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Research article

Assessing the potential of camera traps for estimating activity pattern compared to collar-mounted activity sensors: a case study on Eurasian lynx *Lynx lynx* in south-eastern Norway

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The diel activity patterns of animals convey information about physiology, ecological niches and animal behaviour relevant for both applied conservation and more theoretical research. However, these patterns are challenging to study in the field. The current gold-standard approach to quantify movements and activity patterns of medium to large wildlife species is to use global positioning systems (GPS) collars equipped with activity sensors (e.g. accelerometers). A more recent approach consists of inferring activity patterns from the time-stamped pictures of wildlife obtained from camera traps now routinely used in wildlife monitoring projects. However, few studies have attempted to validate estimates of activity patterns obtained from camera traps against those obtained from activity sensors. In this study, we compared the diel activity pattern of the Eurasian lynx *Lynx lynx* inferred from detections by a network of over 300 camera traps active between 2010 and 2020, to activity patterns obtained from 18 GPS-collared lynx (8 females, 10 males) equipped with 2-axis accelerometer sensors, in the same area of southern Norway. Our results suggest that camera traps can be used to estimate diel activity curves that are comparable to those obtained from accelerometers. In our study, 75 detections were sufficient to approximate the diel activity pattern obtained from accelerometer. Subsampling indicated that a low number of detections results in a coarser approximation of the diel activity pattern.

Keywords: Accelerometer, activity pattern, camera trap, lynx lynx, methodology

Introduction

Animals tend to have predictable activity patterns, alternating between periods of activity and resting, based on their ecological and physiological needs (Rowcliffe et al. 2014).



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Animal activity is affected by a variety of internal factors such as age, sex, reproductive status, body condition and energy budgets (Podolski et al. 2013, Rowcliffe et al. 2014), but also by external factors such as human disturbance, predation risk, access to food/prey, temperature (Beltran and Delibes 1994), daylight (Heurich et al. 2014) and season (Manfredi et al. 2011, Heurich et al. 2014). Investigating factors influencing activity patterns for different species or populations can provide insights into physiology, niche theory, community structure and animal behaviour (Podolski et al. 2013, Frey et al. 2017, Edwards et al. 2021). Furthermore, conservation management can benefit from knowledge derived from activity studies. For example, research has shown that many wildlife species change their activity patterns as a consequence of anthropogenic disturbance (Gaynor et al. 2018, Edwards et al. 2021), hunting pressure (Van Doormaal et al. 2015, Edwards et al. 2021) and the reintroduction of predators that affect prey species' diel patterns (Tambling et al. 2015, Edwards et al. 2021).

Although the study of activity patterns of wild species is often challenging, recent developments in technology have led to different methods being applied that vary in the degree of invasiveness towards animal welfare and the financial and logistical efforts required to operate them. Currently, the most common approach to quantify movements and activity patterns of wildlife is to use global positioning system (GPS) collars (Cagnacci et al. 2010, Eriksen et al. 2011, Kays et al. 2015) equipped with a motion sensor or accelerometer which constantly monitors animal activity independently from its spatial location with respect to the observer (Lottker et al. 2009, Podolski et al. 2013, Edwards et al. 2021). These motion sensors record neck and upper body movement, providing the opportunity to remotely categorize animal behaviour in addition to overall activity (Lottker et al. 2009, Brown et al. 2013, Krop-Benesch et al. 2013, Wang et al. 2015, Roberts et al. 2016). The most advanced sensors store three different values differentiated as vertical and horizontal motion, and tilt angle, whereas less complex models record only vertical and horizontal motion, or simply any forceful motion (Wang et al. 2015, Roberts et al. 2016). Motion sensors and accelerometers record activity at high temporal resolution, and some studies have already demonstrated that the estimations of behaviour made from these tools are comparable to continuous visual observation (Gervasi et al. 2006, Lottker et al. 2009, Gonzales et al. 2015, Roberts et al. 2016, Edwards et al. 2021, Studd et al. 2021). This accelerometer method of studying wildlife behaviour is particularly relevant for elusive, mainly nocturnal, forest-living species, which are difficult to observe directly, such as the Eurasian lynx *Lynx lynx* (Podolski et al. 2013). This species has already been investigated through the lens of accelerometer data: studies by Heurich et al. (2014) and Podolski et al. (2013) demonstrated that collar activity sensors allow the identification of factors that modulate lynx activity.

More recently, the use of digital camera traps, which allow for the non-intrusive detection and monitoring of elusive wildlife at a large spatial scale (Kelly and Holub 2008,

Sollmann et al. 2011), have become a new potential tool for estimating activity patterns (Edwards et al. 2021). Timestamps on camera trap images reflect wildlife occurrences and produce precise temporal data (Sollmann 2018, Edwards et al. 2021). Recent advances in the analyses of circular data (i.e. around the 24 hours of a day) recorded by camera traps (Rowcliffe et al. 2014, Edwards et al. 2021, Meredith and Ridout 2021) allow researchers to extract more details about the activity of the animals detected (Edwards et al. 2021). Following on from these innovations, a wide range of species have already been studied using these novel activity estimation methods (Lynam et al. 2013, Rowcliffe et al. 2014, Frey et al. 2017, Lashley et al. 2018, Edwards et al. 2021). However, there are fundamental differences in the quantity and the nature of camera trap data compared to data recorded by collar mounted activity sensors. For instance, camera traps typically record relatively few detections of activity from each individual of the chosen species but will typically sample a larger proportion of the individuals in the area than collars would do, while also detecting the activity of other species present in the same region (Burton et al. 2015). Cameras also only record activity in the immediate vicinity of the camera trap, and therefore are potentially open to bias toward quantifying specific activities, if for example camera traps are placed in areas or habitat associated with specific behaviours. The age, sex and identity of the individuals photographed is also not always known. On the other hand, collar-mounted activity sensors provide continuous fine-scale individual data, resulting in a more comprehensive picture of activity from a smaller sub-sample of individuals with known age and sex (Frey et al. 2017, Lashley et al. 2018, Edwards et al. 2021). Moreover, camera traps capture single points in space and time exclusively when the animal is moving, often only detecting a few specific behaviours such as walking or running while cutting out a wide range of activities that the animals perform on a daily basis (resting, grooming, eating, etc) (Edwards et al. 2021). On the other hand, accelerometers provide a continuous record of activity with a high frequency, recording a wide range of behaviours (Heurich et al. 2014) and are therefore the most accurate way of studying wildlife activity remotely today.

There are still relatively few studies that compare the reliability of activity estimations obtained from camera traps to those derived from activity sensors (Wolfson et al. 2023). Here, we compared activity pattern estimations obtained from Eurasian lynx detections recorded from more than 300 camera traps distributed in the southern part of Norway during a period of 11 years (from 2010 to 2020) with activity data obtained from GPS collars with 2-axis accelerometers fitted on 18 Eurasian lynx (8 females and 10 males) during an 8-year study period (from 2008 to 2015) in the same broad geographical area. We investigated the following questions:

- 1) Are camera traps reliable for estimating Eurasian lynx activity pattern compared to accelerometer estimations?
- 2) If yes, what is the effort, in terms of number of detections, required to obtain reliable activity estimations from camera traps?

Material and methods

Study area

This study was conducted in five counties in south-eastern Norway: Innlandet, Viken, Oslo, Vestfold og Telemark and Agder (~ 111 019 km² area) (Fig. 1). The northern parts of the study area are characterized by a series of large valleys separated by hills or mountains reaching 1000 m a.s.l. and relatively low human population densities. This area is associated with boreal forests with primarily Norway spruce *Picea abies* and Scots pine *Pinus sylvestris*. The southern parts of the study area have lower altitudinal gradients and higher human population densities; here there are mainly patches of mixed coniferous/deciduous forests alternated with cultivated lands. Eurasian lynx are widespread throughout the study area (Tovmo et al. 2023), with three other large carnivore species present: brown bear *Ursus arctos*, grey wolf *Canis lupus* and wolverine *Gulo gulo*, although these species occur in low densities compared to the lynx. Other species of prey and meso-predators include moose *Alces alces*, red deer *Cervus elaphus*, roe deer *Capreolus capreolus*, badger *Meles meles*, red

fox *Vulpes vulpes*, pine marten *Martes martes* and mountain hare *Lepus timidus*.

Accelerometer data

Accelerometer data were obtained from 18 lynx (8 females and 10 males) equipped with GPS collars that also contained 2-axis accelerometers (GPS plus mini, Vecronic Aerospace) between 2008 and 2015 as part of the SCANDLYNX project (<http://scandlynx.nina.no>). Lynx were captured using a combination of methods including walk-through box-traps and foot snares, following the protocol described by Gervasi et al. (2006) and Arnemo et al. (2011). All procedures were approved by the Norwegian Experimental Animal Ethics Committee, and permits were obtained from the Norwegian Environment Agency. The accelerometers in the collars measured acceleration along two axes: forward/backward motion (x-axis) and sideward/rotary motion (y-axis). The values recorded ranged from 0 (no activity) to 255 ($\pm 2G$ of force) and they were measured with a frequency of 8 Hz (8 records per second) in default mode and eventually recorded as the average value across 5 minutes intervals, generating a massive

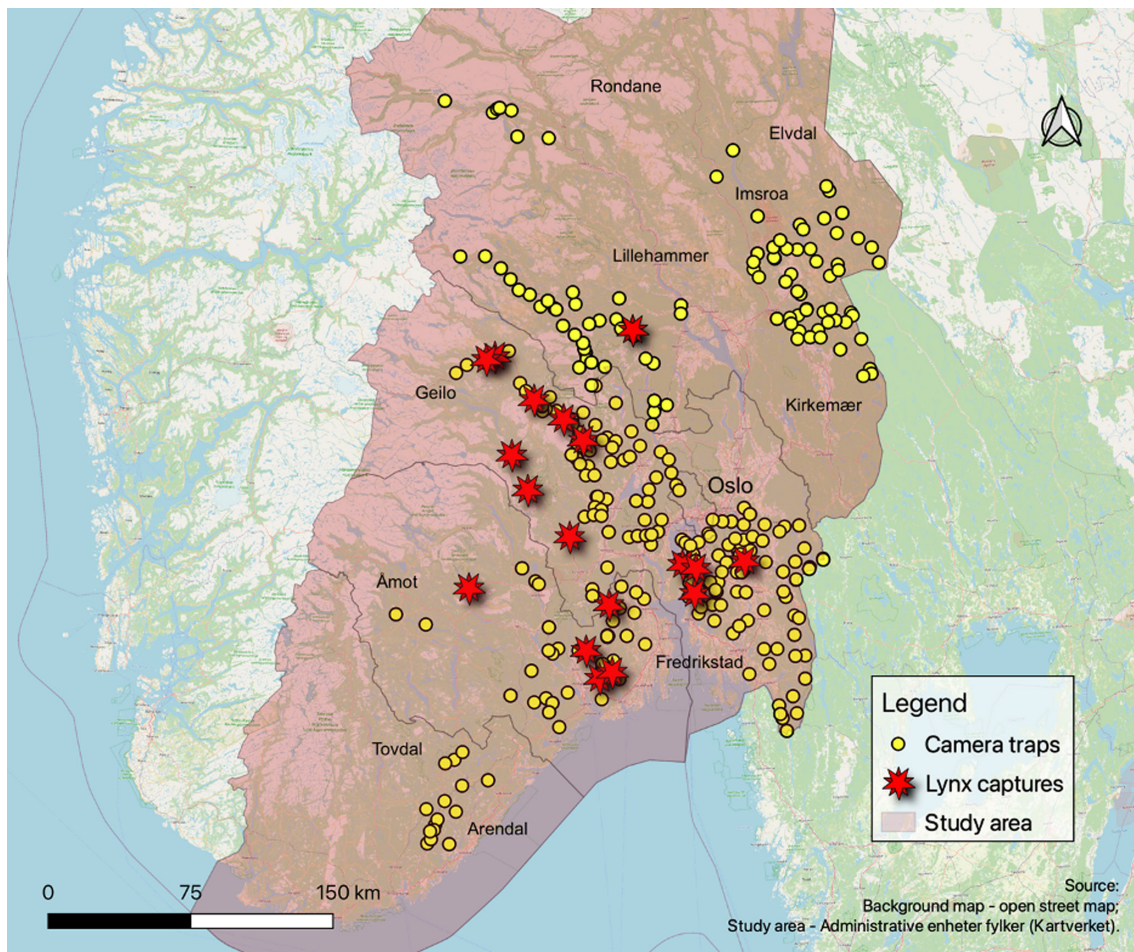


Figure 1. The study area with distribution and locations of camera traps as well as the locations where lynx were captured and equipped with accelerometers.

amount of detailed information about the animal's activity. Only x-activity values were analysed in this study since the two axes have already been shown to be highly correlated in previous studies (Heurich et al. 2014). Previous studies, using identical equipment from the same manufacturer (Podolski et al. 2013, Heurich et al. 2014), considered all values from 0 to 27 as 'inactive' while all values that range from 28 to 255 were considered as 'active'. The same classification was used here. Overall, data from the accelerometers covered a total of 5496 lynx days across an 8-year period, from 2008 to 2015, resulting in ~ 1.5 million 5 minutes recordings of activity.

Camera trap data

Camera trap detections of lynx were obtained from 327 camera traps (Reconyx HC500 HC600, PC850, PC900 and HP2X, Holmen, Wisconsin, USA) distributed in the study area as part of the SCANDCAM project (Fig. 1; <https://viltkamera.nina.no/>). The cameras were widely dispersed using a grid system at a density of one camera per 50 km², which translates as 5 to 10 cameras per lynx home range. Within each grid cell, camera traps were placed at locations chosen to maximize lynx encounters, i.e. locations where lynx tracks were found during snow tracking or where lynx were expected to travel (e.g. forest roads, along the base of a cliff or on a wildlife trail). The cameras were active year-round with memory cards and batteries changed four times every year. More details on camera traps placement and period of activity can be found in Hofmeester et al. (2021), and information about sites and data is available at <https://viltkamera.nina.no>. All images from SCANDCAM were pre-processed with a two-step neural network Artificial Intelligence enabled workflow, where images were first classified as containing humans/vehicles or animals, and those with animals were then classified to species (details can be found in Hofmeester et al. 2021). Images of people were automatically deleted, and animal species classifications were later checked by staff and students at the Norwegian Institute for Nature Research. Data used in this study resulted from 11 years of monitoring, from November 2010 to December 2020, and a total of 2292 independent detections of lynx.

Kernel density estimation of activity patterns and overlap analysis

Eurasian lynx are known to modulate the active phase of their daily activity cycle following the widening and narrowing of the photoperiod (Heurich et al. 2014). For this reason, we compared the activity pattern inferred from camera traps to that obtained from accelerometers for three different distinct seasons which were defined by the daylength (hereafter 'hours of light'). We estimated the daylength of each observation based on the date-time of the observation and reference geographic coordinates (location of the initial lynx capture for the accelerometer data, and the location of each camera trap for camera trap data) using the package 'suncalc'

(Thieurmél and Elmarharaoui 2019) in R (www.r-project.org), considering the package categories where 'sunrise' (top edge of the sun appears on the horizon) and 'sunset' (sun disappears below the horizon, evening civil twilight starts) was used as start and end of day length. We visually inspected plotted curves of activity derived from accelerometers to help us define three distinct levels of hours of light that clearly captured the change in activity across seasons: 5 to 7 hours (winter), 11 to 13 hours (spring and autumn), and 17 to 19 hours (summer).

Since both accelerometers and camera traps record the times of the observations, it is possible to fit kernel density functions to estimate the distribution of activity throughout the day (Ridout and Linkie 2009). We used the R package 'overlap' (www.r-project.org, Meredith and Ridout 2021) to fit a Von Mises kernel (to accommodate circular time data) to observations from camera traps and observations defined as active from the accelerometers to obtain their density distribution, which corresponds to the diel activity pattern. We then used the estimated coefficient of overlap between the two distributions as an indicator of the ability of the camera trap approach to reflect the same activity pattern as that obtained from the accelerometers. Following advice by Meredith and Ridout (2021), we used the so-called Δ_4 estimator for camera trap samples bigger than > 50 detections, and Δ_1 for smaller samples. For each subset of hours of light (i.e. 5–7, 11–13, 17–19 hours), we report the graphical representation of the kernel density distribution of activity for both monitoring methods, together with the corresponding estimate of the coefficient of overlap and its 95% bootstrap confidence interval. All analyses used central European time (CET/UTM+1) which corresponds to local time during winter.

How many detections are needed to recover the 'true' activity pattern?

In order to assess the minimum number of camera trap detections required to capture the 'true' activity pattern, as inferred from accelerometers, we repeated the overlap analysis described above for random subsets of the camera trap detection data, while keeping the accelerometer data set unchanged. For each level of daylight duration, we took a subsample of 300, 350, 200, 150, 100, 75, 50, 25 and 10 detections without replacement, from the total detections of the original camera trap dataset. For each of these subsamples, we then estimated the kernel density distribution, the coefficient of overlap of this distribution with that of the (original) accelerometer data, and the associated 1000-iterations bootstrap confidence interval. In order to capture uncertainty induced by random subsampling of the camera trap detections, we replicated this procedure 1000 times for each subsample size. For performance reasons, we implemented this algorithm in the Julia language (Bezanson et al. 2017). In Julia, we used the least-squares cross-validation to determine the bandwidth of the kernel density estimator, while the 'overlap' package used Silverman's rule. Hence, the results are not directly comparable to those from the 'overlap' package in R (www.r-project.org).

Below, we report the coefficient of overlap averaged over the replicates for each sample size and level of daylight duration, together with the associated 95% bootstrap confidence interval. In addition, we ran a similar procedure using subsampling of the number of cameras rather than the number of detections. However as the number of cameras needed will be strongly dependent on the detectability and density of lynx in the study area as well as the grid design, this analysis has less extrapolation values to other studies, and we only present these results in [Appendix 1](#).

Results

Activity pattern and overlap analysis

Out of the 2292 lynx detections in the original camera trap data set, 639 detections corresponded to periods with 5–7 daily hours of light, 552 to 11–13 hours of light, and 333 to 17–19 hours of light. The plots of the daily activity showed that the curves estimated from camera traps overall matched the activity curves obtained from accelerometer data ([Fig. 2](#), [Table 1](#), coefficient of overlap 0.92–0.97). Both accelerometer and camera trap estimations show that in periods with less daylight (5 to 7 hours of light), the activity curves displayed shorter periods of consistently low activity limited to a few central hours of the day and a longer period of activity coinciding with longer nights. During the short light period, from both estimations, we see that the change of activity (from resting to being active) is more accentuated compared to the period with more daylight (17 to 19 hours of light), and peaks of activity are around 5:00–6:00 (slightly before dawn) and 15:00–16:00 (dusk). In contrast, in periods of the year with more daylight, activity curves estimated from both accelerometer and camera traps show that the activity was more attenuated, with peaks of activity occurring at 2:00–3:00 (dawn) and 21:00–22:00 (dusk).

How many detections are needed to estimate the ‘true’ activity pattern?

The estimates for the coefficient of overlap started to reach an asymptote at 75 camera trap detections ([Fig. 3](#), [Table 2](#), coefficient of overlap 0.91–0.92). Increasing the number of detections further did not improve the overlap significantly. However, the use of 50 detections reduced the coefficient of overlap to only 0.63–0.66. Reducing the number of detections further did not reduce overlap much but increased the variability in the coefficient.

Discussion

In the present study, estimations of activity based on camera traps produced very similar activity curves as those estimated from accelerometer data, showing support for the ability of non-invasive methods to record information on diel activity

pattern comparable to that obtained from more invasive methods. Camera trap detections followed the activity patterns estimated by accelerometers with high coefficients of overlap for all seasons (levels of hours of daylight). Both periods of high activity at night, periods of low activity at midday, and peaks of activity at dawn and dusk were identified successfully from activity estimations of camera trap detections.

These results derive from a large number of lynx detections (~ 1500) which was achievable thanks to an exceptionally high number of camera traps used (327 cameras) covering a long monitoring period (11 years) with year-round deployment. This exceeds the effort that is commonly used in most camera trapping studies. However, further analyses showed that in our study system, 75 lynx detections were sufficient to get a reliable estimate of the daily activity cycle of the lynx during different times of the year, which is a more reasonable number to achieve.

The number of cameras needed to get enough detections for reliable estimates of activity patterns will vary considerably depending on species detectability and density and the general study design (random locations versus camera traps that maximise detection), which makes it difficult to make general recommendations on number of cameras (in [Appendix 1](#) we reported an attempt to explore the effect of the number of camera traps on activity estimations on our case study). Population densities often vary within the same species across different regions because of environmental conditions and management regimes. For Eurasian lynx in Scandinavia home range sizes, and densities, vary by a factor of ten ([Linnell et al. 2001](#), [Aronsson et al. 2016](#)). For studies that will focus on the diel activity patterns, researchers therefore need to design a strategy for how to obtain at least 75 detections rather than focusing on number of cameras.

Activity data obtained from camera traps still differ from collar activity sensor data in the matter of temporal and spatial resolution and type of activity recorded. The comparability of the estimates may thus depend on the movement ecology of the species in question. However, it is important to realise that camera traps capture limited data from many individuals in an area, often lacking information on age, sex, and identity and mainly recording animal movement. Camera traps will not be able to provide activity budgets of individuals or effective linkages between activity and movement, for example. Instead, collar-mounted sensors provide continuous, detailed data from specific individuals with known attributes, offering a high-frequency and comprehensive activity record.

In our study area, the placement of camera traps within the grid cells was chosen to maximise the detection probability of lynx, which is common practice when working with elusive species ([Rowcliffe et al. 2014](#), [Lashley et al. 2018](#)). However, previous studies underlined that for estimating activity curves from camera trap detections it would be preferable to randomly place the devices ([Rowcliffe et al. 2014](#)) to make sure not to include any potential biases in activity depending on the location of the traps. For instance, if lynx use areas close to people more often at night compared to the day. This could potentially result in activity estimations

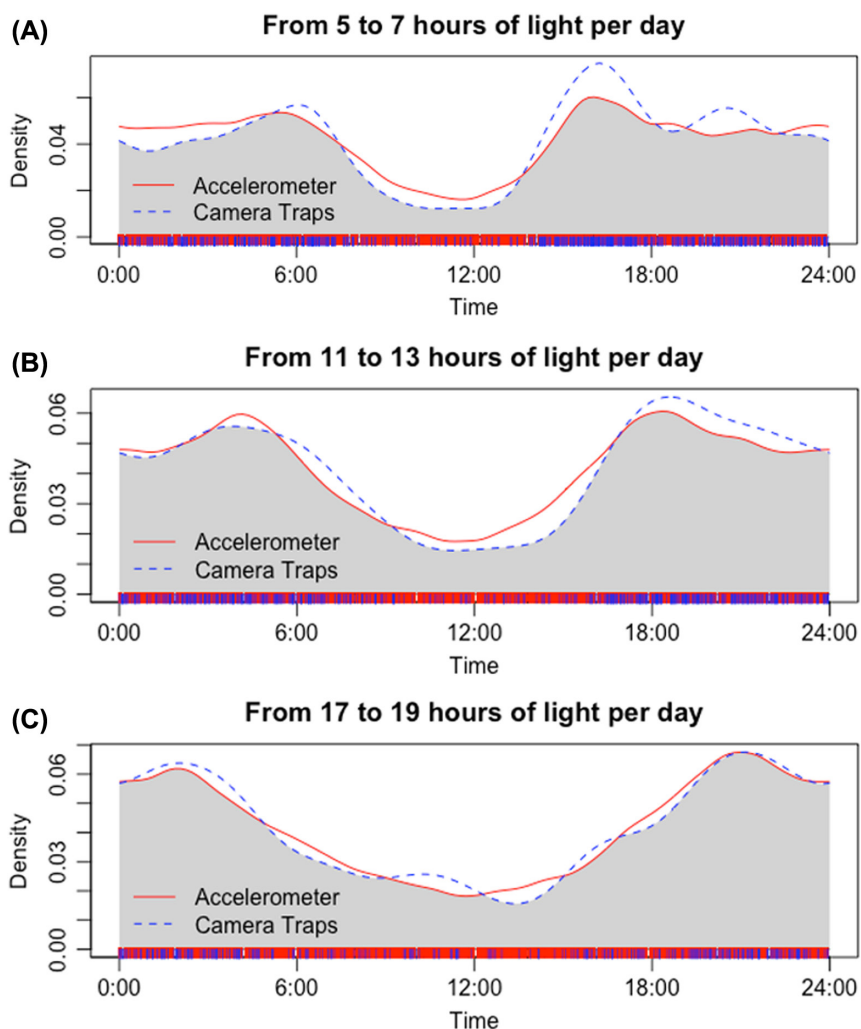


Figure 2. Overlap (grey area) between lynx diel activity pattern obtained from accelerometer data (plain red line) and camera traps data (dashed blue line) for times of the year with (a) 5 to 7 hours of light per day, (b) 11 to 13 hours of light per day and (c) 17 to 19 hours of light per day. The rug plot indicates the actual observations for camera traps (blue) and accelerometer (red).

being biased towards night if cameras were only located in areas close to people (Thorsen et al. 2022). However, in our study, cameras were placed in different habitat with different human pressure and we consider the non-random placement of the camera traps to not affect the overall results obtained, further supported by the high overlap between the camera traps data and the accelerometer data. If our camera trapping data would have suffered from a high bias, i.e. camera traps placed in habitat where lynx is only active during day

or night, one would have expected a lower degree of overlap with accelerometer data. Bias was probably reduced in our case by the very dispersed nature of our camera deployment, and the fact that the cameras were deployed by many different volunteers leading to a large diversity of deployment decisions.

Detection probability can be an important factor to consider in camera trap studies. The probability of detecting an animal through camera traps relies on several factors (Lashley et al. 2018, Smith et al. 2020). For example, habitat at, and around, the camera locations as well as species and/or individual specific characteristics (such as group size, home range size, density, geographical range, response to camera trap) may considerably affect detection probability (Lashley et al. 2018, Broadley et al. 2019, Hofmeester et al. 2019, Delisle et al. 2021). For lynx, detection probability may be lower for females between May and August, as females with kittens move over smaller areas due to a central-place foraging strategy and low mobility of the kittens (Schmidt

Table 1. Summary of estimates of the coefficient of overlap between accelerometers and camera traps dataset (dhat4) and associated 95% bootstrap confidence intervals, taking into account the three levels of hours of light per day.

Hours of light per day	Estimate of overlap	%95 bootstrap CI
5–7	0.92	0.89–0.95
11–13	0.96	0.93–0.98
17–19	0.97	0.94–0.98

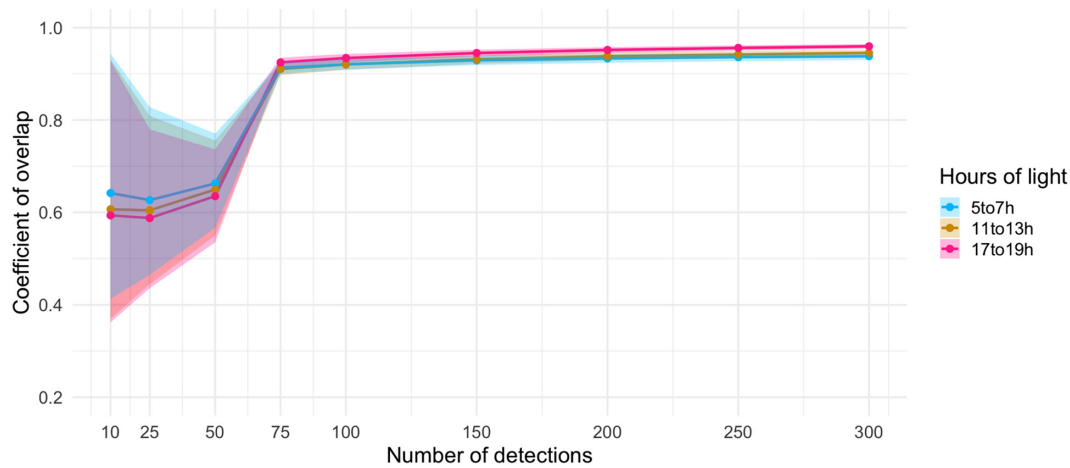


Figure 3. Overlap estimates of activity patterns using the original accelerometer data set compared with down sampled number of detections from the camera trap dataset, separated between different hours of daylight (blue: 5 to 7 hours of light, yellow: 11 to 13 hours of light, and red: 17 to 19 hours of light). Coefficients of overlap are shown with their respective 95% bootstrap confidence intervals.

1999). On the other hand, males generally move over larger areas during the mating season (February–March) compared to the rest of the year. This is a clear example of how the target species ecology and behaviour can influence detectability at camera traps and eventually impact the number of detections (Broadley et al. 2019, Hofmeester et al. 2019). In addition, some camera traps specifications, e.g. battery length, sensor

sensitivity and trigger speed, also affect the detection of the target species (Hofmeester et al. 2019).

Conclusion

Camera traps can be used to estimate overall activity curves with comparable estimations to the ones obtained from accelerometers. In our study, we conclude that 75 detections are sufficient to obtain good estimates of diel activity patterns, and a lower number of detections results in a less accurate activity estimation. Although the camera traps can be efficiently used to estimate activity patterns it is important to keep in mind the fundamental differences that occur between data collected from these two methodologies and the strengths/weaknesses of each method.

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Author contributions

Elena Iannino: Conceptualization (lead), Formal analysis (lead), Methodology (lead), Project administration (lead), Supervision (lead), Validation (lead), Writing – original draft (lead). **John D. C. Linnell:** Conceptualization (lead),

Table 2. Estimates of the coefficient of overlap between accelerometers and camera trap detections and associated 95% bootstrap confidence intervals.

Hours of light per day	No. of detections	Estimate of overlap	%95 bootstrap CI
5–7	300	0.93	0.92–0.94
11–13	300	0.94	0.93–0.95
17–19	300	0.95	0.95–0.96
5–7	250	0.93	0.92–0.94
11–13	250	0.94	0.93–0.94
17–19	250	0.95	0.95–0.96
5–7	200	0.93	0.92–0.94
11–13	200	0.93	0.92–0.94
17–19	200	0.95	0.94–0.95
5–7	150	0.92	0.91–0.93
11–13	150	0.93	0.92–0.94
17–19	150	0.94	0.93–0.95
5–7	100	0.92	0.90–0.93
11–13	100	0.92	0.90–0.93
17–19	100	0.93	0.92–0.94
5–7	75	0.91	0.89–0.92
11–13	75	0.91	0.89–0.92
17–19	75	0.92	0.91–0.93
5–7	50	0.66	0.56–0.77
11–13	50	0.64	0.54–0.75
17–19	50	0.63	0.53–0.73
5–7	25	0.62	0.46–0.82
11–13	25	0.6	0.44–0.80
17–19	25	0.58	0.43–0.77
5–7	10	0.64	0.41–0.93
11–13	10	0.6	0.36–0.93
17–19	10	0.59	0.36–0.92

Methodology (equal), Project administration (supporting), Supervision (lead), Writing – review and editing (equal). **Olivier Devineau**: Formal analysis (lead), Methodology (supporting), Supervision (equal), Validation (equal), Writing – review and editing (equal). **John Odden**: Data curation (equal), Methodology (equal), Resources (lead), Validation (equal), Writing – review and editing (equal). **Jenny Mattisson**: Conceptualization (equal), Data curation (equal), Resources (equal), Supervision (equal), Writing – review and editing (equal). **Neri Horntvedt Thorsen**: Formal analysis (equal), Methodology (equal), Resources (equal), Supervision (equal), Validation (equal), Writing – review and editing (equal).

Transparent peer review

The peer review history for this article is available at <https://www.webofscience.com/api/gateway/wos/peer-review/wlb3.01263>.

Data availability statement

Data are available from the Dryad Digital Repository: <https://doi.org/doi:10.5061/dryad.4f4qrfjmp> (Iannino et al. 2024).

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Appendix 1

Effect of subsampling number of cameras used to produce stable estimates of activity pattern

The number of camera traps was subsampled and resulting activity estimations compared to the estimations obtained from the unchanged accelerometer dataset following the same procedure used for the subsampling of the number of camera traps detections (see main paper). After subsampling our camera traps, it was found that a minimum of 75 camera traps was required to obtain a dependable estimate of true activity (Fig. A1; Table A1, coefficient of overlap 0.87 - 0.9). Increasing the number of camera traps beyond this threshold did not result in a significant improvement in overlap. However, when only 50 camera traps were used, the coefficient of overlap decreased to a range of 0.61-0.66. Further reduction in the number of camera traps not only decreased overlap but also substantially increased the variability in the coefficient.

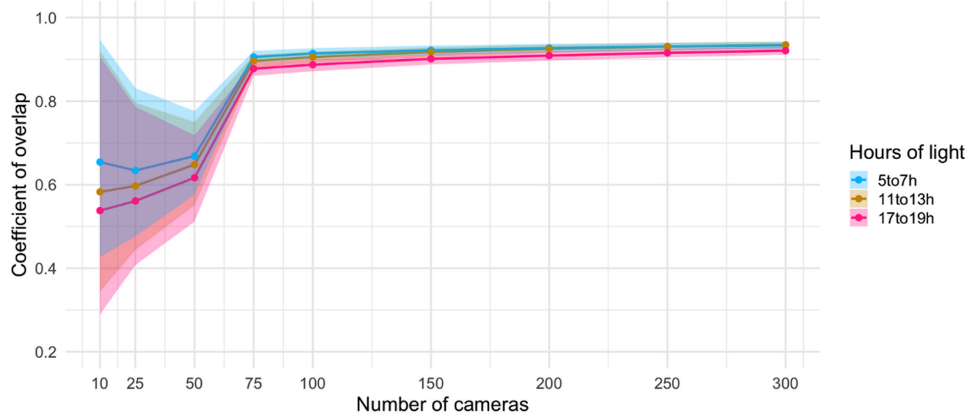


Figure A1. Overlap estimates using the original accelerometer data set compared with down sampled number of camera traps, separated between different amounts of daylight duration (blue: 7 hours of light, yellow: 11 to 13 hours of light, and red: 17 to 19 hours of light). Coefficients of overlap are shown with their respective 95% bootstrap confidence intervals.

Table A1. Estimates of the coefficient of overlap between accelerometers and number of camera traps and associated 95% bootstrap confidence intervals.

Hours of light per day	No. of camera traps	Estimate of overlap	%95 bootstrap CI
5-7	300	0.93	0.920-0.94
11-13	300	0.93	0.92-0.94
17-19	300	0.92	0.91-0.93
5-7	250	0.93	0.92-0.93
11-13	250	0.93	0.92-0.93
17-19	250	0.91	0.90-0.92
5-7	200	0.92	0.91-0.93
11-13	200	0.92	0.91-0.93
17-19	200	0.9	0.89-0.91
5-7	150	0.92	0.91-0.93
11-13	150	0.91	0.90-0.92
17-19	150	0.9	0.88-0.91
5-7	100	0.91	0.90-0.92
11-13	100	0.9	0.89-0.91
17-19	100	0.88	0.87-0.90
5-7	75	0.9	0.89-0.92
11-13	75	0.89	0.88-0.91
17-19	75	0.87	0.86-0.89
5-7	50	0.66	0.57-0.77
11-13	50	0.64	0.55-0.74
17-19	50	0.61	0.51-0.71
5-7	25	0.63	0.47-0.83
11-13	25	0.59	0.44-0.79
17-19	25	0.56	0.40-0.78
5-7	10	0.65	0.42-0.94
11-13	10	0.58	0.34-0.92
17-19	10	0.53	0.28-0.90