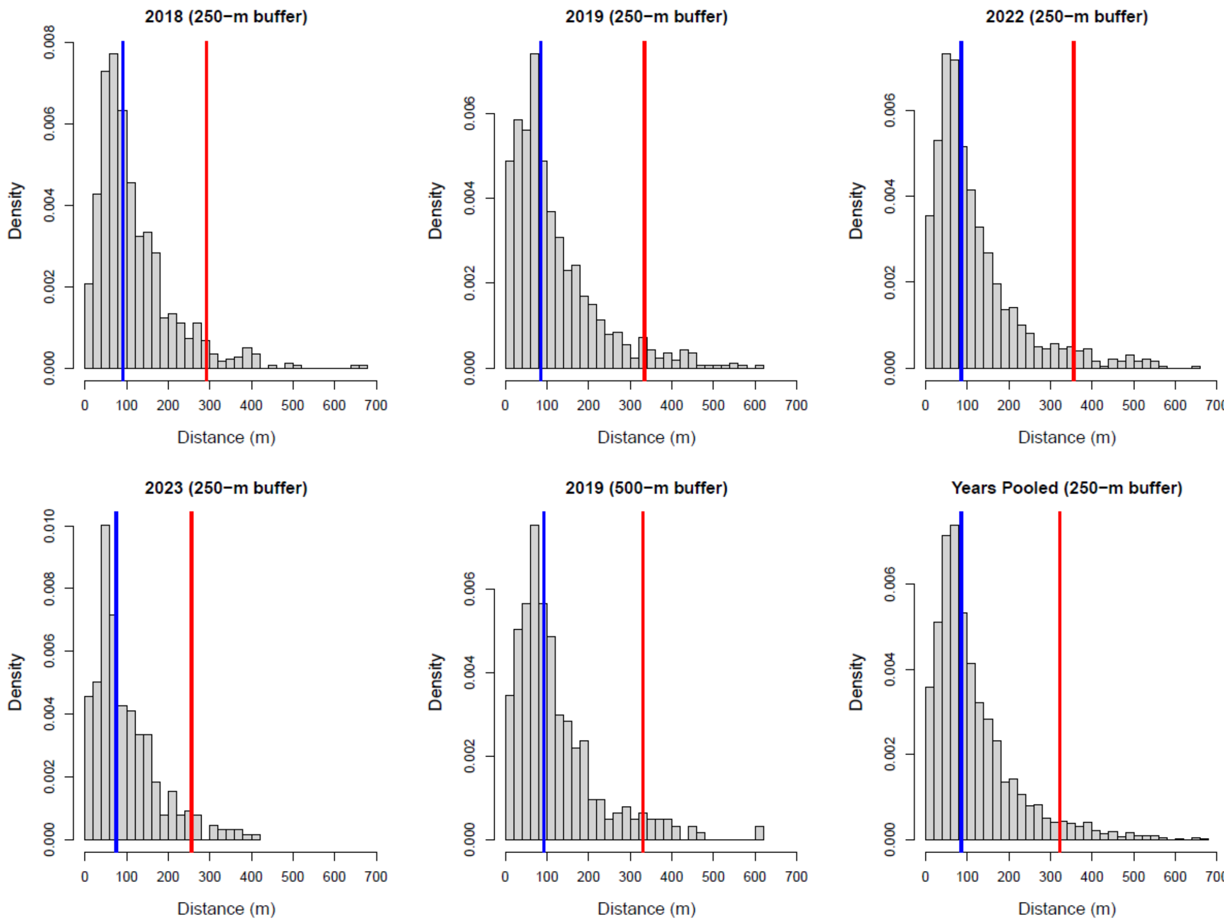

Figure 3. Distribution of perpendicular sighting distances from roadside distance sampling surveys of white-tailed deer in southern Minnesota during spring 2018, 2019, 2022, and 2023. Data include distance measurements collected during 1-3 replicate surveys of 10-15 primary sampling units using 2 stratification schemes (250- and 500-m buffers around deer habitat). Blue vertical lines denote the median and red vertical lines denote the 95% quantile.

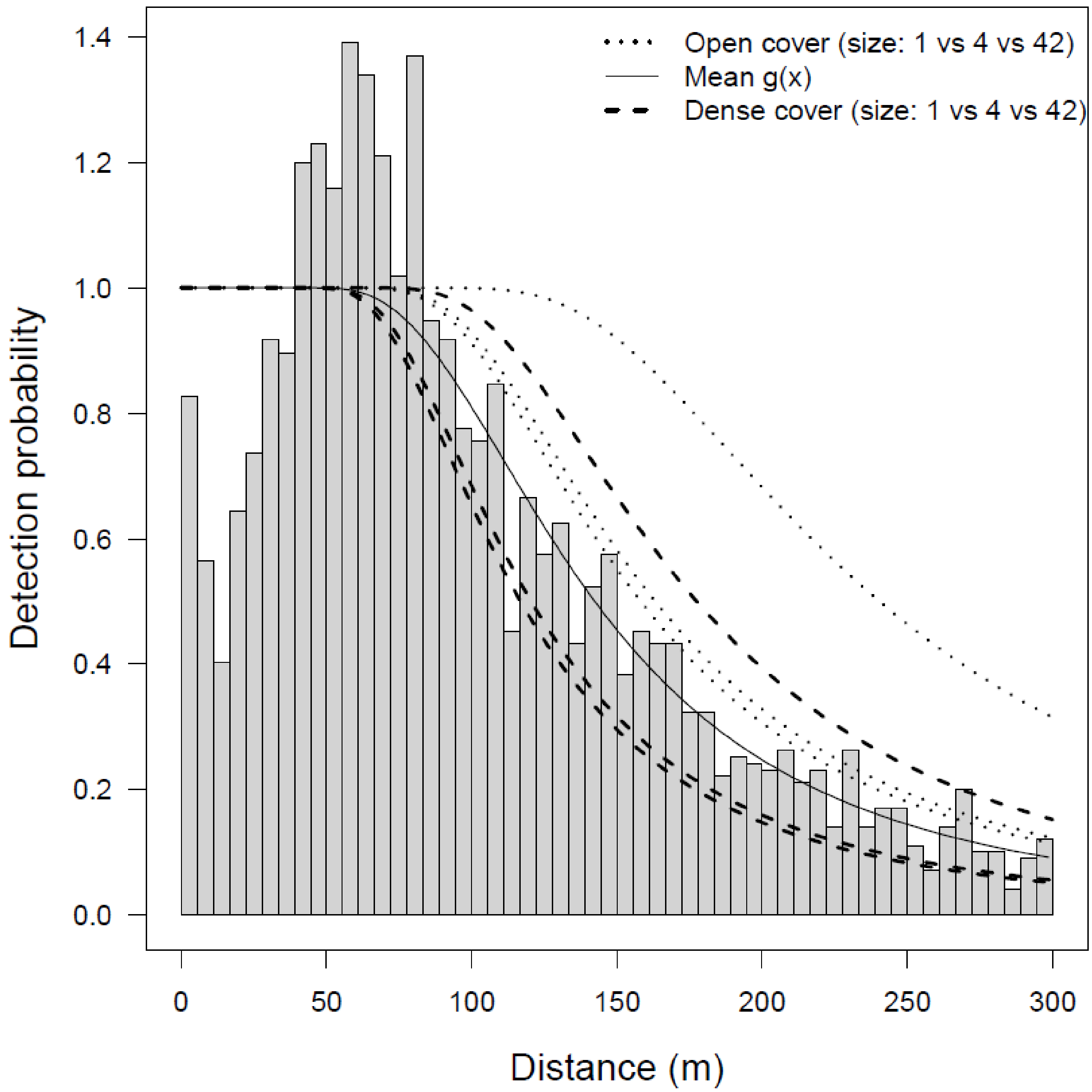

Figure 4. Pooled detection-function estimator, g(x), overlaid on a histogram of deer-group observations as a function of perpendicular sighting distance during roadside surveys of white-tailed deer in southern Minnesota, spring 2018, 2019, 2022, and 2023. The solid curved line denotes the average detection function. The dotted lines denote detection curves for single deer (lower line), a group of 4 deer (middle line; average group size), and a group of 42 deer (upper line; max observed group size) observed in short/open cover types (pasture, farmstead, harvested crops, roadsides, other). The bold dashed lines denote detection curves for a single deer (lower line), a group of 4 deer (middle line), and a group of 42 deer (upper line) in tall/dense cover types (grassland, woodland, standing crops, wetland).

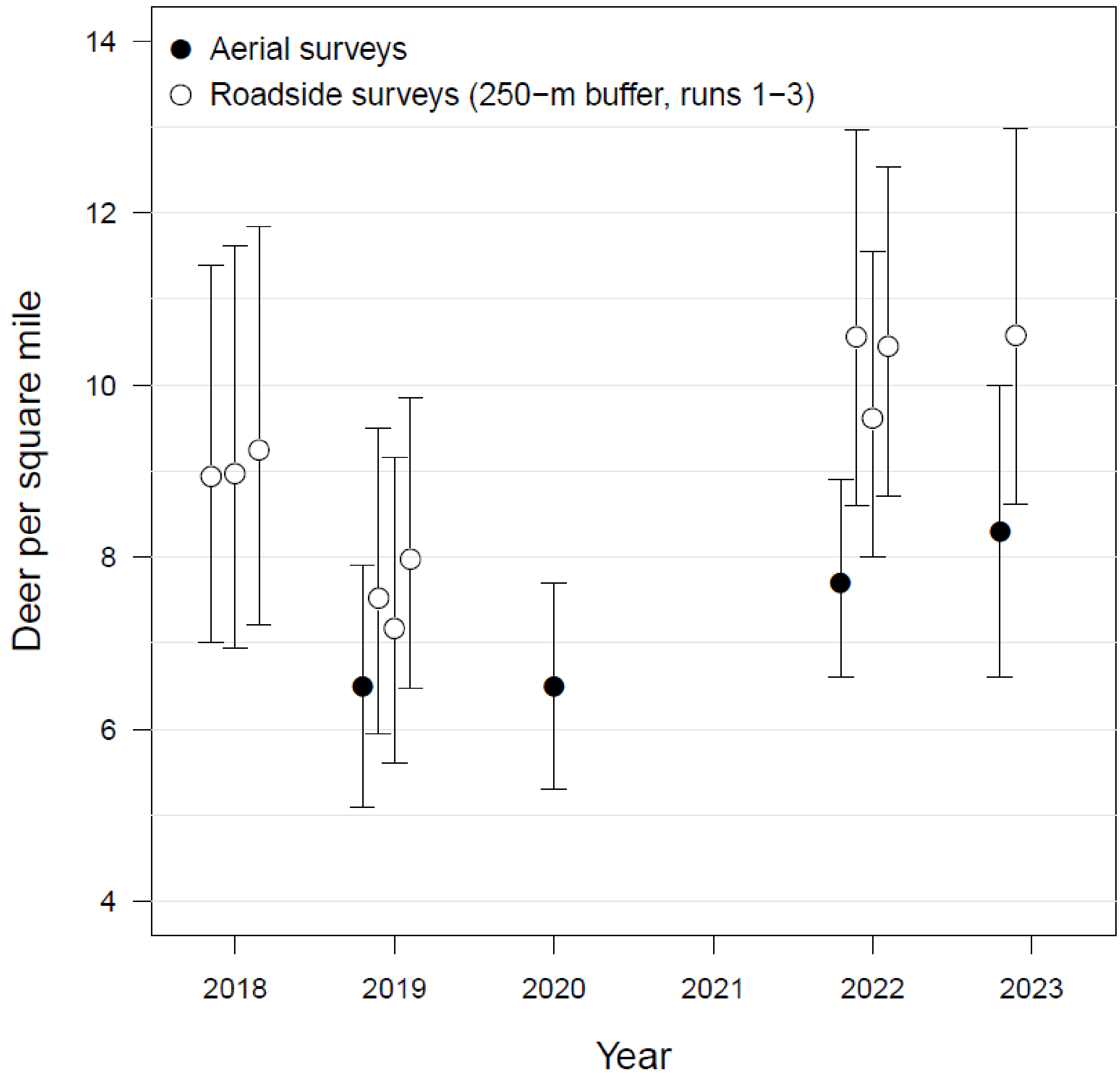

Figure 5. Estimated white-tailed deer density (per mi^2) and 85% CIs from winter aerial quadrat surveys and spring roadside distance sampling surveys in southern Minnesota during 2018-2023.

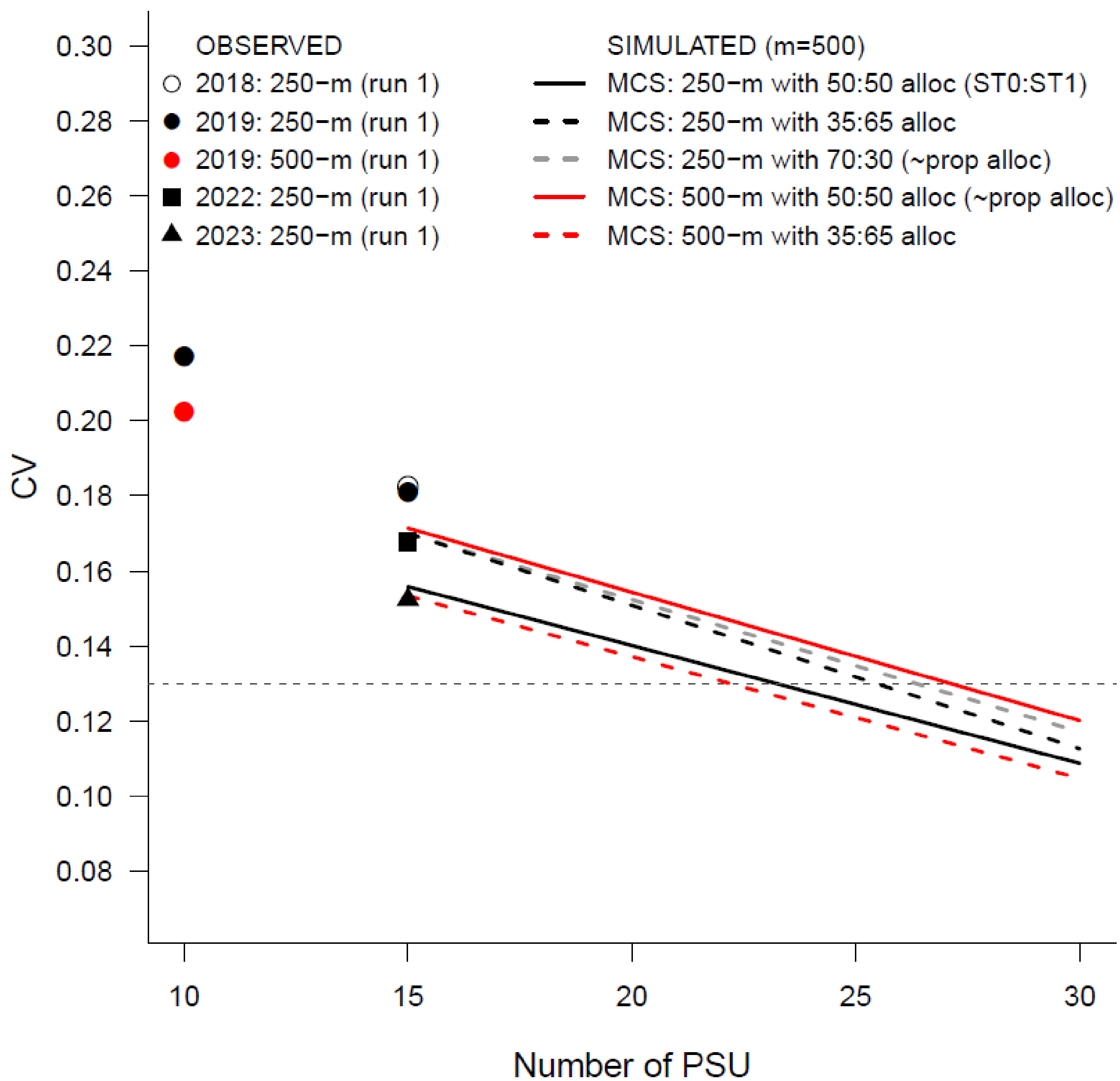

Figure 6. Expected precision of population estimates as a function of sample size (number of primary sampling units; PSU), stratification scheme (250- vs. 500-m buffer around deer-habitat polygons), and allocation of secondary sampling units (road segments) to strata. Estimates were derived from a Monte Carlo simulation with 500 replicates based on data from roadside distance sampling surveys of white-tailed deer in southern Minnesota, spring 2018, 2019, 2022, and 2023. The gray dashed horizontal line denotes a common target level of precision for management surveys. Observed estimates of precision were based on a null detection function model (no detection covariates) to be consistent with the model structure used to generate simulated estimates.