Variation in Detection Among Passive Infrared Triggered-cameras Used in Wildlife Research

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Abstract: Precise and accurate estimates of demographics such as age structure, productivity, and density are necessary in determining habitat and harvest management strategies for wildlife populations. Surveys using automated cameras are becoming an increasingly popular tool for estimating these parameters. However, most camera studies fail to incorporate detection probabilities, leading to parameter underestimation. The objective of this study was to determine the sources of heterogeneity in detection for trail cameras that incorporate a passive infrared (PIR) triggering system sensitive to heat and motion. Images were collected at four baited sites within the Conecuh National Forest, Alabama, using three cameras at each site operating continuously over the same seven-day period. Detection was estimated for four groups of animals based on taxonomic group and body size. Our hypotheses of detection considered variation among bait sites and cameras. The best model ($w = 0.99$) estimated different rates of detection for each camera in addition to different detection rates for four animal groupings. Factors that explain this variability might include poor manufacturing tolerances, variation in PIR sensitivity, animal behavior, and species-specific infrared radiation. Population surveys using trail cameras with PIR systems must incorporate detection rates for individual cameras. Incorporating time-lapse triggering systems into survey designs should eliminate issues associated with PIR systems.

Key words: automated cameras, PIR, motion sensing, passive infrared, detection rates, estimation, population structure

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Precise and accurate estimates of population demographics such as age structure, productivity, and abundance are necessary to determine habitat and harvest management strategies for most wildlife species. Knowledge of these parameters has been acquired through various indices including transect sampling (Silveira et al. 2003), mark-recapture (Soisalo and Cavalcanti 2006), aerial sampling (Amstrup et al. 2004), and automated cameras (Cobb et al. 1996). Surveys using automated cameras are an increasingly popular tool for estimating these parameters; however, many studies fail to incorporate detection rates. Variation in detection rates may bias parameter estimates (MacKenzie et al. 2002), and failure to incorporate detection may lead to parameter underestimation. Three general sources of bias in camera surveys can be identified: those associated with differences among the species of interest, those associated with survey site characteristics, and those directly related to camera function.

The use of automated cameras to photograph wildlife in research was first described by Gysel and Davis (1956). Automated camera systems have evolved rapidly since that time and have been used to study avian nest predation (Lehman et al. 2008), foraging ecology (Weckel et al. 2006), nesting behavior (Margalida et al. 2006), activity patterns (Wong et al. 2004) and estimating population demographics (Cobb et al. 1996, Martorello et al. 2001, Soisalo and Cavalcanti 2006). Despite increasing use of automated cameras to survey wildlife, few researchers have explicitly estimated detection rates for cameras or more specifically, PIR sensors (Swann et al. 2004, Rowcliffe et al. 2008). Researchers applying forward looking infrared (FLIR) in aerial surveys have more frequently noted problems with infrared sensors than researchers using automated cameras. Examples of sources for these problems included snow depth, airborne moisture, sunlight and background structure temperature (e.g., Kingsley et al. 1990, Amstrup et al. 2004, Bernatas and Nelson 2004, Locke et al. 2006).

Our objective was to determine sources of heterogeneity in detection for a commercially available trail camera incorporating a PIR triggering system. We estimated detection rates of one commercially available PIR camera and described variability in PIR detection rates based on taxonomic group and body size. Our hypotheses of detection considered variation among bait sites and differences among individual cameras additive to effects of taxonomic group and body size. Based on our results, we offer explanations of potential contributing factors to variability in detection rates. We also suggest methods of incorporating detection rates into demographic estimates. Finally, we propose an alternative that eliminates differences in detection among cameras.

Methods

We performed this research in conjunction with a wild turkey (*Meleagris gallopavo*) survey on the Conecuh National Forest (73,311 ha) in southern Alabama from 23 August to 6 September 2006. For this analysis, camera bait stations were established in areas consisting of small openings or dirt roads surrounded by managed pine forest. The average high temperature for the survey period was 33 C, and the average low was 19 C. Humidity averaged 76% and one rain event occurred during the study. To ensure cameras had the opportunity to trigger, sites for this research were chosen where turkeys were observed during the survey. A tree at least 20-cm DBH was selected to attach the cameras for each site, and a 10 m semicircle north of the tree was cleared of tall vegetation and overhanging branches to limit camera lens obstruction and unintended camera activation. All cameras were oriented north in order to avoid sun-blurred images. Each site was pre-baited with 4 L of cracked corn for 7 days prior to camera deployment, and bait was replenished only on the day of deployment if necessary. Bait was broadcast from directly in front of the camera to 3 m out. Three PIR activated Penn's Woods model DS-04 cameras (Penn's Woods Products, Inc., Export, PA; Any use of trade, product, or firm names is for descriptive purposes only and does not imply endorsement by the U.S. Government.) were deployed at each site and operated continuously during the same 7-day period. Cameras were attached to the same tree as close to ground as possible, and all were aimed at bait center. Units were set up to operate 24 h/day with a 10-sec delay between pictures. We used settings recommended by Penn's Woods for programming digital cameras. Sites were visited a total of three times during the survey: pre-baiting, camera deployment, and camera retrieval. We examined images and recorded counts of each species.

We developed hypotheses and corresponding models concerning detection rates *a priori*. Species grouped within these hypotheses were added *post hoc:*

We hypothesized that detection varied by site, because each sites had a different vegetative background (different species, ages, vigor, etc.), and distance to background vegetation also varied. This would lead to different detection rates across sites, but cameras at each site would have the same detection rate.

We hypothesized detection varied by camera due to differing sensitivities of PIR sensors. (Manufacturing tolerances, quality control, etc. caused each camera to detect animals at different rates.)

We hypothesized differences in detection occur due to animal size, so we grouped animals accordingly. Large animals (i.e., white-tailed deer [*Odocoileus virginianus*]) have the highest detection rate because they have the larger area of infrared radiation compared to background. Medium animals (i.e., wild turkey) are detected less frequently than large animals. Small animals (i.e., raccoon [*Procyon lotor*], nine-banded armadillo [*Dasypus novemcinctus*], and cottontail rabbit [*Sylvilagus floridanus*]) are detected less than large and medium animals, but more than very small animals (i.e., gopher tortoise [*Gopherus polyphemus*] and mourning dove [*Zenaida macroura*]).

We also hypothesized feathers (i.e., mourning dove and wild turkey) emit less infrared radiation which results in lower detection rates for birds than other animals.

We hypothesized birds had lower detection rates than non-feathered animals, but larger sized birds (i.e., wild turkey) have higher detection rates than smaller birds (i.e., mourning dove).

We hypothesized that a size threshold for detection existed with the PIR sensors. Because white-tailed deer have the greatest area of infrared radiation relative to the background, they have the highest odds of detection. All other animals have the same detection rate.

We combined additive effects of animal groupings with both site and camera models, respectively, to determine the best approximating model.

We used the Huggins closed population estimator (Huggins 1989, 1991) in Program MARK (White and Burnham 1999) to estimate the probability of detection (p) because it allowed us to include individual covariates. We treated each camera as a potential capture event, therefore probability of initial capture and recapture were constrained to be equal. An event occurred when at least one camera was triggered during any 9-sec interval. We created a capture history for each event. The initial capture was the image resulting from the camera that triggered first. Recaptures consisted of the image(s) resulting from the other two camera(s) subsequently triggering within 9 sec of the first camera. This interval was long enough to exclude multiple images of the same event from an individual camera and was enough time to allow potential recapture cameras to initialize, focus, and capture an image. Models were compared in Program MARK using AIC corrected (AICc) for small sample sizes (Burnham and Anderson 2002). We estimated recapture probability in the Huggins model as a surrogate for detection; therefore, assessing goodness-of-fit (White and Burnham 1999) was not appropriate. Actual detection rates were not important for this exercise, so we compared odds ratios (βs) among cameras and animal groups. We used indicator variables for sites and animal groups and a logit link to estimate log odds of detection. To compare among sites and animal groups, we calculated the relative odds of detection as the inverse natural log of the differences in the βs for each group. We did not present animal group-specific detection rates because they were different for each camera. We compared the camera with the highest odds of detection to other cameras, and the animal group with the highest odds of detection to other groups. Model averaging was not incorporated into these results, since model selection was unequivocal (wAICc = 0.9998).

Results

Data at one site were discarded because only one camera recorded any images. Even prior to modeling, the number of events triggered by individual cameras at each site varied considerably. The PIR sensors detected a total of 868 events, 701 of which resulted in an image of an animal (81%). Variation in the number of events was high at each site (Table 1). Two sites (1 and 4) had a high percentage of images with animals present and low variability between cameras (83–93% and 97–100%, respectively). The other two sites (2 and 3) had greater variation (34–62% and 50–83%, respectively) and a greater number of images that did not include any animals.

The most parsimonious and best approximating model was p(camera+size) (Table 2). This model estimated detection rates for individual cameras at each site and four size covariates. It had the largest model probability (w = 0.9998), and best fit (Dev = 1845). The next best approximating model was p(camera+threshold) (ΔAICc = 18), but had negligible model probability (w = 0.0002). Odds of detection ranged from 0.02 to 0.66 among cameras (Figure 1). Therefore the camera with the smallest detection rate was 0.02 times as likely to detect an animal as the one with the largest detection. Large animals were most likely to be detected followed by small, medium, and very small animals, respectively (Figure 2). Despite large differences in relative odds of detection, 95% confidence intervals overlapped in most cases (Figures 1, 2).

Table 1. Number of images captured by each camera at each site and percentage of images with animals present from a wildlife survey of Conecuh National Forest, summer 2006.

Site	Camera	Total images	% images w/animals
1	1	86	83 %
1	2	49	86 %
1	3	107	93 %
2	4	110	62 %
2	5	98	59 %
2	6	56	34 %
3	7	48	83 %
3	8	6	67 %
3	9	4	50 %
4	10	121	98 %
4	11	26	100 %
4	12	157	97 %

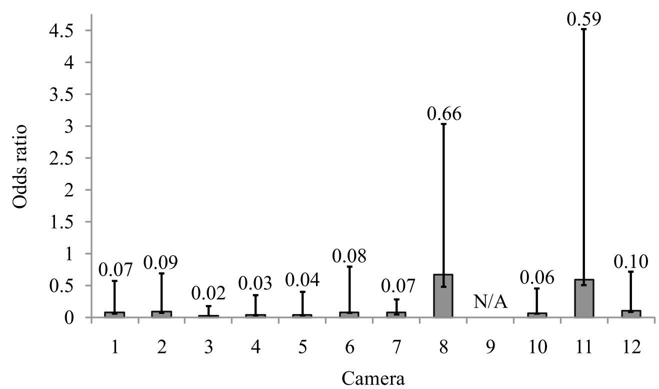

Figure 1. Relative odds of detection among cameras. Bars indicate 95% confidence limits.

Table 2. Comparison of models and hypotheses for estimating detection rates of PIR-activated cameras from Conecuh National Forest, summer 2006.

Model	Hypotheses[1]	AICc[2]	Δ[3]	w[4]	Lik[5]	K	Dev[6]
p(camera+size)	1,3	1877	0	0.9998	1.00	16	1845
p(camera+threshold)	2,6	1895	18	0.0002	0	13	1868
p(camera)	2	1904	27	0	0	12	1880
p(camera+feathers)	2,4	1905	28	0	0	13	1879
p(camera+feathersize)	2,5	1906	29	0	0	14	1878
p(site+size)	1,3	2126	249	0	0	8	2109
p(site+threshold)	1,6	2142	265	0	0	5	2132
p(site)	1	2151	274	0	0	4	2143
p(site+feathers)	1,4	2152	275	0	0	5	2142
p(site+feathersize)	1,5	2153	276	0	0	6	2141
p(.)	Intercept	2184	307	0	0	1	2182

1. Indicates hypothesis(es) supported by the model; see text for descriptions.
2. Akaike's (1973) Information Criterion corrected for small sample size.
3. $AICc_i - \min(AICc)$.
4. $\exp(-0.5\Delta_i) / \sum_{i=1}^{R} \exp(-0.5\Delta_i)$
5. $\exp(-0.5\Delta_i)$
6. $-2\ln(\mathrm{Lik(model|data)})$

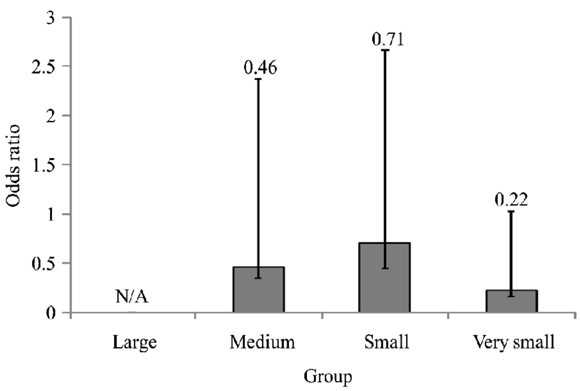

Figure 2. Relative odds of detection among size groups of animals. Error bars indicate 95% confidence limits.

Discussion

One potential cause of variation in detection rates among different animal groups is the variation in intensity of infrared radiation a species emits. Most commercially available trail cameras operate using PIR, which only detects changes in background infrared radiation wavelengths. Therefore, if species have different body temperatures and insulative properties (feathers, fur, shell, scales, etc.), then differences in PIR sensitivity would contribute to variability in detection rates between animal groups. For example, Butler et al. (2006) could not detect turkeys on the roost with a FLIR camera unless their featherless heads were exposed. Counter to our size hypothesis, the odds of detecting medium-sized animals (turkeys) were lower than some smaller animals (small group). Perhaps due to their feathered covering, turkeys might emit less infrared radiation than small mammals. Although the feather hypotheses were not supported by our data, lack of fit for these models could have been caused by limited sample size and clustering non-feathered animals into a single detection group. Ideally, we would have avoided grouping species by modeling detection rates for each; however, some species were not counted frequently enough for estimating detection individually.

Both background temperature and environmental conditions (rain, snow, wind, cloud cover, etc.) are potential causes of lower detection rates. If differences in background temperature and the target species are not large enough, the PIR sensor will not trigger the automated camera to capture an image. Swann et al. (2004) found some models of commercially available automated cameras were more sensitive to changes in background temperature than others. Bernatas and Nelson (2004) determined overcast skies allowed for greater detection of bighorn sheep (*Ovis canadensis*) than sunny skies in aerial FLIR surveys. They also determined that flat rock surfaces emitted more infrared radiation than soil, grass, and sagebrush vegetation; therefore, sheep were detected less frequently in these areas. Kingsley et al. (1990) reported problems with detecting ringed seal (*Pusa hispida*) lairs on ice using FLIR that were related to snow depth, ambient temperature, wind, and sunlight. Known polar bear (*Ursus maritimus*) dens were missed in a FLIR survey due to fresh snow, wind, and airborne moisture (Amstrup et al. 2004). Locke et al. (2006) found external temperatures of wild turkeys and background structure (roost and ground) to be too close, regardless of other weather conditions, which made detecting wild turkeys with FLIR difficult. While these variables could contribute to lower or varied detection rates, we controlled for them by placing sites in similar habitats, aiming all three cameras at the same focal point, and by collecting data at the four sites at the same time.

Manufacturing tolerances of camera components could also contribute to variability in detection rates and could be linked to several sources. The PIR components could have varied in sensitivity, which may have led to variable detection rates. Swann et al. (2004) demonstrated leveling a camera may not align the PIR sensor detection zone perfectly to the area of interest. This misalignment could lead to presumed false detections where an animal is present on site, missed by the camera, but detected by the sensor. Therefore, the direction in which the sensor is facing when mounted inside the camera housing could influence detection rates. Because our intent was to examine performance of the cameras under field conditions, we did not test the aim or sensitivity of PIR sensors in our units; thus, they are plausible explanations for at least some variation we observed. However, we aimed cameras at the same focal point at each site. If our PIR sensors were mounted within the cameras similarly, aim should not have contributed to variability in detection.

Detection rates for individual cameras should be incorporated into population estimation methods to minimize the effects of PIR sensor variability. Failure to account for detection reduces the reliability of estimates. The use of variance inflation factors such as in model selection favors simpler models when model fit is poor, but does not eliminate or reduce the bias in parameter estimates (Burnham and Anderson 2002). An "observer" effect could be included into the models that would account for variability in PIR sensitivity of individual cameras. This method could complicate analyses because a parameter for each camera would be added to the model, potentially increasing amount of data needed to yield reasonable precision. Mixture or random effects models would be more parsimonious than observer effects models and could estimate detection based on groups of cameras with similar rates (Pledger 2000). They also allow for the use of covariates and can be fitted using Program MARK. However, the lack of ability to distinguish among sources of variation is inherent within these models.

Much of the literature that addresses use of trail cameras to estimate population parameters is based on the assumption that a direct relationship exists between the number of images captured over time and density of the species being surveyed (e.g., Jacobson et al. 1997, Main and Richardson 2002, Silveira et al. 2003, McKinley et al. 2006). These estimators do not include measures of detection for individual cameras or environmental factors. Proper use of mark-recapture methods addresses these issues, but is particularly sensitive to un-modeled heterogeneity in detection rates (White et al. 1982). Thus, differences in detection rates among cameras must be estimated to avoid biased estimates of population parameters. Swann et al. (2004) explored measuring zones of detection for several models of trail cameras. Rowcliffe et al. (2008) used animal group sizes and movement rates to accurately estimate density of three of four ungulate species. If PIR triggering systems are used for population estimation, identifying these zones of detection for individual cameras and controlling for group size and environmental conditions may reduce the effect of heterogeneity in animal detection caused by PIR sensors (Swann et al. 2004). This identification would in turn reduce bias in population estimates, but could not fully account for large differences in detection among cameras.

Time-lapse systems provide more reliable estimates and require fewer parameters because they eliminate the need to estimate detection rates for individual cameras. With a time-lapse system, the camera captures an image on a fixed interval, irrespective of species presence, location, or environmental conditions. Digital trail cameras have great advantages over film cameras that allow them to function for several weeks in the field and store thousands of images, thus making surveys using a time-lapse triggering system more feasible. Depending on the time interval, the number of images that must be analyzed could be increased substantially by using time-lapse systems. However, eliminating the effects of PIR sensor variability outweighs this cost because of more parsimonious model selection (fewer parameters and more data) and less biased demographic estimates (less un-modeled variation in detection). Using a time-lapse system would further standardize surveys because they would be performed on a fixed interval. Because of the inherent variability associated with PIR systems, time-lapse systems reduce the potential sources of variation in abundance estimation from repeated count (e.g., Royle 2004) or mark-recapture methods.

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Literature Cited

Akaike, H. 1973. Information theory and an extension of the maximum likelihood principle. Pages 267–281 *in* B. N. Petrov and F. Csaki editors. 2nd International Symposium on Information Theory. Budapest:Akademia Kiado.

Amstrup, S. C., G. York, T. L. McDonald, R. Nielson, and K. Simac. 2004. Detecting denning polar bears with forward-looking infrared (FLIR) imagery. BioScience 54:337–344.

Bernatas, S. and L. Nelson. 2004. Sightability model for California bighorn sheep in canyonlands using forward-looking infrared (FLIR). Wildlife Society Bulletin 32:638–647.

Burnham, K. P. and D. R. Anderson. 2002. Model selection and multi-model inference: a practical information-theoretic approach. Springer-Verlag, New York.

Butler, M. J., W. B. Ballard, M. C. Wallace, S. J. Demaso, and R. D. Applegate. 2006. Comparing techniques for counting Rio Grande wild turkeys at winter roosts. Pages 112–117 *in* J. W. Cain III and P. R. Krausman, editors. Managing Wildlife in the Southwest. Southwest Section of The Wildlife Society, Tucson, AZ.

Cobb, D. T., D. L. Francis, and R. W. Etters. 1996. Validating a wild turkey population survey using cameras and infrared sensors. Proceedings of the National Wild Turkey Symposium 7:213–218.

Gysel, L. W. and E. M. J. Davis. 1956. A simple automatic photographic unit for wildlife research. Journal of Wildlife Management 20:451–453.

Huggins, R. M. 1989. On the statistical analysis of capture-recapture experiments. Biometrika 76:133–140.

Huggins, R. M. 1991. Some practical aspects of a conditional likelihood approach to capture experiments. Biometrics 47:725–732.

Jacobson, H. A., J. C. Kroll, R.W. Browning, B. H. Koerth, and M. H. Conway. 1997. Infrared-triggered cameras for censusing white-tailed deer. Wildlife Society Bulletin 25:547–556.

Kingsley, M. C. S., M. O. Hammill, and B. P. Kelly. 1990. Infrared sensing of the under-snow lairs of the ringed seal. Marine Mammal Science 6:339–347.

Lehman, C. P., M. A. Rumble, L. D. Flake, and D. J. Thompson. 2008. Merriam's turkey nest survival and factors affecting nest predation by mammals. Journal of Wildlife Management 72:1765–1774.

Locke, S. L., R. R. Lopez, M. J. Peterson, N. J. Silvy, and T.W. Schwertner. 2006. Evaluation of portable infrared cameras for detecting Rio Grande wild turkeys. Wildlife Society Bulletin 34:839–844.

MacKenzie, D. I., J. D. Nichols, G. B. Lachman, S. Droege, J. A. Royle, and C. A. Langtimm. 2002. Estimating site occupancy rates when detection probabilities are less than one. Ecology 83:2248–2255.

Main, M. B. and L.W. Richardson. 2002. Response of wildlife to prescribed fire in southwest Florida pine flatwoods. Wildlife Society Bulletin 30:213–221.

Margalida, A., S. Ecolan, J. Boudet, J. Bertran, J-M. Martinez, and R. Heredia. 2006. A solar-powered transmitting video camera for monitoring cliff-nesting raptors. Journal of Field Ornithology 77:7–12.

Martorello, D. A., T. H. Eason, and M. R. Pelton. 2001. A sighting technique using cameras to estimate population size of black bears. Wildlife Society Bulletin 29:560–567.

McKinley, W. T., S. Demarais, K. L. Gee, and H. A. Jacobson. 2006. Accuracy of the camera technique for estimating white-tailed deer population characteristics. Proceedings of the Annual Conference of the Southeastern Association of Fish and Wildlife Agencies 60:83–88.

Pledger, S. 2000. Unified maximum likelihood estimates for closed capture-recapture models using mixtures. Biometrics 56:434–442.

Royle, J. A. 2004. N-Mixture Models for Estimating Population Size from Spatially Replicated Counts. Biometrics 60:108–115.

Rowcliffe, J. M., J. Field, S. T. Turvey, and C. Carbone. 2008. Estimating animal density using camera traps without the need for individual recognition. Journal of Applied Ecology 45:1228–1236.

Silveira, L., A. T. A. Jacomo, and J. A. F. Diniz-Filho. 2003. Camera trap, line transect census and track surveys: a comparative evaluation. Biological Conservation 114:351–355.

Soisalo, M. K. and S. M. C. Cavalcanti. 2006. Estimating the density of a jaguar population in the Brazilian Pantanal using camera-traps and capture–recapture sampling in combination with GPS radio-telemetry. Biological Conservation 129:487–496.

Swann, D. E., C. C. Hass, D. C. Dalton, and S. A. Wolf. 2004. Infrared-triggered cameras for detecting wildlife: an evaluation and review. Wildlife Society Bulletin 32:357–365.

Weckel, M., W. Giuliano, and S. Silver. 2006. Jaguar (*Panthera onca*) feeding ecology: distribution of predator and prey through time and space. Journal of Zoology 270:25–30.

White, G. C., D. R. Anderson, K. P. Burnham, and D. L. Otis. 1982. Capture-recapture and removal methods for sampling closed populations. Los Alamos National. Laoratory. Publication. LA-8787-NERP. Los Alamos, NM.

White, G. C. and K. P. Burnham. 1999. Program MARK: survival estimation from populations of marked animals. Bird Study 46, Supplement: 120–138.

Wong, S. T., C. W. Servheen, and L. Ambu. 2004. Home range, movement and activity patterns, and bedding sites of Malayan sun bears (*Helarctos malayanus*) in the Rainforest of Borneo. Biological Conservation 119:169–181.