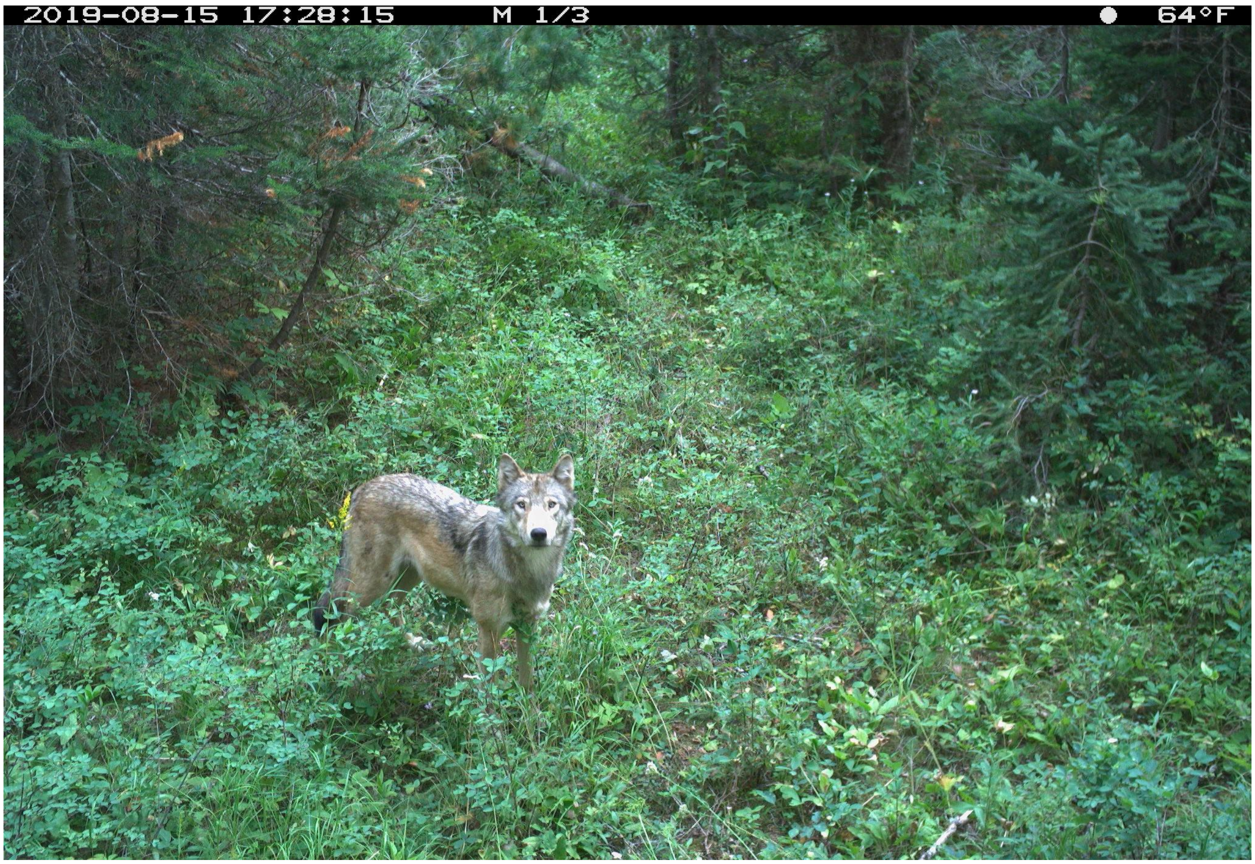
Camera-Based Estimation of Statewide Wolf Abundance in Idaho - 2019–2021

Interim Report
February 28, 2022



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Abstract

Recent advances in remote camera technology and statistical models that utilize detections of unmarked animals on cameras have improved our ability to monitor wildlife populations across very large areas. The accurate monitoring of Idaho's wolf population is important to a variety of constituents in the state but is notoriously difficult to achieve, since wolves exist at relatively low densities compared to many other wildlife species, are secretive, and roam over extremely large areas. Starting in 2019, Idaho Department of Fish and Game collaborated with the University of Montana to utilize a grid of remote cameras spread across areas of the state occupied by wolves, in combination with a space-to-event (STE) statistical model, to annually estimate statewide wolf abundance in Idaho. Idaho Fish and Game personnel deployed and retrieved over 500 spatially dispersed cameras that captured ≈10 million images during the summers (July-August) of 2019–2021. Images were processed with an artificial intelligence image recognition software developed by Microsoft's AI for Earth program that identified images containing an animal. Trained personnel categorized those images identified as animals to species. Images identified as wolves were then analyzed using the STE model to generate annual summer abundance estimates. The annual estimates suggest that Idaho had a stable statewide wolf population of about 1,500 wolves during 2019-2021. This report discusses the detailed methods used to produce the estimates, evaluations of model assumptions, and future directions we plan to investigate to continue the refinement of wolf population monitoring to inform management in Idaho.

Introduction

The U.S. Fish and Wildlife Service (USFWS) reintroduced 66 gray wolves (*Canis lupus*) to central Idaho and Yellowstone National Park in 1995 and 1996 in an effort to restore wolf populations across the northern Rocky Mountain states of Idaho, Montana, and Wyoming. By 2002, wolves in Idaho reached the recovery criteria set forth in their Endangered Species Act (ESA) listing (Hayden 2017). Wolves in Idaho were removed from ESA listing in 2009, temporarily relisted in 2010, and again removed from ESA listing in 2011 (Federal Register Vol. 76, No. 87 [5/5/2011]; https://www.govinfo.gov/content/pkg/FR-2011-05-05/html/FR-2011-05-05-FrontMatter.htm). Wolves in Idaho are currently managed under the 2002 Idaho Wolf Conservation and Management Plan (Idaho Legislative Wolf Oversight Committee 2002), with the Idaho Department of Fish and Game (IDFG) leading the state's wolf management efforts since ESA delisting. Wolves are classified as a big game animal in Idaho and the Idaho Fish and Game Commission has authorized harvest by hunting since 2009 and harvest by trapping since 2011. The goal of IDFG is to manage wolves to reduce human-wildlife conflicts, ensure a self-sustaining wolf population, balance wolf populations with other big game species, and maintain state management authority.

While wolves were ESA listed, and during the subsequent 5-years post-delisting (1995–2016 combined), wolf monitoring in Idaho was primarily focused on assessing population characteristics relative to ESA recovery and delisting criteria (e.g., annual documentation of the number of breeding pairs, number of packs, and average pack size). Intensive capture, radio-collaring, and ground and aerial survey efforts were combined to directly monitor the status and reproductive success of as many packs as possible. Although wolf capture, collaring, and survey efforts were successful in ensuring that ESA recovery and delisting criteria metrics were measured annually, the data provided was less relevant for managing the statewide wolf population in Idaho. Further, capturing wolves and maintaining a suitable number of collared individuals on the landscape became increasingly difficult as harvest increased. Since 2016, IDFG has shifted wolf monitoring efforts to inform overall population management and efforts to mitigate and minimize conflicts. These efforts have included a combination of the use of DNA-based methods to estimate the number of packs and reproductive events; mandatory harvest reporting to monitor the number of wolves harvested by hunters and trappers each year; detailed monitoring of wolf-livestock conflicts and associated wolf removals to enable a better understanding of the effects of targeted wolf removals; development of an integrated population model to estimate wolf packs from GPS-collar data (Horne et al. 2019); and the development of noninvasive, camera-based monitoring methods to monitor statewide wolf occupancy and abundance.

Remote cameras are being used more frequently as an effective tool to monitor populations of elusive wildlife. Since 2016, IDFG has been using remote cameras to estimate wolf occupancy across Idaho, but more recently, IDFG has collaborated with the University of Montana on a multi-year examination of the feasibility of estimating statewide wolf abundance using data from remote cameras in a recently developed statistical model. The objective of this report is to describe the methods and results of the first three years (2019–2021) of this collaborative research effort toward providing reliable estimates of wolf abundance in Idaho.

Methods

Occupancy estimation to inform abundance estimation design - In the absence of a complete census across a geographic area, there is the possibility that a species is present but is not observed even when the area is intensively surveyed (i.e., imperfect detection). Occupancy models are used to estimate the probability a species is present in an area, even though it may not have been detected during a survey. Here, we briefly describe the occupancy estimation methodology that we used during 2016–2018 and how the results of those occupancy analyses were subsequently used to inform the sampling design for our abundance estimation. It should, however, be noted that our estimation of statewide wolf occupancy is a separate research effort that has continued and evolved since 2018. A separate manuscript intended for peer-reviewed publication is currently in preparation that will describe the multi-year (2016–2021) occupancy estimation methods and results in full.

We started the occupancy estimation project by projecting a grid of 686 km^2 cells ($n = 334$) covering Idaho. We selected the cell size to approximate the mean size of a single wolf pack territory (Ausband et al. 2014). We excluded cells in the southern portion of Idaho where high levels of human development and cultivation made the landscape generally unsuitable for wolves (Nadeau et al. 2009). We attempted to place one remote camera in each of the 222 remaining cells. We were unable to place cameras in 13 cells due to extensive private land or restrictions associated with federally designated wilderness areas, but we were able to place and monitor cameras in the 209 remaining cells during the summers of 2016–2018 (Figure 1).

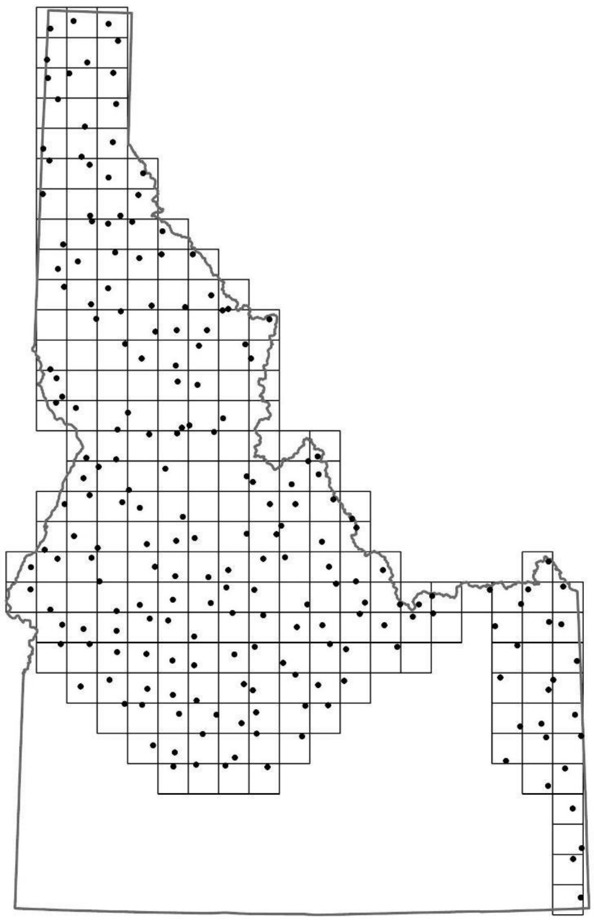

Figure 1. Statewide grid cells (n = 222, area of each cell = 686 km^2) and remote cameras used to estimate wolf occupancy in Idaho, 2016–2018.

We used Reconyx® model PC900 or Hyperfire 2 cameras (Holmen, WI, USA) set to motion-trigger, taking 3 images per trigger event with no pause between triggers. Idaho Fish and Game personnel deployed cameras along trails at historical wolf rendezvous sites (i.e., sites used extensively by wolf packs during summer for pup-rearing) or within predicted wolf rendezvous site habitat as defined by a resource selection function previously developed for Idaho (classes 8, 9, and 10 in Ausband et al. 2010, Jacobs and Ausband 2018a; hereafter “high quality rendezvous site habitat”). In cells without historical wolf rendezvous site locations, we selected points for camera deployment by choosing the largest, most contiguous patch of predicted wolf rendezvous site habitat within the cell. Field personnel were instructed to deploy a camera within 500 m of each selected point, allowing them the flexibility to select an advantageous camera deployment location to detect wolves (e.g., trails or low-use roads that wolves often utilize as travel routes). Each year, personnel deployed cameras by 15 June and retrieved them after 30 Sept. Cameras were not baited and were set at a height of ~3 m when possible to avoid damage from wildlife, deter theft, and focus the camera on the desired viewshed (Jacobs and Ausband 2018b). Cameras were placed >5 m away from the road or trail edge, but angled in a manner that maximized the portion of the camera’s viewshed and motion-sensitive detection bands containing the road or trail. During deployment, personnel also performed a walk test (i.e., “walk test” mode on a Reconyx camera) to determine the motion sensitive detection area of the camera, recording the depth and width of the detection zone.

We examined the resulting images using Timelapse 2.0 software (S. Greenberg, University of Calgary, Alberta, Canada). Idaho Department of Fish and Game personnel reviewed images, recorded all species and the number of individuals present in each image, and noted events that rendered a camera inoperable or changed the viewshed (e.g., animal or wind moving the camera view). We divided the summer sampling season (15 June–Sept 30) into 7, 2-week time periods and used images of wolves to generate cell-specific wolf detection histories for each time period across the season. Detection histories, along with potentially predictive covariates, were imported into Program Presence (MacKenzie et al 2006; https://www.mbr-pwrc.usgs.gov/software/presence.html) and used in a single-season model to estimate wolf occupancy across Idaho. Covariates evaluated for their ability to predict occupancy included IDFG management region, number of humans detected, forest cover (Gap Analysis Project Land Cover Data, U.S. Geological Survey [USGS]), elk and deer harvest, slope (both linear and quadratic effects evaluated), elevation (both linear and quadratic effects evaluated; National Elevation Dataset, USGS), the proportion of neighboring cells (i.e., cells that border the cell of interest) that had at least one wolf detection in the given year, and county-level livestock (cattle + sheep) density (National Agricultural Statistics Service, U.S. Department of Agriculture [USDA]). Additionally, we evaluated the effects of a camera's detection zone length, the amount of predicted high quality rendezvous site habitat within the cell (Ausband et al. 2010), and road density within the cell (TIGER roads, U.S. Census Bureau) on detection probability.

Abundance estimation design – We used our occupancy modeling results to inform our abundance estimation design by averaging the predicted cell-specific occupancy values from the top occupancy model each year across 2016–2018 to produce one average occupancy value for each cell. Then, we used quantiles in ArcGIS 8.0 (ESRI, Redlands, CA) to create 3 bins of occupancy probabilities ≥0.30 (high > 0.58, medium = 0.45–0.58, low = 0.30–0.45). We utilized the "high" (54 cells), "medium" (54 cells), and "low" (53 cells) occupancy bins as 3 strata for abundance estimation. We assumed cells with very low predicted occupancy (<0.3) would be sporadically occupied with very few wolves and would not provide enough detections for accurate estimation of wolf density with cameras. We allocated approximately 50% of our abundance sampling effort to the low stratum, 30% to the medium stratum, and 20% to the high stratum, based on standard sampling theory. Cells with a higher probability of occupancy should require fewer cameras to produce sufficient images of wolves and reasonably precise abundance estimates in comparison to cells with a lower probability of occupancy. We sampled a total of 37 occupancy cells (each ≈686 km^2), allocated across strata (8 high, 11 medium, 18 low), by subdividing each occupancy cell into 16 subcells (≈43 km^2) and placing a camera in each subcell. Some (21–65 each year) of the resulting 592 subcells were not sampled due to private land, federal wilderness restrictions, locations in Canada or Yellowstone National Park, or other deployment issues. We used a Generalized Random Tessellation Stratified (GRTS) sampling scheme in R (R Core Team 2017) package `spsurvey` (Dumelle et al. 2021) to ensure our sample of occupancy cells was unbiased and spatially-balanced across the state (Figure 2).

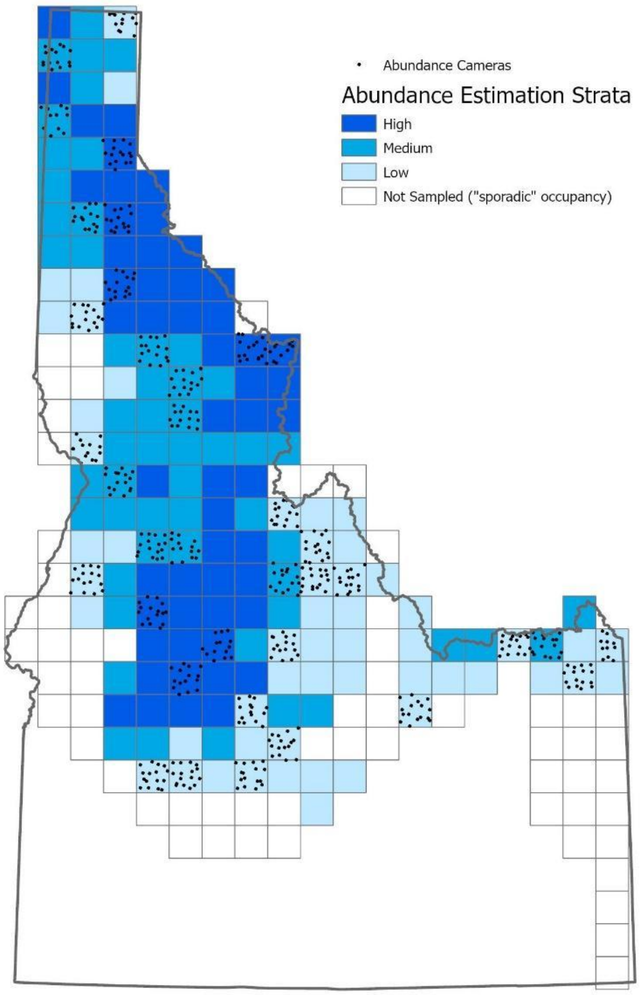

Figure 2. Statewide occupancy cells, colored by abundance estimation stratum (high, medium, low, not sampled), and subcell camera locations used to produce statewide wolf abundance estimates, Idaho, 2019–2021.

Similar to cameras used for occupancy estimation, we used predicted high quality rendezvous site habitat to guide placement of cameras for abundance estimation (Ausband et al. 2010). We omitted patches of predicted high quality rendezvous site habitat that were <1km^2 in size or that overlapped active agricultural crop production (USDA 2018 Idaho Cropland Data Layer, crop categorization codes 1–60 and 195–255, https://www.nass.usda.gov/Research_and_Science/Cropland/Release/), human development (USGS 2016 National Land Cover Dataset, classes 21–24, https://www.mrlc.gov/data?f%5B0%5D=category%3Aurban%20imperviousness), or open water. We then created a spatially-balanced GRTS sample of 10 potential camera locations per subcell, within the extent of the remaining predicted high quality rendezvous site habitat. IDFG camera deployment staff selected the potential camera location within each subcell that they felt struck the best compromise between being 1) close to the center of the cell, 2) as far as possible from a camera placed on the border of a neighboring cell, and 3) accessibility.

We used Reconyx® model Hyperfire 2 cameras (Holmen, WI, USA) set to take both motion-trigger images (3 images per trigger event with no pause between triggers) and time-trigger images every 10 minutes. Abundance estimation cameras were deployed before 1 July and retrieved after 15 September each year. All other camera deployment and orientation protocols were the same as those described above for occupancy estimation cameras.

Image processing - In an effort to streamline our image processing efforts, we incorporated artificial intelligence (AI) to sort images into major categories. The MegaDetector, developed by Microsoft AI for Earth, is an AI object detector that has been trained with diverse image sets from around the world (*note*: IDFG has contributed millions of images to the training set) and specifically detects humans, animals, and vehicles in images (Beery et al. 2019). Each image is reviewed by the MegaDetector algorithm and any potential object that it detects is identified with coordinates (i.e., location within the image) and given a confidence value from 0.0–1.0. The confidence value represents the MegaDetector's certainty that the detected object falls into one of the trained categories (human, vehicle, or animal).

We utilized output from the MegaDetector to restrict human review to only those images that were most likely to contain objects of interest. We used Timelapse 2.0 software (Greenberg et al. 2019) to view and label images; recording the species, number of animals, and other pertinent information (i.e. collars/markings, illness/injury, etc). Timelapse 2.0 incorporated output from the MegaDetector, which allowed reviewers to select subsets of images based on category and confidence level, and also to see the bounding boxes the MegaDetector drew around potential objects. Trained IDFG staff manually reviewed images where any detected object was rated at ≥0.8 confidence. Because we presumed that all images that we do not review were "empty", it is possible that using AI in our workflow caused us to miss some (i.e., never reviewed) images that contained animals. To evaluate this possibility, we compared data generated by humans working with and without the assistance of the MegaDetector. We found that reviewers using the MegaDetector found >99% of the wolves, elk, deer, bears, and moose that were located by humans without AI first eliminating images with <0.8 confidence that an object was identified. Finally, in order to ensure our particular species of interest was correctly identified, IDFG species experts reviewed all images that were labeled wolf or coyote to confirm species classification.

Abundance estimation – We used a space-to-event (STE) model in the R package `spaceNtime` to estimate statewide wolf abundance from images (Moeller et al. 2018, Moeller and Lukacs 2021). The STE model is based on the premise that if there are more wolves in survey area A than survey area B, we should have to sample less space (i.e., view fewer camera viewsheds) in survey area A compared to survey area B to detect an image of a wolf. Consequently, if a survey area is sampled repeatedly by multiple cameras, the units of space sampled during each sampling interval until a wolf is detected can be used by the STE model to estimate wolf density. When compared to many other models that have been developed to estimate abundance from species detection data, the STE model is advantageous because it 1) does not require identification of individual animals; 2) requires only the detection of the species, not an accurate count of individuals in the image; and 3) is an instantaneous estimate, therefore, differences in animal movement rates do not bias the estimate.

Although STE abundance estimation is relatively new, three publications currently exist that describe its development, performance on simulated and field data, and comparison to other estimation methods using real-world data. Moeller et al. (2018) thoroughly describes the STE model, its development, and how it performed with simulated data and real-world elk data in Idaho. Loonam et al. (2020) used cameras and the STE model to estimate abundance of mountain lions in Idaho and compare those estimates to estimates produced from other methods, including more-established genetic, spatial-capture recapture methods. Ausband et al. (2022) compared camera-based STE estimates of wolf abundance in three study areas of Idaho to estimates from an established methodology for estimating summer wolf abundance (i.e., using wolf scats collected from intensive surveys at wolf rendezvous sites and genetic techniques).

We limited our survey period for abundance estimation to images collected during 1 Jul–31 Aug each year to ensure that all individuals were available for detection by cameras (i.e., pups have left the den site and are mobile by July) and most of the survey area was accessible for camera deployment (i.e., after snow melt). We included both time- and motion-trigger images in STE analyses to estimate wolf density (wolves/m^2) separately within each of the three strata. We utilized motion-trigger images in STE analyses if they fell into a defined 2-second interval every 30 seconds throughout the analysis period. The 2-second interval extended from seconds 0:00–0:02 and 0:30–0:32 within each minute. Each 2-second interval that did not contain a motion-trigger image of a wolf was treated the same as a time-triggered image that did not contain a wolf in the STE analysis. We used the area measured during the "walk test" at deployment to define the area of each camera's viewshed.

We selected a 2-second time interval after first estimating how quickly wolves moved across a camera's viewshed using the 3-image bursts following motion trigger events at occupancy cameras. We then used that movement rate, coupled with the direction of travel and distance from the viewshed edge to the nose of a wolf at first motion-triggered detection, to estimate how long the wolf had been in the viewshed before the image was taken. Wolves moved across a viewshed at an average of about 1 meter/second and most wolves were first detected by the motion trigger approximately 2 seconds after entering the viewshed. Those measurements suggested that a motion-trigger sampling interval of <2 seconds may miss wolves that were actually within a camera's viewshed, thereby leading to an abundance estimate that would be biased low. In 2019, we examined the effects of the interval length and the start time of the 2-second interval on abundance estimates. We compared abundance estimates using a 1-second interval to abundance estimates using our 2-second interval. We also evaluated the robustness of the estimate to the start time of the 2-second interval by staggering the start time in 5 second intervals to produce 5 additional estimates, one at each start time from 00:05–00:25. We could not include time-trigger images in this assessment because they all occurred exactly on the minute (0:00, 10:00, etc.).

On rare occasions where a camera viewshed captured an area used extensively by wolves for resting (i.e., most images included wolves resting/feeding/playing, rather than moving through the viewshed), resulting in a large number of repeat detections of the same wolves over consecutive images, we considered the camera an outlier. The large number of repeat images of the same wolves were not independent observations, a violation of STE model assumptions, and therefore we removed these outlier cameras from STE analyses. We chose to keep our methods for handling outlier cameras consistent across these initial 3 years of wolf abundance estimation in Idaho, but we also began to evaluate a recently developed bootstrapping technique as an alternative method for addressing outliers. Bootstrapping has a long history of usage in statistics but has only recently been implemented with STE modeling of camera data (Moeller et al. 2018, Ausband et al. 2022). Under an STE framework, bootstrapping repeatedly generates a random sample (with replacement) of cameras from the total distribution of all cameras, estimates abundance using each random sample, and then averages those estimates to produce a bootstrapped estimate. As an initial evaluation of bootstrapping to objectively deal with outliers, we compared abundance estimates produced after removal of outlier cameras (the method used for estimates in this report) to abundance estimates produced from running all data (including data from cameras we identified as outliers) through 100 iterations of a bootstrap routine in R.

We extrapolated STE wolf density estimates to the area of predicted high quality rendezvous site habitat (Ausband et al. 2010) within each stratum and then added the 3 stratum-specific abundance estimates together to produce an estimate of statewide wolf abundance. Finally, to produce an estimate of statewide wolf density for comparison to published literature that accounted for the varied habitat quality across the landscape, we divided the statewide abundance estimate by the total combined area of all surveyed grid cells (110,446 km^2).

Results

Idaho Fish and Game staff deployed an average of 555 cameras each summer during 2019–2021 (Table 1). Some cameras did not function for the entirety of the survey period due to theft, fire, damage from animals, or general equipment malfunction; resulting in an average of 528 active cameras that captured an average of 10.2 million total pictures per year. The MegaDetector identified approximately 15% of all images as likely containing an object, significantly reducing the IDFG staff resources needed for image review and classification. The number of wolf pictures captured each year ranged from 4,276–8,110, of which 2,933–6,168 occurred during the July–August survey period used for STE modeling. Camera viewshed measurements averaged approximately 39 m^2 (SD = 32) per camera across all years.

Table 1. Summary statistics from cameras deployed for statewide wolf abundance estimation in Idaho, 2019–2021.

Year	Total Cameras Deployed	Cameras Operational Jul-Aug	Total Wolf Pictures	Wolf Pictures Jul-Aug**	Approx. Total Pictures	Approx. Total Pictures Jul-Aug
2019	571	540	8,110*	6,168*	10.7 million	6.7 million
2020	527	506	4,276	2,933	9.8 million	7.0 million
2021	566	537	4,450*	3,371*	10.2 million	6.2 million

* includes pictures from cameras identified as outliers and removed from abundance estimation analyses
** includes all motion-trigger and time-trigger images taken; only motion-trigger images that fell into a 2-second time sampling window were utilized in abundance estimation analyses

Two cameras in 2019, 0 cameras in 2020, and 1 camera in 2021 (i.e., <0.2% of all camera-years combined) were considered outliers and excluded from STE analyses (Table 2). The 2 outlier cameras in 2019 took a total of 3,077 motion-trigger and 66 time-trigger images, and the 1 outlier camera in 2021 took a total of 169 motion-trigger and 76 time-trigger images. In both years, inclusion of the outlier cameras would have significantly biased resulting abundance estimates high (i.e., confidence intervals of estimates with and without outliers were non-overlapping; 2019 with 2 outliers included: N = 3,926, 95% CI = 3,368–4,609; 2021 with 1 outlier included: N = 2,595, 95% CI = 2,117–3,187).

The area predicted as high quality rendezvous site habitat was 13,263 km^2 for the low stratum, 12,153 km^2 for the medium stratum, and 8,123 km^2 for the high stratum, totaling approximately 30% of the area of the statewide survey grid (33,539 km^2 of 110,446 km^2). Annual stratum-specific abundance estimates generally supported our use of occupancy bins to define strata (i.e., higher occupancy strata equaled higher wolf abundance in most years). Abundance estimation results suggested stable statewide wolf abundance from 2019–2021, with point estimates of just over 1,500 wolves and similar lower and upper confidence limits each year (Table 3, Figure 3). Statewide summer wolf density averaged approximately 14 wolves/1,000 km^2 within the survey area each year.

Table 2. Summary of the number of motion-trigger, time-trigger, and total wolf images captured at the 5 cameras that captured the most wolf images each year, Idaho, 2019–2021.

	2019			**2020**			**2021**		
Rank	**Motion**	**Time**	**Total**	**Motion**	**Time**	**Total**	**Motion**	**Time**	**Total**
1	**2,320**	**17**	**2,337***	594	1	595	484	2	486
2	**757**	**49**	**806***	240	0	240	345	2	347
3	558	3	561	164	0	164	**169**	**76**	**245***
4	422	1	423	153	1	154	225	9	234
5	215	0	215	108	0	108	207	1	208

* cameras indicated in **bold** were considered outliers and excluded from abundance analyses

Table 3. Stratum-specific areas (km^2), summer (July-August) wolf abundance estimates (N ± 95% confidence interval) from space-to-event modeling of remote camera data, and estimated wolf density per 1,000 km^2 (D = [N/Total Area]*1,000), Idaho, 2019–2021.

			2019*		**2020**		**2021**	
Stratum	**Total Area (km^2)**	**High Quality Rendezvous Habitat (km^2)**	**N**	**D**	**N**	**D**	**N**	**D**
Low	36,358	13,263	272 (198–374)	7.5	280 (211–373)	7.7	369 (285–478)	10.1
Medium	37,044	12,153	295 (199–436)	8.0	728 (567–935)	19.6	560 (420–746)	15.1
High	37,044	8,123	978 (778–1,230)	26.4	548 (416–723)	14.8	614 (472–799)	16.6
Total	110,446	33,539	1,545 (1,175–2,040)	14.0	1,556 (1,193–2,031)	14.1	1,543 (1,177–2,024)	14.0

* 2019 estimates of N differ slightly from those previously reported in IDFG presentations and news releases due to discovery and correction of a minor data entry error. Previously-reported was Total N = 1,566, Total 95% CI = 1,193–2,064 for 2019.

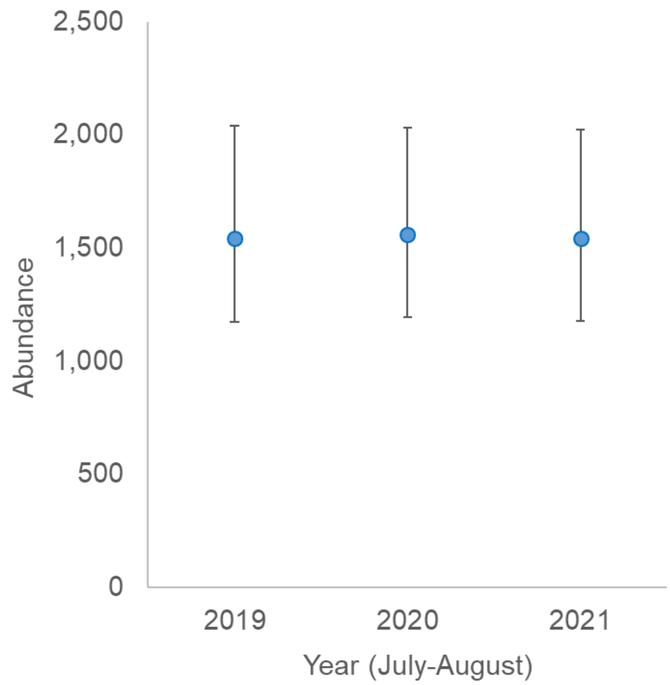

Figure 3. Summer (July–August) statewide wolf abundance estimates (± 95% confidence interval) from space-to-event modeling of remote camera data, Idaho, 2019–2021.

When we reran the 2019 STE analysis using a 1-second interval for inclusion of motion-trigger images, the abundance estimate declined, confirming that a shorter interval resulted in an increased probability of missing wolves that passed through a camera's viewshed and a biased low estimate. We also determined that STE analyses were reasonably robust to shifting the 2-second interval start time, given that all point estimates across the range of start times tested (00:05–00:25) were within the confidence interval of our 2019 abundance estimate.

When we used all camera data (i.e., including data from identified outlier cameras) in 100 bootstrap iterations of the STE model per stratum and compared those results to estimates after manual removal of outliers (reported in Table 2); the bootstrapped estimate was significantly higher when we identified 2 outlier cameras in 2019, the bootstrapped point estimate was lower when no outlier cameras were identified in 2020 , and the bootstrap point estimate was slightly higher when we identified 1 outlier camera in 2021 (Figure 4). Stratum-specific abundance was always lower for bootstrapped estimates, unless the stratum contained the camera that was identified as an outlier (2 outliers in High stratum in 2019, 1 outlier in Medium stratum in 2021). We examined the stabilization of the averaged bootstrap estimate after each iteration to ensure that 100 bootstrap iterations was sufficient to achieve a stable estimate.

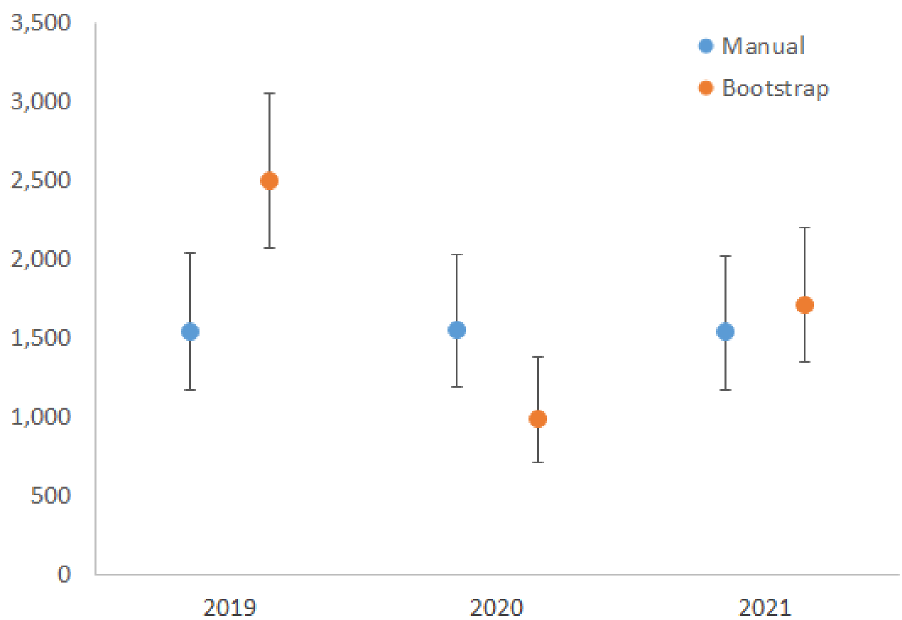

Figure 4. Comparison of annual statewide wolf abundance estimates using two different methods to address outlier cameras, Idaho, 2019–2021. Bootstrap = average of 100 bootstrap iterations of space-to-event abundance, Manual = manual removal of identified outlier cameras before space-to-event abundance estimation.

Discussion

The 2019–2021 Idaho statewide wolf abundance estimates are unique in their scale and approach. No prior or contemporary effort has estimated annual abundance of wolves at a statewide scale (or similar) without reliance on supplemental estimates of, or assumptions about, wolf biology (e.g., territoriality, home range size, pack/litter size, demography, etc). Although we used information from previous research on wolf occupancy and high quality rendezvous site habitat to inform our sampling design, the methods outlined in this report require no additional estimates or assumptions about wolf biology, relying solely on field sampling data to produce an estimate of abundance. Our results support the conclusions of recent publications that STE models utilizing remote camera data are a viable option to estimate the abundance of unmarked wildlife at a variety of spatial scales (Moeller et al. 2018, Loonam et al. 2020, Ausband et al. 2022).

The STE model has underlying assumptions that should be met to ensure unbiased estimates. Important model assumptions relative to our design include 1) cameras are placed randomly throughout the study area, 2) observations of animals are independent in space and time, and 3) animals within camera viewsheds during a sampling interval are always detected. We used spatially balanced random sampling to select cells within strata for abundance sampling and to select locations within those cells that fell within high quality rendezvous site habitat for camera placement. We did, however, orient camera viewsheds toward potential wolf travel routes (e.g., lightly used roads, trails), when available, to ensure a sufficient number of detections for estimation with the STE model. Although positioning cameras to increase wolf detections violates the assumption of random camera placement, concurrent research in Idaho, using the same camera deployment protocols, suggested that the STE model is robust to the violation of random camera placement that occurs by orienting cameras toward travel paths when estimating wolf abundance (Ausband et al. 2022).

Our spatially balanced random placement of cameras ensured that our observations of wolves were independent through space, but we did encounter situations where detections of animals on camera were not independent through time (i.e., same animals resting within a camera viewshed for multiple images). Non-independent detections result in autocorrelated data that will bias the resulting estimates high (Moeller et al. 2018). One camera in 2019 had an unusually high number of motion-trigger wolf detections, and 1 camera in 2019 and 1 camera in 2021 had unusually high numbers of time-trigger wolf detections due to wolves resting in camera viewsheds for extended periods. Since all time-trigger images are included in STE analyses (i.e. they always occur within the defined sampling interval; whereas only some motion-trigger images fall within sampling intervals), a camera with an abnormally large number of time-trigger images due to resting behavior has a large effect on the resulting estimate. Similarly, a camera with an extremely large number of motion-trigger images results in more of those images falling within 2-second motion-trigger sampling intervals, with a similar effect on the resulting estimate. Because we identified cameras with high autocorrelation of wolf images (i.e., outlier cameras) and removed them from analyses, the dataset we used to generate our annual abundance estimates should have reasonably satisfied the model assumption that observations were independent through time.

The camera deployment methods described in this report are the result of extensive testing by IDFG, during both the occupancy and abundance estimation projects, to develop a protocol that maximizes the likelihood that all animals within a camera's viewshed during a sampling interval are detected. By angling camera viewsheds down from a relatively high mounting point and orienting the camera's viewshed perpendicular to a travel corridor, we decreased the size of the viewshed and increased the chance that animals would walk through the motion detection bands of the camera. In addition, deployment personnel conducted walk tests on all cameras to ensure proper motion detection. We also used image data from occupancy cameras to identify an interval length that would allow us to reasonably assume wolves passing through camera viewsheds were detected. Our assessment of interval length suggested that a motion-trigger sampling interval of <2 seconds may miss wolves that were within a camera's viewshed but hadn't yet triggered the camera's motion detection, and therefore produce an estimate that was biased low. Therefore, the final dataset we used should have reasonably satisfied the assumption that we detected all wolves within camera viewsheds in sampling intervals.

Since a bootstrap routine has been proposed as a potential method to deal with the effect of outliers in STE estimation (Moeller et al. 2018, Ausband et al. 2022), we conducted an evaluation of the bootstrap approach by comparing bootstrap estimates to estimates generated after manual outlier removal. By definition, passive sampling for a species that exists at relatively low densities across a landscape is likely to result in few detections of that species. When estimating wolf abundance, the STE model is utilizing a dataset where no wolves were detected in a large number of sampling intervals, thus the few detections that do occur are highly influential on the ensuing abundance estimate. A bootstrap resampling routine that produces many iterative estimates from a randomly selected subsample of cameras will produce some estimates where one or more cameras with the most wolf detections are omitted, by random chance. This may be a useful feature of resampling when the goal is to reduce the effect of an outlier on the resulting estimate. However, when a true outlier does not exist (like our 2020 data), the averaged bootstrap estimate may be biased low due to the random exclusion of relatively rare and important detections. Conversely, when 2 outliers exist in a dataset (like our 2019 dataset), our comparison suggests bootstrapping may not be capable of mitigating their effect on the resulting STE estimate. In that situation, one or both of the outlier cameras were retained in the majority of the random data subsets used for bootstrap iterations and the resulting average bootstrap estimate was still significantly higher than the estimate produced after manual removal of both outliers. These results suggest additional research is needed to fully understand the effects of bootstrapping on STE estimates under different scenarios and guidelines should be developed on how and when to use bootstrapping with STE models. Additionally, future research should investigate additional methods for handling autocorrelated image data; potentially including a method that retains all cameras but identifies and censors wolf detections that meet some predefined criteria for excessive temporal autocorrelation.

We have considered numerous ways to improve the precision of our camera-based statewide wolf abundance estimates, but unfortunately most are unfeasible or cost prohibitive. For instance, the STE method produces more precise estimates when used on populations of animals that exist at higher densities or populations with a homogeneous distribution across the study area, neither of which apply to the biology of wolves. Deploying even more cameras would likely increase the precision of the estimates, but a significant increase in the already large dedication of resources to this effort (see below) would likely be unfeasible. Separating the state into additional strata that more accurately represent differences in local wolf density could also result in a more precise statewide population estimate; but the spatial and temporal dynamics of a highly-mobile, harvested species like wolves make it unlikely that we could accurately predict the boundaries of additional strata of homogeneous density. Ultimately, we recognize that the most expedient and efficient way to improve precision and accuracy of statewide wolf abundance estimates is to utilize multiple data streams, which represent different processes involved in wolf population dynamics (e.g., abundance, mortality, recruitment, etc), as multiple lines of evidence within an integrated population model designed to estimate abundance and other population parameters (see Schaub and Abadi 2011).

The estimation of wolf abundance in Idaho requires a substantial commitment of financial and staff resources. Our current approach entailed a large initial investment in cameras and associated hardware (camera + SD card + lithium batteries ≈ $500/camera), followed by recurring costs associated with replacing camera batteries and lost, stolen, or broken cameras, maintaining field equipment, and paying for vehicle fuel and maintenance needed for the deployment and retrieval of cameras. In addition, camera deployment and retrieval, image processing, and subsequent analyses amount to a significant annual investment of personnel resources. Further, significant costs associated with cloud computing and server hardware required to manage and analyze millions of pictures each year have been offset, to date, by in-kind contributions from Microsoft's AI for Earth program. Collectively, our current camera-based approach likely exceeds the cost of models being used to estimate wolf abundance in some other states that require several underlying assumptions about wolf biology, but is more cost-effective than prior approaches used in Idaho to estimate an annual minimum count of wolves through the maintenance of collared wolves in most packs and extensive ground and aerial survey efforts. Moving forward, we plan to continue to evaluate the methodology outlined here while also considering alternative or complementary methods that may improve efficiency or precision of estimates while continuing to provide reliable data to inform wolf population, predator-prey, and wildlife-human conflict management in Idaho.

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