USING CAMERA TRAPS TO DERIVE DENSITY ESTIMATES FOR WHITE-TAILED DEER IN NORTHEASTERN MINNESOTA

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SUMMARY OF FINDINGS

The Minnesota Department of Natural Resources uses a harvest-based simulation model to estimate white-tailed deer (*Odocoileus virginianus*) densities and population trends and, in turn, uses that information to make harvest designations for each deer permit area. However, a 2016 audit suggested we need additional population trend indices to validate and increase confidence in the harvest-based simulation model output. We deployed 30 trail cameras in deer permit area 679 from 17 July to 12 September 2023 to estimate deer density and age and sex ratios. We recorded a total of 489,517 pictures comprising 197 deer detections. We detected 55 males, 75 females, 28 fawns, and 62 unknown deer. We estimated about 20 deer per square mile (95% CI: 17–23 dpsm, CV = ~7%). Additionally, we estimated a fawn-to-doe ratio of 1.0 fawn to 2.7 does. We also estimated a buck-to-doe ratio of about 0.74 bucks to 1.0 doe. We estimated a biologically reasonable deer density with an acceptable coefficient of variation. Additionally, using artificial intelligence to process photos drastically increased efficiency resulting in a decreased processing time. This methodology is feasible to use to monitor deer populations in northeastern Minnesota while also providing important vital rate information that can be used in the harvest-based simulation model output.

INTRODUCTION

The Minnesota Department of Natural Resources (MNDNR) uses a harvest-based simulation model (hereafter, deer model) to estimate white-tailed deer (*Odocoileus virginianus*; hereafter, deer) densities and population trends for Deer Modeling Units (DMUs; comprised of multiple deer permit areas [DPAs]) across Minnesota. Estimates of deer density and trends in density estimates are important pieces of information managers use to make annual harvest recommendations for each DPA and are considered during population goal setting. However, an audit of Minnesota's deer management program (OLA 2016) suggested that periodic, independent field data (density estimates and/or indices) are needed to calibrate modeled densities and population trends. We historically used aerial surveys to estimate spring deer densities in the transition zone; however, continued use of aerial surveys is being reconsidered because of cost, the inherent danger of flying, and the inconsistent data gained due to the weather-dependent nature of these surveys (e.g., required snow depth). We are currently exploring roadside distance-sampling methods to estimate spring deer densities in the farmland region (Haroldson et al. 2022), but we lack a good method for estimating and monitoring deer densities in the forested region of Minnesota. We need a reliable method to provide reliable deer density estimates in the forest region as deer management is complicated by severe winters, moose management, and increased predator composition not observed in other regions of the state.

Camera traps have been used to estimate deer density since the late 1990s (Jacobson et al. 1997), including a MNDNR pilot study in northwestern Minnesota (Dunbar and Grund 2008). Early project design required identifying individual bucks by their antler characteristics while using bait to attract deer to the camera site. However, biases in sightability (Moore et al. 2014) and parameter estimates (McCoy et al. 2011), animal misclassification (Newbolt and Ditchkoff 2019), and the extensive time required to identify individual bucks and maintain baited camera sites made this methodology logistically unfeasible. Further, disease management concerns make the use of baited surveys undesirable. Newly developed model estimators allow for density estimation using unmarked target animals and unbaited camera sites with stratified randomized designs, allowing for density estimates to be calculated from any species detected in pictures (Moeller et al. 2018, Loonam et al. 2021, Moeller and Lukacs 2022). Some methods require paired movement data from radiocollared animals to help inform camera placement across the landscape to maintain independence of capturing the same animal on multiple cameras (Moeller et al. 2018, Loonam et al. 2021); however, the space-to-event (STE) method does not require paired movement data and makes use of time-lapse technology to address prior concerns about detectability. Therefore, the STE estimator makes this particular camera-trap method more feasible for monitoring deer densities at the DMU level in the forest region of Minnesota.

OBJECTIVES

1. Determine if the total time needed to deploy and retrieve cameras and summarize data obtained from each camera is feasible for a long-term monitoring project.
2. Determine if the total budget needed to conduct fieldwork, review photos, and conduct analyses to derive deer densities is reasonable for a long-term monitoring project.
3. Develop a more time-efficient (and thus cost-effective) way to detect animals in photos using machine learning and Artificial Intelligence (AI) in Program R.
4. Successfully estimate deer densities using a space-to-event (STE) camera-trap estimator.

METHODS

Study Site

We deployed cameras on public lands in DPA 679 (Figure 1), which is about 2,233 km^2. Located in the forest region, DPA 679 is comprised of woody cover (78%), open water (10%), grasslands and wetlands (7%), and developed areas (5%); no annual row crops are found in this DPA. We chose DPA 679 for several reasons including the diverse predator composition, propensity for severe winters, and the recent detection of chronic wasting disease.

Data Collection

We used a stratified random design to remove inaccessible areas of permanent water and to remove private lands. The resulting sampling grid was then comprised of public lands that could be accessed for research purposes. All public lands available were considered for sampling regardless of parcel size. We randomly selected plots using generalized random-tessellation stratified sampling (GRTS: Stevens and Olsen 2004) in the R package spsurvey (Dumelle et al. 2023). GRTS sampling allows for replacement of plots due to inaccessibility. We then selected 50 plots (30 primary, 20 secondary) from the sampling grid in DPA 679. We used a secondary plot if we deemed a primary plot to be inaccessible (e.g., plot located in a sensitive habitat type or in an inaccessible habitat type such as a marsh or sphagnum bog).

We deployed a camera at the center of each randomly selected plot (n = 30) and sampled at 5-minute intervals. MNDNR staff could choose to locate cameras within 50 meters of the center of the plot if they found a location that required less clearing of vegetation. We placed cameras about 1.5 m high on a tree facing north to limit sunlight glare and removed obstructing vegetation from the viewshed. We trimmed vegetation to improve our ability to identify the species, age, and sex of a target individual (Moeller et al. 2018). We determined the maximum distance we could accurately identify a target individual in a controlled setting before we placed cameras in the field. We then used that maximum distance as a guide to obtain a landmark at the camera site. We recorded the distance from the landmark to the camera for use in calculating the viewshed area. We subsetted cameras such that we analyzed photos from the same time period (i.e., starting when the last camera was deployed and ending when the first camera was retrieved). Deploying cameras before we began officially sampling helped lessen the effects of any potential disturbance created during initial deployment.

Statistical Analysis

We processed photos using MegaDetector (Beery et al. 2019) and Timelapse (Greenberg et al. 2019). MegaDetector outputs a .json file including information on animals detected (e.g., confidence intervals that the image captured an animal, a box placed around the detected animal, etc). The .json file is then uploaded into Timelapse, which separates non-detections from detections. Timelapse also allows users to easily tag photos with species, sex, and age of animals detected within each photo for use in later analyses.

We estimated density for DPA 679 using the STE estimator in the spaceNtime package in Program R (R core Team 2023; Moeller et al. 2018, 2023). We used the distance from the predetermined landmark to the camera to calculate the area of the viewshed, which we then used in calculating density from abundance data. We determined the coefficient of variation to be acceptable at ≤15%.

RESULTS

Artificial Intelligence

We deployed 30 cameras over three days (two days for travel, one day to deploy) and retrieved cameras over two days (1 day for travel, 1 day to retrieve) in 2023. Processing photos from DPA 679 using MegaDetector and Timelapse took three technicians about 45 total hours to process photos.

We also used data from the 2021 camera trap feasibility study to assess the efficiency of using MegaDetector and Timelapse in processing photos. We sampled two study areas in 2021, which resulted in a total of 1,359,477 photos to process (Michel et al. 2023). Using MegaDetector and Timelapse to process photos resulted in a false positive rate of 98.30%, a false negative rate of ~0.02%, and an accuracy rate of 1.70%. However, manual processing conducted by MNDNR permanent staff, seasonal technicians, and volunteers took about 6 months to finish, whereas using MegaDetector and Timelapse allowed one seasonal technician to process these photos in about 34 hours. Additionally, using artificial intelligence allowed for 34 additional deer detections in the Bear Study Area from 2021. However, including these missed detections in an updated analysis resulted in a negligible change in deer density (1.6 vs 1.7 deer per square mile).

Estimating Abundance

We deployed cameras on 17 July and retrieved all cameras by 12 September in 2023 for a total of 57 capture days. Cameras recorded 489,517 total pictures. We recorded 197 total deer detections and 220 total deer observations. We detected 55 males, 75 females, 28 fawns, and 62 unknown deer. We also detected 4 black bears (*Ursus americanus*), 4 wolves (*Canis lupus*), and 272 detections of other species.

We restricted the STE analysis to estimate density to only pictures taken from 00:00 hours on 18 July to 23:59 hours on 10 September (54 days). Restricting the analysis to this time frame resulted in a total of 194 deer detections. We observed a total of 217 deer, with 55 males, 74 females, 27 fawns, and 61 unknown deer. We estimated 20,398 deer in DPA 679 (95% CI: 17,699–23,510, CV = 7%), equating to about 20 deer per square mile (95% CI: 17–23 dpsm). We estimated a fawn-to-doe ratio of 1 fawn to 2.7 does and a buck-to-doe ratio of 0.74 bucks to 1.0 doe. About 25% of pictures were of males, 34% of females, 12% of fawns, and 28% of unknown deer.

DISCUSSION

We successfully deployed cameras to estimate the deer density in DPA 679 in 2023. MNDNR staff deployed and retrieved cameras within 5 total days and subsequent photo processing only required just over five days to complete. Camera traps passively collect data resulting in minimal time spent in the field to deploy and retrieve cameras; however, the time required to sample will increase if sampling occurs at a larger scale.

Using MegaDetector and Timelapse drastically increased the efficiency of processing photos, though there were some issues with accuracy rates. The accuracy rate of successfully detecting animals in a photo was low. However, using MegaDector reduced the number of photos to process by about 96% by eliminating blank photos, which led to a substantial decrease in time to process detections. MegaDector also displayed a low false negative rate indicating the number of photos that contained an animal even though MegaDector classified the photo as a non-detection was low. A low false negative rate indicates we obtained most data for capture events. MegaDector can also be trained from photos containing images of known animals, which would ultimately increase accuracy. Regardless, the low false negative rate can facilitate increased photo processing efficiency without concern for missing a substantial number of detections.

We successfully estimated a biologically reasonable deer density in DPA 679. Initial efforts to estimate deer density in northeastern Minnesota resulted in an estimate of under 2 deer per square mile (Michel et al. 2023). This deer density was rather low relative to the deer model (Michel and Giudice 2023) and was one of the reasons we focused our efforts on estimating deer density in DPA 679. The deer density estimated in DPA 679 in 2023 was more comparable to density estimates derived from the deer model, though they may still be on the high end of estimates. Regardless, the coefficient of variation was acceptable indicating a relatively precise point estimate. We also estimated age and sex ratios, which can be used in the current deer model. The ability to estimate deer densities in combination with deriving age and sex ratios from camera traps make this methodology effective and efficient for monitoring the deer population in northeastern Minnesota.

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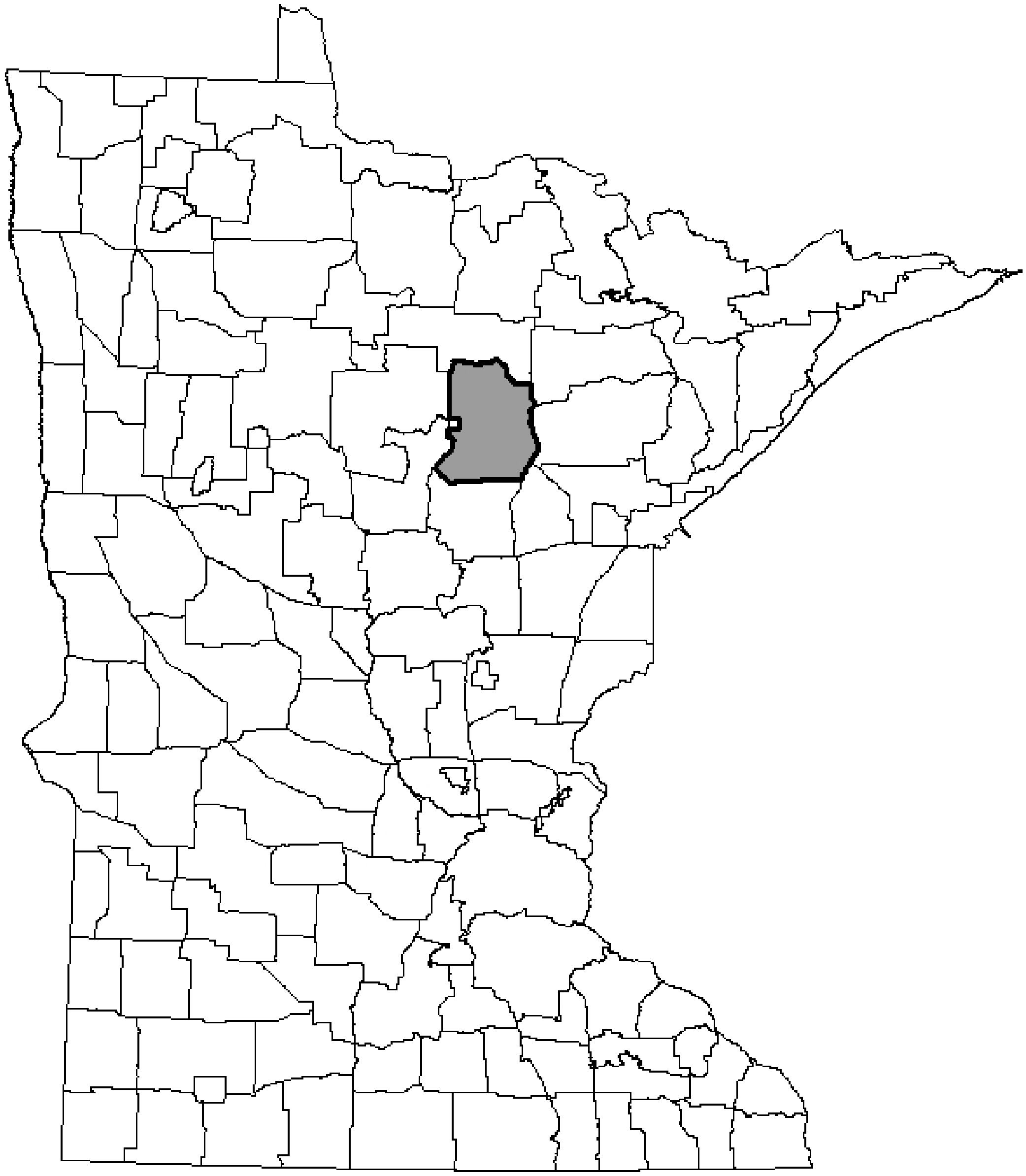

Figure 1. Location of deer permit area 679 (shaded area) in northeastern Minnesota where camera traps were deployed on public lands from 17 July – 12 September 2023.