Tools and Technology

Evaluating the Use of Drones Equipped with Thermal Sensors as an Effective Method for Estimating Wildlife

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ABSTRACT Drones equipped with thermal sensors have shown ability to overcome some of the limitations often associated with traditional human-occupied aerial surveys (e.g., low detection, high operational cost, human safety risk). However, their accuracy and reliability as a valid population technique have not been adequately tested. We tested the effectiveness of using a miniaturized thermal sensor equipped to a drone (thermal drone) for surveying white-tailed deer (*Odocoileus virginianus*) populations using a captive deer population with a highly constrained (hereafter, known) abundance (151–163 deer, midpoint 157 [87–94 deer/km^2, midpoint 90 deer/km^2]) at Auburn University's deer research facility, Alabama, USA, 16–17 March 2017. We flew 3 flights beginning 30 minutes prior to sunrise and sunset (1 morning and 2 evening) consisting of 15 nonoverlapping parallel transects (18.8 km) using a small fixed-wing aircraft equipped with a nonradiometric thermal infrared imager. Deer were identified by 2 separate observers by their contrast against background thermal radiation and body shape. Our average thermal drone density estimate (69.8 deer/km^2, 95% CI = 52.2–87.6), was 78% of the mean known value of 90.2 deer/km^2, exceeding most sighting probabilities observed with thermal surveys conducted using human-occupied aircraft. Thermal contrast between animals and background was improved during evening flights and our drone-based density estimate (82.7 deer/km^2) was 92% of the mean known value. This indicates that time of flight, in conjunction with local vegetation types, determines thermal contrast and influences ability to distinguish deer. The method provides the ability to perform accurate and reliable population surveys in a safe and cost-effective manner compared with traditional aerial surveys and is only expected to continue to improve as sensor technology and machine learning analytics continue to advance. Furthermore, the precise replicability of autonomous flights at future dates results in methodology with superior spatial precision that increases statistical power to detect population trends across surveys.

KEY WORDS aerial, deer, density estimation, drones, *Odocoileus virginianus*, population methods, thermal imaging, wildlife surveys.

One of the primary tenets of population management is that abundance and monitoring information accurately describe the current population state or trend (Collier et al. 2013). The testing and adoption of methods that provide rigorous, accurate estimates of population size is not only relevant, but requisite for informed population management of many wildlife species (Williams et al. 2002, Collier et al. 2013). However, true population size for most wild populations is unknown (e.g., Yoccoz et al. 2001, Hodgson et al. 2016). Unless a survey method has been tested on a population of known size, it is not possible to directly assess the accuracy of any count method.

Few, if any, species have had more work focused on population size estimation and methodological evaluation than the

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white-tailed deer (*Odocoileus virginianus*; hereafter, deer; Gill et al. 1997, Lancia et al. 2005, Collier et al. 2013). A variety of survey techniques have been developed for estimating deer population size: browse surveys (Aldous 1944, Tremblay et al. 2005), harvest data reconstruction (Roseberry and Woolf 1991, Millspaugh et al. 2009), pellet counts (Eberhardt and Van Etten 1956, Van Etten and Bennett 1965, Goode et al. 2014), ground-based infrared and thermal imaging surveys (Wiggers and Beckerman 1993, Gill et al. 1997, Collier et al. 2007), spotlight surveys (McCullough 1982, Mitchell 1986, DeYoung 2011), and camera surveys (Jacobson et al. 1997, Koerth and Kroll 2000) among others. However, aerial surveys remain the best option for counting large mammals, especially over large areas (Caughley 1974, Jachmann 1991, Linchant et al. 2015). Aerial surveys provide more reliable estimates of population size than ground-based techniques (Naugle et al. 1996, Beaver et al. 2014) because of high detection rates (Bernatas and Nelson 2004, Millette et al. 2011). Their ability to randomly sample across the landscape avoided biases inherent to road-based sampling (Diefenbach 2005, Drake et al. 2005, Kissell and Nimmo 2011, Beaver et al. 2014).

Aerial surveys conducted using human-occupied aircraft have been primarily based on human visual detection (Caughley 1974, Poole et al. 2013, Chrétien et al. 2016), are logistically difficult to implement, costly (Watts et al. 2010, Linchant et al. 2015), and pose a health risk for operators (Jones et al. 2006, Watts et al. 2010). Aviation accidents are the most common cause of work-related death for wildlife biologists in the United States (Sasse 2003). The risks and costs associated with use of human-occupied aircraft for aerial surveys makes drones (also known as unmanned aerial vehicles/systems, remotely piloted aircraft; UAV/S, RPA) particularly attractive for wildlife population assessments. Early use of drones has shown a vast array of diverse ecological applications (e.g., Vermeulen et al. 2013, Christiansen et al. 2016, Evans et al. 2016, Wich et al. 2016) and the ability to reduce cost and risk to humans (Watts et al. 2010, Seymour et al. 2017). Additionally, they provide easier logistics and manipulation than manned aircraft and avoid disturbances associated with ground surveys (Linchant et al. 2015, Hodgson et al. 2018). These benefits have led many practitioners to label drones as a powerful tool for wildlife ecology (Chabot and Bird 2012, Linchant et al. 2015, Christie et al. 2016, Seymour et al. 2017).

An emerging area in drone research is miniaturized sensors that allow data to be collected at extremely fine spatial and temporal resolutions highly suited to ecological applications (Watts et al. 2012, Anderson and Gaston 2013, Messinger et al. 2016, Hodgson et al. 2018). Among the most popular of the commercially available is thermal infrared sensors (hereafter, thermal; Kissell and Nimmo 2011), which provides a high-contrast method of discriminating endotherms from their surroundings (Stark et al. 2014, Burke et al. 2019) and allows for detection of animals at night and in low light conditions, which is an advantage over conventional multispectral (red–green–blue; RGB) cameras (Israel 2011, Witczuk et al. 2018). However, previous approaches using thermal infrared sensors in heterogeneous landscapes have experienced visibility limitations similar to those found in traditional photographic methods in similar environments, with the landscape obscuring animals not only through occlusion, but also through isothermality, or lack of difference between the animal's thermal signature and that of the background (Witczuk et al. 2018).

Early results indicate the use of drones equipped with RGB and thermal cameras in wildlife monitoring may be a viable alternative to typical field methods (e.g., Christie et al. 2016, Seymour et al. 2017, Hodgson et al. 2018, Linchant et al. 2018, Witczuk et al. 2018), though direct comparisons of wildlife population estimates to known populations remains unstudied. Furthermore, as drone platforms, sensors, and computer vision techniques develop, the accuracy and cost-effectiveness of drone-based approaches also will likely improve (Hodgson et al. 2018). Yet, important issues must be resolved prior to wider drone application, including short flight endurance, optimizing resolution with area coverage, and regulatory hurdles such as the requirement in many jurisdictions to maintain visual line-of-sight with the aircraft at all times (Linchant et al. 2018). Additionally, methods for estimating wildlife populations remain poorly understood because most drone-based surveys to date have focused on the plausibility of wildlife monitoring applications rather than their effectiveness as a viable improvement upon current survey methods (Linchant et al. 2015).

The primary objective of our study was to determine the effectiveness of using drones equipped with thermal for surveying wildlife populations by estimating deer density and abundance for a captive deer population with a highly constrained (hereafter, known) abundance. We predicted this method would provide improved detection rates and more reliable population estimates than current aerial survey methods while also providing biologists and wildlife managers with a benchmark by which to compare and validate their existing survey methods. We also identify strengths and weaknesses of the drone-based thermal approach as a real-time survey tool and suggest paths for improvements and future directions.

STUDY AREA

We conducted our study at Auburn University's deer research facility located in Lee County, which lies in the Piedmont region of east-central Alabama, USA (Fig. 1). The facility was constructed in October 2007 and consisted of 174 ha enclosed by 2.5-m steel fence. The enclosed population consisted of wild animals captured during the construction of the facility and their descendants. Vegetation was approximately 40% open fields maintained for hay production; 13% bottomland hardwoods (various oak [*Quercus* spp.]); 26% mature, naturally regenerated mixed hardwoods (various oak and hickory [*Carya* spp.]) and loblolly pine (*Pinus taeda*); 11% early regenerated thicket areas consisting primarily of *Rubus* spp., sweetgum (*Liquidambar styraciflua*), eastern red cedar (*Juniperus virginiana*), and Chinese privet (*Ligustrum sinense*);

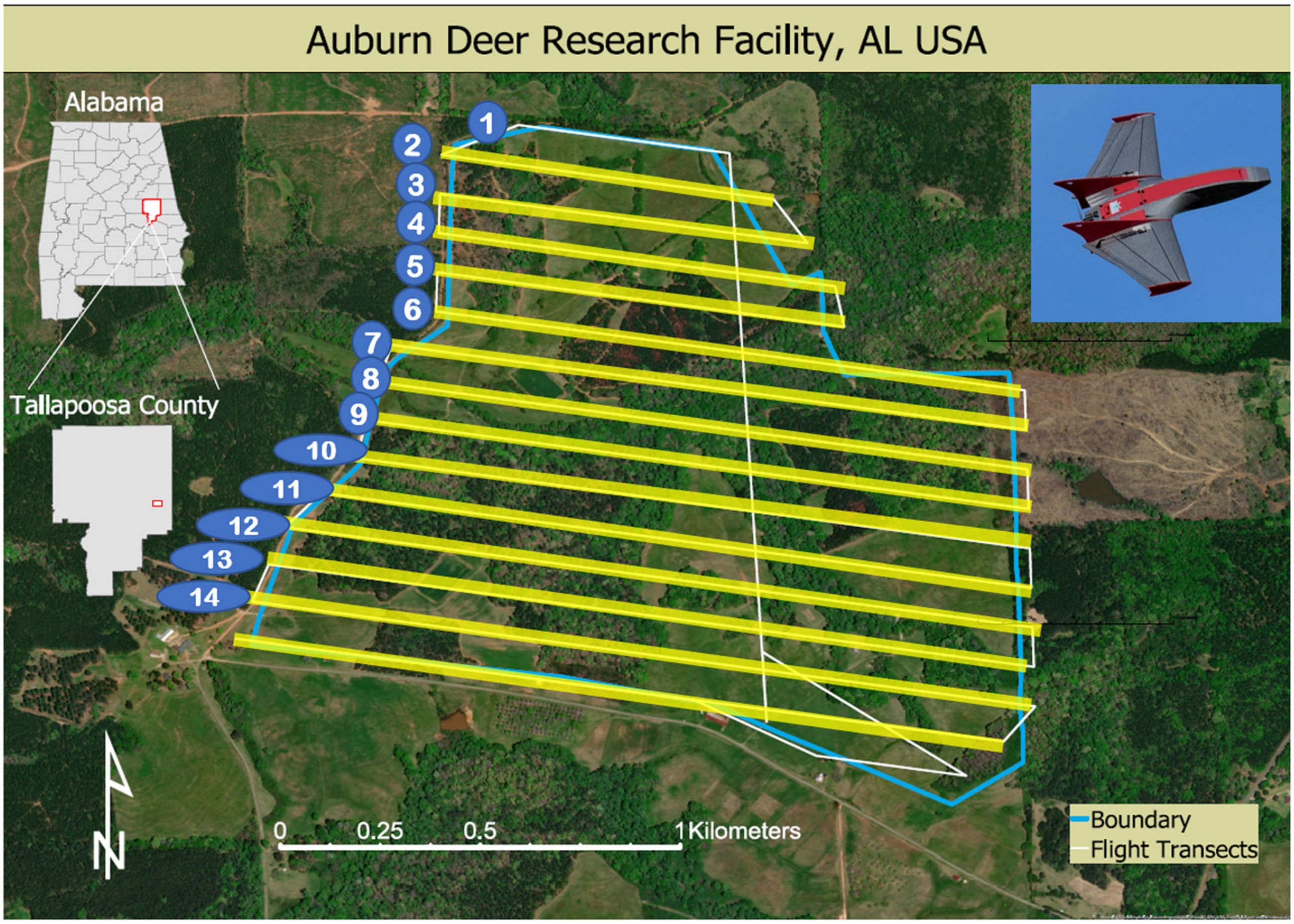

Figure 1. Flight path (white lines) and transects flown (highlighted in yellow and labelled) at Auburn University deer research facility, Alabama, USA, 16–17 March 2017, for white-tailed deer thermal drone surveys.

and 10% 10–15-year-old loblolly pine. A second-order creek bisected the property and provided a stable source of water year-round. For a more complete description of the facility, see Neuman et al. (2016) and Newbolt et al. (2017).

METHODS

Data Collection

We conducted all surveys over the study area using the Ritewing Drak aircraft, a small flying-wing style fixed-wing aircraft with a 1.5-m wingspan and maximum takeoff weight of 4.3 kg. The aircraft was controlled by a Cube Autopilot (Hex Technology Ltd, Hong Kong, CN) running the ArduPlane software stack (ArduPilot, http://firmware.ardupilot.org/Plane/, accessed 10 Mar 2017), which is common in research applications because it provides a powerful suite of capabilities in an open source environment. We programmed flight paths using Mission Planner (Mission Planner Version 1.3, http://ardupilot.org/planner/, accessed 10 Mar 2017) using the integral terrain-following feature to allow for precise, repeatable flights at a fixed altitude above-ground-level (AGL; postflight data logs show altitude on mapping legs of flight were constrained to within ±2.5 m with little to no variation in speed). The drone was hand-flown during take-off and landing using the remote-control system while all other phases of flight were under autopilot control and monitored using Mission Planner.

The aircraft was equipped with the 640 × 480-pixel nonradiometric thermal infrared imager (FLIR Vue Pro 640, 13-mm lens, 45° horizontal FOV, 30 Hz; FLIR Systems, Inc., Wilsonville, OR, USA). All sensors were fixed to the airframe, flight plans identical, and thermal sensor internally calibrated, ensuring repeatability among flights. The camera was mounted looking vertically downward to obtain the nadir view, and the horizontal axis of the camera was aligned perpendicular to the flight path. This sensor was self-calibrating, with a precision of 0.05° C (<50 mk).

We made 3 total flights, with 1 morning flight on 16 March 2017 and 2 evening flights on 16 and 17 March 2017, all of which were initiated 30 minutes prior to sunrise and sunset. Mean temperature during the morning flight was −2° C while the mean temperatures during the evening flights were 13° C on 16 March and 21° C on 17 March (Auburn Airport weather station, Auburn, AL, USA). Weather was calm (winds <6 km/hr) and clear on both days (Auburn Airport weather station).

We performed flights at 100 m AGL (±2.5 m), providing an 84-m horizontal field of view and a resolution (pixel-size)

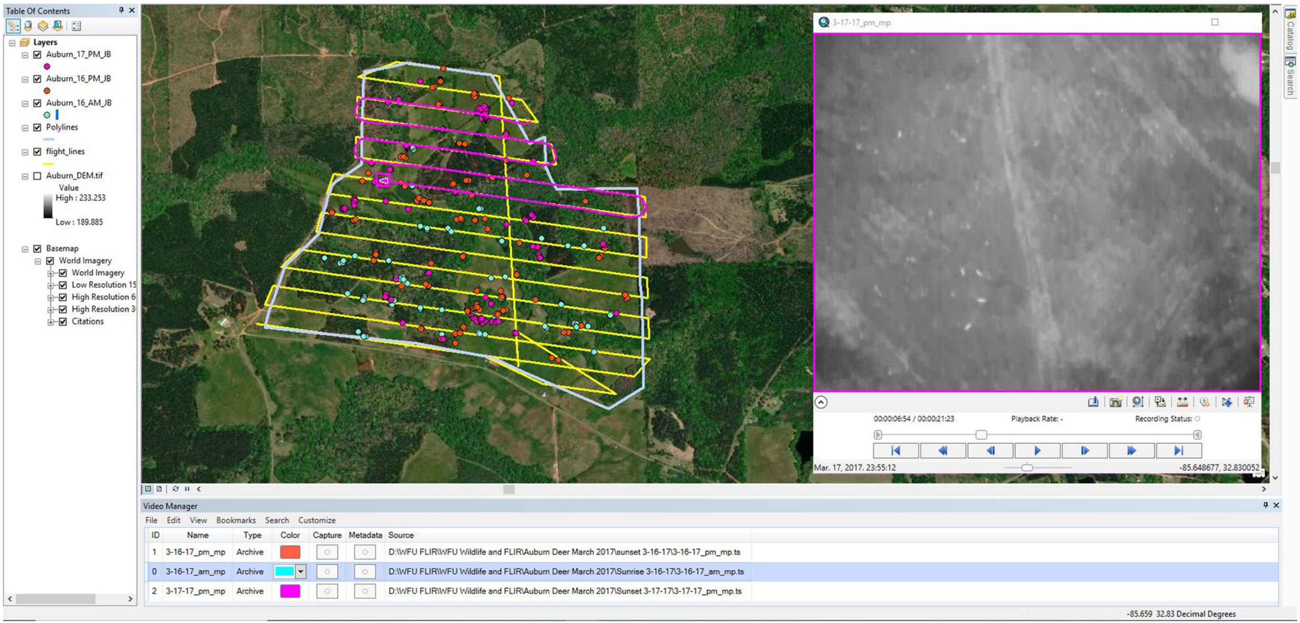

Figure 2. Screenshot illustrating ESRI's Full Motion Video add-in tool used to identify and georeference individuals (or group of animals) detected during aerial thermal drone flights, within the Auburn University deer research facility in Alabama, USA, 16–17 March 2017. Full Motion Video allowed us to observe the flight footage and current location of the aircraft along our flight path when marking locations of each individual and for comparison among observers. Yellow lines indicate programed aircraft flight path and transects and purple lines indicate actual aircraft flight path. Colored dots indicate marked white-tailed deer observations.

of 13-cm ground sample distance, which determines the size of the smallest object that can be resolved in imagery. The aircraft flew at a nominal ground speed of approximately 21 m/second (75 km/hr) in an east–west-oriented transect pattern, with 15 parallel transects, totaling 18.8 km in length, spaced evenly 100 m apart across the study area (Fig. 2). We collected video and telemetry data continuously in flight. After flight, we trimmed telemetry logs from the autopilot to correspond with video clips, reformatted for ingestion into ArcGIS Full Motion Video (FMV; Environmental Systems Research Institute, Inc., Redlands, CA, USA), and multiplexed the 2 in FMV to create georeferenced video.

Video Analysis

We analyzed georeferenced video footage from each of the 3 flights at half speed by 2 separate observers to compare the effects of observer performance and flight conditions on resulting density estimates. We identified deer by their contrast against background thermal radiation and body shape. When a thermal signature of an animal (or group of animals) was detected, we marked the location and time of each observation and recorded using FMV to mark locations of each individual and ensure density estimates were generated from observations of the same animals (Fig. 2). We evaluated observation agreement among observers by binning individual observations within 5-second windows and comparing the kernel-smoothed probability density of the observation time (time a deer was detected) for each observer to control for small differences in observer recognition (package sm; Bowman and Azzalini 2018) in Program R (R Version 3.4.0, www.r-project.org, accessed 2 Feb 2019).

Population Estimation

We conducted data analysis in Program R using package *car* (Fox and Weisberg 2011). We used 2 methods to assess deer abundance from thermal footage. The first used transects to provide a sample-based density estimate (deer/km^2). We summed deer observations by flight transect and divided by their respective areas (transect length × estimated strip width [field of view]) to calculate transect-specific densities per observer (Naugle et al. 1996). We then subsetted transect densities into 3 groups of every third transect so that each used transect was 300 m apart to avoid the possibility of multiple observations of animals across consecutive transects (i.e., transects for Group 1: 1, 4, 7, 10, 13; Group 2: 2, 5, 8, 11, 14; Group 3: 3, 6, 9, 12, 15). However, it is worth noting that multiple detections of the same animals on different transects do not introduce bias if animal movement is random relative to the transect lines (Buckland et al. 2001). We then calculated a mean density per flight by averaging the 3 mean group densities. We repeated this process per observer.

The second method to assess abundance used the total number of deer counted per complete flight. We adjusted total count values by flight area to account for incomplete area coverage (87%) of flights. We generated confidence intervals (95% CI) of calculated abundances and densities from a 10,000-iteration bootstrapped distribution of transect-specific densities and counts averaged between observers. We compared mean population estimates and their 95% CIs between flights to access the reliability of the method. We also calculated the mean and standard error of estimate difference between observers as an additional measure of reliability. We conducted both estimates without prior knowledge of the known population size.

Accuracy Assessment

The deer population at Auburn University's deer research facility was intensively monitored, with capturing and camera surveys occurring each year to track the population. Researchers previously had captured individuals within the facility and assigned them a unique number, freeze-branded them, and tagged them in both ears with cattle ear tags (see Neuman et al. [2016] and Newbolt et al. [2017] for specific capture and handling techniques). Capture techniques followed American Society of Mammalogists' guidelines (Sikes et al. 2011) and were in accordance with Auburn University's Institutional Animal Care and Use Committee (PRNs 2008-1417, 2008-1421, 2010-1785, 2011-1971, 2013-2372, 2016-2964, 2016-2985). Researchers captured and released a number (10–15 individuals) of young-of-the-year deer outside the facility at approximately 6 months of age each year to control deer density and maintain appropriate numbers of individuals across age classes. Natural mortalities further mediated the population density of the facility. The deer within the facility had no movement restrictions other than the high fence boundary. Occasionally, researchers missed a deer during annual tagging, and the vegetation characteristics and large size of the facility did not allow for continuous monitoring of all individuals over the course of the study. As such, we used a combination of methods similar to Keever et al. (2017) to estimate our known deer abundance. No hunting occurred within the research facility.

RESULTS

At the time of our study, the Auburn deer facility contained approximately 151–163 deer (86.8–93.7 deer/km^2), with a midpoint of 157 deer (90.2 deer/km^2; Fig. 3). The average density estimate from the thermal camera equipped drone from all flights (hereafter, thermal drone) was 69.8 deer/km^2 (95% CI = 52.3–87.40), resulting in an average sighting probability of 78% (56–100%) of the known estimate, resulting in an overall correction factor of 1.28. Total abundance from thermal drone counts, adjusted for incomplete coverage (87%) of the study area, was 120 deer (95% CI = 90.9–142.2; Fig. 3) or 56–94% of the known estimate.

Video analysis indicated differing video contrast between morning and evening flights (Fig. 4). The mean estimated population density was lower in the morning flight (44.4 deer/km^2, 95% CI = 19.6–73.3) than in either evening flight (82.6 deer/km^2, 95% CI = 48.8–121.8; and 82.7 deer/km^2, 95% CI = 37.7–145.2, respectively). Estimates based on total counts of deer for the combined evening flights were 82.7 deer/km^2 (147 total deer, 95% CI = 64.0–101.4 deer/km^2), or 92% of the mean known density (90.2 deer/km^2) and 94% of the total abundance midpoint (157 deer; Fig. 3).

Observers differed overall in their estimates by <6% of the total, with the estimated difference broadly overlapping zero (mean inter-observer difference in counts 4.07 ± 11.6 deer/km^2, mean ± SE) and were largely similar during morning and evening flights. The probability density distributions of observations differed between observers in the morning flight but the shape and structure were nearly identical for evening flights (Fig. 5), indicating consistent identification of heat signatures by separate observers in the evening flight but not in the morning flight.

DISCUSSION

Performance Assessment

Autonomous thermal drone surveys provided an accurate, time-efficient, and highly repeatable method of estimating deer population abundance. Our total counts and density estimates (147 deer, 82.7 deer/km^2) during high-contrast evening flights were within approximately 8% of the

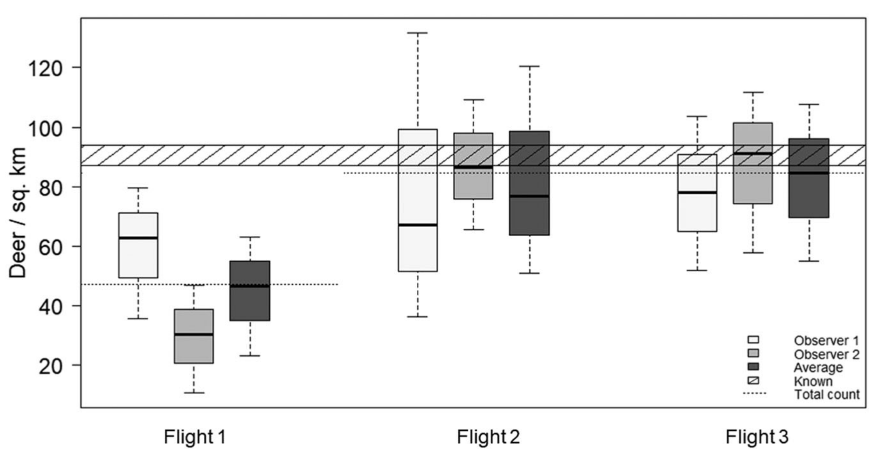

Figure 3. Thermal white-tailed deer population estimates by flight and observer for Auburn University deer research facility, Alabama, USA, 16–17 March 2017. Estimates were calculated using 2 separate approaches: transect-specific density and total count. Boxes represent interquartile range of transect-specific population estimates, midline estimate, and dashed lines represent the range. Dotted lines indicate the total count estimates. Slash line indicated midpoint for the highly constrained known deer population within the high-fenced research facility.

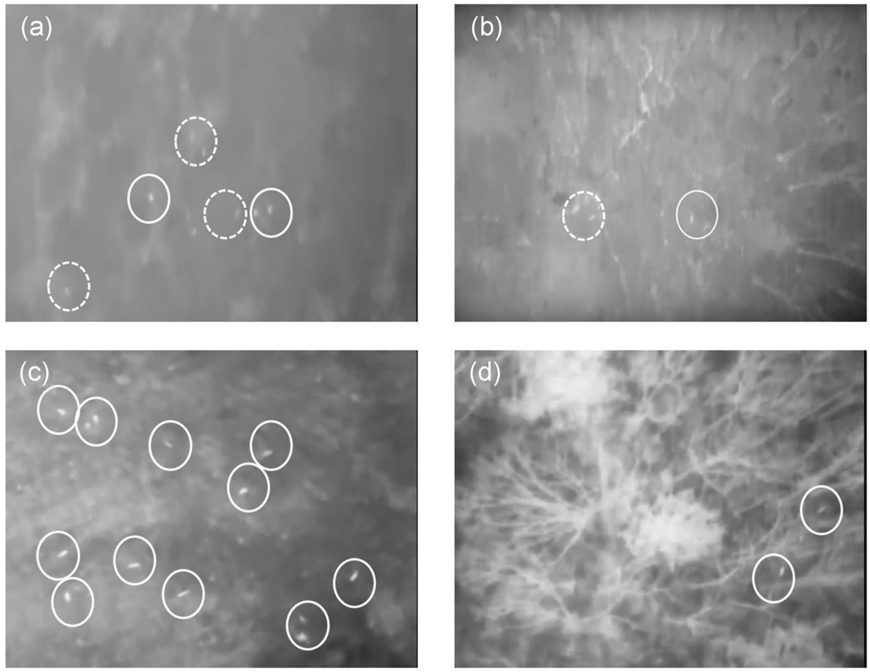

Figure 4. Thermal images of white-tailed deer observations in both open vegetation cover and mixed-deciduous forest from an altitude of 100 m above ground level during both morning (AM; sunrise) and evening (PM; sunset) flights conducted within the Auburn University deer research facility in Alabama, USA, 16–17 March 2017. Morning flights occurred within 0619–0719 and evening flights within 1821–1921. Confident thermal signatures of animals are marked with solid line circles and dashed line circles marked unclear signatures. Time (AM vs. PM) and cover type for each image: (a) AM, open; (b) AM, forested; (c) PM, open; (d) PM, forested.

midpoint of the highly constrained known population (151–163 deer, midpoint 157 [87–94 deer/km^2, midpoint 90 deer/km^2]) of the captive deer herd. Averaged thermal drone density estimate from all 3 flights had an estimated sighting probability of 78% of the assumed 157 individuals, exceeding the estimated accuracy often reported from similar aerial surveys for captive ungulates (usually <75%) conducted using human-occupied aircraft (Parker and Driscoll 1972, Bartmann et al. 1986, Beasom et al. 1986). Flights under high-thermal-contrast conditions achieved an estimated sighting probability of 92% relative to the assumed density. Several studies have also found that the detection of deer with thermal imagery from human-occupied aerial flights offered a varied performance, with estimates ranging from 37% to 98% (Croon et al. 1968, Wiggers and Beckerman 1993, Naugle et al. 1996, Potvin and Breton 2005). In fact, detection rates reported specifically for deer-occupied enclosures are usually 60–80% under optimal conditions, and <50% when detection conditions are less favorable (Bartmann et al. 1986, Beasom et al. 1986, Potvin et al. 1992, Chrétien et al. 2016), much lower than those found in our study. Recently, some attempts utilizing drone platforms equipped with either thermal or RGB sensors have been made to overcome these limitations influencing sighting probability (e.g., Chrétien et al. 2016, Linchant et al. 2018, Witczuk et al. 2018).

Sighting probabilities obtained in this study led to estimated correction factors ranging from 8% for the evening flights to 28% overall. Linchant et al. (2018) used drones equipped with RGB for a survey of hippopotamuses (*Hippopotamus amphibius*) over a homogenous landscape and estimated a similar correction factor (22%) to our overall average, and approximately 3 times greater than our correction factor under optimal contrast conditions. One advantage of thermal imagers over conventional RGB cameras is the ability to distinguish animals based on their body heat and increased detection of animals at night and during low light conditions (Burke et al. 2019). Chrétien et al. (2016) concluded that detection of thermal objects was more accurate than RGB. Witczuk et al. (2018) concluded that terrestrial ungulates could be identified in both leafless deciduous forests and coniferous forests using thermal cameras. During our winter surveys (leaf off) deer were detected in all major vegetation types (deciduous, mixed, and coniferous forest, open areas).

Timing of surveys is a critical study component in studies using thermal imaging because heat emission is not constant throughout the day (Felton et al. 2010) and can fluctuate depending on a variety of factors such as weather condition (e.g., ambient temperature, cloud cover; Burke et al. 2019) and environment (e.g., land cover, aspect; Franke et al. 2012, Chrétien et al. 2016, Witczuk et al. 2018, Burke et al. 2019). This and topographical complexity can result in unequal warming of areas (thermal cluttering) mediated by exposure to sunlight (i.e., background thermal radiation varies across the landscape), and becomes especially important in areas with objects with high thermal inertia, such as rocks or boulders and wet ground or water (Burke et al. 2019). Witczuk et al. (2018) indicated that the contrast between trees and ground can influence the ability to detect animals in forested areas, and found that during morning flights, some sun-exposed tree trunks and branches

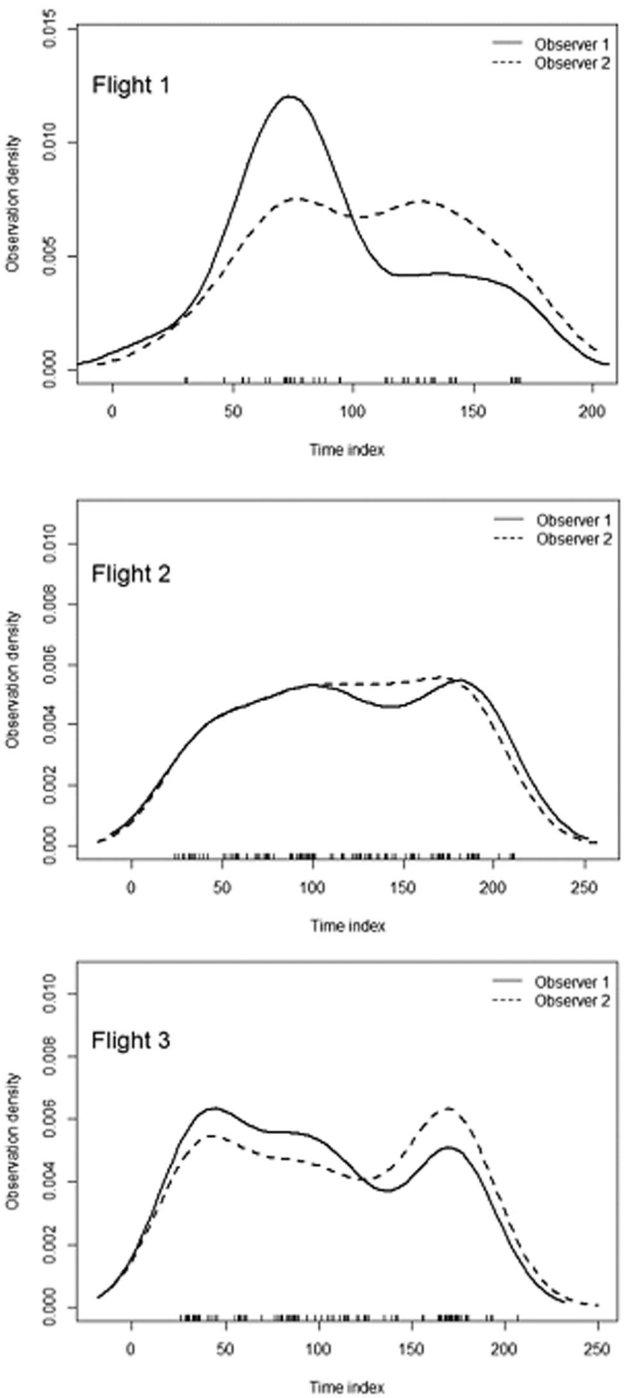

Figure 5. Kernel-smoothed probability density distribution of recorded white-tailed deer observation times for surveys conducted at Auburn University deer research facility, Alabama, USA, 16–17 March 2017. Identically shaped curves indicate consistency of observation between observers.

were just beginning to heat up, resulting in thermal cluttering and low contrast. Whereas, for evening flights, we observed that the images had a more homogenous background such that animal signatures stood out with enough contrast for relatively easy detection (e.g., Witczuk et al. 2018). We attribute this to the fact that residual heat captured during the day by vegetation allowed better distinction of foliage in forested habitats during evening flights, causing the ground signature to be relatively cooler. The accuracy of our data collected during evening flights suggests a correction factor may not be needed when flight conditions are optimized for a particular area and time. Conversely, during morning flights, vegetation was cold as a result of thermal radiation exchange with the clear sky at night while the ground remained relatively warm, and deer then became difficult to distinguish from the background during this period because of decreased contrast.

We used a nonradiometric sensor that did not allow temperature thresholds to be set. Thermal exchange between animals and their environment is well-understood (Porter and Gates 1969), and using a radiometric sensor thermal threshold that can be tailored to the calculated radiative properties of the organism(s) of interest can greatly increase the thermal contrast between an animal and the terrain and likely improve accuracy of this technique (e.g., Burke et al. 2019).

The ability to conduct flights autonomously allowed for precisely replicated flight plans. This, in turn, gives wildlife managers ability to detect relatively small changes in populations in similar conditions, thereby improving the ability to apply and evaluate management efforts while simultaneously allowing surveys of difficult terrain and drastic reductions in risk to personnel.

Human Observers

The vast amount of data and need for multiple observers to minimize potential observer bias are often described as an important drawback for using drones for wildlife surveys (Linchant et al. 2015). However, Linchant et al. (2018) noted that experienced observers needed smaller correction factors to estimate the total population of deer and that estimates from separate observers quickly converge with small amounts of experience. Our results support this conclusion—our experienced human observers had consistency in both the time of deer observations and resulting density estimates of their respective video analyses. Observer-specific probability density curves of observation time were nearly identically shaped for high-contrast evening flights, indicating observers generally counted the same individual animals during the study. However, in the evening flights there was an approximately 12% difference in estimates between observers, and observers were consistent among days to within 2% and 5%, respectively (152 and 154 deer, observer 1; 132 and 135 deer, observer 2), and the timing of observations show that the observers were counting the same deer during the flights. During the morning flight both observers differed by a factor of two in the number of deer counted (47 vs. 100) and they did so at different times because of the difficulty in separating the thermal image of the deer from the thermal clutter in the landscape, emphasizing the role of flight planning in obtaining accurate results.

Thermal and RGB drone surveys can collect detailed information rapidly (Linchant 2015), potentially creating scenarios where the time and cost of manual classification of imagery from aerial surveys become exorbitant. Our study area was 1.74 km^2 (each flight provided near complete coverage of our study area and the complete video footage for each survey was ~20 min only) and our observers only had 64 total minutes of video footage to analyze. Larger study areas and more complex data sets might necessitate automated object recognition and image classification, which would save time and costs associated with human-observer analysis, but would require additional testing and evaluation (Chabot and Francis 2016, Seymour et al. 2017). However, development of these technologies is still in its infancy, and these approaches are of limited use if automated image classification must be retrained for new data sets or require extensive set up (e.g., Seymour et al. 2017). Additionally, Hodgson et al. (2018) illustrated that while semiautomated counts did streamline the process after algorithm training, manual counts performed equally well. However, when the number of subjects is large or repeat counts are required at different time points, labor investment needed for manual counting can be substantial and incorporation of machine-learning capabilities will be more necessary (Chabot and Francis 2016, Burke et al. 2019).

The enclosed nature of our study area and sole dedication of the facility to research with deer meant we were unable to evaluate the ability to distinguish between multiple species, a potential limitation of the method in areas with multiple species that are closely related or of similar morphology. Further research on characteristics of thermal signatures for other large land-dwelling mammal species is needed, and future studies should assess and integrate a correction method that considers the sighting probability of deer for different cover types (e.g., deciduous forest, evergreen forest, open–field; Chrétien et al. 2016). With further development of drone platforms, sensors, and computer vision techniques, drone-based approaches to wildlife estimation are also expected to continue to improve and become more widespread (Longmore et al. 2017, Seymour et al. 2017, Hodgson et al. 2018). Currently available sensors are easily mounted on existing camera gimbals on drones and software programs aid in flight setup and allow for autonomous flight plans. Although the basic flight operation and computer software require a learning curve, the primary concern will be matching adequate sample design to species of interest.

For thermal aerial surveys to be successfully applied to wildlife management and conservation issues, several aspects of these surveys must also be considered. First, data quality will be a function of vegetation cover, topography, and thermal contrast, and the interactions of these variables will vary with season, time of day, and region. Second, observer bias and experience must be accounted for during data analysis. The effect of training on observer performance is poorly understood, but common sense dictates that performance will benefit from training. It will be imperative to have an adequate understanding of the thermal landscape of a study area and how these variables influence thermal video contrast before attempting thermal drone surveys. Finally, study area size will influence successful collection of data because of technological limitations with drones. Currently, small drones are limited to flights of several minutes to a few hours depending on the model and payload, forcing managers to balance coverage area with the minimum resolution for animal identification. However, expansion of the survey coverage to larger areas can be expected in the near future as regulations for civilian use of drones are constantly changing. As drone surveys are expanded to larger areas, image processing and analysis workflow will become of increasing importance.

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