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Research article

The performance of drones and artificial intelligence for monitoring sage-grouse at leks

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Accurately monitoring sage-grouse populations is critical for conservation, yet traditional ground-based visual surveys face challenges in scalability and consistency, prompting the exploration of innovative drone-based methodologies enhanced by artificial intelligence. We evaluated the effectiveness of drone-based survey protocols combined with an AI count model relative to traditional ground-based visual surveys for counting sage-grouse at leks. Drone-induced flushing of sage-grouse from leks occurred in 16% of flight attempts. Point-of-interest (POI) flight profiles outperformed linear flight profiles in counting accuracy for both AI and manual methods. POI flights provided more images and a larger field of view, resulting in counts similar to traditional ground-based visual (GBV) lek surveys, while linear flights consistently produced undercounts. Our custom AI counter (INDECS) yielded counts of sage-grouse similar to manual counts in POI surveys, but not in linear surveys. When integrated into modified N-mixture models, drone surveys with POI profiles yielded precise estimates of detection probabilities and abundance for all survey methods that resulted in similar inference to GBV surveys. Our results suggest that AI-enhanced drone surveys, particularly with POI flight profiles, offer a promising alternative to traditional surveys with reduced bias and improved consistency in sage-grouse population monitoring.

Keywords: artificial intelligence (AI), Bayesian analysis, machine-learning, N-mixture model, population monitoring, unoccupied aerial system (UAS)

Introduction

A primary goal in wildlife ecology and conservation is the development of efficient and unbiased methods of indexing population size that can be used to infer changes in abundance over space and time. Counts of individuals at communal display grounds have been the standard method of monitoring populations of lek-mating species of grouse (*Centrocercus* and *Tympanuchus* spp.) for ≥ 60 years (Connelly and



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Schroeder 2007, McNew et al. 2023). Lek survey protocols vary somewhat across management jurisdictions but generally involve the observation of leks from a blind or vehicle, where an observer uses binoculars to visually identify and count the number of individuals attending the lek (Cook et al. 2022). Rigorous ground-based visual (GBV) lek surveys can provide unbiased indices of population size and trends for several lekking species, including greater sage-grouse (*C. urophasianus*; hereafter 'sage-grouse'), a species of conservation concern and focal species for sagebrush ecosystem conservation (Rowland et al. 2006, Hanser and Knick 2011). Using GBV lek surveys, researchers have estimated a > 80% decline in the range-wide population of greater sage-grouse during 1960–2022 (Coates et al. 2022), motivating significant investment in habitat and population restoration and conservation (Maher et al. 2023) and making lek surveys of sage-grouse the foundational source of information for the management for millions of acres of wildlife habitat in the western US.

Lek surveys will likely continue to be the standard approach to monitoring sage-grouse populations (Beck et al. 2023). However, ensuring that the surveyed sample of leks represents the larger population of sage-grouse is critical for unbiased population monitoring. Random sampling for GBV lek surveys may be problematic, however, because leks are non-randomly located in space and some leks may be inaccessible due to habitat conditions or land ownership. Another issue affecting the utility of conventional GBV lek surveys is spatiotemporal variation in the detectability of individuals associated with leks. Lek counts may vary among survey locations or survey time due to site- or survey-specific conditions that affect both 1) the probability that an individual is attending the lek at the time of the survey (p_a) and 2) the probability of detecting an individual if it is available to be detected (p_d). Spatiotemporal variation in both p_a and p_d may result from differences in survey timing, among age- and sex-classes, as well as site (e.g. habitat) or survey conditions (e.g. weather) (Walsh et al. 2004, Blomberg et al. 2013, Baumgardt et al. 2017, Fremgen et al. 2019). For example, the frequency and intensity of breeding display behaviors and grouse visibility, which influence p_d , change throughout the day and season, and with habitat conditions (Gibson 1996, Baumgardt et al. 2017, Logsdon 2022). To address variability in p_a and p_d , lek counts are sometimes repeated at leks multiple times per lekking season (e.g. April–May) and the maximum count of sage-grouse is retained to use in the annual indexing of population size for trend monitoring (Connelly et al. 2004). Using maximum counts from repeated visits reduces downward biases in population estimates that may result from variation in the combined detection probability of sage-grouse, $p = p_a p_d$ (Fedy and Aldridge 2011). Moreover, repeated surveys within a period of population closure allow for the application of hierarchical binomial-Poisson mixture models (e.g. N-mixture models; Royle 2004) that correct for spatiotemporal variation in negative observation error and yield unbiased and precise estimates of sage-grouse abundance (McCaffery et al. 2016, Coates et al. 2019). However, conducting repeat surveys at

each lek during a period of time that ensures the local number of grouse has not changed (e.g. population closure) can be challenging using GBV protocols due to the logistical constraints of observers and lek accessibility.

Drones (aka 'uncrewed aerial vehicles or systems') are a powerful tool for surveying a variety of wildlife species, including birds, reptiles, and terrestrial and marine mammals (Beaver et al. 2020, Charbonneau and Lemaitre 2021, Dundas et al. 2021, Petso and Jamisola 2023, Blum et al. 2024). Drones traverse rugged and inaccessible habitats easily and depending on local laws regarding airspace ownership, can be used to count animals in areas where landownership precludes permissible GBV surveys. Thus, survey areas can often be covered more easily and at lower costs with drones than ground-based observation. Nevertheless, evaluations of the effects of drones on the disturbance and detection probabilities of target species should precede application to population monitoring (de Leila et al. 2023).

The ability of drones to cover large survey areas easily, combined with the ability of payloads to record images and videos with a variety of sensor types at fine resolutions often results in large amounts of data (i.e. images, video) that need to be reviewed and processed post-flight. This high data volume often results in a 'big-data, small-information' problem because manually processing drone imagery is laborious and time-consuming. Recent advancements in artificial intelligence (AI) models and applications promise to greatly reduce or eliminate the need for manual image annotation. For example, artificial neural networks and machine learning can greatly reduce image processing times and improve subject detection rates from images and video recordings (Marchowski 2021, Infantes et al. 2022, AlZubi and Alkhanifer 2024, Axford et al. 2024). However, AI algorithms need to be trained and validated on the species of interest before being broadly applied to population monitoring programs.

The utility of drones for monitoring lek-mating grouse populations is unclear. Augustine and Burchfield (2022) found that drones were ineffective for monitoring greater prairie-chickens *Tympanuchus cupido* because birds flushed from their leks at the approach of a drone (quadcopters) in 96% of trials. Richette et al. (2020) observed lower rates of flushing (35–83%) by lekking sharp-tailed grouse *T. phasianellus*, that improved at higher flight heights. The behavioral responses of sage-grouse to drones are more uncertain; Thompson (2018) observed that sage-grouse did not flush during 4 of 5 drone (octocopter) flights at a single lek but the small number surveys and variability in flight profiles precluded conclusions about the effectiveness of drones for counting grouse at leks. Although small multirotor drones (e.g. quadcopters) are at least as effective as GBV surveys at counting other species of grouse-sized birds in breeding habitats (Lyons et al. 2019, Dundas et al. 2021), the ability of drone-based counts to produce unbiased lek counts and inference about sage-grouse population size is unknown.

In this study we evaluated the performance of drone-based surveillance of sage-grouse leks relative to traditional

ground-based visual (GBV) lek counts using both manual and AI counting of birds on imagery recorded by drones. Our objectives were to quantify:

1. the probability that sage-grouse flush from leks due to drone survey flights of different profiles, and
2. differences in lek counts for eight combinations of
 - a. two drone flight types,
 - b. two flight heights, and
 - c. two sage-grouse counting methods (manual versus AI-generated counts). Finally
3. we evaluated whether the probability of detecting a sage-grouse at a lek and estimates of local and total lek abundance using an N-mixture model differed between
 - a. drone surveys with AI-generated counts,
 - b. drone surveys with manual counts, and
 - c. conventional ground based visual surveys. Results of our study will inform best practices for monitoring sage-grouse at leks with drones.

Study area

We surveyed 23 sage-grouse leks within a 5000 km² area in southern Phillips County in north-central Montana, USA (47.8906°N, 107.8639°W). Leaks occurred in some of the most expansive and intact sagebrush-steppe habitats in Montana where sage-grouse populations are considered relatively stable (Garton et al. 2011). Wyoming big sagebrush *Artemisia tridentata wyomingensis* was the dominant shrub, but silver sagebrush *A. cana*, black greasewood *Sarcobatus vermiculatus* and saltbush *Atriplex gardneri* also occurred. Herbaceous vegetation was dominated by western wheatgrass *Agropyron smithii*, bluebunch wheatgrass *A. spicatus*, blue grama *Bouteloua gracilis*, needle-and-thread *Stipa comata*, green needle-grass *S. viridula*, fringed sagewort *A. frigida*, dandelion (*Taraxacum* spp.), American vetch *Vicia americana*, and yellow sweetclover *Melilotis officinalis*. The average elevation of the study area is ~ 800 m and weather is characterized by high annual variation in daily temperature (−9° to 22°C) and low precipitation (~ 32 cm annually), which primarily occurs during May–June.

Material and methods

Field methods

During 19 March to 4 May 2021 and 2022, we conducted ground-based visual surveys (GBV) at 23 known sage-grouse leks between 30 min before and 30 min after sunrise according to standard protocols for statewide sage-grouse monitoring (Cook et al. 2022). Most (20 of 23) leks were surveyed only in a single survey season (2021 or 2022); surveys were conducted at 3 leks in both 2021 and 2022. On days without precipitation and wind speeds ≤ 20 kph, we observed leks from a vehicle or ground blind located within 1000 m of the lek using binoculars or spotting scope. We observed the lek for up to 15 min to confirm and record the most accurate count of sage-grouse possible. Ground-based visual surveys always preceded drone surveys and are henceforth

denoted by GBV_b. Immediately after a GBV_b survey at a lek, we programmed and deployed a Phantom 4 pro quad-rotor drone (model M210, DJI, Shenzhen, Guangdong, China) equipped with a Zenmuse XT2 thermal camera (FLIR Systems, Bozeman, MT) for up to 4 separate aerial surveys of the lek characterized by combinations of two flight profiles and two flight heights. The four flight profiles were: 1) a point-of-interest (POI) flight path at 200 feet above ground level (~ 61 m AGL; hereafter POI.200), 2) a POI flight path at 150 ft (~ 46 m) AGL (hereafter POI.150); 3) a linear flight path at 61 m AGL (hereafter linear.200); 4) a linear flight path at 46 m AGL (hereafter linear.150). In POI flight profiles, the thermal imager was pointed at the lek as the drone flew a circular route around the lek at 100–300 m from the center of the lek (Fig. 1). For the linear flights, the drone was programmed to fly a straight line over the center of the lek (Fig. 1). A lek flight was discontinued and surveys abandoned for the morning if ≥ 2 sage-grouse flushed from the lek as a result of the drone flight. If a flush occurred, we resumed our drone flight trials at a later date during the survey season. We recorded the flush response for a lek (birds flushed: Y/N) during each flight attempt.

Manual drone-collected sage-grouse counts

After each morning's successful drone flights (i.e. no sage-grouse flushed), the SD card was removed from the drone and a video segmented into recordings for each flight profile. A single observer (JH) reviewed all videos and counted and recorded the number of sage-grouse observed during each flight.

AI sage-grouse counts

We used a custom artificial intelligence (AI) object detection algorithm, Infrared Detection Classification System (INDECS; developed by coauthor IB), to identify and count sage-grouse from infrared videos collected by our drone-mounted thermal camera. INDECS leverages the YOLO (You Only Look Once; Redmon et al. 2016) object detection algorithm for its core bird identification capability. YOLO is a real-time object detection system that offers a good balance between speed and accuracy (Redmon et al. 2016, Axford et al. 2024). Unlike traditional object detection methods that involve regional proposal and classification steps, YOLO performs detection as a single regression problem, directly predicting bounding boxes and class probabilities from the input image. To train the YOLO model for sage-grouse detection in infrared imagery, we curated a distinct dataset of ~ 5600 images of sage-grouse leks from drone flights occurring during this study; training images were different than images used to count sage-grouse. These images were manually annotated with bounding boxes around each individual sage grouse. We used YOLOv4, an open-source convolutional neural network framework written in C and CUDA, for implementing and training the YOLO model (Bochkovski and Liao 2020). The training process involved feeding the annotated images to the network and optimizing its parameters to minimize the difference between predicted

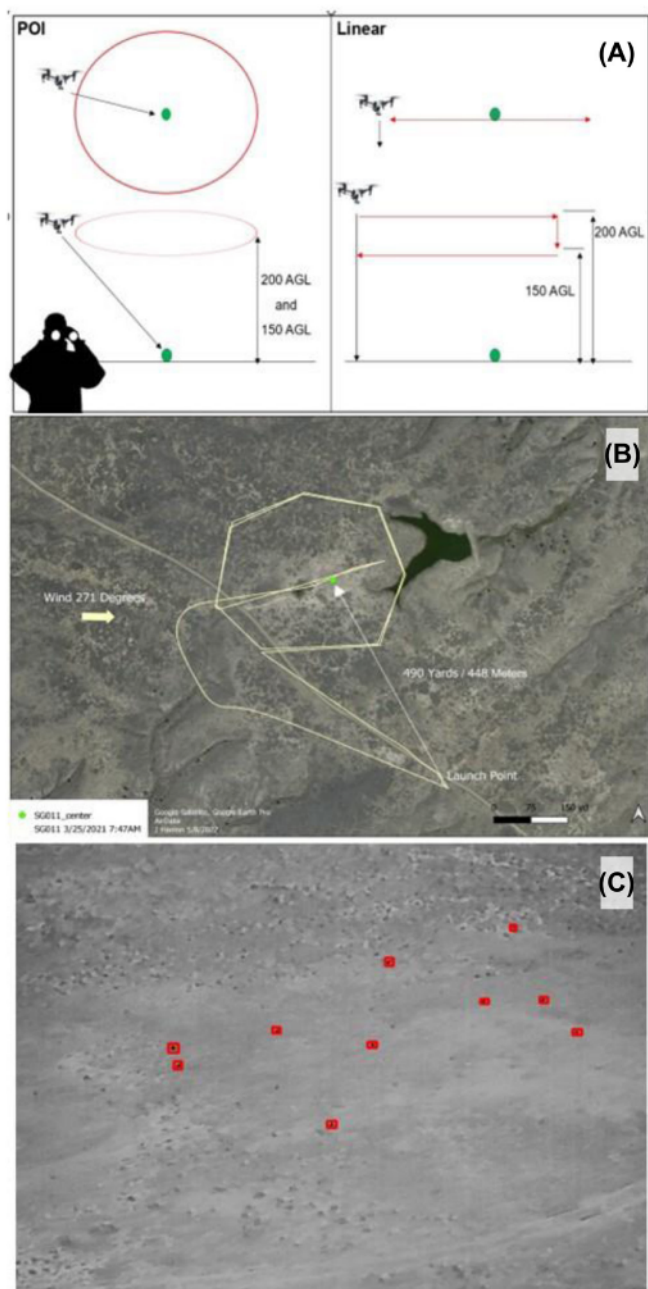


Figure 1. (A) Diagram of POI and linear drone flight profiles, (B) example track POI flight profile for a sage-grouse survey, and (C) example thermal image of a lek with 10 individual sage-grouse identified by YOLO object identifier algorithm in red bounding boxes. The green dot indicates the estimated lek centroid.

bounding boxes and the ground truth annotations. This optimization was achieved through a loss function that penalizes both localization errors (incorrect bounding box predictions) and classification errors (incorrect object identification).

After training, we used INDECS to identify and count sage-grouse from infrared video footage from our drone flights at leks. The INDECS process was broken down into the following steps:

1. Frame extraction: the video was processed frame-by-frame extracting individual frames for analysis.
2. Object identification: every 10th frame was fed to the trained YOLO model, which predicts the bounding boxes of potential sage grouse within the image.
3. Coordinate transformation: the bounding box coordinates predicted by YOLO were normalized to the original image space.
4. Bird count per frame: the number of detected sage-grouse was determined for each frame of the video, providing a time-series of sage-grouse counts.
5. Maximum counts: to avoid overcounting due to multiple detections of the same bird in consecutive frames or minor fluctuations in bird positions, a peak detection algorithm was applied that identifies local maxima in the sage-grouse count time series at a lek during a survey flight.
 - a. Windowing for accuracy: A configurable window size was used in the peak detection process. This window helped to ensure that only distinct peaks, representing actual gatherings of sage-grouse, are counted, and prevented spurious peaks from being included in the final count. The window size was determined based on factors like the video's duration and frame rate.
 - b. Data filtering: The peak detection results were then processed to remove any duplicate peaks that might occur due to very similar sage-grouse counts in consecutive frames. This ensured that each peak represents a distinct gathering of sage-grouse.

By combining YOLO object detection with this peak detection and filtering process, INDECS achieved a more robust and accurate count of sage-grouse in infrared video footage. This approach addressed the challenges of individual bird identification and movement within the lek environment, providing valuable data for population monitoring and conservation efforts. A complete description of INDECS and associated open-source code is provided at GitHub (<https://github.com/biasintelligence/INDECS.git>).

Analyses

Probability of drone-caused flushing of sage-grouse

We used a generalized linear mixed effects model with Bernoulli error distribution and logit-link to evaluate the effects of flight height and profile on the probability that ≥ 2 sage-grouse flushed from a lek:

$$y_i \sim \text{Bernoulli}(p_i),$$

$$\text{logit}(p_i) = \beta_0 + \beta_1(\text{linear.150}) + \beta_2(\text{linear.200}) + \beta_3(\text{POL.150}) + \beta_4(\text{POL.200}) + \gamma_{(i)},$$

$$\gamma_{(i)} \sim \text{Normal}(\mu, \sigma^2)$$

Because up to 4 surveys (1 for each of 4 flight profile) occurred at the same lek each morning, a random intercept

term for lek ($\gamma_{(i)}$) was included to account for non-independence of flush observations. Random effects of lek ($\gamma_{(i)}$) were assumed to be drawn from a normal distribution with a mean μ and variance σ^2 . We used JAGS to analyze the model in a Bayesian framework called from R package 'rjags' (Plummer 2024). We used vague priors for the parameters (β) and hyperparameters μ and σ^2 (Supporting information for description of the models in BUGS language). We ran three chains of length 100 000 after a burn-in of 50 000 and thinned the posterior chains by three. We assessed convergence using the Gelman–Rubin ($\hat{R}$) statistic, which examines the variance ratio of the Markov chain Monte Carlo (MCMC) algorithm within and between chains across iterations (Gelman and Rubin 1992). We accepted parameter estimates when they came from Markov chains with $\hat{R}$ between 1.0 and 1.1 (Gelman and Rubin 1992). We conducted a posterior predictive check of model fit predicting a new data set (y_{pred}) from the model and comparing the summed deviance of the observations to the summed deviance of predicted values. We considered the model to fit the data well if the 95% credible interval (CrI) of difference between the summed deviances ($\Delta \text{Dev}_{\text{obs-pred}} = \text{Dev}_{\text{observed}} - \text{Dev}_{\text{predicted}}$) overlapped 0. We considered the effects of flight profiles to be meaningful if the 95% CrI of the estimated effects β did not include 0.

Comparison of lek counts among survey protocols

Combinations of 4 flight profiles and 2 methods of counting grouse (manual, AI) resulted in 8 distinct drone survey protocols (Table 1). We evaluated the effects of the 8 drone survey protocols on lek counts (relative to GBV_b surveys) using a generalized linear mixed model analyzed in a Bayesian framework. Specifically, our model for the maximum counts (c) of sage-grouse at each lek (i) was described as:

$$c_i \sim \text{Poisson}(\lambda_i),$$

$$\begin{aligned} \log(\lambda_i) = & \alpha_i + \beta_1 (\text{AC.lin.150}) + \beta_2 (\text{AC.POI.150}) \\ & + \beta_3 (\text{AC.lin.200}) + \beta_4 (\text{AC.POI.200}) \\ & + \beta_5 (\text{MC.lin.150}) + \beta_6 (\text{MC.POI.150}) \\ & + \beta_7 (\text{MC.lin.200}) + \beta_8 (\text{MC.POI.200}), \end{aligned}$$

$$\alpha_i \sim \text{Normal}(\mu_{\alpha_i}, \sigma_{\alpha_i}^2)$$

Thus, the log expected count (c) during a survey, $\log(\lambda_i)$, is a linear function of random site (lek) effects (α_i) and the fixed effects of survey type described in Table 1. The random intercepts term of lek (α_i) was included because counts were conducted at individual leks up to 7 times during the lekking season and were not truly independent. Random intercepts α_i were assumed to be drawn from a normal distribution with a mean μ_{α_i} and variance $\sigma_{\alpha_i}^2$, representing the mean and variance of the number of sage-grouse counted at leks during the GBV_b surveys.

We used JAGS to analyze all models in a Bayesian framework called from R package 'rjags' (Plummer 2024). We used vague priors for the parameters (β) and hyperparameters ($\mu_{\alpha_i}, \sigma_{\alpha_i}^2$; see Supporting information for description of the models in BUGS language). We ran three chains of length 10 000 after a burn-in of 3000 and thinned the posterior chains by three. We assessed convergence using the Gelman–Rubin ($\hat{R}$) statistic and accepted parameter estimates when they came from Markov chains with $\hat{R}$ between 1.0 and 1.1 (Gelman and Rubin 1992). We conducted a

Table 1. Descriptions of ten types of sage-grouse lek surveys conducted in northcentral Montana during March–April 2021, 2022. All drone- and ground-based surveys were conducted by the same individual.

Protocol Type	Count type	Profile	Height	Description
GBV _b	GBV _b	–	–	Traditional ground-based visual (GBV) survey of lek conducted by trained observer with binoculars before drone surveys occurred. Total number of sage-grouse observed recorded
AC.Lin.150	AC	Linear	150	Linear drone survey occurring at 150' above ground level; Total number of sage-grouse determined by AI algorithm
AC.Lin.200	AC	Linear	200	Linear drone survey occurring at 200' above ground level; Total number of sage-grouse determined by AI algorithm
AC.POI.150	AC	POI	150	Drone survey occurring at 150' above ground level using a point-of-interest survey flight; Total number of sage-grouse determined by AI algorithm
AC.POI.200	AC	POI	200	Drone survey occurring at 200' above ground level using a point-of-interest survey flight; Total number of sage-grouse determined by AI algorithm
MC.Lin.150	MC	Linear	150	Linear drone survey occurring at 150' above ground level; Total number of sage-grouse determined by manual counts from drone video
MC.Lin.200	MC	Linear	200	Linear drone survey occurring at 200' above ground level; Total number of sage-grouse determined by manual counts from drone video
MC.POI.150	MC	POI	150	Drone survey occurring at 150' above ground level using a poi-of-interest survey flight; Total number of sage-grouse determined by manual counts from drone video
MC.POI.200	MC	POI	200	Drone survey occurring at 200' above ground level using a poi-of-interest survey flight; Total number of sage-grouse determined by manual counts from drone video

Table 2. Mean and 95% credible interval (CrI) of sage-grouse counts observed at 23 leks using eight drone survey protocols of count types (AV, MC), two flight profiles (linear, POI), occurring at two flight altitudes (150', 200' AGL). AC=automatic counts obtained using AI-algorithm; MC=manual counts of drone video by observer; linear=linear flight path; POI=point of interest flight path. GB=estimated sage-grouse counts from traditional ground-based observation.

Type	Profile	Height	Mean no. grouse (SE)	CV (%)	95% CrI
GB	—	—	22.1 (8.9)	40.4	0.7–35.1
AC	Linear	150	9.4 (3.8)	40.7	0.3–15.3
AC	Linear	200	9.8 (3.9)	40.6	0.3–16.0
AC	POI	150	23.0 (9.3)	40.5	0.7–36.8
AC	POI	200	22.5 (9.1)	40.5	0.7–35.9
MC	Linear	150	17.6 (7.1)	40.5	0.5–28.4
MC	Linear	200	19.5 (7.9)	40.5	0.6–31.4
MC	POI	150	22.2 (8.9)	40.5	0.7–35.6
MC	POI	200	22.1 (8.9)	40.5	0.7–35.3

posterior predictive check of model fit by deriving the difference between the observed and predicted c_i from the model; we considered the model to fit the data if the mean of the observed c_i was within the 95% CrI of the predicted values derived from the model. We calculated the predicted number of sage-grouse at each lek survey at each MCMC iteration as $(\exp(\alpha_i + \beta_1[\text{SurveyType}]))$. In addition, we calculated posterior distributions of the differences between predicted lek counts from each drone survey type and those from ground-based visual surveys conducted prior to flights (GBV_b) and considered differences to be significant if the 95% CrI of the posterior did not include 0.

N-mixture model

We used a modified N-mixture model to estimate lek-specific detection probabilities and abundances. Previously, N-mixture models were found to perform well for estimating the abundance of sage-grouse even when up to 90% of the lek counts are missing from a dataset (McCaffery et al. 2016). Initial assessment indicated that the basic N-mixture model (Royle 2004) did not fit the observation data well due to overdispersed count data. Therefore, we modified the model to account for extra-Poisson dispersion in both local abundance (λ_i) and the probability of detecting a grouse at a lek during a survey (p_{ij}) by introducing latent random effects into linear predictors of each parameter (Millar 2009, Kery and Schaub 2012):

$$\begin{aligned}
 N_i &\sim \text{Poisson}(\lambda_i), \\
 \log(\lambda_i) &= \alpha + \varepsilon_i, \\
 \varepsilon_i &\sim \text{Normal}(0, \sigma_\lambda^2), \\
 y_{i,j} &\sim \text{Binomial}(N_i, p_{i,j}), \\
 \text{logit}(p_{i,j}) &= \beta + \delta_{i,j}, \\
 \delta_{i,j} &\sim \text{Normal}(0, \sigma_p^2),
 \end{aligned}$$

where (N_i) is a latent random variable estimated from a Poisson distribution with a mean lek abundance of λ_i . The parameters ε_i and $\delta_{i,j}$ adjust for extra-Poisson dispersion resulting from spatial variation in the latent abundance parameter (λ) and spatial-temporal variation in detection probability (p), respectively, which likely result from variable observation conditions (Kery and Royle 2010). Based on results from Objective 1, we limited our evaluation of drone-based lek counts to those collected using the POI flight profile. Because sage-grouse counts using the POI profile produced nearly identical counts at 150 ft (45 m) and 200 ft (61 m) heights, we combined these datasets into a single dataset where the 23 leks were surveyed between 1 and 7 times each (mean = 5.3 replicate surveys per lek).

We used JAGS to analyze all models in a Bayesian framework called from R using 'rjags' (Plummer 2024). We specified vague priors for all hyperparameters (α , β , σ_λ^2 , σ_p^2 ; see Supporting Information for description of the models in BUGS language). We ran three chains of length 200 000 after a burn-in of 100 000 and thinned the posterior chains by a factor of 4. We accepted parameter estimates when they came from Markov chains with $\hat{R}$ between 1.0 and 1.1 (Gelman and Rubin 1992). We conducted a posterior predictive check of model fit by deriving the difference between the observed and predicted $y_{i,j}$ from model and calculating a χ^2 discrepancy (fit) statistic for observed and predicted observation data at each MCMC iteration. We calculated a Bayesian p -value as the ratio of the mean value of the fit statistic for the predicted data to that of the observed data; a p -value near 0.5 indicates good model fit to the data (Kery and Schaub 2012). We estimated the average and 95% CrI of the lek-specific detection probabilities (p_i), mean detection probability ($\bar{p}$), local abundance of sage-grouse at each lek (N_i), average lek abundance (λ_i), and the total number of sage-grouse at all

leks ($\widehat{\text{TSG}} = \sum_{i=0}^n N_i$) at each MCMC iteration. We ran separate models for GBV_b surveys and those conducted by drone using POI flight profiles where maximum counts from each flight survey were obtained via our AI algorithm (Drone.AI) and by manual count (Drone.MC). We deemed $\bar{p}$, N_{ij} , and TSG for Drone.AI and Drone.MC survey protocols to be biologically different from ground-based visual surveys (GBV_b) if 95% CrI did not overlap the mean values for the GBV_b survey type.

Results

We conducted 325 surveys (80 GBV_b, 245 drone) of 23 sage-grouse leks (8–29 total surveys per lek) in 83 survey days during 19 March to 28 April 2021–2022. Each lek was surveyed 2–7 times using the GBV_b surveys and 0–11 times using drone-based survey protocols described in Table 1. All ground- and drone-based surveys occurred between –15 and 106 min from sunrise (mean = 8.6 min after sunrise). Average (SE) lek counts from ground-based visual surveys conducted

before drone flights (GBV_b) ranged in size from 0.9 (1.2) at the smallest lek to 32.4 (1.01) sage-grouse at the largest lek.

Effects of drone flights on lek flushing

The approach of a drone caused ≥ 2 sage-grouse to flush from the lek in 40 of 245 flight attempts (16.3%). All parameter estimates in our models converged ($\hat{R} < 1.1$). We found no support for the effects of flight profile and height on the probability that grouse flushed from the lek; 95% credible intervals of the four flight profile effects overlapped 0 ($\beta_{Lin,150} = -19.3, 19.5$; $\beta_{Lin,200} = -21.0, 17.7$; $\beta_{POI,150} = -18.9, 19.7$; $\beta_{POI,200} = -17.2, 21.6$). Moreover, the model did not fit the data well; the difference between the observed and predicted deviance ($\Delta\Sigma Dev_{obs-pred}$) was large 394 and uncertain (95% CrI: -176, 1,568). Therefore, we removed the fixed effects of flight profile from model and reran to estimate overall and lek-specific estimates that a drone flight caused ≥ 2 sage-grouse to flush from the lek. This simpler model converged on parameter estimates rapidly ($\hat{R} < 1.1$) and had much improved fit to the data ($\Delta\Sigma Dev_{obs-pred} = 35.4$; 95% CrI: -153, 296). The overall probability that sage-grouse flushed from a lek was 0.16 (95% CrI: 0.12, 0.21). Flush probabilities varied among leks from 0.05 (95% CrI: 0.001, 0.18) to 0.25 (95% CrI: 0.10, 0.46).

Effects of survey protocols on lek counts

The mean difference between the observed and model predicted number of grouse per lek survey was -0.001 (95% CrI: -0.37 to 0.38) indicating excellent model fit (Supporting information). There was strong support that lek counts conducted using the linear flight profiles AC.lin.150 ($\beta = -0.86$; 95% CrI: -0.93, -0.71), AC.lin.200 ($\beta = -0.78$; 95% CrI: -0.88, -0.68), MC.lin.150 ($\beta = -0.19$; 95% CrI: -0.27, -0.11), and MC.lin.200 ($\beta = -0.09$; 95% CrI: -0.16, -0.014) resulted in fewer sage-grouse observed than GBV_b surveys (Fig. 2). In contrast, lek counts conducted using POI flight profiles resulted in similar number of sage-grouse as GBV_b surveys: MC.POI.150 ($\beta = 0.03$; 95% CrI: -0.04, 0.10), MC.POI.200 ($\beta = 0.02$; 95% CrI: -0.05, 0.09), AC.POI.150 ($\beta = 0.07$; 95% CrI: -0.004, 0.14), AC.POI.200 ($\beta = 0.03$; 95% CrI: -0.03, 0.10; Fig. 2). Surveys conducted with linear flight protocols resulted in -12.4 (95% CrI: -22.4, -0.4 for AC.lin.150), -12.0 (95% CrI: -21.5, -0.38 for AC.lin.200), -3.9 (95% CrI: -7.6, -0.12 for MC.lin.150), and -1.9 (95% CrI: -4.5, -0.04 for MC.lin.200) fewer sage-grouse counted than the GBV_b protocol (Fig. 3, Table 2). Drone surveys using POI flight profiles resulted in mean predicted sage-grouse counts within 1.5 sage-grouse of those from GBV_b surveys, on average, regardless of whether counts occurred manually or via our AI grouse counter INDECS (Fig. 4)

Estimates of abundance using N-mixture model

We surveyed 23 leks an average of 4.1 times per lek using the GBV_b survey protocol and 5.3 times per lek using the Drone.AI and Drone.MC protocols during the 6-week survey window in 2021–2022. All parameters for GBV_b , Drone.AI, and

Drone.MC lek surveys converged ($\hat{R} < 1.1$) and Bayesian p -values were near 0.5 (0.48, 0.53, 0.57) for all datasets, indicating excellent model fit to the data (Supporting information). For GBV_b surveys, the probability of detection was variable among leks, ranging from 0.15 (0.06SE) to 0.90 (0.11) and averaging 0.70 (95% CrI: 0.46–0.77; Table 3). Detection probability ($\bar{p}$) for Drone.AI and Drone.MC surveys were similar and averaged 0.64 (95% CrI: 0.51–0.73) and 0.57 (95% CrI: 0.35–0.69), respectively (Table 3). Mean $\bar{p}$ from GBV_b surveys were within the 95% credible interval of $\bar{p}$ estimated for the Drone.AI protocol but was greater than the upper 95% credible limit for $\bar{p}$ estimated using data from the Drone.MC protocol (Table 3). Estimated average lek abundance (λ), as well as the total estimated number of sage-grouse associated with the 23 leks (TSG) was similar across the three survey types and 95% credible intervals overlapped means in all cases (Table 3). Estimated number of sage-grouse associated with each lek (N_i) ranged between 1–104, 1–72, and 1–83, using GBV_b , Drone.AI, and Drone.MC survey protocols, respectively (Table 4). Posterior estimates of mean N_i were correlated among methods ($r = 0.75, 0.75, 0.99$ for Drone.AI– GBV_b , Drone.AI–Drone.MC, and Drone.AI–Drone.MC, respectively).

Discussion

We evaluated the effectiveness of drone-based survey protocols in combination with an AI count model compared to traditional ground-based visual surveys (GBV_b) for counting sage-grouse at leks. The results demonstrate the potential benefits and limitations of using drones for monitoring populations of sage-grouse and potentially other wildlife.

Drone-caused flushing of leks

In total, drone flights resulted in the flushing of ≥ 2 sage-grouse in 16% of lek survey attempts. After accounting for underlying differences in the probability of flushing among leks, we found no difference in the probability that sage-grouse flushed among our four flight types (profile $\times$ height combinations). Notably, our protocol to abandon drone surveys if just 2 sage-grouse flushed was conservative. In most cases, less than half of the sage-grouse attending a lek flushed as a result of drone flights, and sage-grouse typically returned to the lek soon after we ended flights. Our finding of relatively low impact of drone flights on temporary lek abandonment in sage-grouse differs from previous research that reported much greater flush responses of prairie grouse (*Tympanuchus* spp.) using similar models of drones. Drone surveys caused greater prairie-chickens *T. cupido* to flush from leks in 96% of attempts (Augustine and Burchfield 2022). The probability of a drone producing a flush response of sharp-tailed grouse *T. phasianellus* at leks was somewhat lower and depended on flight height; drone flights at 30 m and 121 m resulted in flush responses on 83 and 35% of attempts, respectively (Rischette et al. 2020). Differences in the drone-induced flush responses between sage-grouse and

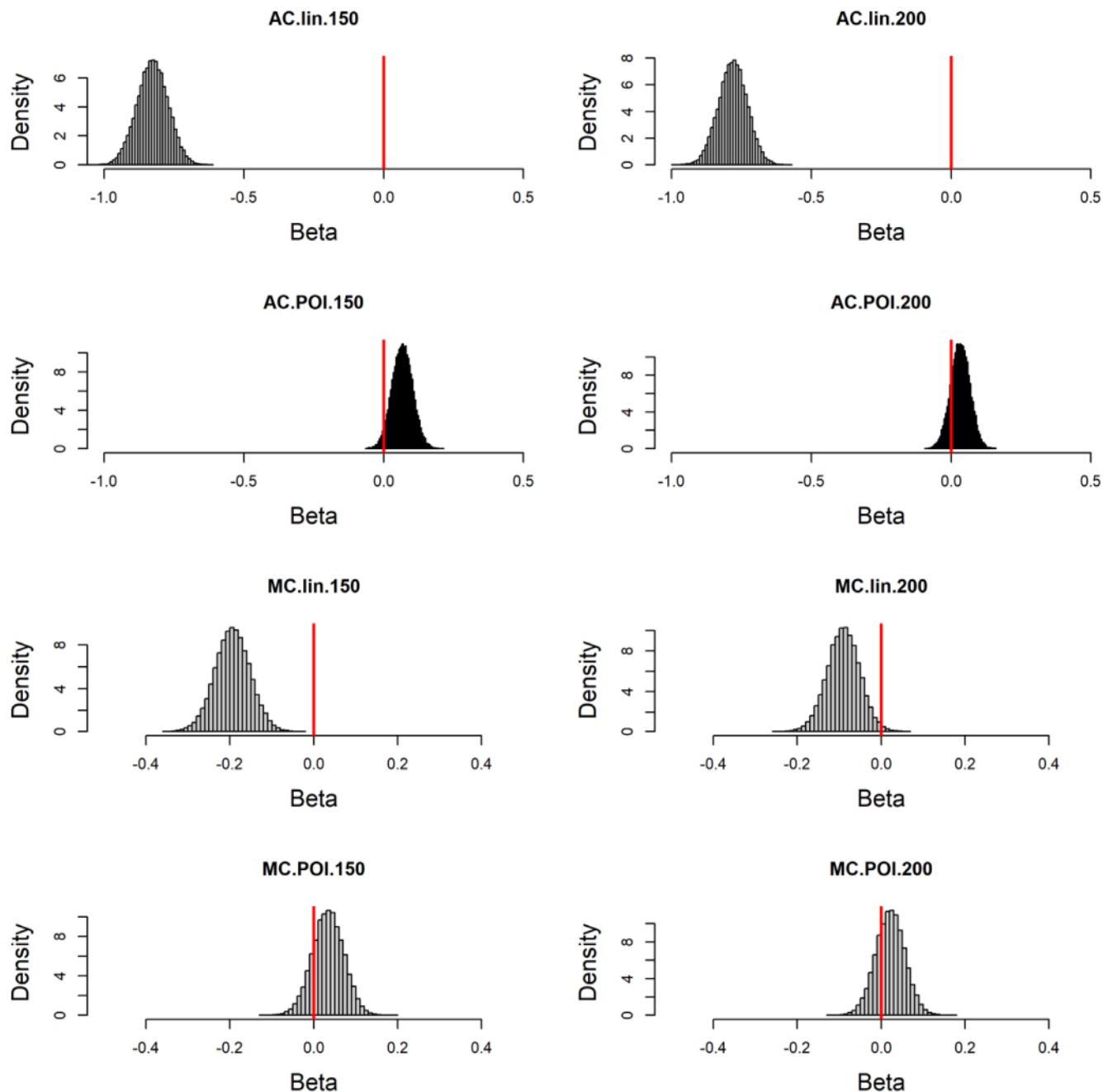


Figure 2. Posterior distributions of the effects (Beta (β)) of eight different drone survey protocols of two count types (AC, MC), two flight profiles (linear, POI), occurring at two flight altitudes (150', 200' AGL) on lek counts of sage-grouse. AC= automatic counts obtained using AI-algorithm applied to drone video; MC= manual counts of drone video by observer; linear=linear flight path; POI= point of interest flight path. The red line represents $\beta=0$ or no effect. A posterior distribution with a 95% credible interval less than the red line indicates a survey protocol with a significant negative effect of survey protocol on lek count relative to a GBV_s survey.

prairie grouse are likely due to intrinsic behavioral responses to aerial predators. Predation of sage-grouse at leks by avian predators is rare, especially in north-central Montana where the primary avian predators of sage-grouse (e.g. golden eagles [*Aquila chrysaetos*]) are uncommon or occur at lower densities than primary avian predators of their small prairie grouse cousins (Conover and Roberts 2017, Augustine and Burchfield 2022).

An important caveat to our study is that our survey flights of different types were always conducted in the same order to minimize time spent flying, and on the same morning to maximize survey efficiency. The consequence of this design is that the probability of grouse flushing during each of our sequential drone flights within a morning may not be truly independent observations. Future research should consider the random assignment of a single flight type to a lek within

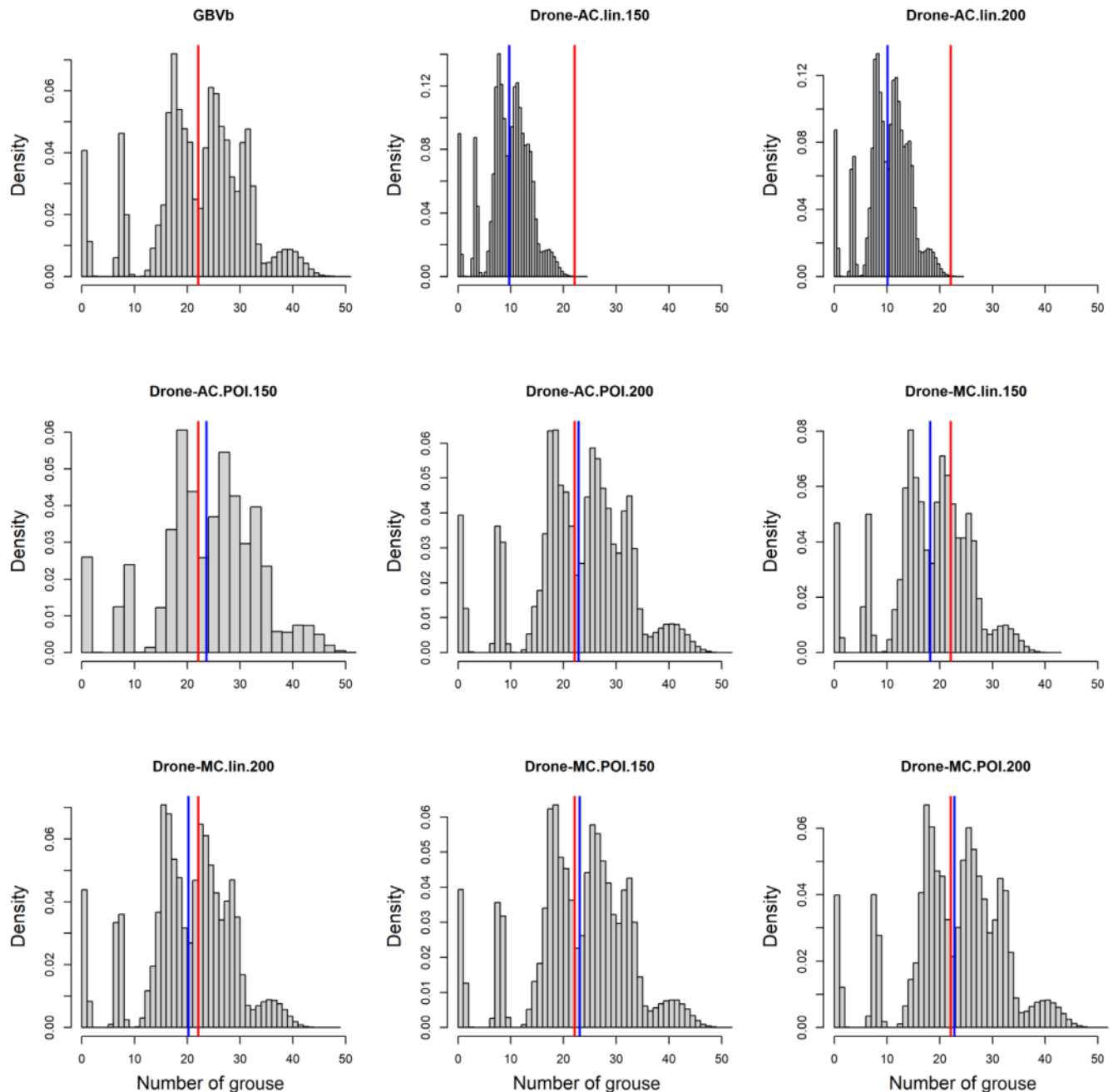


Figure 3. Posterior distributions of the average number of sage-grouse at leks estimated from eight different drone survey protocols of two count types (AV, MC), two flight profiles (linear, POI), occurring at two flight altitudes (150', 200' AGL). AC= automatic counts obtained using AI-algorithm applied to drone video; MC= manual counts of drone video by observer; linear= linear flight path; POI= point of interest flight path. GB= estimated sage-grouse counts from traditional ground-based observation. The blue line represents the average lek size from the posterior for each protocol; the red line represents the average lek size estimated from traditional ground-based surveys at the same leks.

each morning, although this approach may require a prohibitively large number of leks depending on the number of survey flight protocols being tested.

Comparison of counts among survey protocols

For flights that did not result in sage-grouse flushing from leks (~ 84% of attempts), counts from drone surveys using

either manual or our AI grouse counter (INDECS) and point-of-interest (POI) flight profiles were similar to those from GBV_b surveys. In contrast, linear flight profiles, regardless of flight height or counter type, consistently resulted in undercounts compared to GBV_b surveys. The difference between the count accuracy of linear and POI flight profile may be due to differences in the field of view resulting from

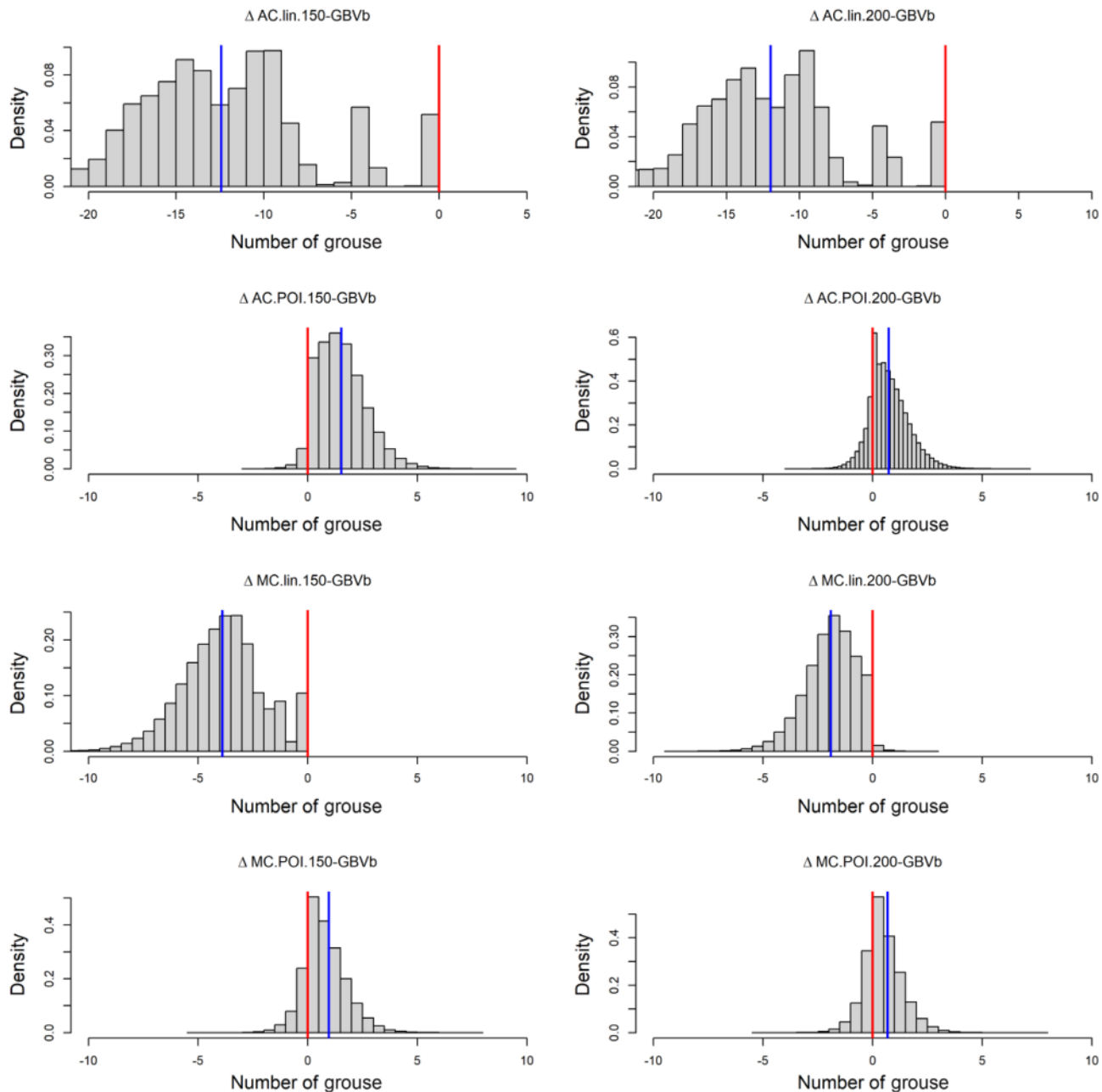


Figure 4. Posterior distributions of the differences (Δ) between the lek-specific grouse counts using 8 different combinations of drone and count protocols (described in Table 1) and those obtained using standard ground-based lek counts obtained visually before any drone flights occurred (GBVb). For example, the panel labeled Δ AC.lin.150-GBVb illustrates the posterior distribution of the difference in the number of sage-grouse estimated using the AC.lin.150 protocol and that obtained via GBVb. The red line represents a difference of 0 between the protocols. The blue line represents the average difference in counts between protocols.

each flight profile. For linear flights, the camera's field of view is downward which results in a smaller and incomplete view of all sage-grouse attending a lek at flight heights of 150–200 feet (45–61 m). A slight (~ 2 bird) improvement in count accuracy of linear flights at 61 m over those at 45 m AGL supports that restricted field of views at these flight heights contribute to downward-biased counts relative to POI surveys. POI profiles provide an oblique and larger view of a

lek as the drone circles it. Notably, counts of sage-grouse using POI flight profiles did not differ between the two flight heights. Thus, POI profiles provided more accurate counts of sage-grouse than linear flight profiles at any flight height. Although waypoint-based (lek centroid) POI flight profiles are much less common than linear flight paths in drone-based surveillance of wildlife (Lyons et al. 2019), they are commonly applied to inspect objects occurring at specific

Table 3. Comparison of mean (95%CrI) detection probability (p), lek abundance (λ), and total number of sage-grouse ($\widehat{TSG}$) estimated using ground-based (GBV_b) lek surveys, drone-based surveys with POI flight profiles in which grouse were counted with an AI algorithm (Drone.AI) and manual counts (Drone.MC) from recorded infrared videos.

	GBV _b	Drone.AI	Drone.MC
p	0.70 (0.58–0.77)	0.64 (0.51–0.73)	0.57 (0.35–0.69)
λ	36 (31–46)	34 (28–49)	41 (33–66)
$\widehat{TSG}$	823 (730–1026)	789 (700–989)	964 (765–1505)
Mean number of surveys per lek (range)	4.1 (1–7)	5.3 (1–11)	5.3 (1–11)

geographic locations (Bezas et al. 2022, Huang et al. 2025), and our results indicate POI surveys to be most appropriate for lek surveys of sage-grouse.

Comparison of AI versus manual counting of sage-grouse

Overall, POI survey profiles resulted in maximum counts identified by our AI counter INDECS that were very similar (within 1.5 sage-grouse) to 1) manual counts from POI surveys, and 2) counts of sage-grouse from conventional ground-based visual surveys (GBV_b). However, sage-grouse counts using INDECS were approximately half that counted by a human in videos from linear flight profiles. Downward bias in AI-based counts for linear flight profiles was likely due to a lack of a sufficient number of annotated images in the training dataset for linear profiles and higher complexity in bird shapes in images taken from overhead flights. Linear flights of leks were shorter and resulted in fewer image frames than POI profiles on which to train YOLO object identification. In addition, sage-grouse in closer overhead images from

linear flights appear larger and have more complex shapes. Sage-grouse in overhead images were often partially hidden by shrubs which makes YOLO detection more difficult than a human observer, especially when the number of training observations are sparse. A larger and changing field of view coupled with longer observation periods of the lek for POI surveys result in a larger number of image frames on which INDECS can count sage-grouse, which produces a more accurate maximum count from INDECS for POI surveys. Future research might evaluate the effects of habitat conditions (e.g. shrub cover) on the relative performance of drone survey protocols.

Inference on abundance from N-mixture model

N-mixture models have become a common method for obtaining unbiased estimates of abundance and population trends for a wide range of wildlife species, including sage-grouse (McCaffery et al. 2016, Coates et al. 2017, Coates et al. 2019). Using a modified N-mixture model applied to data collected using POI flight profiles, we

Table 4. Estimated number of sage-grouse (SD) per lek using ground-based visual surveys (GBV_b), drone-based surveys with AI counts (Drone.AI), and drone-based surveys with manual counts (Drone.MC) at 23 leks in north-central Montana during 2021 and 2022. $\hat{R} < 1.1$ indicates adequate model convergence on parameter estimate.

Lek ID	GBV _b			Drone.AI			Drone.MC		
	E(N)	SD	$\hat{R}$	E(N)	SD	$\hat{R}$	E(N)	SD	$\hat{R}$
1	36	8.4	1.04	33	5.7	1.01	45	15.2	1.14
2	104	34.5	1.01	43	6.4	1.01	54	18.7	1.13
3	41	9.1	1.06	47	10.2	1.00	48	20.2	1.07
4	35	5.5	1.08	42	4.0	1.01	50	13.6	1.17
5	94	23.0	1.04	72	8.8	1.00	83	22.1	1.15
6	17	1.8	1.05	14	1.4	1.00	19	4.7	1.18
7	58	11.6	1.04	47	5.4	1.00	55	15.6	1.16
8	48	10.0	1.04	51	7.4	1.00	60	16.7	1.13
9	29	5.8	1.06	46	5.1	1.01	57	15.7	1.16
10	31	7.8	1.04	36	5.2	1.01	45	15.4	1.15
11	1	2.1	1.00	2	0.9	1.00	4	2.0	1.10
12	33	5.9	1.08	13	3.1	1.00	18	7.0	1.10
13	32	6.0	1.08	48	6.1	1.01	61	19.3	1.16
14	44	7.7	1.07	50	5.6	1.01	63	17.7	1.17
15	27	6.2	1.04	26	3.8	1.01	33	11.2	1.14
16	1	0.6	1.01	1	0.3	1.00	2	1.1	1.13
17	25	4.5	1.07	24	3.5	1.01	31	10.3	1.15
18	32	6.3	1.08	40	7.1	1.01	53	18.8	1.13
19	17	2.7	1.02	26	4.3	1.00	30	8.5	1.11
20	24	4.0	1.07	28	3.7	1.01	35	10.7	1.15
21	19	3.4	1.07	24	4.4	1.01	29	9.7	1.15
22	34	3.5	1.05	33	3.7	1.00	39	9.8	1.15
23	41	20.1	1.01	43	13.9	1.00	51	21.9	1.07

found that detection probability (p), mean local abundance (λ), lek-specific abundances (N_i), and total number of sage-grouse associated with all leks (TSG) were similar for AI-counted drone surveys (Drone.AI), manually-counted drone surveys (Drone.MC) and GBV_b survey protocols, indicating that all three yielded similar inference on the estimated size of the study population. However, estimates of λ and TSG from flights using the Drone.MC protocol were less than half as precise (95% CrI: ± 541 sage-grouse) than the Drone.AI protocol (95% CrI: ± 203 sage-grouse) and GBV_b protocol (95% CrI: ± 203 sage-grouse). Increased variation in lek counts over replicate surveys, was the cause of lower and less precise estimates of detection probability for Drone.MC surveys, which translated to less precise estimates of abundance. Our finding that the AI algorithm (INDECS) produced less variable counts, and therefore more precise estimates of local and total abundance, than a human counter is consistent with the other studies finding that properly training machines can produce consistent and unbiased counts (Banno et al. 2022, AlZubi and Alkhanifer 2024), although more research is needed to refine and evaluate AI tools for object identification and counting (Axford et al. 2024).

Collectively, our work builds upon recent research finding that AI-based counting tools, applied to appropriate drone flight protocols, can provide accurate and efficient counts of wildlife (Lyons et al. 2019, Dundas et al. 2021, Marchowski 2021, Petso and Jamisola 2023). In our study, an AI sage-grouse counter applied to infrared drone-collected images using POI flight profiles resulted in virtually identical counts as conventional ground-based visual (GBV_b) surveys at sage-grouse leks.

Management implications

Our results indicate that drone-based surveys that use artificial intelligence tools (e.g. computer vision, machine learning) to count sage-grouse at leks may offer an effective and efficient alternative to traditional ground-based lek surveys, potentially reducing observer bias and logistical constraints (e.g. accessibility of leks). However, higher accuracy of counts suggests that POI flight profiles should be preferred over linear flight profiles for drone-based monitoring of leks, regardless of whether counts from drone images occur via human or machine. The lower precision of abundance estimates from drone surveys with manual grouse counts (Drone.MC) further highlights the importance of consistency in manual counting and the potential benefits of automation of lek counts. Future studies might evaluate observer variability in manual counting of grouse in drone-collected images, as well as the efficiency (e.g. time invested) of drone-based versus traditional ground-based surveillance of leks.

Drone survey flights caused ≥ 2 sage-grouse to flush from leks on 16% of drone survey attempts. Our criteria for abandoning drone flights at a lek for the day was conservative (≥ 2 grouse flushing) to prevent 1) disturbance of leks,

and 2) downward bias in drone-based lek counts resulting from behavioral changes caused by the drone. Although the proximal cause of sage-grouse behavioral responses to drones remains unknown, future research should evaluate additional drone flight heights and survey conditions that further reduce behavioral responses. For example, we did not evaluate the effects of additional flight heights above 200 ft (61 m) and up to the FAA regulated drone flight ceiling of 400 ft (121 m), or explore how wind, that may mask drone noise, influences behavioral responses or the probability of detecting a grouse at leks. Nevertheless, results of this study indicate that POI-based drone surveys that incorporate AI counting models can significantly enhance the accuracy and efficiency of sage-grouse population monitoring, providing valuable insights for conservation and management.

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Permits – At the time this research was conducted, a scientific collection permit to observe wildlife with a drone was not required by Montana's state wildlife management agency. The Montana State University Institutional Animal Care and Use Committee exempts remote observation of wildlife from protocol review (MSU IACUC Policy: 'Field Studies: Criteria for Exemption from IACUC Approval Policy'). The drone pilot had Federal Aviation Administration Part 107 certification.

Author contributions

Lance B. McNew: Conceptualization (equal); Data curation (equal); Formal analysis (lead); Investigation (equal); Methodology (equal); Project administration (equal); Resources (equal); Supervision (equal); Validation (lead); Writing – original draft (lead); Writing – review and editing (equal). **Jason Hanlon:** Conceptualization (equal); Data curation (equal); Investigation (equal); Methodology (equal); Project administration (equal); Resources (equal); Writing – review and editing (supporting). **Ilya Butyzsky:** Data curation (equal); Formal analysis (supporting); Investigation (equal); Methodology (equal); Resources (equal); Software (equal); Writing – review and editing (equal).

Data availability statement

Data are available from the Dryad Digital Repository: <https://doi.org/10.5061/dryad.v41ns1s6v> (McNew et al. 2025).

Supporting information

The Supporting information associated with this article is available with the online version.

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