Received: 13 April 2023 | Revised: 16 November 2023 | Accepted: 16 January 2024

DOI: 10.1111/csp2.13094

RESEARCH NOTE

Conservation Science and Practice
A journal of the Society for Conservation Biology
Open Access

WILEY

Camera trap sampling protocols for open landscapes: The value of time-lapse imagery

Scott Leorna | **Todd Brinkman**

University of Alaska Fairbanks, Institute of Arctic Biology, Fairbanks, Alaska, USA

Correspondence
Scott Leorna, Institute of Arctic Biology, University of Alaska Fairbanks, P.O. Box 757000 Fairbanks, AK 99775-7000, USA.
Email: sleorna@alaska.edu

Funding information
Office of Polar Programs, Arctic System Science Program Award, Grant/Award Number: 1839192

Abstract

Camera traps (CT) have been used to study a wide diversity of wildlife around the world. However, despite their widespread use, standardized protocols are lacking, potentially leading to reduced efficiency and inhibiting study comparisons, generalizability, and repeatability. While there are general guidelines and considerations researchers should be aware of when designing a CT survey, studies have shown the vital importance of selecting sampling schemes and camera settings tailored to specific characteristics of the wildlife system of interest. For many species and regions, optimal sampling protocols have not been thoroughly evaluated, especially in vast open landscapes. We used CT data on barren-ground caribou (*Rangifer tarandus*) in the open landscape of arctic Alaska as a case study to evaluate and quantify the influence of camera trigger type (i.e., motion detection vs. time-lapse) and time-lapse interval on data generation to inform sampling protocols for future CT research in this system or others like it. Comparing camera trigger types, we found 5 min interval time-lapse generated seven-times more images containing caribou compared to motion detection. However, the detection rate of motion detection was over 11-times greater than time-lapse resulting in more efficient data collection with respect to camera battery life, data storage, and data processing time. Exploring the effect of time-lapse interval length, we found detections were highly sensitive to interval length with a 30 min interval producing 33.7% fewer images containing caribou and identifying 22.2% fewer trap days containing caribou compared to a 5 min interval. Our results provide insight into effective CT sampling protocols for open landscapes and highlight the importance of critically evaluating and selecting camera settings that account for characteristics of the study system to ensure adequate data is generated efficiently to address study objectives.

KEYWORDS
arctic, best-practices, caribou, remote sensing, sampling design, trail camera

1 | INTRODUCTION

Camera traps (CT) have been used to gain insight into a wide diversity of ecological systems and have become a standard tool in wildlife ecology over the last few decades (Burton et al., 2015; O'Connell et al., 2011; Wearn & Glover-Kapfer, 2019). Despite growing volumes of CT studies exploring animal ecology around the world, relatively few studies have explicitly tested how different camera settings influence data generation in particular study systems. Most studies that have explored this topic have focused on developing recommendations for the use of motion detection camera settings (Apps & Mcnutt, 2018; Palencia et al., 2022; Trolliet et al., 2014). However, in systems where motion detection may be ineffective (e.g., open landscapes), there remains a need to identify and evaluate potential alternatives (Hamel et al., 2013; Leorna & Brinkman, 2022; Pomezanski & Bennett, 2018). This information gap has led to the lack of standardized protocols for CT data collection, inhibiting effective and efficient data collection, study comparisons, and study generalizability (Burton et al., 2015; Hamel et al., 2013; Meek et al., 2014; Scotson et al., 2017).

When determining which camera settings to use for a wildlife study, generally the goal is to minimize “empty” images (i.e., images not containing animals of interest) and maximize detections (i.e., images containing animals of interest). To do so, many guides to camera trapping suggest to program camera settings with consideration of several factors including project specific questions or goals (e.g., species diversity/richness, occupancy, movement), characteristics of targeted animal species (e.g., size, behavior, density), environmental and habitat characteristics (e.g., weather, vegetation, season), and camera performance (e.g., detection range, sensitivity, trigger speed) (Palencia et al., 2022; Rovero et al., 2013; Wearn & Glover-Kapfer, 2017). Most modern CT provide users options to adjust a number of settings including the time of day when the camera is active (e.g., day vs night), how cameras are triggered (e.g., time-lapse vs motion detection), and how images are recorded (e.g., number of images, duration between images, etc.) (Rovero et al., 2013; Trolliet et al., 2014). Using CT sampling protocols tailored to landscape and species-specific conditions can help ensure adequate data are collected to address study objectives while maintaining an ideal balance of battery life, data storage, and processing time, all of which can be significant limitations to CT studies (Driessen et al., 2017; Glover-Kapfer et al., 2019; Hamel et al., 2013; Palencia et al., 2022).

Open landscapes present several unique challenges for monitoring wildlife using CTs. For example, while motion detection sensors are often used to trigger images of passing wildlife, they have a limited detection range (i.e., distance between camera and animal) and can underutilize the area in the camera's viewshed where animals can be seen in open landscapes (Leorna & Brinkman, 2022). Also, motion sensor detection ranges and trigger speeds have been documented to vary greatly among CT makes and models, leading to challenges in consistency and study replication (Driessen et al., 2017; Trolliet et al., 2014). To combat these challenges, time-lapse settings can be used which record images based on a pre-defined time interval. However, because images are triggered independently from animal presence, they can result in a large number of “empty” images. Therefore, the challenge of using time-lapse is to select an interval that balances the tradeoffs of detecting the animal with the resources spent on collecting, storing, and processing the data (Hamel et al., 2013; Pomezanski & Bennett, 2018). While there are pros and cons to each trigger setting, some CTs allow simultaneous motion detection and time-lapse recording, providing more versatility in sampling protocols and data collection. However, not all CTs offer this functionality, highlighting the importance of understanding which setting is most ideal under different circumstances.

To inform CT sampling protocols in open landscapes, we used CT data on barren-ground caribou (*Rangifer tarandus*) collected in the open landscape of Alaska's arctic tundra as a case study and examined how image collection protocols influenced data generation. Our objectives were to explore and quantify the influence of camera trigger type (i.e., motion detection vs. time-lapse) and time-lapse interval length (i.e., pre-defined time between images) on the total volume of data generated, detection rate of images collected (i.e., proportion of images containing ≥1 caribou out of all images collected), and detection rate of trap days containing caribou (i.e., days determined to contain ≥1 image of caribou based on pooled data). Our study builds on a limited body of research exploring the application of CTs for monitoring a migratory species in open landscapes and contributes empirical data to help CT users better understand the impact of CT sampling protocols on data generation.

2 | METHODS

2.1 | Study area

CT data used in this study were collected on the arctic coastal plain of Alaska, USA during Summer 2019 (Figure 1). This open landscape is dominated by arctic tundra and low shrubs with flat topography near the

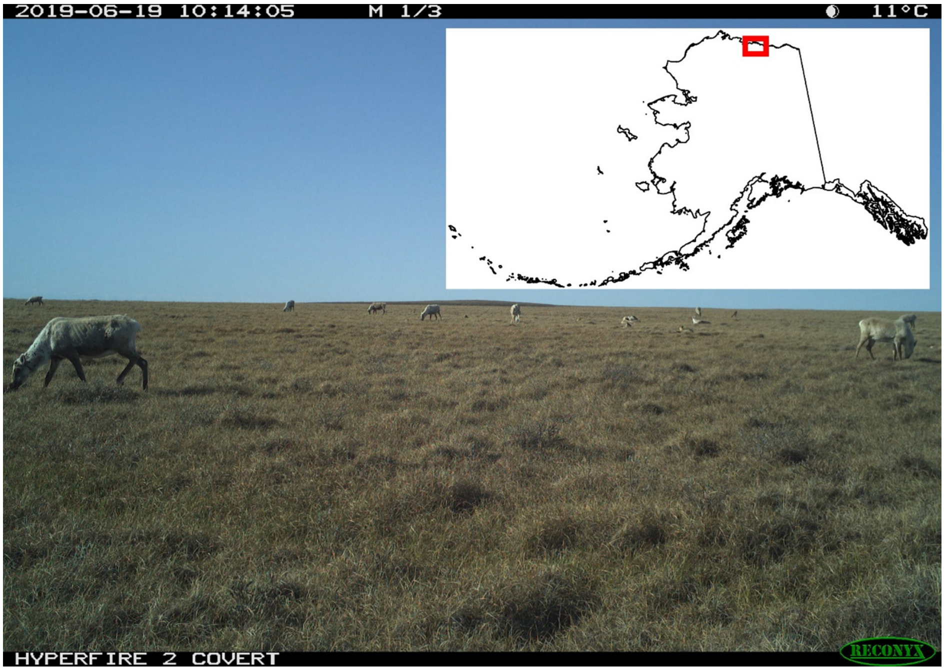

FIGURE 1 Study area (i.e., red square, top right) where images were collected and example of one camera viewshed showing caribou captured in the open landscape of arctic Alaska, USA. For reference, this image was triggered by motion detection of the closest caribou on the left of the image. Other caribou further away were not within the motion detection range of the camera, however, they could be captured using time-lapse camera settings.

coast of the Arctic Ocean which gradually becomes more rolling further south in the foothills of the Brooks Range (Walker et al., 2005). Generally, caribou herds move into this area during the end of their northward spring migration to calve, spend the summer on the northern reaches of the arctic coastal plain and other windswept areas, and return south to their wintering grounds during fall (Nicholson et al., 2016). In this region, there is 24 h daylight from mid-May to the end of July.

2.2 | Camera settings

We used 20 Reconyx Hyperfire 2 HF2X CTs installed in a systematic grid with sites separated by approximately 20 km (i.e., maximum day range of caribou during our study period) which were active between May 2 and September 4, 2019. Camera settings and recording schedule included simultaneous 5 min interval time-lapse and motion detection for a 24 h period. When cameras were triggered by motion, 3 images were recorded with a 10 s interval between images followed by a 30 s quiet period during which additional motion would not trigger a new image sequence. The motion sensor sensitivity was set to “very high,” image aspect ratio to 4:3, image resolution to 3 MP (i.e., 2048 × 1440), battery type to lithium, and “night mode” to “optimized” (i.e., 1/30s shutter speed and max ISO of 3200 to balance blurred motion and infrared illumination range) (Reconyx Inc., 2018). Cameras were revisited at the beginning of July to swap memory cards and batteries.

2.3 | Image processing

We used a manual approach to detect and label images with caribou using the software package TimeLapse2 (Version 2.2.3.6) (Greenberg et al., 2019). Images from each site were viewed at up to 25 frames/s to detect subtle changes between consecutive images. The default value for each image was set to 0 (i.e., caribou absent) and images where ≥1 caribou was detected were recorded as 1 (i.e., caribou present). All images from each site were first independently classified by at least two reviewers followed by a final detailed review by an experienced reviewer who resolved discrepancies in initial classifications to make the final determination of whether an image contained caribou. Image metadata included the trigger type (motion vs time-lapse), date, and time.

2.4 | Data analysis

To examine the influence of camera trigger type and time-lapse interval length, we compared subsets of data generated by motion detection and time-lapse images corresponding to interval lengths of 5, 10, 20, 30, 60, 120, 240, and 360 min, each starting at a time of 00:00 (i.e., midnight). For each data subset, we summarized the total number of images recorded, the number of images containing ≥1 caribou, and the number of trap days when ≥1 image containing caribou was recorded within a 24 h period. Using these values, for each subset, we calculated the caribou image detection rate (i.e., number of images containing ≥1 caribou divided by the number of images recorded within each camera setting), proportion of caribou images (i.e., the number of images containing ≥1 caribou within each camera setting divided by the combined number of caribou images recorded by both time-lapse and motion detection), and caribou trap day detection rate (i.e., the number of trap days with ≥1 caribou image within each camera setting divided by the combined number of caribou trap days recorded by both time-lapse and motion detection).

Our goal for summarizing the raw data in different ways was to provide a broad perspective on how image collection protocols may influence different types of CT analyses. Individual image detections of caribou were used as this information is commonly used in relative abundance indices and ultimately drives all other types of CT analyses (Palmer et al., 2018). Trap days when caribou were detected were used as this type of information may be used in a wide variety of occupancy analyses often used in CT studies (Burton et al., 2015). As the characteristics and volume of data required to address different study objectives vary greatly, our focus was to determine the influence of CT sampling protocols on overall data generation rather than estimation of specific ecological metrics, as ultimately, this type of data can be used to answer many different types of ecological questions (Burton et al., 2015; Sollmann, 2018).

3 | RESULTS

Combining all data among days and sites, there were a total of 2403 trap days when cameras were active. Pooling motion detection and 5 min interval time-lapse images, a total of 692,122 images were recorded with 11,177 containing caribou accounting for 458 trap days when caribou were present (Table 1). For camera trigger types, 5 min interval time-lapse accounted for 87.5% of the total number of images containing caribou with an overall detection rate of 1.4% (Table 1). Motion detection accounted for the remaining 12.5% of caribou images with an overall detection rate of 16.0% (Table 1). Of all trap days when caribou were detected, 5 min interval time-lapse accounted for 94.3% and motion detection for 33.6% (Table 1). For increased time-lapse interval lengths of 10, 20, 30, 60, 120, 240, and 360 min, the proportion of caribou images captured by time-lapse decreased to 77.7%, 63.6%, 53.8%, 37.2%, 23.0%, 13.0%, and 9.5%, respectively, and the trap day detection rate decreased to 86.0%, 79.5%, 72.1%, 59.8%, 45.4%, 31.9%, and 26.9%, respectively (Figure 2, Table 1).

4 | DISCUSSION

Using an empirical dataset of caribou CT observations in arctic Alaska, we gained valuable insight to inform CT sampling protocols for open landscapes. By comparing images collected by time-lapse and motion detection settings, we found 5 min interval time-lapse contributed seven-times more images containing caribou accounting for almost three-times more caribou trap days compared to motion detection (Table 1). These findings are explained by time-lapse images being able to capture caribou at greater distances in open landscapes than the effective range of the camera's motion detection sensor, ultimately increasing the overall area sampled in the

TABLE 1 Summary of images captured by time-lapse and motion detection camera settings.

	Time-lapse interval length (min)								Motion detection
	5	***10***	***20***	***30***	***60***	***120***	***240***	***360***	
Images recorded	683,402	341,706	170,854	113,902	56,951	28,478	14,242	9491	8720
Images ≥1 caribou	9783	4862	2436	1624	824	417	209	146	1394
Trap days ≥1 caribou[a]	432	394	364	330	274	208	146	123	154
Image detection rate[b]	1.4%	1.4%	1.4%	1.4%	1.4%	1.5%	1.5%	1.5%	16.0%
Proportion of Caribou Images[c]	87.5%	77.7%	63.6%	53.8%	37.2%	23.0%	13.0%	9.5%	12.5%[5]
Trap day detection rate[d]	94.3%	86.0%	79.5%	72.1%	59.8%	45.4%	31.9%	26.9%	33.6%

[a]Trap day ≥1 caribou includes all days when ≥1 image was recorded within a 24 h period which was determined to contain ≥1 caribou.

[b]Image detection rate was calculated by dividing the number of images containing ≥1 caribou by the number of images recorded within each camera setting.

[c]Proportion of caribou images was calculated by dividing the number of images containing ≥1 caribou within each camera setting by the combined number of images containing ≥1 caribou recorded by the corresponding time-lapse interval and motion detection.

[d]Trap day detection rate was calculated by dividing the number of trap days with ≥1 caribou within each camera setting by the total number of trap days ≥1 caribou ($n = 458$).

[5]Value calculated from pooling all motion detection and 5 min interval time-lapse images containing caribou.

camera's viewshed (Leorna & Brinkman, 2022). The significant increase in detections using time-lapse images enhances opportunities for, and the statistical power of, many common CT analysis techniques (Sollmann, 2018). Therefore, these results highlight the potential added value of using time-lapse settings in open landscapes.

While short interval time-lapse generated a greater number of caribou detections overall, the image detection rate was over 11-times greater for motion detection compared to time-lapse (Table 1). This result is intuitive as motion detection relies on the animal being present to trigger the camera to record an image. In contrast, time-lapse images are recorded independent of animal presence which is supported by caribou image detection rates remaining relatively constant for time-lapse images regardless of interval length (Table 1). We found to generate approximately the same number of images containing caribou as motion detection required a 30 min time-lapse interval which produced about 13-times the total volume of data (i.e., total images recorded) compared to motion detection (Table 1). Additionally, to generate approximately the same number of trap days containing caribou as were determined using motion detection required a 240 min time-lapse interval which produced about 1.6-times the total volume of data compared to motion detection (Table 1). These findings suggest motion detection may be more efficient (i.e., yield a higher proportion of detections to non-detections) at the expense of being less informative (i.e., generating fewer overall detections and trap days containing caribou) and provide valuable insight into thresholds at which time-lapse and motion detection settings result in comparable data collection.

By examining the effect of time-lapse interval length on data generation, we found increases in interval length had a dramatic effect on the proportion of caribou images and caribou trap day detection rate (Figure 2). For example, increasing the time-lapse interval length from 5 min to 30 min decreased the proportion of caribou images and number of trap days determined to contain caribou by 33.7% and 22.2%, respectively (Table 1). These results align with similar studies in different systems and highlight the importance of selecting time-lapse intervals in consideration of landscape and species-specific study conditions (Hamel et al., 2013; Pomezanski & Bennett, 2018). Collectively, our results demonstrate some of the tradeoffs of using motion detection compared to time-lapse settings and how the choice of camera trigger type and time-lapse interval length can have a substantial impact on the data available to inform study objectives. While this study represents one of few that has explicitly evaluated the influence of time-lapse interval length on animal detections, we note our evaluation

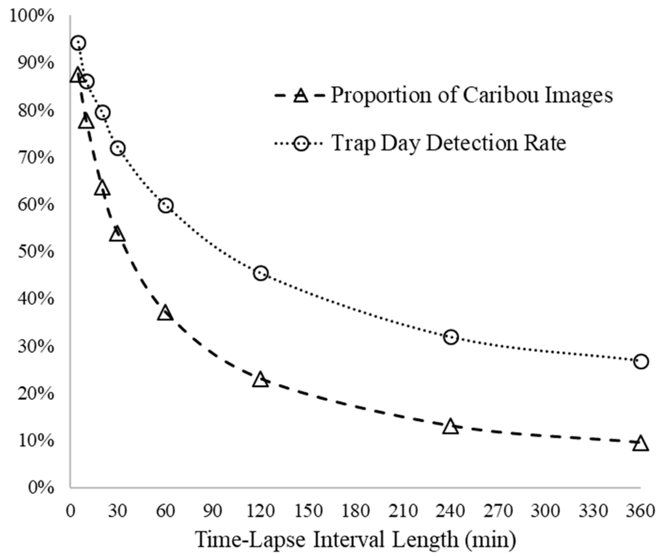

FIGURE 2 Influence of time-lapse interval length on the proportion of images and trap days determined to contain ≥1 caribou. Proportion of caribou images was calculated by dividing the number of images containing ≥1 caribou within each camera setting by the combined number of images containing ≥1 caribou recorded by the corresponding time-lapse interval and motion detection. Trap day detection rate was calculated by dividing the number of trap days with ≥1 caribou within each camera setting by the total number of trap days ≥1 caribou ($n = 458$).

focused on only one species and landscape type, and further research is needed to better understand how study system characteristics influence the optimal time-lapse interval length.

4.1 | Implications and considerations

One possible concern about using time-lapse is the abundance of "empty" images due to the low detection rate and the resulting processing time required to sort out empty images from non-empty images. For example, in our system, we found using time-lapse generated on average about one image of caribou per 70 images captured compared to one-in-six using motion detection (Table 1). Fortunately, tools and techniques that utilize machine learning and computer vision have become more widely available which can quickly automate image labeling with minimal effort and help expedite CT data processing to some extent (Tuia et al., 2022; Vélez et al., 2023; Young et al., 2018). Other concerns related to the low detection rate of time-lapse may be limited data storage and battery life compared to the higher detection rate of motion detection. During our mid-season memory card and battery swap, we found most memory cards only held about 3GB of data (approximately 18,000 images) accounting for <1% of the maximum 512GB card size supported by our cameras. Also, most cameras showed "full" battery, indicating our cameras would have likely remained operational for the full four-month sampling period despite our intensive 5 min interval time-lapse and motion detection sampling. However, for especially demanding applications, modern CTs also offer new features such as real-time image filtering and wireless data transfer via satellite reducing the need for on-board data storage, and auxiliary battery life can be supplied by solar panels or external battery packs (Glover-Kapfer et al., 2019; Meek & Pittet, 2012; Nazir et al., 2017). Additional benefits of using time-lapse include standardizing sampling effort across sites and studies, avoiding technical issues related to false-triggers or differences in motion sensor performance, better planning for battery life, data storage, and image processing time as the total volume of data to be collected would be known prior to data collection, and opportunities to apply newly developed analytical approaches for estimating abundance and density of unmarked animals which require time-lapse images (Gilbert et al., 2020; Moeller et al., 2018).

Having a thorough understanding of how camera settings influence data generation is essential to making informed decisions about CT study design to fully optimize available resources and generate sufficient data to appropriately address study objectives. Ultimately, based on our results, we found utilizing short interval time-lapse offered many benefits compared to motion detection in our open landscape and techniques and technology offer feasible solutions to many associated concerns or limitations (Glover-Kapfer et al., 2019; Thomson et al., 2018). Therefore, in cases where targeted animals can be seen beyond the camera's motion detection sensor range, utilizing time-lapse can expand the effective area sampled in the camera's viewshed and contribute animal detections that would have otherwise been missed. While there are many project specific aspects to designing effective and efficient CT studies researchers must carefully consider, our study provides a practical example of how selection of camera settings can substantially influence data generated to inform study objectives.

AUTHOR CONTRIBUTIONS

S. L. and T. B. conceived the research idea and collected field data. S. L. designed methodology, analyzed data, and led writing of the manuscript. Both authors contributed critically to drafts and gave final approval for publication.

ACKNOWLEDGMENTS

We thank the National Science Foundation for providing funding for this study [Office of Polar Programs, Arctic System Science Program Award # 1839192]. We also thank technicians Michael Apperson, Anja Maijala, and Katja Diekgers for their many hours of manually reviewing and labeling images.

CONFLICT OF INTEREST STATEMENT

Authors declare no conflicts of interest.

DATA AVAILABILITY STATEMENT

Labeled images and data used in this study are intended to be archived with the National Science Foundation Arctic Data Center and made publicly available with upon publishing.

ORCID

Scott Leorna https://orcid.org/0000-0001-8689-8197

REFERENCES

Apps, P. J., & Mcnutt, J. W. (2018). How camera traps work and how to work them. *African Journal of Ecology*, *56*, 702–709. https://doi.org/10.1111/aje.12563

Burton, A. C., Neilson, E., Moreira, D., Ladle, A., Steenweg, R., Fisher, J. T., Bayne, E., & Boutin, S. (2015). Wildlife camera trapping: A review and recommendations for linking surveys to ecological processes. *Journal of Applied Ecology*, *52*(3), 675–685. https://doi.org/10.1111/1365-2664.12432

Driessen, A., Michael, M., & Peter, J. (2017). Animal detections vary among commonly used camera trap models. *Wildlife Research*, *44*(4), 291–297.

Gilbert, N. A., Clare, J. D. J., Stenglein, J. L., & Zuckerberg, B. (2020). Abundance estimation of unmarked animals based on camera-trap data. *Conservation Biology*, *35*(1), 1–13. https://doi.org/10.1111/cobi.13517

Glover-Kapfer, P., Soto-Navarro, C. A., & Wearn, O. R. (2019). Camera-trapping version 3.0: Current constraints and future priorities for development. *Remote Sensing in Ecology and Conservation*, *5*(3), 209–223. https://doi.org/10.1002/rse2.106

Greenberg, S., Godin, T., & Whittington, J. (2019). Design patterns for wildlife-related camera trap image analysis. *Ecology and Evolution*, *9*, 13706–13730. https://doi.org/10.1002/ece3.5767

Hamel, S., Killengreen, S., Henden, J.-A., Eide, N., Roed-Eriksen, L., Ims, R., & Yoccoz, N. (2013). Towards good practice guidance in using camera-traps in ecology: Influence of sampling design on validity of ecological inferences. *Methods in Ecology and Evolution*, *4*, 105–113. https://doi.org/10.1111/j.2041-210x.2012.00262.x

Leorna, S., & Brinkman, T. (2022). Human vs. machine: Detecting wildlife in camera trap images. *Ecological Informatics*, *72*, 101876. https://doi.org/10.1016/j.ecoinf.2022.101876

Meek, P. D., Ballard, G., Claridge, A., Kays, R., Moseby, K., Sanderson, J., Swann, D. E., Tobler, M., & Townsend, S. (2014). Recommended guiding principles for reporting on camera trapping research. *Biodiversity and Conservation*, *23*, 2321–2343. https://doi.org/10.1007/s10531-014-0712-8

Meek, P. D., & Pittet, A. (2012). User-based design specifications for the ultimate camera trap for wildlife research. *Wildlife Research*, *39*(8), 649–660. https://doi.org/10.1071/WR12138

Moeller, A. K., Lukacs, P. M., & Horne, J. S. (2018). Three novel methods to estimate abundance of unmarked animals using remote cameras. *Ecosphere*, *9*(8), 1–15. https://doi.org/10.1002/ecs2.2331

Nazir, S., Newey, S., Irvine, R. J., Verdicchio, F., Davidson, P., & Fairhurst, G. (2017). WiseEye: Next generation expandable and programmable camera trap platform for wildlife research. *PLoS One*, *12*(1), 1–15. https://doi.org/10.1371/journal.pone.0169758

Nicholson, K. L., Arthur, S. M., Horne, J. S., Garton, E. O., & Del Vecchio, P. A. (2016). Modeling caribou movements: Seasonal ranges and migration routes of the central arctic herd. *PLoS One*, *11*(4), e0150333. https://doi.org/10.1371/journal.pone.0150333

O'Connell, A., Nichols, J., & Karanth, K. (2011). In A. O'Connell, J. Nichols, & K. Karanth (Eds.), Vol. 1) *Camera traps in animal ecology*. Springer. https://doi.org/10.1007/978-4-431-99495-4

Palencia, P., Vicente, J., Soriguer, R. C., & Acevedo, P. (2022). Towards a best-practices guide for camera trapping: Assessing differences among camera trap models and settings under field conditions. *Journal of Zoology*, *316*(3), 197–208. https://doi.org/10.1111/jzo.12945

Palmer, M. S., Swanson, A., Kosmala, M., Arnold, T., & Packer, C. (2018). Evaluating relative abundance indices for terrestrial herbivores from large-scale camera trap surveys. *African Journal of Ecology*, *56*(4), 791–803. https://doi.org/10.1111/aje.12566

Pomezanski, D., & Bennett, L. (2018). Developing recommendations for monitoring wildlife underpass usage using trail cameras. *Environmental Monitoring and Assessment*, *190*, 1–9.

Reconyx Inc. (2018). Reconyx Hyperfire 2 user manual. In *Reconyx Inc* www.reconyx.com

Rovero, F., Zimmermann, F., Berzi, D., & Meek, P. (2013). "Which camera trap type and how many do I need?" A review of camera features and study designs for a range of wildlife research applications. *Hystrix*, *24*(2), 148–156. https://doi.org/10.4404/hystrix-24.2-6316

Scotson, L., Johnston, L. R., Iannarilli, F., Wearn, O. R., Mohd-Azlan, J., Wong, W. M., Gray, T. N. E., Dinata, Y., Suzuki, A., & Willard, C. E. (2017). Best practices and software for the management and sharing of camera trap data for small and large scales studies. *Remote Sensing in Ecology and Conservation*, *3*(3), 158–172. https://doi.org/10.1002/rse2.54

Sollmann, R. (2018). A gentle introduction to camera-trap data analysis. *African Journal of Ecology*, *56*(4), 740–749. https://doi.org/10.1111/aje.12557

Thomson, R., Potgieter, G., & Bahaa-El-Din, L. (2018). Closing the gap between camera trap software development and the user community. *African Journal of Ecology*, *56*, 721–739. https://doi.org/10.1111/aje.12550

Trolliet, F., Huynen, M., Vermeulen, C., & Hambuckers, A. (2014). Use of camera traps for wildlife studies. A review. *Biotechnology, Agronomy, Society and Environment*, *18*(3), 446–454. https://doi.org/10.1016/0308-0161(78)90006-6

Tuia, D., Kellenberger, B., Beery, S., Costelloe, B. R., Zuffi, S., Risse, B., Mathis, A., Mathis, M. W., van Langevelde, F., Burghardt, T., Kays, R., Klinck, H., Wikelski, M., Couzin, I. D., van Horn, G., Crofoot, M. C., Stewart, C. V., & Berger-Wolf, T. (2022). Perspectives in machine learning for wildlife conservation. *Nature Communications*, *13*, 1–15. https://doi.org/10.1038/s41467-022-27980-y

Vélez, J., McShea, W., Shamon, H., Castiblanco-Camacho, P. J., Tabak, M. A., Chalmers, C., Fergus, P., & Fieberg, J. (2023). An evaluation of platforms for processing camera-trap data using artificial intelligence. *Methods in Ecology and Evolution*, *14*(2), 459–477. https://doi.org/10.1111/2041-210X.14044

Walker, D. A., Reynolds, M. K., Daniëls, F. J. A., Einarsson, E., Elvebakk, A., Gould, W. A., Katenin, A. E., Kholod, S. S., Markon, C. J., Melnikov, E. S., Moskalenko, N. G., Talbot, S. S., Yurtsev, B. A., Bliss, L. C., Edlund, S. A., Zoltai, S. C., Wilhelm, M., Bay, C., Gudjónsson, G., … Vairin, B. A. (2005). The circumpolar Arctic vegetation map. *Journal of Vegetation Science*, *16*(3), 267–282. https://doi.org/10.1111/j.1654-1103.2005.tb02365.x

Wearn, O. R., & Glover-Kapfer, P. (2017). Camera-trapping for conservation: A guide to best-practices. https://www.wwf.org.uk/sites/default/files/2019-04/CameraTraps-WWF-guidelines.pdf

Wearn, O. R., & Glover-Kapfer, P. (2019). Snap happy: Camera traps are an effective sampling tool when compared with alternative methods. *Royal Society Open Science*, *6*, 1–13.

Young, S., Rode-Margono, J., & Amin, R. (2018). Software to facilitate and streamline camera trap data management: A review. *Ecology and Evolution*, *8*(19), 9947–9957. https://doi.org/10.1002/ece3.4464

How to cite this article: Leorna, S., & Brinkman, T. (2024). Camera trap sampling protocols for open landscapes: The value of time-lapse imagery. *Conservation Science and Practice*, *6*(3), e13094. https://doi.org/10.1111/csp2.13094