Motion detection or time lapse? A comparison of camera trap triggers in the monitoring of elusive ground dwelling birds

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Abstract

Wildlife cameras have emerged over the recent years as an effective research tool for collecting various types of data on wild animals, and they are used increasingly also in avian studies. However, choosing the best method to collect data depends on the aim of the research and the characteristics of the target species and its habitat. Here, we compared the performance of game cameras taking images by passive infrared motion sensitive (PIR) and time-lapse triggering in gathering occurrence and relative abundance data of the taiga bean goose (Anser fabalis fabalis) in peatlands across Finland in 2020-2021. We found the time lapse trigger mode to be more efficient in collecting data on goose presence than PIR triggering. However, there was no significant difference in the goose numbers between the two trigger modes. We also found the capture probability and relative abundance to vary between years, but this could be attributed to random inter-annual variation. In general, we find time lapse to be a more suitable method to study elusive ground dwelling birds like the taiga bean goose due to fewer required visits to camera sites compared to motion triggered cameras that may produce a lot of empty images due to false triggering. This reduces the disturbance to the geese and other wildlife during the sensitive breeding period.

Introduction

Camera trapping has become a powerful research tool for collecting data on wildlife because it can be carried out at a relatively low cost compared to some other survey or monitoring methods that would require extended human presence in the study area. Moreover, its non-invasive nature in data collection enables the monitoring of elusive species, also in remote locations (Burton et al. 2015, Caravaggi et al. 2017). This approach has traditionally been used to gather information on various aspects of large terrestrial mammals such as occurrence (Salvatori et al. 2023), abundance (Taylor et al. 2022, Santini et al. 2022) and behaviour patterns (Li et al. 2020, Gracanin and Mikac 2022), but nowadays it is used increasingly also for birds (Caravaggi et al. 2017). It is especially useful in the study of ground dwelling birds, where game cameras have been recently used to describe, for example, activity patterns (Nykänen et al. 2021), foraging (Sperry et al. 2021), habitat use (Firth et al. 2020, Puffer et al. 2021), abundance (Kanka et al. 2023) and predation pressure (Laux et al. 2022).

Despite the great potential of game cameras as an effective research tool in a range of applications (Wearn and Glover-Kapfer 2019), they may also have several limitations associated to them, such as variability in camera performance or challenges in sampling design (Rovero et al. 2013, Jacobs and Ausband 2018, Palencia et al. 2022, Santini et al. 2022). One key aspect in camera performance is the trigger mode: in motion sensitive triggering a passive infrared (PIR) sensor triggers the camera to capture an image, whereas in time lapse triggering the camera is programmed to take images at a predefined time interval. Problems may occur, if the camera produces false triggers leading to vast amounts of blank or empty images and therefore drains batteries and fills memory card space. On the other hand, detections of target species can be missed, if the
camera is not triggered appropriately. This all causes extra work for researchers and may bias the results of studies.

Here, we compare the performance of motion sensitive and time lapse camera settings in gathering occurrence and relative abundance data of the bean goose (*Anser fabalis*) in its breeding areas in Finland. The bean goose is breeding sporadically in remote and inaccessible habitats in the arctic and boreal zones from Fennoscandia to Western and Eastern Siberia (Scott and Rose 1996, Karr 2005). The Western Palearctic population of the species, consisting mainly of individuals belonging to the subspecies taiga bean goose (*A. f. fabalis*), has declined in recent decades (Fox et al. 2010, CAFF 2018), the conservation status of the subspecies being considered Vulnerable in Finland (Lehikoinen et al. 2019). While efforts have been put into increasing the accuracy of methods used to estimate taiga bean goose numbers in the nonbreeding season (Piironen et al., 2023), monitoring its numbers in the breeding season remains a challenging obstacle to efficient conservation of the subspecies. During the breeding season taiga bean goose is highly elusive, and any survey method involving disturbance caused by the presence of human observers will further reduce the detectability of the species (Pirkola and Kalinainen 1984).

Hence, the main objective of this study was to gain a better understanding of game camera trap performance for reaching more reliable results with the most cost-effective data collection procedure for ground dwelling avian studies, bean goose serving as a research species. A specific aim of the study was to find out which trigger type, motion sensor or time lapse, captures greater goose numbers or is associated with higher daily capture probability, the latter being critical in providing occurrence data.

Materials and Methods

The study regions covered altogether 19 known bean goose peatlands across Finland in 2020 and 2021 (Fig. 1). The peatlands were located in the provinces of North Karelia (N = 5), Northern Ostrobothnia (N = 8) and Lapland (N = 6). Fifty-six and fifty-three camera traps were deployed in 2020 and 2021, respectively, for the duration of the breeding season from the beginning of May to August, covering the season when the geese were nesting, caring for the offspring and moulting. Study locations were divided into 6.25 ha grids and one or two grids were used for camera trap monitoring, depending on size of the peatland (see Nykänen et al., 2021). In each study location, 2–4 game cameras were placed by experts specialized in bean goose ecology on peatlands with ponds/water bodies. Motion sensitive cameras were set to capture two still images with a 10 s delay between triggers, and time lapse cameras were programmed to take two still images every 15 minutes. Cameras were attached on top of each other (time lapse above the motion sensor camera) to a tree or wooden pole at a height of 1 m above the ground. Cameras were typically visited once or twice during the study period to replace the memory cards and batteries, if needed. After each field season, adult taiga bean geese and goslings were detected and counted manually from the images (Fig. 2).

No permits concerning animal welfare/ethics for bean goose camera trapping were required as birds were not intentionally approached, and remote camera traps are considered to be a non-invasive study method. Camera traps were set with landowners’ permission on private land and on state-owned areas with Metsähallitus permit (permit number MH1145/2018).

Generalized linear mixed modelling (GLMM) approach was used to investigate whether there was a difference in total taiga bean goose numbers (adults and goslings added together) captured by cameras triggered by motion sensor vs cameras set to time lapse. The GLMM was run in R (R Core Team 2023) using the package glmmTMB (Brooks et al. 2017) with the factors ‘trigger type’ (motion sensor and time lapse) and ‘year’ (2020 and 2021) as fixed factors and with the factor ‘site’ (19 individual peatland ponds) included as a random intercept in the model. The varying effort, resulting from the different number of cameras deployed on the study sites and the amount of time that the cameras were recording over the study period, was accounted for by including an offset-term in the model that was calculated by totalling the number of time periods of recording per trigger type for each day. Due to the data including a large number of zero values (some days and time-periods had zero goose counts), we ran different candidate models with a Tweedie, Poisson and two types of negative Binomial distributions (NB1 and NB2 parameterizations; Hardin and Hilbe 2018, Bolker
2022) with and without accounting for the zero-inflation.

In addition, we ran a set of logistic models (see Table 1) to investigate whether the camera trigger type affects the daily capture probability (presence or absence in photos) of taiga bean geese. Here, we define capture probability as “the probability that an animal is captured in a photo given it is present in the camera’s viewshed” as per Moeller et al. (2023). Since it was not possible to include the offset-term in this type of model, we added the camera effort as a continuous covariate in the models. Other covariates were included as fixed (‘trigger type’ and ‘year’) or random (‘site’) factors the same way as in the count models.

We then compared model fits using Akaike’s Information Criterion (AIC) values to determine the best fitting models. The goodness of fit of the models were assessed by creating scaled quantile residual plots via simulation using the R-package DHARMa (Hartig 2022).

**Results**

Altogether, the motion sensor triggered cameras captured 24,596 and 45,387 images and the time lapse cameras 134,979 and 142,506 images in 2020 and 2021, respectively.

The best fitting count model had a negative Binomial distribution (NB1 parameterization) and it accounted for zero-inflation (zero-inflation p < 0.001, Table 1). It included the fixed factors ‘trigger type’ and ‘year’ without their interaction and the random intercept of ‘site’ (random effect variance (σ²) of 0.9062 and standard deviation (SD) of 0.952). Taiga bean goose count was significantly higher in 2021 compared to 2020 (p < 0.001, Fig. 3), however, the camera trigger type had no significant effect on the number of geese (p = 0.129).

As the AIC values were within < 2 of each other, the best fitting logistic model on goose capture probability was selected based on parsimony and it included the fixed terms ‘trigger type’, ‘year’ and ‘effort’ without interactions and the random intercept of ‘site’ (random effect σ² = 0.6215 and SD = 0.7883, Table 1). The capture probability increased significantly with increasing camera effort (p < 0.001) and was significantly higher in the year 2021 (p < 0.001) and marginally significantly higher (p = 0.049) with game cameras set to time lapse (Fig. 4).

**Discussion**

Time lapse cameras may allow the collation of more standardized data than motion triggered cameras and potentially reduce the number of empty images produced by false triggering. Our study shows that the overall daily capture probability of taiga bean geese was higher with cameras set to time lapse compared to motion sensitive cameras. However, there was no significant difference in the daily number of geese captured with the two trigger types. This difference in the results of the two models, albeit quite subtle, could at least partly be explained by the motion triggered cameras failing to capture the more distant animals, whereas the time lapse method captures both near-by and distant animals. This makes positioning of the camera traps on time lapse setting less critical as animals can be detected even if they do not use their exact assumed route or habitat. Indeed, in order for the animal to be captured with the motion trigger mode, the PIR sensor must detect motion in the trigger area while the animal is within the camera’s viewable area (Moeller et al. 2023).

Our study on taiga bean geese in their breeding areas shows that time lapse cameras are more useful than motion triggered cameras in collecting data on the habitat use of animals because of the higher capture probability of the former. In addition, required memory card space and battery needs are predictable. This is an important finding, because the use of time lapse cameras reduces the need to visit the camera sites for changing batteries and memory cards, hence reducing the disturbance during the sensitive breeding period of the geese. An important advantage also is that time lapse cameras will produce more reliable data of sites that are used by taiga bean geese in the breeding areas, an information crucially important for protection of the species. This information is difficult to obtain using human observers as the species is highly elusive and occupies very remote breeding areas.
Choosing the triggering mode depends on the research objectives and characteristics of the target species and its habitat. As our study shows, time-lapse may be more suitable, for example, in studies involving habitat use and the designation of protected areas where it is important to distinguish between used and unused sites. Motion trigger mode, on the other hand, may be more useful in studies on movement or behaviour, or in cases where the density of the animals is low, as it is possible that the time lapse method may fail to detect the target species altogether (Moeller et al. 2023). Moreover, motion triggered cameras have been shown to capture a higher proportion of animals than cameras operating on time lapse, such as in a study monitoring wildlife underpass usage (Pomezanski and Bennett 2018).

Camera trapping has gained popularity in wildlife studies over the recent years due to its efficiency to collect opportunistic image data without the need to dedicate numerous hours of researchers’ time present on the study site. At the same time, large volumes of images collected with this method continue to be one of the challenges in the subsequent data management and analysis. For example, a single camera operating on time lapse with a 15-minute interval, a setting used in this study, outputs 96 photos in a 24-hour period, and accumulates a dataset containing more than a thousand images over a study period longer than ten weeks. On the other hand, motion sensitive triggering may produce thousands of “empty” images in a short time period that still need to be checked for the presence of the target species. In total, our two-year study period produced nearly 350,000 images, which all were gone through manually, forming the most labour intensive and costly part of the study. In order to reduce the time allocated to this painstaking process, machine learning techniques (automatic identification algorithms) together with citizen science approach (e.g., Wei et al. 2020, Hilton et al. 2022, Bjerge et al. 2023) have the potential to become some of the most important innovations in the cost-effective identification and counting of animals from large camera trap datasets in future studies.

We found a difference in the number of geese and in their capture probability (i.e., presence) between the two study years. Unfortunately, because standardized monitoring data of the annual numbers of the taiga bean goose in the breeding areas are not available, it is not possible to say if the between-year difference reflects a real difference of breeding numbers or just random variation. Nevertheless, the findings of this study and those of Nykänen et al. (2021), together covering data from four successive breeding seasons (2018-2021), suggest that wildlife cameras are a feasible method for monitoring taiga bean goose during the breeding season. First, they can reveal between-year differences both in the numbers and occurrence of the species. Second, wildlife cameras set at fixed sites are a cost-effective method to gather highly comparable long-term data from remote breeding areas that are difficult to access and cover using other survey methods. And finally, non-expert citizens could be engaged in the monitoring based on wildlife cameras, making it possible to cover a large number of potentially important breeding sites (peatlands).

Data availability
Data and the R-script used to generate the analyses can be found in the online supporting information.

References

Bolker, B., 2022. Getting started with the glmmTMB package. 8pp. <https://cran.r-project.org/web/packages/glmmTMB/vignettes/glmmTMB.pdf>


Wearn, O.R., Glover-Kapfer, P., 2019. Snap happy: camera traps are an effective sampling tool when compared with alternative methods. R. Soc. open sci. 6, 181748. https://doi.org/10.1098/rsos.181748


Figure legends
Fig. 1. Study areas. Location of the study areas (in provinces of Lapland (1), Northern Ostrobothnia (2), and North Karelia (3)), the peatlands where camera traps were deployed in 2020 and 2021. The maps were drawn using R-packages ggplot2 (Wickham, 2016) and ggmap (Kahle and Wickham, 2013) with map tiles by Stamen Design, under CC BY 3.0 (data by OpenStreetMap, under ODbL). The inset map was drawn using Natural Earth map data.

Fig. 2. Taiga bean goose captured with a PIR sensor triggered camera in Pirttilammit, North Karelia, in 2021.

Fig. 3. Conditional effects of a) year and b) trigger type on the number of taiga bean goose captured with game camera traps on peatland ponds in Finland between 2020 and 2021. The difference was significant between years (p < 0.001) but not significant between trigger types (p = 0.129).

Fig. 4. Conditional effects of a) year, b) trigger type, and c) camera effort on the capture probability of taiga bean goose photographed with game camera traps. The difference was significant between years (p < 0.001) and marginally significant between trigger types (p = 0.049). The amount of camera effort had a significant positive effect on capture probability (p < 0.001).

Tables

Table 1. Summary of candidate models ran to investigate the effect of trigger type on the number and presence of taiga bean goose captured on game camera traps. NB stands for negative Binomial with two different parameterizations (Bolker, 2022; Hardin and Hilbe, 2018).

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<th>Model formula</th>
<th>Distribution and type</th>
<th>ΔAIC</th>
<th>df</th>
</tr>
</thead>
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<td>NB1 + zero-inflation</td>
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† random intercept of ‘site’