Remote Camera Survey Guidelines

Guidelines for Western Canada

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Version 1.0

Prepared by

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on behalf of the

Alberta Remote Camera Steering Committee (RCSC) and Wildlife Cameras for Adaptive Management (WildCAM)

Remote Camera Survey Guidelines: Guidelines for Western Canada

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For more information about these guidelines or regarding the Alberta Remote Camera Steering Committee, please email Anne.Hubbs@gov.ab.ca.

To learn more about Wildlife Cameras for Adaptive Management (WildCAM), please visit the WildCAM website (https://www.wildcams.ca).

For further information about The Fisheries and Wildlife Management Information System (FWMIS), please visit the FWMIS website (https://www.alberta.ca/fisheries-and-wildlife-management-information-system-overview.aspx).

For further information about WildTrax, please visit the WildTrax website (http://www.wildtrax.ca/).

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1.0 Background

Effectively managing and conserving wild species and their habitats requires an understanding of species' distributions, population levels and habitat requirements, along with knowledge of the factors that may threaten their long-term survival.

Remote cameras (also referred to as "wildlife cameras" or "camera traps") are a valuable tool for detecting a wide range of wildlife species (Burton et al., 2015; Lahoz-Monfort & Magrath, 2021; O'Connell et al., 2011a). While they are most commonly used to monitor medium to large-sized mammals, they have also been used to detect small mammals (e.g., Lazenby et al., 2015; Mills et al., 2016; Tschumi et al., 2018) and birds (e.g., Kruger et al., 2018; Lynch et al., 2015; Randler & Kalb, 2018; Suwanrat et al., 2015).

Remote cameras consist of a digital camera with an external flash and/or passive infrared (PIR) detector (sensor) (see Lahoz-Monfort & Magrath, 2021; Rovero et al., 2013 for detailed reviews). Cameras can be triggered through different means (e.g., mechanical triggers, active infrared sensors); PIR detectors followed by time-lapse triggers are most commonly used (Welbourne et al., 2016). The camera is triggered when motion is sensed within the camera's detection zone and the infrared sensor registers a difference in infrared radiation above a certain threshold emitted from an object's surface (e.g., animal's fur; Welbourne et al., 2016).

Cameras may capture images or video, based on the user settings. The resulting images or videos are stamped with the date and time. Date and time stamps are valuable because this provides a permanent spatial and temporal record of wildlife occurrences.

Remote cameras have been used to measure presence / absence (e.g., Kucera & Barrett, 2011), relative abundance (e.g., Carbone et al., 2001), density of marked (e.g., Karanth et al., 2006) and unmarked (e.g., Becker et al., 2022) animals, population composition (age/sex ratios; e.g., Duquette et al., 2014), species richness / diversity (e.g., Ahumada et al., 2011), habitat use / distribution (e.g., Bowkett et al., 2008; O'Connell et al., 2006; Whittington et al., 2019), diel / seasonal activity patterns (e.g., Frey et al., 2017), individual breeding status (e.g., Fisher et al., 2014; Muhly et al., 2011), and behaviour (e.g., Holinda et al., 2020; Murray et al., 2016).

There are several advantages to using remote cameras over other inventory methods, including their ability to continuously collect data (images or video) for multiple species simultaneously in a cost-effective and non-invasive fashion (Kucera & Barrett, 2011; O'Brien, 2011; Steenweg et al., 2017). The advantages of remote cameras have led to a large increase in their use over time and the growing need to standardize survey methods (and metadata reporting) (Fisher & Burton, 2012; Steenweg et al., 2017).

These guidelines were developed by the Alberta Remote Camera Steering Committee (RCSC) in collaboration with the Alberta Biodiversity Monitoring Institute (ABMI) and Wildlife Cameras for Adaptive Management (WildCAM). The Alberta RCSC and B.C. Advisory Committee (WildCAM; https://wildcams.ca/about-us/) are remote camera experts from academia, government and not-for-profit organizations who aim to advance the science of remote camera monitoring and research while facilitating collaboration and sharing knowledge among users in western Canada.

These guidelines are intended to be a "living document" that will be updated as new information becomes available. At a minimum, they will be reviewed on an annual basis.

2.0 Intended Audience and How to use this document

The purpose of the Remote Camera Survey Guidelines is to provide recommendations on study design and implementation (including equipment and deployment recommendations) for novice to advanced users of remote cameras in western Canada in a format aligned with standardized methods for metadata reporting. The intended audience for this document includes consultants, researchers, and wildlife biologists working for government, non-government agencies and industry.

Summary tables, step-by-step procedures, and field data sheets have been provided in Appendix A to help readers quickly locate and distill key information. There is also a useful decision tree for selecting density models for remote camera data in Appendix B - Figure B1 (Clarke et al. [2022] adapted from Gilbert et al. [2021] and Sun [unpublished]). This document addresses the more common modelling approaches (e.g., species diversity and richness, occupancy, relative abundance, and density). Research is ongoing to test the different approaches and to develop new methods. Refer to WildCAM's resource library (https://wildcams.ca/library/camera-trapping-papers-directory/) and the sources provided for more information on the different approaches. For information on other methods, please refer to the literature (e.g., intensity of use [Keim et al., 2019, 2021]; resource selection functions [Manly et al., 1993] etc.).

The goal of this document is to support consistency in the collection of remote camera data across western Canada by offering guidance on the appropriate study design, camera deployment methods and data management.

There are several benefits to having standardized methods for remote cameras, including:

- Enabling province-wide consistency and reliability in data collection;
- Enabling data consolidation amongst projects and enhancing the ability to answer large-scale management / research questions;
- Facilitating comparison between surveys or studies;
- Promoting higher quality of data which facilitates data sharing and tracking;
- Enhancing common design standards for reproducible research;
- Allowing for efficient project and data review;
- Ensuring project planning meets required government and research institute standards.

The information provided in these guidelines is intended to be as prescriptive as possible to support consistency in data collection while allowing for flexibility where needed. The deployment of remote cameras following this standard can help establish a robust foundation for camera programs. These guidelines build on the experiences of remote camera specialists in Alberta, British Columbia and other jurisdictions and should help guide camera users, even where no regulatory requirements exist.

Two companion documents exist, the Remote Camera Metadata: Standards for Alberta (Alberta Remote Camera Steering Committee [RCSC], 2023; “AB Metadata Standards” hereafter) and Wildlife Camera Metadata Protocol: Standards for Components of British Columbia’s Biodiversity No. 44 (RISC, 2019; “B.C. Metadata Standards” hereafter), which should be viewed alongside this document to establish a clear and consistent understanding of the recommendations and requirements. The AB Metadata Standards (RCSC, 2023), as well as this Remote Camera Survey Guidelines, are available on the WildTrax (https://www.wildtrax.ca/home/resources/methods-and-protocols.html) and Wildlife Cameras for Adaptive Management (WildCAM) (https://wildcams.ca/library/other-organizations-protocols/) webpages. The B.C. Metadata Standards (RISC, 2019) are available on the WildCAM (https://wildcams.ca/library/other-organizations-protocols/) and B.C. Government’s webpages (https://www2.gov.bc.ca/gov/content/environment/natural-resource-stewardship/laws-policies-standards-guidance/inventory-standards/terrestrial-ecosystems-biodiversity).

2.1 Supporting documents

Additional to the AB Metadata Standards (RCSC, 2023) and B.C. Metadata Standards (RISC, 2019), there are several other supporting documents that are consistent with these guidelines and standards, including the following:

- Remote Camera Survey Guidelines supporting documents:
    - Camera Deployment Field Datasheet (RCSC et al., 2023)
    - Camera Service/Retrieval Field Datasheet (RCSC et al., 2023),
    - Test Image Sheet (RCSC et al., 2023),
    - Survey123 Template (RCSC et al., 2023), and
    - EpiCollect Template (RCSC et al., 2023) (https://five.epicollect.net/project/rcsc-and-wildcam-remote-camera-survey-guidelines)
- Alberta Remote Camera Metadata Standards: Metadata Template (RCSC, 2023)

Copies of the Camera Deployment Field Datasheet, Test Image Sheet and Camera Service/Retrieval Field Datasheet are also available within this document in Appendix A.

3.0 Design hierarchy

When designing a remote camera project (e.g., inventory, monitoring, or research program), it is helpful to think of the hierarchy of information collected throughout the study. Doing so will:

- help the user align with the AB Metadata Standards and B.C. Metadata Standards (RISC, 2019), thus promoting standardized data collection and information sharing;

- provide those designing remote camera studies with the foundational concepts required to align their design with best practices and to implement appropriate data analyses.

The AB Metadata Standards (RCSC, 2023) propose that data should be collected at six broad levels (project, study area, survey, sample station / camera location, deployment, and image/sequence). This hierarchy was adapted from Forrester et al. (2016) and the B.C. Metadata Standards (RISC, 2019) by adding one more level (sample station / camera location):

- **Project** – a scientific study or inventory/ monitoring program that has a certain objective, defined methods, and a defined boundary in space and time (recorded as "Project ID").
- **Study area** – a unique research, inventory or monitoring area(s) (spatial boundary) within a project (there may be multiple study areas within a single project) (recorded as "Study Area ID").
- **Survey** – a unique period (temporal extent) within a project (recorded as "Survey ID").
- **Sample station / Camera location –**
    - **Sample station** – a grouping of two or more non-independent camera locations such as when cameras are clustered or paired (recorded as "Sample Station ID")
    - **Camera location** – the location where a single camera was placed (recorded as "Camera Location ID").
- **Deployment** – a unique placement of a camera in space and time (recorded as "Deployment ID"); there may be multiple deployments for one camera location. Deployments are often considered as the time between visits (i.e., deployment to service, service to service, and service to retrieval). Any change to camera location, sampling period, camera equipment (e.g., Trigger Sensitivity setting, becomes non-functioning), and/or conditions (e.g., not baited then baited later; camera SD card replaced) should be documented as a unique deployment.
- **Image/sequence**
    - **Image** – an individual image captured by a camera, which may be part of a multi-image sequence (recorded as "Image ID").
    - **Sequence** – a user-defined group of images or video clips considered as a single "detection event" (recorded as "Sequence ID); often users choose a certain time threshold (or "inter-detection interval") to define independent 'events'. For example, 30 minutes (O'Brien et al., 2003; Gerber et al., 2010; Kitamura et al., 2010; Samejima et al., 2012) or 1 hour (e.g., Tobler et al., 2008; Rovero & Marshall, 2009). The threshold should be recorded in the Survey Design Description).

Note that these levels do not equate to individual CSV files. Refer to the AB Metadata Standards (RCSC, 2023) for more information.

4.0 Objectives

An essential first step when designing any survey is to clearly define its objectives. Survey Objectives should be specific, measurable, achievable, relevant and time-bound (i.e., SMART). Survey Objectives should describe the following:

- Target Species - the specie(s) that the survey is designed to detect,
- state variable(s) - a formal measure that summarizes the state of a community or population at a particular time (Wearn & Glover-Kapfer, 2017) (e.g., species richness or population abundance), and
- proposed modelling approach(es) - the method used to analyze the camera data that will also depend on the state variable (e.g., occupancy models [MacKenzie et al., 2002], spatially explicit capture-recapture (SECR) models [e.g., Royle et al., 2009] for density estimation, etc.). To learn more about the different modelling approaches, refer to Appendix A - Table A1, and Appendix A - Table A2 and the WildCAM's resource library (https://wildcams.ca/library/camera-trapping-papers-directory/).

An example of a clearly defined survey objective could be "to monitor trends in wolverine occupancy at 5-year intervals from March – December 2020 to 2030 in wildlife management unit 539".

The survey objective will determine the appropriate study design and deployment considerations (e.g., camera spacing, survey effort, attractants or not). For example, based on the above objective for our wolverine occupancy project, we "randomly selected camera locations within a 15 km x 15 km grid cell with one camera per location and a total of 60 stations across our study area. We will place lure dispensers at each camera location to increase the likelihood of detecting a wolverine." to increase the likelihood of detecting a wolverine."

5.0 Detection probability

Before study design choices are made, there is one critical concept to understand in remote camera research, which may impact study design choices at all levels of the data hierarchy. Reliable use of remote cameras to detect wildlife species hinges on the assumption that what is captured on the cameras accurately reflects what is present on the landscape. However, species are often detected "imperfectly," meaning that they are not always detected when they are present (i.e., imperfect detection; MacKenzie et al., 2004). Imperfect detection can occur because the camera failed to capture an individual present at the site or because the animal was simply not present during the survey period (Martin et al., 2005). Imperfect detection results in "false absences" and may lead to incorrect conclusions from the data. Understanding and correcting for sources of "false absences" is often thought of in terms of probabilities. Detection probability is the probability (likelihood) that an individual of the population of interest is included in the count at time or location i (MacKenzie & Kendall, 2002). Detection probability can be influenced through multiple processes and at multiple scales. Understanding the sources of "false absences" and factors that affect detection probabilities is an essential step when designing a study, deploying cameras and analyzing camera data.

[Detection probability](#) of an animal by a camera depends on three **conditional probabilities (Pr) of detection** that may operate alone or potentially, in combination ([Figure 1](#)).

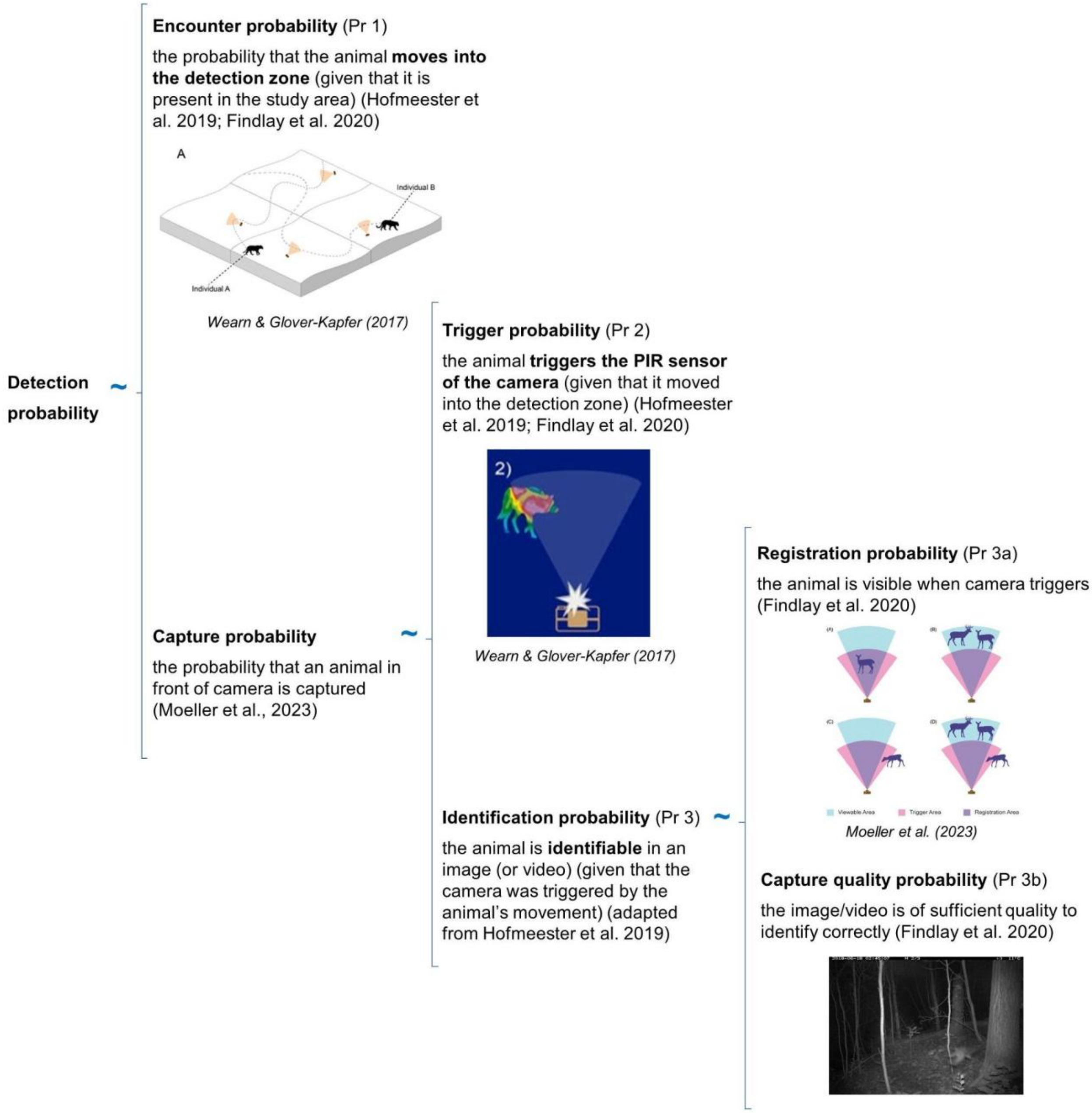


Figure 1. Three conditional probabilities (Pr) of detection that may impact [detection probability](#) of an animal (or species) by a camera (adapted from Moeller et al. [2023], Hofmeester et al. [2019], and Findlay et al. [2020]).

[Detection probability](#) can be affected by species-specific characteristics, [Camera Model](#) specifications and set-up, and environmental variables (Hofmeester et al., 2019). For example, **species-specific characteristics** (individuals or populations), such as body size (e.g., O'Brien et al., 2011), behaviour (e.g., Caravaggi et al., 2020; Rowcliffe et al., 2011), and rarity can influence [detection probability](#), with larger, bolder and more common species generally having higher detection rates. **Camera Model specifications and set-up**, such as the Trigger Sensitivity, Camera Height, or angle may affect detection probability in that smaller species might not be detected or identifiable if the Trigger Sensitivity is low, or the Camera Height or angle is too high. The Camera Direction could impact the probability of an animal triggering a camera if it is directed towards an object that impedes the Field of View (FOV) or image quality (e.g. due to sun glare). **Environmental factors** (e.g., vegetation cover, snow depth) may affect detection probability and occurrence (e.g., Becker et al., 2022; Hofmeester et al., 2019; Iknayan et al., 2014; Steenweg et al., 2019). For example, a low number of detections in a densely vegetated site might be because of poor camera visibility or avoidance of this habitat by the species of interest.

Hofmeester et al. (2019) suggested there are **six scales (orders) that may impact** detection probability and that should be considered within an explicit time period (adapted from Hofmeester et al. [2019]; Figure 2):

1) **Distribution range** (1st order; i.e., the physical or geographical range of a species)
2) **Landscape** (2nd order; i.e., the location of an individual's home range within the geographic range)
3) **Habitat patch** (3rd order; i.e., usage of habitat components within an individual's home range)
4) **Microsite** (4th order; usage of microhabitats such as food items/feeding patches/nest sites/movement trails, etc. within a habitat)
5) **Camera specification / set-up** (5th order; i.e., factors that affect the probability that an animal triggers the camera if present)
6) **Image** (6th order; i.e., factors that affect correct identification of animals or individuals)

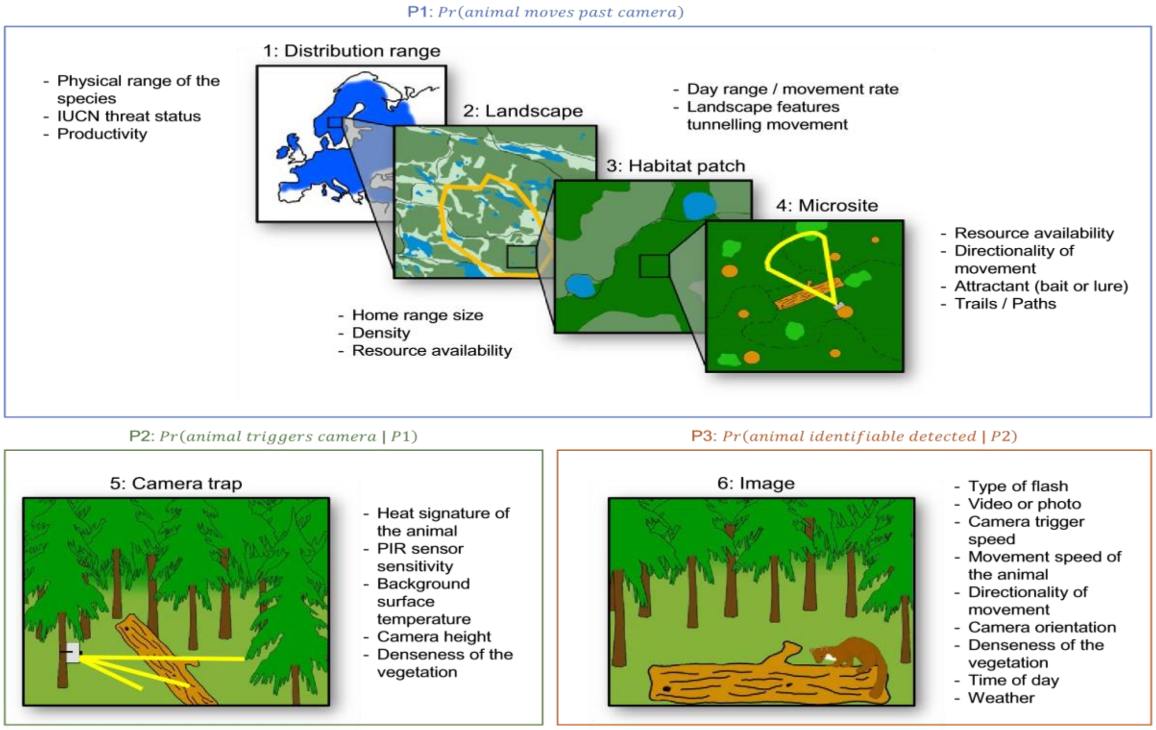


Figure 2. Spatial scales (1-6) and processes that determine the probability of detection (Hofmeester et al., 2019; abbreviated figure caption).

It is important to consider how all these factors and scales will impact study design.

Unmeasured variation in detection probability can result in the inability to differentiate the effects of detection probability *vs.* habitat preference (Jennelle et al., 2002) and, in turn, cause erroneous estimates of occurrence and abundance (Burton et al., 2015; Dénes et al., 2015; Kays et al., 2021).

Factors that influence detection probability at the microsite and camera specification / set-up scales are likely to result in the largest biases and thus warrant the most consideration (see Hofmeester et al. [2019] for details). Therefore, it is particularly important to consider *how* to place cameras to avoid such biases. Deploying cameras in a consistent fashion (e.g., carefully ensuring that cameras are always set at the same Camera Height, orientation (direction), and angle) is essential.

6.0 Study design

Project or survey-level aspects of design that camera users should consider (at a minimum) are:

- Study area extent and method of delineation (e.g., watershed or minimum convex polygon)
- Criteria for site selection (e.g., random, systematic, or targeted habitat types or features)
- Camera arrangement (e.g., random vs. cameras ‘clustered’ into hierarchical groups with common characteristics)’ into hierarchical groups with common characteristics)

- Camera spacing (e.g., 1 km spacing between cameras) km spacing between cameras)
- Number (or density) of cameras
- Survey effort and timing (i.e., the number of days the camera was active and functioning during the survey period; the “camera days per camera location“, the total number of camera days, time of year, and survey duration)

These decisions will depend on the study objectives as well as resources available.

Decisions concerning study design are a critical component to any wildlife project. These decisions can be complex, and, in these cases, it is highly advisable to consult an expert for direction.

6.1 Study area

A study area is a unique area(s) within a project. There may be multiple study areas within a larger study area. Aspects to consider when identifying the study area include the spatial extent (and method of delineation), shape (Foster & Harmsen, 2011), and composition and configuration of features within it (including habitat types, land uses and disturbances).

Several factors influence the size (spatial extent) of the study area, including the objectives, ecosystem, the biology of the Target Species' (e.g., dispersal ability, habitat preferences, etc.) and/or modelling approach.

For example, density models using the capture-recapture (CR) modelling approach requires that the study area encompasses the entire area in which individuals can move during the survey and that each individual can be detected by a camera (Karanth & Nichols, 1998). In this case, the animal’s home range size could be used (e.g., 4 times the home range size [Maffei & Noss, 2008]) (Wearn & Glover-Kapfer, 2017) in combination with a finite number of cameras available (e.g., 20 cameras are available; ideally, they should be paired and there should be >4 cameras in each home range [Wearn & Glover-Kapfer, 2017]) to define the project’s spatial extent.

Methods to delineate the appropriate spatial extent include, for example, minimum convex polygons (i.e., a polygon surrounding the locations of previous detections) or kernel density estimators (e.g., via the probability of "utilization" [Jennrich & Turner, 1969]). Geographic Information Systems (GIS, e.g., ESRI software) or programming language (e.g., R) contain useful tools for these delineation methods.

6.2 Site selection and camera arrangement

Remote camera locations (or sample stations) and their spatial arrangement are integral components of any study design; these choices will affect the user’s ability to draw inference(s) about the species or question of interest. There are many species-specific characteristics (e.g., body size, behaviour, rarity, etc.) and environmental factors (e.g., vegetation cover, snow depth) that influence the detection probability and probability of occurrence of a species, as well as the size of the area that should be surveyed (e.g., Becker et al., 2022; Hofmeester et al., 2019;

Iknayan et al., 2014; Steenweg et al., 2019). When there are multiple Target Species, a mix of study designs may be valuable (Iannarilli et al., 2021; van Wilgenburg et al., 2020).

The objectives of the survey will determine the most appropriate study design (Appendix A - Table A2). There are five commonly used study designs in camera studies: simple random, systematic random (grid), stratified random, clustered (including paired design) and targeted (or opportunistic) (Wearn & Glover-Kapfer 2017). A convenience sampling study design is also used when it is impractical to use another design. Sampling design can occur hierarchically, where one approach is used at a larger scale (i.e., to select grids to place cameras within), and another approach is used at a smaller scale (i.e., to select the location within each grid to place the camera). Refer to the following literature for additional recommendations on study design: Burton et al., 2015; Cusack et al., 2015; Fisher & Burton, 2012; Kolowski and Forrester, 2017; Meek et al., 2014b; O'Connell et al., 2011b; Rovero et al., 2013; Steenweg et al., 2015; Wearn & Glover-Kapfer, 2017 and WildCAM's "sampling design & effort" section of their resource library (https://wildcams.ca/library/camera-trapping-papers-directory/).

Note that we refer to different configurations of cameras more generally as study design and sampling design; however, the term "**Survey Design**" is how the study design is referred to when it applies to an individual survey. There may be multiple Survey Designs for surveys within a project; the Survey Design should be reported separately for each survey within a project. When the Survey Design is heirarchical, "Heirarchical (multiple)*" should be reported and additional details should be included in the Survey Design Description. Refer to the AB Metadata Standards (RCSC, 2023) for more information.

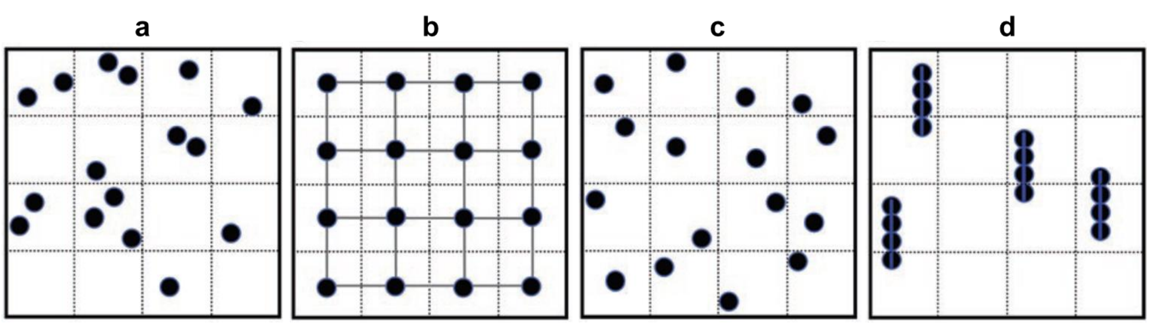


Figure 3. Examples of sampling designs: (a) simple random, (b) systematic, (c) stratified (each grid cell is a stratum), and (d) clustered (adapted from Schweiger, 2020).

6.2.1 Simple random design

Simple random design (Figure 3a) – cameras occur at randomized locations across the study area, sometimes with a predetermined minimum distance between stations. A random design may help reduce biases that arise from selecting camera locations deliberately. It may also allow the user to make inferences to areas that were not surveyed when employing use-based approaches (e.g. occupancy models [MacKenzie et al., 2002]; intensity of use methods [Keim et al., 2019]). Some modelling approaches (e.g., random encounter and staying time [REST];

Nakashima et al., 2018) and random encounter models [REM; Rowcliffe et al., 2008, 2013]) require a simple random design (Appendix A - Table A2).

A disadvantage of using a simple random design is the tendency to see fewer animals (i.e., is less efficient) when animals are clustered or exhibit habitat preferences, and possibility of missing rare habitat types. The proportion of different strata (e.g., habitat types) sampled should be the same as (or close to) the true proportion in the study area. For example, if the study area consists of 25% young deciduous forest, then 25% of randomly selected sites should be within young deciduous forest, on average.

6.2.2 Systematic design

Systematic design (Figure 3b) – camera locations occur within a regular pattern (e.g., a grid pattern) across the study area.

Systematic random – camera locations are selected using a two-stage approach. Firstly, girds are selected systematically (to occur within a regular pattern) across the study area. The location of the camera within each grid is then selected randomly. This method is similar to the simple random design. The same advantages apply in terms of unbiased landscape representation, and the same modelling approaches can be used. The disadvantage of using a systematic random (or simple random design) is that rare habitat types may be missed.

Systematic non-random design – sets of clustered cameras can be deployed within a systematic non-random approach (i.e,. “systematic clustered” or “systematic paired”) to assess the effects of disturbance along a gradient, over time, at multiple scales and/or with control (i.e., reference) sample stations. **Hierarchical Before-After Dose-Response (BADR)** is one such method that requires cameras to be placed within a systematic non-random approach, where camera locations occur along transects or in clustered arrays (sample stations), selected using a nested spatial hierarchy of sampling to control for variability in land-use type and large-scale patterns (Bayne et al., 2022). The study area is divided into land-use regions based on land-use type, then into landscape units, which are assessed for environmental variability to determine where sample stations should be placed (Bayne et al., 2022). The “Before-After” component of BADR incorporates the phase of stressors (i.e., proposed, or current development) (Bayne et al., 2022). The “Dose-Response” component of BADR controls for the variable distribution of activity (and the potential impacts) by incorporating control (or reference) sample stations and/or by placing cameras in sample stations along a gradient of disturbance (Bayne et al., 2022).

6.2.3 Stratified design

Stratified random design (Figure 3c) – the area of interest is divided into smaller strata (e.g., habitat type, disturbance levels), and then a proportional random sample of sites is selected within each stratum (e.g., 15%, 35% and 50% of sites within high, medium and low disturbance strata). This design can help ensure that the sample adequately reflects the major or uncommon strata of interest and may be an efficient approach when users are limited by accessibility constraints (Wearn & Glover-Kapfer, 2017). This design can also be used to increase precision if animal densities are known to be highly variable (Junker et al., 2021) or when a species is expected to occur in certain habitat types more often (Gillespie et al., 2015). For example, studies that wish to assess species richness, or occupancy rates for a particular species, amongst strata would use a stratified random design.

6.2.4 Clustered / Paired designs

Clustered design (Figure 3d) – multiple cameras are deployed at a sample station. The distance between cameras (camera spacing) will be influenced by the chosen sampling design, the Survey Objectives, the Target Species and data analysis. A clustered design can be used within a systematic or stratified approach (i.e., systematic clustered design or as a clustered random design) (Wearn & Glover-Kapfer, 2017). A clustered design is common when users are interested in individual identification, such as density estimation from marked or partially marked populations (e.g., spatially explicit capture-recapture [SECR; Borchers & Efford, 2008; Efford, 2004; Royle & Young, 2008] or spatial mark-resight [SMR; Doran-Myers, 2018]). A clustered design can also be used in an occupancy framework (O'Connell & Bailey, 2011; Pacifici, 2015) when interested in measures of species richness (O'Brien et al., 2011).

A clustered design can be a cost-efficient approach to increase the number of replicates at each site (especially when accessibility is limiting; Gálvez et al., 2016) and to reduce measurement error and improve precision (Clarke et al., 2019). However, spatial autocorrelation may occur with this design (Moqanaki et al., 2021), depending on the camera spacing (see section 6.2.7).

Paired design – a form of "clustered design" when two cameras are deployed in close proximity to one another at a sample station ("paired cameras"). A paired design may also refer to when one or more cameras are deployed at two separate locations that are in close proximity or with some characteristics in common ("paired sites", e.g. when interested in comparing "control" versus "experimental" sites, or on- versus off-trails). For some objectives, pairs of cameras might be considered subsamples within another sampling design (e.g., simple random, stratified random, systematic).

6.2.5 Targeted design

Targeted design – cameras are placed in areas that are known or suspected to have higher activity levels (e.g., game trails, mineral licks, etc.). This design is useful when monitoring rare or cryptic species that are unlikely to be detected with other designs. This design is commonly used when estimating densities of marked populations (e.g., spatially explicit capture-recapture [SECR; Borchers & Efford, 2008; Efford, 2004; Royle & Young, 2008]) or behaviour studies. It is, however, important to understand that targeted sampling may impede one's ability to make inferences beyond the survey area. For some objectives, targeted sampling may be used within another sampling design (e.g., a stratified random sample of game trails and seismic lines; Keim et al. 2021).

6.2.6 Convenience design

Convenience sampling design – camera locations or sample stations are chosen based on logistic considerations (e.g., remoteness, access constraints, costs). When cost is a key consideration, other more rigorous sampling designs (e.g., stratified; van Wilgenburg et al., 2020) that can incorporate cost should be considered first. One should be cautious when generalizing or drawing conclusions from data collected using convenience sampling, given that estimates can be biased if the sample poorly represents the population of interest. The convenience sampling design can be used where the goal is to survey a specific location(s) without the intent to generalize to un-surveyed areas (Gillespie et al., 2015; e.g., Kusi et al., 2020) or to survey an area following a report of the occurrence of a rare species. Both randomized (e.g., Found & Patterson, 2020) or targeted approaches can be used within a convenience sampling approach, although the user should still be cautious about extrapolating inferences to areas (or habitat types in an occupancy framework [MacKenzie et al., 2002]) that were not sampled and, therefore, not represented in the data (Gillespie et al., 2015).

6.2.7 Psuedoreplication

Spatial autocorrelation (i.e., the tendency for sites that are close together to be more similar) may occur when multiple cameras are placed nearby (such as in *clustered, paired or array sampling*). Spatial autocorrelation is a form of pseudoreplication (Hurlbert, 1984; when observations are not statistically independent but are treated as if they are) and can be problematic because it can artificifically inflate or diminish ecological effects. The degree to which this is a problem will depend on the Target Species (i.e., how far they can travel may dictate the distance at which another camera is too near) and modelling approach. In these cases, users should consider an analytical framework that accommodates autocorrelation to avoid issues of spatial pseudoreplication (Hurlbert, 1984) and false conclusions (Ramage et al., 2013) (e.g., using random effects [Wearn & Glover-Kapfer, 2017] or spatial autoregressive models [Kelejian & Prucha, 1998]).

Note that pseudoreplication (Hurlbert, 1984) can also occur over time (e.g., if camera locations are sampled repeatedly to obtain detection rates as a repeated counts, or if the inter-detection interval is too short for a sebsequent detection to be truly independent of the first detection).

6.3 Camera spacing

The distance between cameras (the "camera spacing“, also referred to as "inter-trap distance") is an important consideration when designing a camera survey. This will be influenced by the chosen sampling design, the Survey Objectives, the Target Species, modelling approach and data analysis.

For example, if the objective is to estimate grizzly bear occupancy and cameras are placed close together, detections may not be statistically independent if the same individual is detected at neighbouring camera sites within a short time period. In contrast, if the objective was to estimate occupancy for a different species such as marten, the camera spacing may be statistically independent in this case.

It is important that you understand how the Survey Objectives influence sampling design and decisions about camera spacing (Wearn & Glover-Kapfer, 2017). When estimating density from marked populations using a clustered design and SECR modelling approach (Borchers &

Efford, 2008; Efford, 2004; Royle & Young, 2008), for example, the spacing between clusters and cameras within a cluster are important considerations (Clarke et al., 2019). In this case, placing cameras in close proximity to one another can increase the detection probability, and in turn, increase statistical power, shorten survey lengths, and reduce costs (WildCAM Network, 2019). However, detections from nearby cameras may not be independent and could lead to issues with pseudoreplication (Hurlbert, 1984) and false conclusions (Ramage et al., 2013).

The spacing requirements of the different modelling approaches (dictated by the objectives) vary and should be considered carefully. The recommendations for camera spacing for various modelling approaches are summarized below and in Appendix A - Table A2.

6.3.1 Modelling approach

The spacing requirements of the different modelling approaches (dictated by the objectives) vary and should be considered carefully. The recommendations for camera spacing for various modelling approaches are summarized below.

- There are no guidelines for spacing requirements for species inventory projects.
- For **species richness**, **species diversity**, and relative abundance, spacing of at least 1–2 kilometres apart should be adequate to ensure that cameras are spatially independent (Colyn et al., 2018; Rovero et al., 2013; Wearn & Glover-Kapfer, 2017). It is important when combining relative abundance data from multiple surveys to use the same camera spacing, as relative abundance estimates can increase as camera spacing decreases (and vice-versa; Anile & Devillard, 2016)]. camera spacing decreases (and vice-versa; Anile & Devillard, 2016)].
- For occupancy models (MacKenzie et al., 2002), the camera spacing should be comparable to the size of the home range of the Target Species (i.e., one home range diameter apart) to ensure that only one animal is recorded per sampling unit (Linden et al., 2017; Neilson et al., 2018; Rovero et al., 2013; Steenweg et al., 2018; Wearn & Glover-Kapfer, 2017). (i.e., one home range diameter apart) to ensure that only one animal is recorded per sampling unit (Linden et al., 2017; Neilson et al., 2018; Rovero et al., 2013; Steenweg et al., 2018; Wearn & Glover-Kapfer, 2017).
- For capture-recapture (CR) models (density; Karanth, 1995; Karanth & Nichols, 1998), camera spacing should be analogous to the home-range scale or smaller. With the advent of spatially explicit capture-recapture [SECR; Borchers & Efford, 2008; Efford, 2004; Royle & Young, 2008] models, CR models (Karanth, 1995; Karanth & Nichols, 1998) are seldom used and no longer recommended. (Karanth, 1995; Karanth & Nichols, 1998) are seldom used and no longer recommended.
- For spatially explicit capture-recapture (SECR; Borchers & Efford, 2008; Efford, 2004; Royle & Young, 2008) models, the optimum camera spacing is 0.3 times the home range diameter of the Target Species, with up to 0.8 times the home range diameter being acceptable (O'Brien & Kinnaird, 2011; Rovero et al., 2013; Soria-Díaz et al., 2010; Wearn & Glover-Kapfer, 2017). SECR models (Borchers & Efford, 2008; Efford, 2004; Royle & Young, 2008) are, however, robust to increased camera spacing (Sollmann et

al., 2012; Zimmermann, 2013). Sampling over a larger spatial extent may be more important in some cases than preserving recommended camera spacing (Sollmann et al., 2012; Zimmermann et al., 2013). (Sollmann et al., 2012; Zimmermann, 2013). Sampling over a larger spatial extent may be more important in some cases than preserving recommended camera spacing (Sollmann et al., 2012; Zimmermann et al., 2013).

- For random encounter models (REM; density; Rowcliffe et al., 2008), the camera spacing should be large enough to avoid sampling the same individual repeatedly (i.e., observations are independent; Rovero et al., 2013; Wearn & Glover-Kapfer, 2017). Cameras should be spaced farther apart than the home range diameter of the Target Species (Wearn & Glover-Kapfer, 2017). (Wearn & Glover-Kapfer, 2017).

Refer to Appendix A - Table A2 for additional recommendations on camera spacing for the different modelling approaches.

6.3.2 Avoidance behaviour

Interactions between species can also influence the choice of camera spacing. For example, a study of interactions between Tasmanian devils and domestic cats found that cats avoided Tasmanian devils over short distances. Such avoidance behaviours can be problematic when a survey targets the species showing these behaviours, or when the behaviours are not accounted for in the study design or data analyses (Fancourt, 2016).

6.3.3 Site closure assumption

Many modelling approaches (e.g. occupancy models [MacKenzie et al., 2004]; Appendix A - Table A1) assume "site closure" (i.e., that there is no change in state (e.g. species presence/ absence, immigration/ emigration, births/deaths) during the survey period (MacKenzie et al., 2004). For some approaches, violation of the site closure assumption can result in an underestimate of detection probabilities and, in turn, over-estimate density (e.g., with spatial recapture models) or result in simply averaging detections over the sampling period (e.g., REM [Rowcliffe et al., 2008, 2013], REST [Nakashima et al., 2017] models). To meet the "site closure" assumption, the study design might include spacing cameras far enough apart that the same individual is not detected at multiple sites (e.g., larger than the species' home range size). The survey duration might also be short enough that the probability of occupancy does not change (i.e., not confounded by other processes, e.g., by changes in the population since occupancy is a function of abundance) (O'Connell & Bailey, 2011). Refer to Appendix A - Table A2 for recommendations on how to deploy cameras to meet "site closure" assumptions.

6.4 Survey effort and timing

6.4.1 Survey effort – Number of cameras

Appendix A - Table A2 shows the recommended minimum of cameras according to the Survey Objectives and modelling approach. The optimal number of cameras required will be influenced by factors such as landscape heterogeneity, survey duration and spatial scale, species rarity and desired level of precision (Colyn et al., 2018; Rovero et al., 2013). For example, Kays et al. (2020) found that 25–35 cameras were needed for precise estimates of species richness, depending on the spatial scale of the survey and landscape diversity. The number of cameras required for precise estimates of occupancy was highly sensitive to the occurrence rate of species, with <20 cameras required for common species and >150 cameras required for rare species (Kays et al., 2020). In general, deploying more cameras and/or for longer durations always results in more precise estimates; however, users can consider rotating cameras across multiple sites for shorter durations (if feasible). There are several useful references and applications available to help determine the optimal number of cameras for a survey (e.g., Efford & Boulanger, 2019).

When the objectives and modelling approach warrant, placing multiple cameras at a site (either on the same attachment point or nearby) can significantly increase the detection probability of less common species (more than increasing the number of camera days per camera location; O'Connor et al., 2017; Pease & Holzmueller, 2016; Stokeld et al., 2016) or be useful for individual identification.

6.4.2 Survey effort – Camera days per camera location

A second related consideration in terms of survey effort is how long to survey (i.e., the number of "camera days per camera location") at each camera location. Specifically, the number of camera days per camera location is the number of days that each camera was active and functioning during the survey. It is important to consider how the Survey Objectives and assumptions of the chosen modelling approach may influence this decision.

Wearn and Glover-Kapfer (2017) suggested that for estimates of density, species richness, relative abundance and occupancy, each camera should remain active for a minimum of 30 camera days. Steenweg et al. (2019) found that increasing the number of camera days per camera location improved the likelihood of detecting a change in occupancy, but only when the cumulative detection probability (i.e., "the probability of detecting a species at least once during the entire survey" [Steenweg et al., 2019]) was below a certain threshold (<0.80). In other words, if cameras were deployed long enough to reach a cumulative detection probability >0.8 for the Target Species and survey period, there was no benefit to surveying longer at one camera location (Long et al., 2008; Steenweg et al., 2019) (see also section 6.4.4).

For measures of species richness or diversity, it is presumed that a camera is active long enough to detect rare species that may occur at a specific location (Wearn & Glover-Kapfer, 2017). If this is not the case, the results will indicate that the species was not present when it was (i.e., a "false negative"). False negatives may also be problematic for other measures, such as **relative abundance indices** (count data, with or without zero-inflation and/or overdispersion), even if the model type used can account for imperfect detection explicitly (e.g., combined occurrence/relative abundance; N-mixture models).

Variability in sampling effort amongst cameras can be accounted for in many approaches (e.g., for count data, an "offset" can be used to convert the count to a rate per unit time while still abiding by the assumptions of count-distributed data [Gallo et al., 2022; Moll et al., 2020]).

6.4.3 Survey effort – Total number of camera days

The **total number of camera days** is the number of days that all cameras were active during the survey. Appendix A - Table A2 provides recommendations on the minimum number of total number of camera days.

An adequate sample size (in terms of the total number of camera days) in multiple seasons is often required to capture seasonal variation in occupancy or detection rates. As a general guideline, Kays et al. (2020) recommended that cameras run for 3-5 weeks across 40-60 sites per array and that small-scale variation in detection probability across sites (e.g., microhabitats) should be accounted for in subsequent statistical analyses.

Becker et al. (2022) evaluated how the effective detection distance of cameras changed across species, habitat type and season. Effective detection distance refers to the distance from a camera that would give the same number of detections if all animals up to that distance are perfectly detected and no animals that are farther away are detected; Buckland [1987], Becker et al. [2022]). In general, deploying more cameras and/or for longer durations always resulted in more precise estimates (Becker et al., 2022).

6.4.4 Species rarity

Species' rarity can influence the ideal number of cameras and survey length (Chatterjee et al., 2021) (see also section 6.4.2). Low detection probability of rare or cryptic species can result in imprecise estimates if there are too few cameras or if cameras are not deployed for long enough (e.g., Steenweg et al. 2019). Chatterjee et al. (2021) suggested that for occupancy models (MacKenzie et al., 2002) of common species, to survey a minimum of 50 sites for 15–20 days. For rare, elusive species, they recommended surveying 100 sites at minimum for 20–30 days (Chatterjee et al., 2021).

6.4.5 Number of cameras vs. Camera days per camera location

If a user must choose between more cameras *vs.* fewer cameras with longer surveys, Chatterjee et al. (2021) suggested that for rare species, the optimal precision can be obtained by increasing the number of sites, whereas for common species, increasing the number of samples is more effective. For measuring species richness, Si et al. (2014) found that rotating cameras to new sites was more efficient than leaving cameras at fewer sites for longer periods. O'Connor et al. (2017) also recommended utilizing more cameras *vs*. increasing study length to increase detection probabilities. Spatially explicit capture-recapture (SECR; Borchers & Efford, 2008; Efford, 2004; Royle & Young, 2008) models were the only models shown to be quite robust to small camera quantities, with just spacing cameras farther out being a more efficient way to increase precision (Sollmann et al., 2012).

In general, regardless of species and objective, increasing the number of survey locations or the survey length improved precision (Chatterjee et al., 2021). Tools such as the secrdesignapp can help camera users determine the optimal study design for improved precision (Efford & Boulanger, 2019).

6.4.6 Survey timing

The season of the survey should be considered when designing a remote camera study. Detection probability of species may vary seasonally due to changes in species movement rates, behaviour, use patterns, and vegetation growth. Certain species may not be detectable during certain times of year (e.g., hibernation or migration; Kays et al., 2020). Other species have seasonal activity patterns (e.g., birthing period, wet/dry seasons) that influence detection probability and, thus, the data collected.

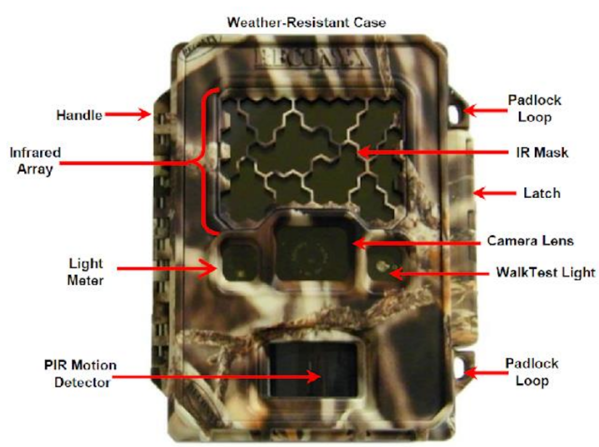
7.0 Camera deployment

Once the project-level aspects of a survey have been decided, the next step is to consider the camera hardware options (e.g., Camera Make and Camera Model), camera settings, field equipment, whether to use attractants (bait or lure), camera placement considerations, and 1 collect.

7.1 Camera hardware options

Remote cameras consist of a digital camera with a lens, external flash, and a passive infrared and/or motion detector (among other features; Figure 4).

a)



b)

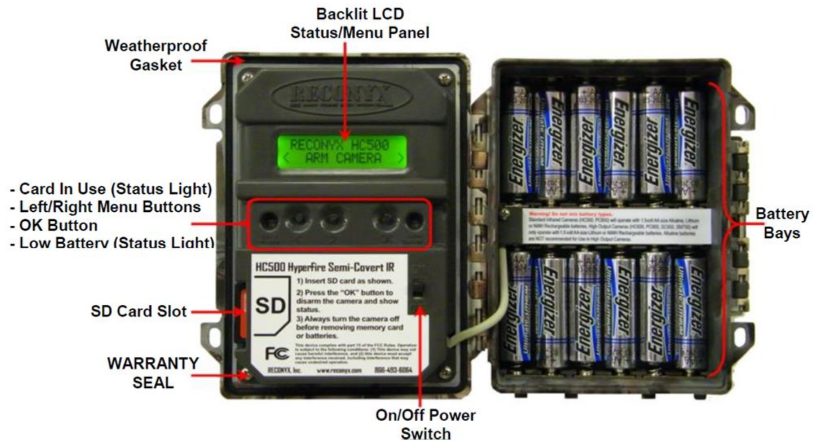


Figure 4. Examples of the a) external components and b) internal controls and components of a remote camera (Reconyx PC900) (Reconyx Inc., [2017]).

The camera "make" is the manufacturer of a particular camera (e.g., Reconyx), and the "model" is the model number of a particular camera (e.g., PC900). There are many different options and features to choose from when deciding upon the best Camera Make and Camera Model for a particular study, which differ in their impacts on detection probability. For this reason, deploying multiple Camera Models within a study is not advisable (Palencia et al., 2022; Wellington et al., 2014).

It is common for new camera users to confuse the specifications of a particular Camera Make and Camera Model with the camera's settings. Specifications refer to the camera's features (characteristics), while settings are options that the user can change. When choosing a Camera Make and Camera Model, important specifications include trigger speed, recovery time, detection zone (i.e., the area [conical in shape] in which a remote camera can detect the heat signature and motion of an object [Rovero & Zimmermann, 2016; see Figure 5), battery life and flash type. The best choice of Camera Model will depend on the Survey Objectives, modelling approach, Target Species, and physical environment.

Here are a few examples of specifications to achieve certain Survey Objectives:

- To estimate density with the random encounter models (REM; density) approach – use a camera with a fast trigger speed, a wide detection zone, no-glow infrared (IR) flash, and the ability to take bursts of photos (Rovero et al., 2013).
- To estimate density or abundance with mark-recapture methods – use a camera with a white flash, a short recovery time, and a fast trigger speed (Rovero et al., 2013). Note that white flashes may scare some animals and potentially reduce the number of recaptures (Sequin et al., 2003; Wegge et al., 2004).
- Occupancy studies need a fast trigger speed (Trigger Sensitivity - high) (although the importance of which is species-dependent; Rovero et al., 2013).

Faunal detections generally require a fast trigger speed (Trigger Sensitivity - high) and a wide detection zone.

Note: most modelling approaches require a fast trigger speed (however, the use of bait or lure may compensate for slower trigger speeds in some cases).

Given the numerous Camera Models available and the frequent release of new models, it would be difficult to recommend a make and model to fit all users' needs. However, there are many studies and reviews that compare the specifications and the utility of different Camera Models (e.g., see https://www.trailcampro.com/collections/trail-camera-reviews; https://www.mammalweb.org/images/schools/Camera-trap-buying-guide.pdf; Fisher & Burton, 2012; Rovero et al., 2014; Rovero & Zimmermann, 2016; Seccombe, 2017; Wearn & Glover-Kapfer, 2017).

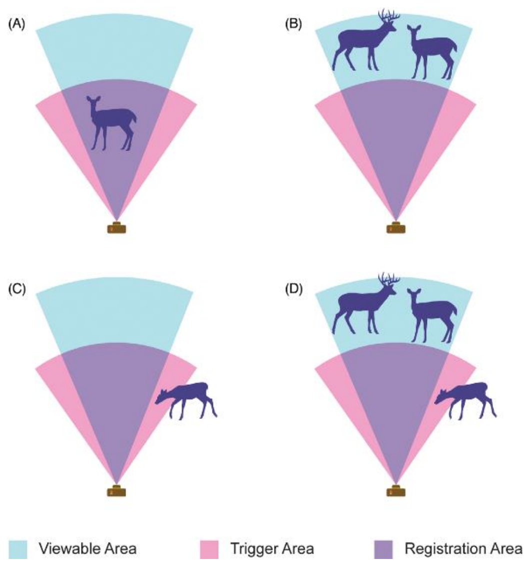


Figure 5. The ability to detect an animal will vary according to the camera specifications (and settings). Important specifications include the camera's detection zone (here termed "trigger area"), Field of View (FOV; "viewable area'), and "registration area" (the area in which an animal entering has at least some probability of being captured on the image) (Moeller et al., 2023).

7.1.1 Battery type

Most remote cameras require AA batteries. It is recommended to use **lithium batteries,** as opposed to alkaline or nickel metal hydride, because they are less affected by cold temperature. Battery life will be affected not only by the type of batteries but also by the camera settings, temperature, and number of images or videos taken (which are dependent on the camera settings, placement, and level of activity in front of the camera) (Wearn & Glover-Kapfer, 2017). However, some camera user manuals contain information on battery performance and the total number of images a camera can be expected to collect before the batteries die (based on operating temperature and battery type, e.g., Reconyx HyperFire Instruction Manual [Reconyx Inc., 2017]).

7.1.2 SD cards

It is important to consider the **size**, **type**, and **class** of **SD (Secure Digital) card** since the available options vary in storage capacity, compatibility, and write-speed (Wearn & Glover-Kapfer, 2017).

The **size of the SD card** (i.e., storage capacity) should be considered in relation to the expected duration of deployment, the deployment area, and the level of activity expected to occur in front of the camera. For example, a camera placed in a grassy area might be expected to produce more false triggers due to grass waving in front of the camera. While a camera placed near a den might be expected to have higher animal activity. Both situations might warrant using a larger SD card. A 4 GB SD card is capable of storing ~8,000-20,000 images (400-900 KB in size), which might be sufficient if you plan to revisit the camera frequently (~every 4 weeks) (Wearn & Glover-Kapfer, 2017). We suggest using a card with at least 16 GB, and Wearn & Glover-Kapfer (2017) suggest larger (32 GB) if the video is enabled or if the camera will be active for long periods.

There are three **types of SD card:** standard (SD; maximum memory of 2 GB), high-capacity (SDHC; maximum memory of 32 GB) and extended-capacity (SDXC; maximum memory of > 32 GB) (Wearn & Glover-Kapfer, 2017). Note that SDHC cards are not compatible with most Camera Models. Be sure to check the camera user manual to confirm the compatible SD card type(s) (Wearn & Glover-Kapfer, 2017).

The **"class" of an SD card** (e.g., class 2, 4, 6, or 10) indicates the "write-speed" (i.e., the speed at which the SD card can read and write data; Wearn & Glover-Kapfer, 2017). Slower write-speeds may perform poorly if the camera is set to collect images continuously, as fast as possible (i.e., rapidfire or "near-video") or if the video setting is activated. It is recommended to use an SD card of class 4 or higher, ideally, class 10 (Wearn & Glover-Kapfer, 2017).

Caution should be used when deploying older SD cards (Wearn & Glover-Kapfer, 2017) and, perhaps, microSD card types; a few remote camera users in Alberta have described a 50% SD card failure rate with microSD cards (St. Clair, personal communications). See Wearn & Glover-Kapfer (2017) for additional information on choosing and maintaining (i.e., regularly formatting) SD cards.

7.2 Camera settings

As mentioned above, in camera hardware options, it is important to distinguish between camera specifications (features) versus settings (user-defined options). Important settings often include Trigger Sensitivity (which may affect detection probability), Motion Image Interval and Quiet Period. The setting option selected may vary according to the Survey Objectives, modelling approach, Target Species, and use (or not) of attractants. Consideration of the camera settings is an important step when designing a survey and in the interpretation of the resulting images.

An example of the settings available in a Reconyx camera is included in Appendix A - Table A3.

7.2.1 Photos vs video

Some Camera Models allow the user to record video as well as photos. Videos typically use more memory on SD cards, drain camera batteries sooner and are more difficult to process (i.e., extract data) than images. Limiting the length of video taken when the camera is triggered (possible for most Camera Models) could help slow how quickly an SD card becomes full. Some Camera Models have hybrid settings, which lets you capture photos and videos for each animal detection.

It is generally recommended that cameras are set to capture images rather than videos unless the objective is related to monitoring animal behaviours, understanding group size and/or determining recruitment (e.g. calves per female), in which case continuous observation may be important. Video is also useful when individual identification is needed, such as for creating "marked" individuals for use in machine learning or computer vision (e.g., Schneider et al., 2019; Vidal et al., 2021).

By default, cameras are set to record images when an animal is detected by the motion and/or infrared detector(s).

7.2.2 Trigger Mode(s) – Time-lapse vs motion detector

By default, remote cameras are triggered to take photos when the motion detector detects an animal. Many Camera Models allow you to set your camera in both time-lapse and default motion detector settings.

Time-lapse images are images taken at regular intervals (e.g., hourly or daily, on the hour), regardless of whether an animal is present or not. It is critical to take a minimum of one time-lapse image per day at a consistent time (e.g., 12:00 pm [noon]) to create a record of camera functionality. Time-lapse images can also be used to monitor vegetation phenology and productivity, and they may be useful in measuring wildfire and snow regimes (Sun et al., 2021).

Time-lapse images may always be useful for modelling approaches that require estimation of the "viewshed" (i.e., "viewshed density estimators," such as REM or time-to-event (TTE) models; see Moeller et al., [2018] for advantages and disadvantages).

7.2.3 Trigger Sensitivity, Photos Per Trigger, Motion Image Interval and Quiet Period

The **Trigger Sensitivity** determines how easily the camera is activated ("triggered") via the passive infrared (PIR) detector (sensors) once the animal enters the detection zone. A high Trigger Sensitivity is ideal when estimating density or abundance using mark-recapture or occupancy modelling (Rovero et al., 2013). The more easily (and faster) the camera is triggered, the more likely it is to photograph approaching animals as they enter the area (Apps & McNutt, 2018). High Trigger Sensitivity (and fast Motion Image Intervals) are less necessary if attractants are present (Rovero et al., 2013). Refer to section 6.2 for examples of ideal Trigger Sensitivity settings to achieve certain Survey Objectives.

The camera user can also predefine how many photos are taken per photo burst upon detecting an animal (i.e., “Photos Per Trigger, e.g., 1, 2, 3, 5 or 10 photos). The user can specify the time interval between images (i.e., the “Motion Image Interval“) or the time interval between image sequences (i.e., the “**Quiet Period**“ or “time lag,” depending on the Camera Make and Camera Model). The Quiet Period differs from the Motion Image Interval in that the delay occurs between multi-image sequences, rather than between the images contained within multi-image sequences (as in Motion Image Interval). Setting the camera to take continuous photos (i.e., the Quiet Period set to “no delay”) will fill the SD card with more photos per detection; however, it may provide important information for identifying individual animals, determining enter-leave times and regarding animal behaviours / interactions.

Generally, it is recommended to set the Trigger Sensitivity to “high,” Photos Per Trigger to “1” and the Quiet Period to “no delay” between consecutive triggers (Appendix A - Table A3).

7.3 Attractants *vs.* no attractants

Attractants (i.e., bait or lure) can increase the detection probability by drawing animals into the camera’s detection zone , thereby effectively increasing the sampled area.

Bait is a food item (or other substance) that is placed to attract animals via the sense of taste and olfactory cues (Schlexer, 2008). Lure is any substance that draws animals closer; lures include scent (olfactory) lure, visual lure and audible lure (Schlexer, 2008).

There are many options of bait and lure available, and those used in camera studies have included commercial scent lures, food baits, carcasses and compact disks (see Wearn & Glover-Kapfer, 2017 for details and examples). Scent lure is typically applied to objects in the detection zone (e.g., trees or rocks), whereas food lure is generally hung up or placed behind wire mesh to limit tampering by animals. Food rewards (baits or carcasses) are also used but are more likely to influence behaviour and inter- and intra-specific interactions (e.g., avoidance of an area or conflict between individuals or species) and may result in food conditioning, which in turn may lead to human-wildlife conflict.

Some options are costly and require frequent reapplication during the survey deployment. Users should consider the additional cost of supplies and labour required to revisit the field to reapply at the frequency necessary to maintain effectiveness. Scent lure dispensers, such as those developed by the Woodland Park Zoo, may help reduce the number of visits needed for reapplication and associated costs.

Few studies have compared the efficacy of different types of attractants, but both Espartosa et al. (2011) and Thorn et al. (2009) suggested that food baits are more effective than scent lures for many species (although these evaluations did not include wildlife species from Canada).

Since species may respond to lure types and scents differently, the type of lure chosen (if any) should be based on the biology of the Target Species but also on the Survey Objectives and the survey environment. For example, liquid products may be less suitable in areas where precipitation is high. Some lure types smell like the urine of a particular species, which could result in higher detections of certain species by activating an investigative response while resulting in avoidance by other species. Interestingly, a study (Holinda et al., 2020) by members of WildCAM found no evidence that scent lure placed at camera stations repelled non-target (i.e., prey) animals (see also Mills et al., 2019); rather, both predators and prey showed varied responses to the scent lure.

For many modelling approaches, placing bait or lure may violate model assumptions and increase the likelihood of biased results (e.g., lure might amplify measures of occurrence, biasing estimates of space use [Stewart et al., 2019]). Attractants may also introduce variation in the response by species, individuals or Sex Classes (or over space or time) that would not naturally occur. It may be possible to address biased samples in the analysis stage, but this can require substantial amounts of data.

In contrast, placing bait or lure can also help to better satisfy the assumptions of some modelling approaches. For example, attractants might be deployed to help satisfy the assumption of constant detection probability of occupancy (when using a systematic random design), relative abundance and capture-recapture (CR; Karanth, 1995; Karanth & Nichols, 1998) models by increasing individuals' detection probability (Wearn & Glover-Kapfer, 2017).

Bait or lure may be a "necessity" for species (or areas) where detection is unlikely without a large number of remote cameras or lengthy surveys. Most studies that use attractants target carnivore species, which are often elusive, difficult to monitor and occur at low densities.

In general, we recommend against the use of bait or lure for projects focused on unbiased detection of as many species as possible. Overall, the use of attractants is not recommended unless the study is an occupancy or capture-recapture study of a Target Species with low detection probability (Wearn & Glover-Kapfer, 2017).

We advise against the use of bait in or near urban areas due to the possible increase in human-wildlife conflict. To minimize this potential, bait or lure should not be placed within 200 m of residences, industrial or recreational facilities, campgrounds, 100 m of active human-use trails (e.g., hiking trails), or 50 m of roads.

Where attractants are used, users must follow provincial policy and legislation (e.g., BC Wildlife Act – Section 33.1, Alberta Wildlife Act and Wildlife Regulation), as well as local bylaws. Before deploying any remote cameras in the field, users must also obtain the necessary permits from provincial and/or research institutions (e.g., animal care permits). In Alberta, a wildlife research and collection permit is required when using bait or lure. Special conditions or restrictions may also apply. Refer to https://www.alberta.ca/wildlife-research-and-collection.aspx for further details. In British Columbia, a research permit is required when using bait, but not scent lure. Special conditions or restrictions may also apply in each province.

Consideration of placement locations should include proximity and potential impacts to First Nations Reserves and Metis Settlements. You can find information on First Nations Reserves and Metis Settlements using the Landscape Analysis Indigenous Relations Tool (LAIRT) (Government of Alberta, 2023a) located within the Landscape Analysis Tool (LAT) (Government of Alberta, 2023b) (see "Non-Administered Areas"). The results produced by LAIRT do not provide an official list of First Nations and Metis settlements to consult if consultation is required since "LAIRT will report on where government ordinarily considers requiring consultation with a particular First Nation or Metis Settlement, which is subject to be revised at any time” (Government of Alberta, 2023a).

7.4 Camera placement

When deploying a remote camera, important considerations include whether to place cameras on or aim cameras towards specific features, as well as the Camera Attachment point, height, angle and direction.

The information in this section is also included in a step-by-step description of the deployment process (Appendix A - Table A5).

7.4.1 FOV Target Feature

Remote cameras may be deployed to capture detections on specific man-made or natural features (i.e., “**FOV Target Feature**“) to maximize the detection of uncommon wildlife species or to measure the use of that feature. FOV Target Features may include, for example, game trails, human trails, watering holes, mineral licks, rub trees, nest sites etc.

FOV Target Features differ from Camera Location Characteristics (see below) in that FOV Target Features are features the camera is aimed towards (e.g., a seismic line). In contrast, a Camera Location Characteristics may include features outside of the camera’s FOV (e.g., meadow habitat).

The decision of where exactly to place the camera will be influenced by the feature to target, the Survey Objectives and the number of Target Species, and, importantly, the sampling design, intended analysis and associated statistical assumptions.

Deploying cameras on or near FOV Target Features can provide meaningful information for some objectives, but often introduces detection biases (Wearn & Glover-Kapfer, 2017). These biases make it difficult to extrapolate findings to areas without these features or to collect data on multiple Target Species that vary in their use of these features (Wearn & Glover-Kapfer, 2017). To reduce potential biases, cameras should ideally be deployed using a paired design, with cameras on- and off-FOV Target Features (e.g., on- and off-trails).

In general, cameras should be placed approximately **3–5 m from the** FOV Target Feature (Figure 6; the “FOV Target Feature Distance (m)“ [Figure 7]). If cameras are placed too close to the FOV Target Feature, some species may not be detected since the camera may be too high to capture smaller species or the movement speed of certain species. In contrast, if cameras are placed too far from the FOV Target Feature (e.g., >5 m), animals detected at night may not be visible in the images because they are less likely to be illuminated by the infrared flash.

This recommendation can be relaxed if users plan to estimate the detection distance (i.e., “the maximum distance that a sensor can detect a target” [Wearn and Glover-Kapfer, 2017]) and account for variability in detection probability.

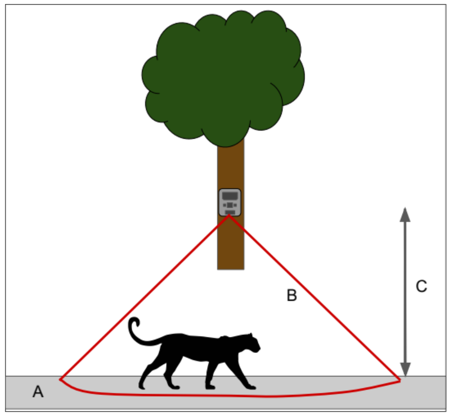


Figure 6. Illustration of a remote camera showing (A) the FOV Target Feature (a trail), (B) the camera's detection zone (everything inside the red outline), and (C) the distance of the camera to the FOV Target Feature. Note that the detection zone will vary according to Camera Make and Camera Model. Camera users will need to identify a suitable attachment point (e.g., tree, fence post/ stake) near the target area. The most suitable attachment point will depend on the Camera Height, angle, and direction since these choices will impact the FOV (see section 7.4). Figure from WildCAM Network (2019).

7.4.2 Camera Height

The **Camera Height** is the height from the ground (below snow) to the bottom of the lens (recorded in metres to the nearest 0.05 m). Cameras should be positioned and secured to an attachment point at **~0.5–1 m height** (from the ground to the bottom of the lens; Meek et al., 2014). The most appropriate Camera Height will be influenced by the terrain (e.g., slope), the angle of the tree, as well as the Target Species. Cameras placed closer to the ground reduce the probability that large animals (e.g., moose) will be fully in the frame in the photos. Similarly, if the camera is placed too high, only larger animals will activate the motion detector, and smaller species may be missed (e.g., hares, squirrels, marten) (Meek et al., 2016). The user should ensure that the Camera Height adequately detects motion at a specified Walktest Distance (m) and Walktest Height (m). If snow is a consideration, users may need to place cameras higher or plan to revisit seasonally to adjust as needed, being sure to record adjustments that could affect detection probability.

7.4.3 Camera angle

The **camera angle** is the degree to which the camera is pointed towards the FOV Target Feature relative to the horizontal ground surface (with respect to slope, if applicable). The camera angle differs from the camera viewshed angle, which is the area visible to the camera as determined by its camera lens angle and trigger distance (Moeller et al., 2023).

Cameras should be **angled slightly downward**, such that they should be able to detect both small and large species at a target distance of approximately **3–5 m** from the camera and/or the user ensures that the angle adequately detects motion at a specified Walktest Distance (m) and Walktest Height (m). Cameras should not be angled upwards, as upward facing angles will result in fewer detections, especially of smaller species (Glen et al., 2013). If snow is a consideration, users may need to angle cameras higher or plan to revisit seasonally to adjust as needed, being sure to record adjustments that could affect detection probability.

7.4.4 Camera Direction

The Camera Direction is the cardinal direction that a camera faces. Cameras are usually positioned to maximize detections of the Target Species (except when random placement is required).

The direction a camera faces is an important consideration because it affects the amount of light that reaches the area, which has implications for both detection probability and image quality (reduced quality via sun glare). Ideally, cameras should face north (N; i.e. “0” degrees), or south (S; i.e. “180” degrees) if north is not possible. Sun glare is the most problematic for cameras that face east or west by causing false triggers unless there is thick tree cover blocking the sun (standing water may also produce similar problems with sun glare).

The camera direction should be chosen to ensure the field of view (FOV) is of the original FOV target feature. Generally, cameras should be placed **perpendicular to the expected direction of animal travel** (e.g., along a game or human trail). Since there is a delay between when an animal enters the camera’s detection zone and when it captures an image, placing the camera perpendicular to the trail increases the likelihood that an animal will be in the frame when the camera triggers (Apps & McNutt, 2018). The delay is typically <1 s, depending on the trigger speed for a particular camera and the settings applied. The size of the detection zone will depend on the Camera Make and Camera Model.

7.4.5 Field of View (FOV) and Walktest

It is important to try to ensure an unobstructed Field of View (FOV) from the camera to avoid impairing the detection rates of wildlife (or humans). Moll et al. (2019) reported decreased detection rates with increasing obstruction for most mammals in their study and two- to three-fold decreases in detections per week per camera. They concluded that it was critical to account for viewshed obstruction when interpreting detection rates as indices of abundance and habitat use.

To determine a camera’s FOV, a walktest should be performed every time a camera is deployed or re-positioned. See the camera’s user manual for instructions on how to perform the walktest for your particular Camera Make and Camera Model (see also Appendix A - Table A5).

An **unobstructed FOV of at least 5 m wide and 10 m long** is ideal for capturing wildlife images in most cases. To achieve this desired FOV, ensure that the camera is detecting motion 5 m in front of the camera, at both 0 m and 0.5–1 m heights (Figure 7).

This may require repositioning the camera to avoid large objects (e.g., rocks, logs) and/or trimming or removing vegetation that interferes with the visibility of the target area (or is likely to in the future). These objects may block areas within the camera’s FOV and reflect the flash, making it more difficult to detect animals at night. Trimming or removing vegetation will also minimize the likelihood of false triggers (i.e., blank images (no wildlife or human present) that can occur because of blowing vegetation). False triggers will drain batteries and fill SD cards and increase the time to process images.

Important considerations with respect to FOV include:

- Situations (e.g., open habitats) where animals in background my be viewable but would not trigger the detector (sensor),
- how animals in the distance should be treated (i.e., at what distance is an animal captured in an image no longer considered a detection)

Placing a stake in front of the camera at a specified distance (i.e., the “stake distance”) is one method used to standardize the FOV. Applying a standardized reference distance can help with interpretation and analysis (ABMI, 2021).

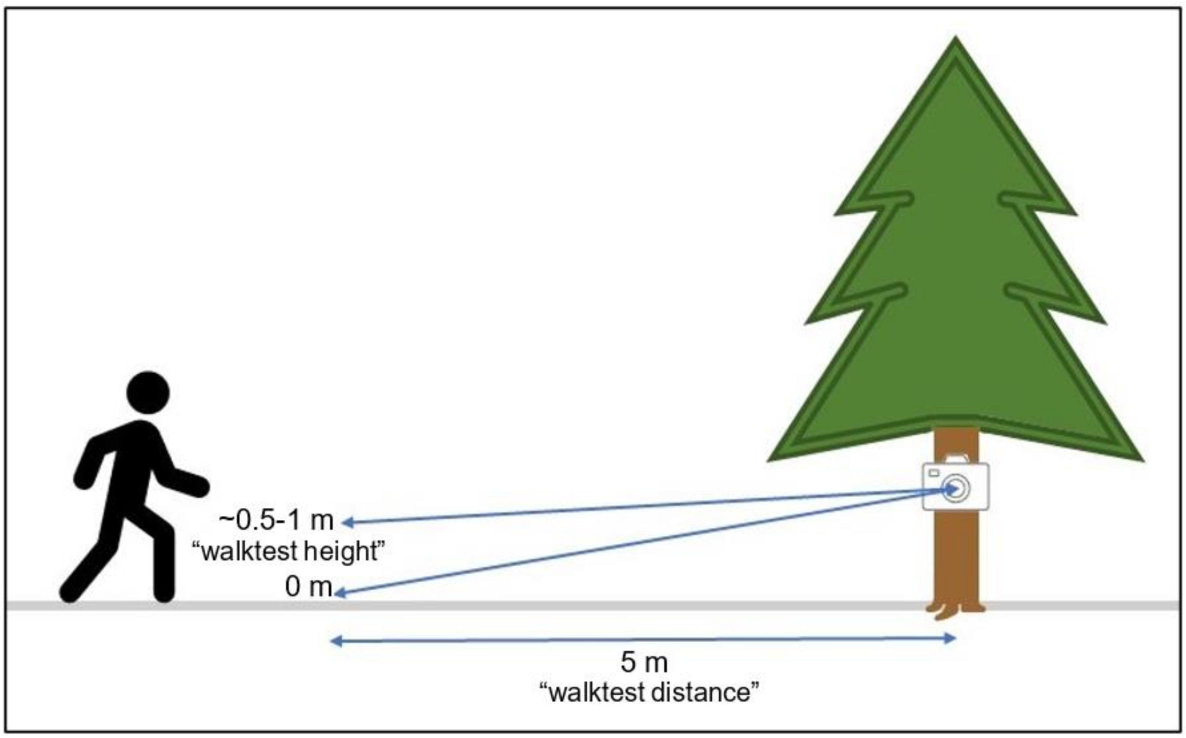


Figure 7. The Walktest Distance and Walktest Height are the horizontal and vertical distances from the camera, respectively, at which the user performs the walk test. A walktest should be performed 5 m away from the camera, at both 0 m (ground) and 0.5–1 m heights.

7.4.6 Test image

A **test image** should be taken from the camera after the walktest is complete to provide a permanent record of the service/ retrieval metadata. A test image should each include a Test Image Sheet or whiteboard with information on the Sample Station ID, Camera Location ID, crew, and Deployment Start Date Time (DD-MMM-YYYY HH:MM:SS). Taking a test image can be useful to compare the information from the test image to that which was collected on the Camera Service/Retrieval Field Datasheet after retrieval, which can help in reducing recording errors.

See Appendix A - Table A5 for details on how to capture a test image, and to the provided Test Image Sheet.

7.4.7 Deployment Area Photos (optional)

It is useful to collect photos of the area around the camera location (i.e., **deployment area photos**) as a permanent, visual record of the FOV Target Features, Camera Location Characteristics, environmental conditions (e.g., vegetation, ecosite, or weather), or other variables of interest.

Take deployment area photos with a handheld digital camera or phone at each camera location at deployment, service and retrieval. The recommendation includes collecting four photos taken from the centre of the target detection zone (Figure 5), facing each of the four cardinal directions. The documentation of the collection of these photos is recorded as "deployment area photos taken" (Yes/No).

Record the image numbers (e.g., DSC100; “Deployment Area Photo Numbers“) for each set of camera deployment area photos on a Camera Deployment Field Datasheet.

7.4.8 Camera Location Characteristics

Camera Location Characteristics are any significant characteristics (human-made or natural, e.g., game trail, seismic line, culvert, burn, etc.), habitat types (e.g., forest - conifer, agricultural field, etc.), animal-made structures (e.g., beaver dam, den, burrow, etc.), attractants (e.g., carcass, mineral licks, etc.) in front of, or around the camera location at the time of the visit. Camera Location Characteristics can include those outside the camera’s FOV.

Researchers typically record information about the environment at camera locations to better understand how this might affect animal occurrence or behaviour. It is recommended to record all Camera Location Characteristics and upload these to a digital data-collection platform with private or open settings like Epicollect (https://five.epicollect.net/), using the template provided. Alternatively, you may choose to upload these photos using species identification models to an open-source platform like iNaturalist (https://inaturalist.ca), WildTrax (http://www.wildtrax.ca/) and/or FWMIS.

7.4.9 Field equipment

Refer to Appendix A - Table A4 for a recommended list of field equipment for remote camera studies.

7.5 Metadata

Metadata (i.e., data that provides information about other data) is critical to any scientific study or monitoring program. It helps to ensure that data are consistent and accurate and facilitates data sharing across projects. Alberta and British Columbia have established metadata standards (AB Metadata Standards [RCSC, 2023] and the B.C. Metadata Standards [RISC, 2019]) that all camera projects in the provinces should follow. In these guidelines, we focus on the metadata fields that pertain to the deployment of cameras, that should be collected when the user "visits" the location.

Note: These guidelines do not describe all fields relevant to/required by the AB Metadata Standards (RCSC, 2023) and B.C. Metadata Standards (RISC, 2019). Similarly, there may be additional/alternative fields required by the Alberta Government's FWMIS loadform for camera studies (https://www.alberta.ca/wildlife-loadforms.aspx) compared to those within these guidelines or the AB Metadata Standards (RCSC, 2023). Every effort has been made to align the various sources where possible.

7.5.1 Metadata – Deployment, Service and Retrieval

A **visit** is when a crew has gone to a location to deploy ("deployment visit"), service, or retrieve ("service/retrieval visit") a remote camera.

A "**deployment visit**" is when a Deployment Crew has gone to a location to deploy a remote camera. Relevant metadata should be recorded when a camera is initially set up (deployed) using the Camera Deployment Field Datasheet. Each event should have its own Camera Deployment Field Datasheet.

If a camera is deployed for more than one survey, the field crews will need to revisit the camera location to "**service**" the camera and/or equipment ("Service/Retrieval Crew"; e.g., to refresh batteries or swap out SD cards. If the Service/Retrieval Crew visits the camera location to collect the camera and other equipment (i.e., the camera location will no longer be used and cameras, SD cards, and batteries are not replaced), this is referred to as a "**retrieval**" (i.e., the camera location will no longer be used, and the camera, SD card, and batteries are not replaced).

Whether the crew services or retrieves the camera, relevant Service/Retrieval metadata should be collected if there have been any changes to camera location, sampling period, and/or setting type (e.g., not baited and then baited later) using the Camera Service/Retrieval Field Datasheet.

Note: the list of Service/Retrieval metadata include additional metadata fields that are not included in the list of deployment metadata.

Nested under the deployment level of the hierarchy, there are a few "groups" of information that help to comprehend the field metadata; these include:

- Visit Metadata (collected at deployment and service/retrieval)
- Equipment Information (collected at both deployment and service/retrieval; fields vary by visit type)
- Camera Settings (collected at deployment)

- Camera Placement (collected at deployment)
- Site Characteristics (collected at deployment)
- Equipment Checks (collected at both deployment and service/retrieval)
- Image Set Information (collected as a combination of information from deployment and service/retrieval visits metadata)

Refer to Appendix A - Table A5 for a detailed step-by-step and full lists of metadata fields and to the Camera Deployment Field Datasheet, and the Camera Service/Retrieval Field Datasheet.

7.5.2 Spatial information

Coordinates collected in the field are often used to obtain land cover information via GIS and can be imperative to finding camera locations later. A large margin of error in collecting coordinates may result in the misclassification of land cover (Robinson et al., 2020) or increase the difficulty of another field crew finding a camera. It is important to record the accuracy (margin of error) of the GPS unit used to record spatial information (coordinates) (i.e., the GPS unit accuracy, e.g., Garmin GPS devices are accurate to within +/- 15 metres 95% of the time). GPS unit accuracy may vary by the make and model of the GPS unit (Hall et al., 2008), but it also may be affected by nearby vegetation, infrastructure, atmospheric interference, etc. (Ganskopp & Johnson, 2007).

7.5.3 SD card retrieval

When retrieving camera SD cards, remove the SD card from the camera and place it into a SD card case, a 2.25" x 3.5"-coin envelope, or a similar pouch labelled with the Deployment ID and SD card number. If certain camera units are part of a larger survey area, group these pouches into a larger envelope and mark it with the Project ID/Survey ID.

8.0 Data management and processing

8.1 Software and tools

There are several software platforms and tools available to help camera users enter metadata as well as store, process, and analyze their image data (refer to Table 1 for a subset of those currently available). Commonly used platforms include WildTrax, Timelapse2 (Greenberg, 2018), and eMammal (McShea et al., 2015). Reconyx MapView (Reconyx, Holmen, WI, USA) may be especially useful for batch renaming (see section 8.4).

For a summary of software programs for managing and processing camera data, refer to Wearn and Glover-Kapfer (2017), Young et al. (2018) and Scotson et al. (2017). For a comprehensive comparison of data platforms and their capabilities, we strongly recommend referring to WildCAM's "A comparison of different camera data platforms."

These guidelines do not endorse any specific remote camera image processing software but do highly recommend the use of such software.

8.2 Data storage (archival)

It is strongly encouraged/may be required that camera datasets (images, deployment area photos and metadata) are submitted to an open data repository.

There are regulatory requirements to submit data to the FWMIS database (not images, although this is strongly encouraged) according to specific government policies (e.g., Sensitive Species Inventory Protocols, Research and Collection permits, etc.). Refer to the Government of Alberta web pages, and the AB Metadata Standards (RCSC, 2023) and B.C. Metadata Standards (RISC, 2019) for further information.

There are other cloud or server-based repositories available to house all camera datasets, including WildTrax, eMammal (McShea et al., 2015), Wildlife Insights (Ahumada et al., 2019) and others (see Young et al., [2018] for a comparison of 12 available programs for the management of camera data).

WildTrax is the recommended data storage (and data analysis) platform in Alberta. It has multiple privacy options and can accommodate all categories of images that users may prefer to manage separately, including false triggers and images of humans (which require special handling for privacy reasons; see section 8.2.5). All data, including the images, deployment area photos and complete metadata, can be uploaded and stored in the WildTrax repository. WildTrax can be used to then collaborate to manage data or share data to answer broader scientific questions.

Users are strongly encouraged to submit all the original images from each deployment for storage to a data repository. Although only the first image of a sequence is often used to characterize the sequence, other images within the sequence provide additional information (e.g., images of all individuals in a group). If it is not possible to submit all of the images from a deployment, ideally, users should submit the image(s) from a sequence that best represents the sequence (e.g., those that can be used to verify the species and number of individuals).

8.3 Image processing

Image processing is the series of operations taken to extract information from images. In the case of remote camera data, it can include loading the images into a processing platform (see section 8.4), extracting information from the image metadata (e.g., the date and time the image was taken), running an artificial intelligence (AI) algorithm to identify empty images, or classifying animals or other entities within the image (see section 8.2.4).

8.3.1 Image names

If you wish to rename your images, it is highly recommended that users develop a photo naming convention prior to entering data. Using naming conventions will minimize the risk of having images from different deployments, study areas, or surveys with the same name.

Note that it is not always necessary to rename images. For example, renaming would not be required if data are stored in a folder structure that identifies the camera location and the survey from which it was collected). Refer to the AB Metadata Standards (RCSC, 2023) and B.C. Metadata Standards (RISC, 2019) for more information on the suggested naming conventions. Data entry software can be used for batch processing of image names, which can significantly reduce data processing time compared to renaming images manually (e.g., Timelapse2 [Greenberg, 2018], Reconyx MapView [Reconyx, Holmen, WI, USA]) or other tools (e.g., WildCo Lab's Image Renamer [WildCo Lab, 2021b]).

8.3.2 Image classification and tagging

Image classification refers to the process of assigning class labels to an image according to the wildlife species, other entity (e.g., human, vehicle, empty, etc.), or conditions within the image (e.g., snow presence or depth [Sirén et al., 2018]). Image classification can be performed manually or automatically by an artificial intelligence (AI) algorithm (see section 8.2.4). Classifying images with AI is commonly used to filter images into relevant categories prior to image tagging (Fennell et al., 2022). Image classification is sometimes used interchangeably with "image tagging."

Image tagging is the process of characterizing wildlife species, other entities (e.g., human, vehicle), or conditions within an image. Image tagging may follow image classification to further describe characteristics of individuals (e.g., Age Class, Sex Class, Behaviour), entities within the image, or information about the conditions of the camera location (e.g., the FOV, presence of bait or lure) or the environment (e.g., weather).

A single Analyst ("observer," "interpreter" or "tagger") should tag all images from a deployment. At a minimum, the Analyst should record the species, number of individuals (count), Age Class and Sex Class of wildlife, as well as other entities of interest (e.g., humans).

Refer to the AB Metadata Standards (RCSC, 2023) and B.C. Metadata Standards (RISC, 2019) for more information.

8.3.3 Use of artificial intelligence (MegaDetector)

Artificial intelligence (AI) has improved the efficiency and precision of classifying camera images (Fennell et al., 2022; Norouzzadeh et al., 2020; Tabak et al., 2018). Microsoft's MegaDetector (Beery et al., 2019) is the most used AI platform for this purpose. MegaDetector (Beery et al., 2019) is a free, open-source platform that classifies images as false triggers ("EMPTY"), humans, vehicles or animals based on probability distributions. It indicates the classification confidence for each image, which can be used to filter false triggers (or other unwanted) images from view based on the confidence level. The remaining images can then be tagged more efficiently. Studies of MegaDetector's performance in classifying images with humans and animals found it to have a higher accuracy rate than classification by human observers (99% vs 82%, respectively) and significantly faster processing times (500% higher and 8.4x less time) (e.g., Fennell et al., 2022). MegaDetector also had higher precision and recall when classifying images as 'empty' or 'animal' than some other AI platforms (Velez et al., 2023). Refer to Velez et al. (2023) for a comprehensive review of the requirements and advantages/disadvantages of MegaDetector relative to other platforms.

Before filtering out images, however, it is important to manually verify the classification of a sub-sample of images within each classification category (false triggers, humans, animals, vehicles). At least 5,000 auto-tagged images should be reviewed each year for each classification category.

The online version of MegaDetector online does not currently classify animals according to species. However, researchers have developed models using Megadetector to “train” machine learning algorithms to classify species in some regions. Tabak et al. (2018) reported that their models were very accurate for a few more common species (over 97.7%) in their area-of-interest but markedly less accurate for rare species. Since species and ecosystems differ by region, pre-trained models are only applicable to the area in which they were developed.

MegaDetector can also be downloaded and run on a Windows-based machine (most simply using EcoAssist (https://github.com/PetervanLunteren/EcoAssist#windows-installation), or images can be submitted to Dan Morris (see https://saul.cpsc.ucalgary.ca/timelapse/pmwiki.php?n=Main.DownloadMegadetector for more information).

Some software, such as Timelapse2 or WildTrax, can then be used to further classify the MegaDetector image files by human observers (see Greenberg [2020] for a primer). WildTrax automatically uses Megadetector to filter out blank images when data is uploaded to the platform. Some software can incorporate the outputs from Megadetector for species identification (e.g., Timelapse2 [Greenberg, 2018]).

Refer to Microsoft’s MegaDetector GitHub page (Beery et al., 2019) or WILDLABS Tech Tutors tutorial for more information on how to get started.

8.3.4 Human images

Images that allow for the identification of people (e.g., faces or vehicle license plates) should not be uploaded to some databases for privacy reasons. Detections of humans can be managed locally using specific “face-blurring” tools that are available using some R-scripts (e.g., WildCoLab’s FaceBlur R-script (WildCo Lab, 2021a) or databases (e.g., WildTrax). Users should follow the Freedom of Information and Protection of Privacy Act and any other relevant Acts (e.g., British Columbia’s Personal Information Protection Act (PIPA) and Federal Personal Information Protection and Electronic Documents Act (PIPEDA) when collecting and managing data on people.

8.4 Data analysis

There are many analytical resources available online, such as the step-by-step guide to data exploration and analysis "best" way to explore or analyse your data bookdown produced by the WildCo Lab (2021), which includes many helpful examples and tips. New camera users may also find Sollman’s (2018) introduction to the analysis of remote camera data useful.

As well, Wearn and Glover-Kapfer (2017) contains a detailed summary of analytical software (including R packages) for camera users (see pg. 160–162 in Wearn & Glover-Kapfer, 2017).

Some software packages (e.g., eMammal [McShea et al., 2015], Wildlife Insights [Ahumada et al., 2019]) provide useful data analytics (summary tables or dashboards) for a variety of metrics (e.g., number of cameras, species richness, occupancy estimates).

See Table 1 for useful software platforms and tools for data analysis/ analytics, as well as data storage and image processing.

8.5 Useful websites

Table 1. A subset of software platforms and tools for data storage, image processing, and data analysis / analytics. Refer to https://wildcams.ca/library/camera-trap-software-and-data-management/ for a comprehensive comparison of commonly used software platforms.

Software / tool	Data storage	Image processing	Data analysis / analytics	Reference	Link
Software					
MegaDetector	No	Yes	No	Beery et al., 2019	https://github.com/microsoft/CameraTraps/blob/main/megadetector.md
Timelapse2	No	Yes	Yes	Greenberg, 2018	http://saul.cpsc.ucalgary.ca/timelapse/
WildTrax	Yes	Yes	Yes	-	https://www.wildtrax.ca/home
eMammal	Yes	Yes	Yes	McShea et al., 2015	https://emammal.si.edu/
Wildlife Insights	Yes	Yes	Yes	Ahumada et al., 2019	https://www.wildlifeinsights.org/
Reconyx MapView	No	Yes	No	Reconyx Inc., 2021	http://www.reconyx.com/software/mapview
WildCo Lab's Renamer	No	Yes	No	WildCo Lab, 2021b	https://github.com/WildCoLab/WildCo_Image_Renamer
WildCoLab's FaceBlur R-script	No	Yes	No	WildCo Lab, 2021a	https://github.com/WildCoLab/WildCo-FaceBlur
Tools					
WILDLABS Tech Tutors tutorial	Yes	Yes	Yes	The WILDLABS Partnership, 2021	https://www.wildlabs.net/event/how-do-i-get-started-megadetector
Step-by-step guide to the "best" way to explore or analyse your data bookdown	No	No	Yes	Dr. Chris Beirne; WildCo Lab, 2021	https://bookdown.org/c_w_beirne/wildCo-Data-Analysis/
Chris Beirne's Tips and Tricks for the Organization and Analysis of Camera Trap Data	No	No	Yes	Canadian Mountain Network, CMN 2020	https://www.youtube.com/watch?v=VadXgBMhiTY
Secrdesignapp	No	No	Yes	Efford & Boulanger, 2019	https://www.stats.otago.ac.nz/secrdesignapp/
Everything I know about machine learning and camera traps	No	Yes	Yes	Morris, 2022	https://agentmorris.github.io/camera-trap-ml-survey/

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10.0 Glossary

Term	Description
***Access Method**	The method used to reach the camera location (e.g., on "Foot," "ATV," "Helicopter," etc.).
Age Class	The age classification of an individual or multiple individuals (if the classification is the same) being categorized (e.g., "Adult," "Juvenile," "Subadult," "Subadult - Young of Year," "Subadult – Yearling," or "Unknown").
Analyst	The individual who provided the observation data point (species identification and associated information). The Analyst should be recorded as the individual's full name.
Audible lure	Sounds imitating noises of prey or conspecifics that draw animals closer by eliciting curiosity (Schlexer, 2008).
Bait	A food item (or other substance) that is placed to attract animals via the sense of taste and olfactory cues (Schlexer, 2008).
Behaviour	The behaviour of an individual or multiple individuals being categorized (e.g., "Standing," "Drinking," "Vigilant," etc.).
Camera angle	The degree at which the camera is pointed toward the FOV Target Feature relative to the horizontal ground surface (with respect to slope, if applicable).
Camera days per camera location	The number of days each camera was active and functioning during the period it was deployed (e.g., 24-hour periods or the difference in days between the Deployment Start Date Time and the Deployment End Date Time if there were no interruptions).
Camera Direction (degrees)	The cardinal direction that a camera faces. Ideally, cameras should face north (N; i.e. "0" degrees), or south (S; i.e. "180" degrees) if north is not possible. The Camera Direction should be chosen to ensure the field of view (FOV) is of the original FOV Target Feature.
Camera Height (m)	The height from the ground (below snow) to the bottom of the lens (recorded in metres to the nearest 0.05 m).
Camera ID	A unique alphanumeric ID for the camera that distinguishes it from other cameras of the same make or model.
Camera location	The location where a single camera was placed (recorded as "Camera Location ID").
Camera Location Characteristic(s)	Any significant features around the camera at the time of the visit. This may include for example, manmade or natural linear features (e.g., trails), habitat types (e.g., wetlands), wildlife structure (e.g., beaver dam). Camera Location Characteristics differ from FOV Target Features in that landscape features could include those not in the camera's field of view.
Camera Location Comments	Comments describing additional details about a camera location.
Camera Location ID	A unique alphanumeric identifier for the location where a single camera was placed (e.g., “BH1,” “BH2”).
Camera Make	The make (i.e., the manufacturer) of a particular camera (e.g., “Reconyx” or “Bushnell”).
Camera Model	The model number or name of a particular camera (e.g., “PC900” or “Trophy Cam HD”).
Camera Serial Number	The serial number of a particular camera, which is usually found inside the camera cover (e.g., “P900FF04152022”).

Camera spacing	The distance between cameras (i.e., also referred to as "inter-trap distance"). This will be influenced by the chosen sampling design, the Survey Objectives, the Target Species and data analysis.
Capture-recapture (CR) model / Capture-mark-recapture (CMR) model (Karanth, 1995; Karanth & Nichols, 1998)	A method of estimating the abundance or density of marked populations using the count of the number of animals detected and the likelihood that animals will be detected (detection probability). CR (Karanth, 1995; Karanth & Nichols, 1998) can be used to estimate vital rates where all newly detected unmarked animals become marked and are distinguishable in future (Efford, 2022). Spatially explicit capture-recapture (SECR; Borchers & Efford, 2008; Efford, 2004; Royle & Young, 2008) models have largely replaced CR and CMR models and provide more accurate density estimates (Blanc et al., 2013, Obbard et al., 2010, Sollmann et al., 2011).
Categorical partial identity model (catSPIM) (Augustine et al., 2019; Sun et al., 2022)	A method used to estimate the density of partially marked populations in which the "spatial locations of where partial identity samples are captured to probabilistically resolve their complete identities" (Augustine et al., 2018, 2019). catSPIM models use partial identity traits (e.g., Sex Class, antler points) to help infer individual identities (Augustine et al., 2019; Sun et al. 2022). catSPIM is an extension of the SC model (Chandler & Royle, 2013).
Clustered design	Multiple cameras are deployed at a sample station (Figure 3d). A clustered design can be used within a systematic or stratified approach (i.e., systematic clustered design or as a clustered random design [Wearn & Glover-Kapfer, 2017]).
Convenience design	Camera locations or sample stations are chosen based on logistic considerations (e.g., remoteness, access constraints, and costs).
Crew	Individuals who collected data for a deployment or a service/retrieval.
Cumulative detection probability	The probability of detecting a species at least once during the entire survey (Steenweg et al., 2019).
Density	The number of individuals per unit area.
Deployment	A unique placement of a camera in space and time (recorded as "Deployment ID"); there may be multiple deployments for one camera location. Deployments are often considered as the time between visits (i.e., deployment to service, service to service, and service to retrieval). Any change to camera location, sampling period, camera equipment (e.g., Trigger Sensitivity setting, becomes non-functioning), and/or conditions (e.g., not baited then baited later; camera SD card replaced) should be documented as a unique deployment.
Deployment area photos	Photos of the area around the camera location, collected as a permanent, visual record of the FOV Target Features, Camera Location Characteristics, environmental conditions (e.g., vegetation, ecosite, weather) or other variables of interest. The recommendation includes collecting four photos taken from the centre of the target detection zone (Figure 5), facing each of the four cardinal directions. The documentation of the collection of these photos is recorded as "Deployment Area Photos Taken" (Yes/No).
Deployment Area Photo Numbers	The image numbers for the deployment area photos (if collected, e.g., "DSC100"). These are optionally documented on a Camera Deployment Field Datasheet for each set of camera deployment area photos. If not applicable, enter "NULL."
Deployment Comments	Comments describing additional details about the deployment.
Deployment Crew	The first and last names of the individuals who collected data during the deployment visit.
Deployment End Date Time (DD-	The date and time that the data was retrieved for a specific deployment (e.g., 27-JUL-2019 23:00). The Deployment End Date Time may not coincide with when the last image or

MMM-YYYY HH:MM:SS)	video was collected (i.e., the "Image Set End Date Time"). Recording this field allows users to account for deployments where no images were captured and to confirm the last date and time that the camera was active.
Deployment ID	A unique alphanumeric identifier for a unique camera deployed during a specific survey period (ideally recorded as: "Camera Location ID"_"Deployment Start Date Time" (or …_"Deployment End Date Time") (e.g., "BH1_17-JUL-2018" or "BH1_17-JUL-2018_21-JAN-2019"). Alternative naming conventions may be used, but the goal should be to minimize duplicate image names.(e.g., "BH1_17-JUL-2018" or "BH1_17-JUL-2018_21-JAN-2019"). Alternative naming conventions may be used, but the goal should be to minimize duplicate image names.
Deployment metadata	Metadata that is collected each time a camera is deployed. Each deployment event should have its own Camera Deployment Field Datasheet. The relevant metadata fields that should be collected differ when a camera is deployed *vs.* serviced or retrieved. Refer to Appendix A - Table A5 and Camera Deployment Field Datasheet.
Deployment Start Date Time (DD-MMM-YYYY HH:MM:SS)	The date and time that a camera was placed for a specific deployment (e.g., 17-JUL-2018 10:34:22). The Deployment Start Date Time may not coincide with when the first image or video was collected (i.e., the "Image Set Start Date Time"). Recording this field allows users to account for deployments where no images were captured and to confirm the first date and time a camera was active.
Deployment visit	When a crew has gone to a location to deploy a remote camera.
Detection distance	"The maximum distance that a sensor can detect a target" (Wearn and Glover-Kapfer, 2017).
Detection probability (aka detectability)	The probability (likelihood) that an individual of the population of interest is included in the count at time or location i.
Detection "event"	A group of images or video clips that are considered independent from other images or video clips based on a certain time threshold (or "inter-detection interval"). For example, 30 minutes (O'Brien et al., 2003; Gerber et al., 2010; Kitamura et al., 2010; Samejima et al., 2012) or 1 hour (e.g., Tobler et al., 2008; Rovero & Marshall, 2009).
Detection rate	The frequency of independent detections within a specified time period.
Detection zone	The area (conical in shape) in which a remote camera can detect the heat signature and motion of an object (Rovero & Zimmermann, 2016) (Figure 5).
Distance sampling (DS) model (Howe et al., 2017)	A method to estimate **abundance** by using distances at which animals are detected (from survey lines or points) to model abundance as a function of decreasing detection probability with animal distance from the camera (using a decay function) (Cappelle et al., 2021; Howe et al., 2017).
Easting Camera Location	The easting UTM coordinate of the camera location (e.g., 337875). Record using the NAD83 datum.
Effective detection distance	The distance from a camera that would give the same number of detections if all animals up to that distance are perfectly detected, and no animals that are farther away are detected; Buckland, 1987, Becker et al., 2022).
False trigger	Blank images (no wildlife or human present). These images commonly occur when a camera is triggered by vegetation blowing in the wind.
Field of View (FOV)	The extent of a scene that is visible in an image (Figure 5); a large FOV is obtained by "zooming out" from a scene, whilst "zooming in" will result in a smaller FOV (Wearn & Glover-Kapfer, 2017).

Flash output	The camera setting that provides the level of intensity of the flash (if enabled).
FOV Target Feature	A specific man-made or natural feature at which the camera is aimed to maximize the detection of wildlife species or to measure the use of that feature.
FOV Target Feature Distance (m)	The distance (in metres) from the camera to the FOV Target Feature (recorded to the nearest 0.05 m). If not applicable, enter "NULL."
GPS Unit Accuracy (m)	The margin of error of the GPS unit used to record spatial information (coordinates). For example, GPS coordinates might be accurate to within +/- 3.5 m.
Hurdle model (Mullahy, 1986)	A regression model used in the setting of excess zeros (zero-inflation) and overdispersion (Mullahy, 1986). Hurdle models (aka “zero-altered” models) differ from zero-inflation models in that they are two-part models, and the zero and non-zero counts are modelling separately (thus, they are only adequate when the counting process cannot generate a zero value) (Blasco-Moreno et al., 2019). [relative abundance indices]
Image	An individual image captured by a camera, which may be part of a multi-image sequence (recorded as "Image ID").
Image classification	The process of assigning class labels to an image according to the wildlife species, other entities (e.g., human, vehicle), or conditions within the image. Image classification can be performed manually or automatically by an artificial intelligence (AI) algorithm. Image classification is sometimes used interchangeably with “image tagging.”
Image classification confidence	The likelihood of an image containing an object of a certain class (Fennell et al., 2022).
Image ID	A unique alphanumeric file name for the image. It is important to include (at a minimum) the camera location, date, time, and image number when generating an Image ID to avoid duplicate file names (e.g., "BH1_17-JUL-2018_22-JUL-2018 10:34:22_IMG_100").
Image Set End Date Time (DD-MMM-YYYY HH:MM:SS)	The date and time of the last image or video collected during a specific deployment (e.g., “17-JUL-2018 12:00:02”). The Image Set End Date Time may not coincide with the Deployment End Date Time. Recording this field allows users to account for deployments that were conducted but for which no data was found and to confirm the last date and time a camera was active (if functioning) if no images or videos were captured prior to service/retrieval (especially valuable if users did not collect Time-lapse images or if the camera malfunctioned).
Image Set Start Date Time (DD-MMM-YYYY HH:MM:SS)	The date and time of the first image or video collected during a specific deployment (e.g., “17-JUL-2018 12:00:02”). The Image Set Start Date Time may not coincide with the Deployment Start Date Time. Recording this field allows users to confirm the first date and time a camera was active (reliable if Time-lapse images were collected; especially valuable if the user scheduled a start delay).
Image tagging	The process of classifying an image according to the wildlife species, other entities (e.g., human, vehicle), or conditions within the image. Image tagging may follow image classification to further classify characteristics of the individuals (e.g., Age Class, Sex Class, or Behaviour) or entities within the image.
Image processing	The series of operations that are taken to extract information from images. In the case of remote camera data, it can include loading the images into a processing platform, extracting information from the image metadata (e.g., the date and time the image was taken), running an artificial intelligence (AI) algorithm to identify empty images, classifying animals or other entities within the image.

Imperfect detection	Species are often detected "imperfectly," meaning that they are not always detected when they are present (e.g., due to cover of vegetation, cryptic nature or small size) (MacKenzie et al., 2004).
Independent detections	Detections that are deemed to be independent based on a user-defined threshold (e.g., 30 minutes).
Individual Count	The number of unique individuals being categorized. May refer to the total number of individuals or according to Sex Class and/or Age Class.
Infrared illuminator	The camera setting that can be enabled (if applicable to the Camera Make and Camera Model) to obtain greater visibility at night by producing infrared light.
Instantaneous sampling (IS) (Moeller et al., 2018)	A method used to estimate **abundance** or **density** from time-lapse images from randomly deployed cameras; the number of unique individuals (the count) is needed (Moeller et al., 2018).
Intensity of use (Keim et al., 2019)	"The expected number of use events of a specific resource unit during a unit of time… [which characterizes] how frequently a particular resource unit is used" (Keim et al., 2019). The intensity of use differs from the probability of use (which characterizes "the probability of at least one use event of that resource unit during a unit of time"; Keim et al., 2019).
Inter-detection interval	A user-defined threshold used to define a single "detection event" (i.e., independent "events") for group of images or video clips (e.g., 30 minutes or 1 hour). The threshold should be recorded in the Survey Design Description).
Inventory	Rapid assessment surveys to determine what species are present in a given area at a given point in time; there is no attempt made to quantify aspects of communities or populations (Wearn & Glover-Kapfer, 2017).
Kernel density estimator	The probability of "utilization" (Jennrich & Turner, 1969); describes the relative probability of use (Powell & Mitchell, 2012).
Latitude Camera Location	The latitude of the camera location in decimal degrees to five decimal places (e.g., 53.78136).
Longitude Camera Location	The longitude of the camera location in decimal degrees to five decimal places (e.g., -113.46067).
Lure	Any substance that draws animals closer; lures include scent (olfactory) lure, visual lure and audible lure (Schlexer, 2008).
Marked individuals / populations / species	Individuals, populations, or species (varies with modelling approach and context) that **can** be identified using natural or artificial markings (e.g., coat patterns, scars, tags, collars).
Metadata	Data that provides information about other data (e.g., the number of images on an SD card).
Mark-resight (MR) model (Arnason et al., 1991; McClintock et al., 2009)	A method used to estimate the **abundance** of partially marked populations using the number of marked individuals, the number of unmarked individuals, and the detection probability from marked animals (Wearn & Glover-Kapfer, 2017). MR is similar to capture-recapture (CR; Karanth, 1995; Karanth & Nichols, 1998) models, except only a portion of animals are individually identified.
Modelling approach	The method used to analyze the camera data, which should depend on the state variable, e.g., occupancy models [MacKenzie et al., 2002], spatially explicit capture recapture (SECR) for density estimation [Chandler and Royle, 2013], etc. and the Target Species.
Model assumption	Explicitly stated (or implicitly premised) conventions, choices and other specifications (e.g., about the data, wildlife ecology/behaviour, the relationships between variables, etc.) on

	which a particular modelling approach is based that allows the model to provide valid inference.
Motion Image Interval (seconds)	The time (in seconds) between images within a multi-image sequence that occur due to motion, heat, or activation of external detector devices. The Motion Image Interval is pre-set in the camera's settings by the user, but the time at which the camera collects images because of this setting is influenced by the presence of movement or heat. For example, if the camera was set to take 3 images per event at a Motion Image Interval of 3 seconds when the camera detects motion or heat, the first image will be collected (e.g., at 09:00:00), the second image will be collected 3 seconds later (09:00:03), and the third will be collected 3 seconds after that (09:00:06). This setting differs from the Quiet Period in that the delay occurs between images contained within a multi-image sequence, rather than between multi-image sequences (as in Quiet Period). If a Motion Image Interval was not set, enter "0" seconds (i.e., instantaneous).
Negative binomial (NB) regression (Mullahy, 1986)	A regression model used for count data with overdispersion but without zero-inflation. [relative abundance indices]
N-mixture models	A class of models for estimating absolute abundance using replicated counts of animals from several different sites; site-specific counts are treated as independent random variables to estimate the number of animals available for capture at each site; detection is imperfect (Royle 2004). N-mixture models are a type of site-structured model (i.e., that "treat each camera as though it samples... [a] distinct population within a larger meta-population" [Clarke et al., 2023]).
Northing Camera Location	The northing UTM coordinate of the camera location (e.g., 5962006). Record using the NAD83 datum.
Occupancy	The probability a site is occupied by the species.
Occupancy model (MacKenzie et al., 2002)	A modelling approach used to account for imperfect detection by first evaluating the detection probability of a species via detection histories (i.e., present or absent) to determine the probability of the true presence or absence of a species at a site (MacKenzie et al., 2002).
Overdispersion	A variance significantly larger than the mean (Bliss & Fisher, 1953); greater variability in a set of data than predicted by the error structure of the model (Harrison et al., 2018); excess variability can be caused by zero inflation, non-independence of counts, or both (Zuur et al., 2009).
Paired design	A form of clustered design when two cameras that are placed closely together to increase detection probability ("paired cameras") or to evaluate certain conditions ("paired sites", e.g., on- or off trails). Paired placements can help to account for other variability that might occur (i.e., variation in habitat quality).
Partially marked individuals / populations / species	Individuals, populations, or species (varies with modelling approach and context) that have a suite of partially identifying traits (e.g., antler points, Sex Class, Age Class). For populations/species, those in which **a proportion** of individuals carry marks or in which individuals themselves are partially marked.
Photos Per Trigger	The camera setting that describes the number of photos taken each time the camera is triggered.
Poisson regression	A regression model for count data used when data are not overdispersed or zero-inflated (Lambert, 1992). [relative abundance indices]
Project	A scientific study or inventory/ monitoring program that has a certain objective, defined methods, and a defined boundary in space and time (recorded as "Project ID").

Project ID	A unique alphanumeric identifier for each project (e.g., "UofA_WildEdmonton-Urban-Wildlife-Monitoring_2018").
Pseudoreplication	When observations are not statistically independent (spatially or temporally) but are treated as if they are independent.
Quiet Period (seconds)	The user-defined camera setting which provides the time (in seconds) between shutter "triggers" if the camera was programmed to pause between firing initially and firing a second time. Also known as "time lag" (depending on the Camera Make and Camera Model; Palmer et al., 2018). Report as "0" if a quiet period was not set. The Quiet Period differs from the Motion Image Interval in that the delay occurs between multi-image sequences rather than between the images contained within multi-image sequences (as in the Motion Image Interval).
Random (or "simple random") design	Randomized camera locations (or sample stations) across the area of interest, sometimes with a predetermined minimum distance between camera locations (or sample stations).
Random encounter and staying time (REST) model (Nakashima et al., 2017)	A recent modification of the REM (Nakashima et al., 2017) that substitutes staying time (i.e., the cumulative time in the cameras' detection zone) for movement speed (staying time and movement speed are inversely proportional) (Cappelle et al., 2021).
Random encounter model (REM) (Rowcliffe et al., 2008, 2013)	A method used to estimate the density of unmarked populations; uses the rate of independent captures, an estimate of movement rate, average group size, and the area sampled by the remote camera.
Recovery time	The time necessary for the camera to prepare to capture the next photo after the previous one has been recorded (Trolliet et al., 2014).
Registration area	The area in which an animal entering has at least some probability of being captured on the image
Relative abundance indices	An index of relative abundance. When observational data is converted to a detection rate (i.e., the frequency [count] of independent detections of a species within a distinct time period). An index can be a count of animals or any sign that is expected to vary with population size (Caughley, 1977; O'Brien, 2011).
Royle-Nichols model (Royle & Nichols, 2003; MacKenzie et al., 2006)	A method used to estimate population **abundance** or density, which assumes that individuals are counted only once per sampling occasion (Royle, 2004), but that does not require all individuals to be marked. Royle-Nichols models are a type of site-structured model (i.e., that "treat each camera as though it samples... [a] distinct population within a larger meta-population" [Clarke et al., 2023]).
Sample station	A grouping of two or more non-independent camera locations, such as when cameras are clustered or paired (recorded as "Sample Station ID"). Sample Station ID").
Sample Station ID	A sequential alphanumeric identifier given to each camera location within a grouping of two more non-independent camera locations when cameras are deployed in clusters, pairs or arrays (e.g., "SS1" in "SS1-BH1," "SS1-BH2," "SS1-BH3," and "SS1-BH4"). If not applicable, enter "NULL."
Scent lure	Any material that draws animals closer via their sense of smell (Schlexer, 2008).
Sequence	A user-defined group of images or video clips considered as a single "detection event" (recorded as "Sequence ID); often users choose a certain time threshold (or "inter-detection interval") to define independent 'events'. For example, 30 minutes (O'Brien et al.,

	2003; Gerber et al., 2010; Kitamura et al., 2010; Samejima et al., 2012) or 1 hour (e.g., Tobler et al., 2008; Rovero & Marshall, 2009). The threshold should be recorded in the Survey Design Description).
Sequence ID	A unique alphanumeric for a multi-image sequence. The Sequence ID should ideally consist of the Deployment ID and the names of the first and last images and videos in the sequence (separated by "_") (i.e., "Deployment ID"_"IMG_#[name of first image in sequence]"_"IMG_#[name of last image in sequence] (e.g., "BH1_22-JUL-2018 IMG_001-IMG_005").
Service/retrieval	When a crew has gone to a location to service or retrieve a remote camera.
Service/Retrieval Comments	Comments describing additional details about the service/retrieval.
Service/Retrieval Crew	The first and last names of the individuals who collected data during the service/retrieval visit.
Service/retrieval metadata	Metadata that should be collected each time a camera location is visited to service or retrieve a camera, including data on any change to the camera location, sampling period, and/or setting type (e.g., not baited and then baited later). The relevant metadata fields that should be collected differ when a camera is deployed vs. serviced or retrieved. Refer to Appendix A - Table A5 and the Camera Service/Retrieval Field Datasheet
Service/Retrieval visit	When a crew has gone to a location to service or retrieve a remote camera.
Sex Class	The sex classification of an individual or multiple individuals (if the classification is the same) being categorized (e.g., "Male," "Female," or "Unknown").
Space-to-event (STE) model (Moeller et al., 2018)	A method used to estimate **abundance** or density that accounts for variable detection probability through the use of time-lapse images and is unaffected by animal movement rates (collapses sampling intervals to an instant in time, and thus estimates are unaffected by animal movement rates) (Moeller et al., 2018).
Spatial autocorrelation	The tendency for locations that are closer together to be more similar.
Spatially explicit capture-recapture (SECR) / Spatial capture-recapture (SCR) (Borchers & Efford, 2008; Efford, 2004; Royle & Young, 2008; Royle et al., 2009)	The SECR (or SCR) method is used to estimate the density of marked populations; an extension of traditional capture-recapture (CR; Karanth, 1995; Karanth & Nichols, 1998) models (Karanth, 1995; Karanth & Nichols, 1998) that explicitly accounts for camera location and animal movement (Burgar et al., 2018). SECR models use spatially referenced individual capture histories to infer where animals' home range centres are, assuming that detection probability decreases with increasing distance between cameras and home range centres (Clarke et al., 2023). SECR models can be implemented using different statistical frameworks, including Bayesian estimation (Royle and Young, 2008; Morin et al., 2022).
Spatial count (SC) model / Unmarked spatial capture-recapture (Chandler & Royle, 2013)	A method used to estimate the density of unmarked populations; similar to SECR (Borchers & Efford, 2008; Efford, 2004; Royle & Young, 2008; Royle et al., 2009); however, SC models account for individuals' unknown identities using the spatial pattern of detections (Chandler & Royle, 2013; Sun et al., 2022). SC uses trap-specific counts to estimate the location and number of activity centres to estimate density.
Spatial mark-resight (SMR) (Chandler & Royle, 2013; Sollmann et al., 2013a, 2013b)	A method used to estimate the density of "partially marked populations by combining... [detection] histories of marked [individuals] and counts of unmarked [individuals]" (Doran-Myers, 2018) over several occasions (Sollman et al., 2013a; Rich et al., 2014; Whittington et al., 2018). SMR models can be implemented using different statistical frameworks, including Bayesian estimation (Royle and Young, 2008; Morin et al., 2022).

Spatial partial identity model (2-flank SPIM) (Augustine et al., 2018)	A method used to estimate the density of partially marked populations in which the “spatial locations of where partial identity samples are captured to probabilistically resolve their complete identities” (Augustine et al., 2018). Paired sampling design is commonly used to capture both the right and left flanks of an animal to resolve individual identities (Augustine et al., 2018). 2-flank SPIM is an extension of the SCR model (Borchers & Efford, 2008; Efford, 2004; Royle & Young, 2008; Royle et al., 2009). A method used to estimate the density of partially marked populations in which the "spatial locations of where partial identity samples are captured to probabilistically resolve their complete identities" (Augustine et al., 2018). Paired sampling design is commonly used to capture both the right and left flanks of an animal to resolve individual identities (Augustine et al., 2018). 2-flank SPIM is an extension of the SCR model (Borchers & Efford, 2008; Efford, 2004; Royle & Young, 2008; Royle et al., 2009).
State variable	A formal measure that summarizes the state of a community or population at a particular time (Wearn & Glover-Kapfer, 2017), e.g., species richness or population abundance.
Stratified design	The area of interest is divided into smaller strata (e.g., habitat type, disturbance levels), and cameras are placed within each stratum (e.g., 15%, 35% and 50% of sites within high, medium, and low disturbance strata).
Stratified random design (Figure 3c)	The area of interest is divided into smaller strata (e.g., habitat type, disturbance levels), and then a proportional random sample of sites is selected within each stratum (e.g., 15%, 35% and 50% of sites within high, medium and low disturbance strata).
Study area	A unique research, inventory or monitoring area within a project (there may be multiple study areas within a single project) (recorded as “Study Area ID“).
Study Area ID	A unique alphanumeric identifier for each study area (e.g.,"OILSANDS_REF1," "OILSANDS_REF2"). If only one area was surveyed, the Project ID and Study Area ID should be the same.
Survey	A unique deployment period (temporal extent) within a project (recorded as "Survey ID").
Survey Design	The spatial arrangement of remote cameras within the study area.
Survey Design Description	A description of any additional details about the Survey Design.
Survey ID	A unique alphanumeric identifier for each survey period (e.g., "FORTMC_001").
Survey Objectives	The specific objectives of each survey within a project. Survey objectives should be specific, measurable, achievable, relevant, and time-bound (i.e., SMART). Objectives may include include the Target Species, the state variables, proposed modelling approach(es) and the variables of interest (e.g., occupancy, density). If a project has only one survey or multiple surveys with identical methods and locations, the project and Survey Objectives may be the same. Otherwise, the differences between each unique survey should be documented carefully.
Systematic design (Figure 3b)	Camera locations occur in a regular pattern (e.g., a grid pattern) across the study area.
Systematic random design	Camera locations are selected using a two-stage approach. Firstly, girds are selected systematically (to occur within a regular pattern) across the study area. The location of the camera within each grid is then selected randomly.
Target Species	Singular or multiple species that a survey is designed to detect.
Targeted design	Camera locations or sample stations are placed in areas that are known or suspected to have higher activity levels (e.g., game trails, mineral licks).

Test image	An image taken from a camera after it has been set up to provide a permanent record of the visit metadata (e.g., Sample Station ID, Camera Location ID, Deployment ID, Crew, and Deployment Start Date Time [DD-MMM-YYYY HH:MM:SS]). Taking a test image can be useful to compare the information from the image to that of which was collected on the Camera Service/Retrieval Field Datasheet after retrieval and can help in reducing recording errors.
Time in front of the camera (TIFC) (Huggard, 2018; Warbington & Boyce, 2020; tested in Becker et al., 2022)	A method used to estimate density that treats camera image data as quadrat samples (Becker et al., 2022).
Time-lapse image	Images that are taken at regular intervals (e.g., hourly or daily, on the hour). It is critical to take a minimum of one time-lapse image per day at a consistent time (e.g., 12:00 pm [noon]) to create a record of camera functionality and local environmental conditions (e.g., snow cover, plant growth, etc.). Time-lapse images may always be useful for modelling approaches that require estimation of the “viewshed“ (“viewshed density estimators“ such as REM or time-to-event (TTE) models; see Moeller et al., [2018] for advantages and disadvantages).
Time-lapse interval (minutes)	The camera setting which provides the time (in minutes) between automated, regularly timed recording events (triggers) when the camera is set to take photos at defined time intervals. The time-lapse interval is pre-set in the camera’s settings by the user; the time at which the camera collects images because of this setting is not influenced by the presence of movement or heat (as opposed to Motion Image Interval). If time-lapse images were not collected (and thus, no time-lapse interval was defined), this field should be reported as “NULL.”
Time-to-event (TTE) model (Moeller et al., 2018)	A method used to estimate **abundance** or **density** from the detection rate while accounting for animal movement rates (Moeller et al., 2018). The TTE model assumes perfect detection (though there is a model extension to account for imperfect detection that requires further testing).
Total number of camera days	The number of days that all cameras were active during the survey.
Trigger “event”	An activation of the camera detector(s) that initiates the capture of a single or multiple images, or the recording of video.
Trigger speed	The time delay necessary for the camera to shoot a photo once an animal has interrupted the infrared beam within the camera's detection zone (Trolliet et al., 2014). Trigger speed differs from Motion Image Interval (a camera setting specified by the user) in that the trigger speed is inherent to the Camera Make and Camera Model (e.g., two different cameras, models both with a motion image interval set to "no delay," may not be able to capture images at the same speed).
Trigger Mode(s)	The camera settings that determine how the camera will trigger: by motion ("Motion Image"), at set intervals ("Time-lapse image"), and/or by video ("Video"; possible with newer Camera Models, such as Reconyx HP2X).
Trigger Sensitivity	The camera setting responsible for how sensitive a camera is to activation (to "triggering") via the infrared and/or heat detectors (if applicable, e.g., Reconyx HyperFire cameras have a choice between "Low," "Low/Med," "Med," "Med/High," "High," "Very high" and "NULL").
Unmarked individuals / populations / species	Individuals, populations, or species (varies with modelling approach and context) that **cannot** be identified using natural or artificial markings (e.g., coat patterns, scars, tags,

	collars). Unmarked population models rely on supplementary data (e.g., animal movement speed) and/or assumptions as a surrogate for individual identification; that is, to distinguish between multiple detections of the same individual from detections of multiple individuals when individuals do not have unique features (Gilbert et al., 2020; Morin et al., 2022).
User label	A label (up to 16 characters) that can be programmed in the camera's settings, and that will be visible in the data band of all photos and videos taken by the camera (Reconyx, 2018). It is recommended that users program the Sample Station ID/Camera Location ID as the user label, which serves as a means to confirm which Sample Station ID/Camera Location ID is associated with the images/videos.
UTM Zone Camera Location	The coordinate system that divides geographic areas into north-south zones. In Alberta the UTM zones are either 11, 12, or TTM. Enter all other UTM zones in the Camera Location Comments field (e.g., zones 7-10 for British Columbia), or use latitude and longitude instead of UTM coordinates.
Viewshed	The area visible to the camera as determined by its lens angle (in degrees) and trigger distance (Moeller et al., 2023).
Viewshed density estimators	Methods used to estimate the abundance of unmarked populations from observations of animals that relate animal observations to the space directly sampled by each camera's viewshed (Moeller et al., 2023); they result in viewshed density estimates that can be extrapolated to abundance within broader sampling frames (Gilbert et al., 2020; Moeller et al., 2023).
Video Length (seconds)	If applicable, describes the camera setting that specifies the minimum video duration (in seconds) that the camera will record when triggered.
Visit	When a crew has gone to a location to deploy, service, or retrieve a remote camera.
Visit metadata	Metadata that should be collected each time a camera location is visited to deploy, service or retrieve a camera. Other relevant metadata fields that should be collected differ when a camera is deployed *vs.* serviced or retrieved. Refer to Appendix A - Table A5, Camera Deployment Field Datasheet, and Camera Service/Retrieval Field Datasheet.
Visual lure	Any material that draws animals closer via their sense of sight (Schlexer, 2008).
Walktest	A test performed to ensure the camera height, tilt, etc., adequately captures the desired detection zone. The user will 1) activate the walktest mode, 2) attach the camera at the desired height / angle, 3) walk in front of the camera to a specified distance (i.e., the "Walktest Distance," e.g., 5 m), and 4) wave their hand in front of the camera (usually at ground level and a chosen height [i.e., the "Walktest Height," e.g., 0.8 m]) to determine if the camera is activating (a light on the camera will flash).
Walktest Distance (m)	The horizontal distance (recorded in metres to the nearest 0.05 m) from the camera at which the crew performs the walktest (using the walktest mode, if applicable) to ensure the camera height, tilt, etc., adequately captures the desired detection zone. See "walktest" above for the necessary steps. If not applicable, enter "NULL."
Walktest Height (m)	The vertical distance (recorded in metres to the nearest 0.05 m) from the camera at which the crew performs the walktest (using the walktest mode, if applicable) to ensure the camera height, tilt, etc., adequately captures the desired detection zone. See "walktest" above for the necessary steps. If not applicable, enter "NULL."
Zero-inflated negative binomial (ZINB) regression	A regression model used in the setting of excess zeros (zero-inflation) and overdispersion. This approach is a two-part model, where the zero-inflation is modelled separately from the counts and assumes that the count (abundance) is "conditional" on the zero-inflation model (occurrence) model. [relative abundance indices]

(McCullagh & Nelder, 1989)	
Zero-inflated Poisson (ZIP) regression (Lambert, 1992)	A regression model for count data that both follows the Poisson distribution and contains excess zeros (Lambert, 1992). ZIP models are only appropriate for data for which the overdispersion is not solely due to zero-inflation. [relative abundance indices]
Zero-inflation	An excess of zeros that is “so large that those expected in standard distributions (e.g., normal, Poisson, binomial, negative binomial and beta)” (Heilbron, 1994) violate the assumptions of such distributions (Martin et al., 2005). Excess zeroes can be a result of ecological effects (“true” zeros) or due to sampling or observer error (“false zeros”) (Martin et al., 2005). Excess zeroes contribute to overdispersion, but they don’t necessarily account for all excess variability (Blasco-Moreno et al., 2019).

11.0 Appendix A

Table A1. Summary of the assumptions and pros/cons of the different modelling approaches (adapted from Wearn & Glover-Kapfer [2017] and Clarke et al. [2022]).

Objective	Approach	Assumptions	Pros	Cons	References
Species inventory	Species inventory	• No formal assumptions[1]	• Maximum flexibility for study design (e.g., camera days per camera location or use of lure[2])[1]	• Not reliable estimates for inference ("considered as unfinished, working drafts")[1]	[1] Wearn & Glover-Kapfer, 2017 [2] Rovero et al., 2013 [3] MacKenzie et al., 2002 [4] MacKenzie et al., 2006 [5] Lambert, 1992 [6] Mullahy, 1986 [7] McCullagh & Nelder, 1989 [8] Zorn, 1998 [9] Royle & Nichols, 2003 [10] MacKenzie et al., 2006 [11] Karanth & Nichols, 1998 [12] Karanth, 1995 [13] Clarke et al., 2023 [14] Noss et al., 2003 [15] Kelly et al., 2008 [16] Moeller et al., 2018
Species richness	Species richness	• Cameras are randomly placed[1] • Cameras are independent[1] • detection probability of different species is equal[1] ("True" species richness estimation involves attempting to correct for "imperfect detection"[1])	• Fundamental to ecological theory and often a key metric used in management[1] • Simple to analyze, interpret and communicate[1] • Models exist to estimate asymptotic species richness, including unseen species (simple versions of these models - EstimateS and the "vegan" R-packages)[1]	• Dependent on the scale (as captured in the species-area relationship)[1] • All species have equal weight in calculations, and community evenness is disregarded[1] • Insensitive to changes in abundance, community structure and community composition[1]	
Species diversity	Species diversity	• Cameras are randomly placed[1] • Cameras are independent[1] • The detection probability of different species remains the same[1]	• Captures evenness and richness (although some indices only reflect evenness)[1] • Most indices are easy to calculate and widely implemented in software packages (e.g., EstimateS and "vegan" in R)[1]	• Many diversity indices exist, and it can be difficult to choose the most appropriate[1] • Interpretation/communication not always straightforward[1] • Insensitive to changes in community composition[1] (though this may be conditional on study design)	
Species diversity	β-diversity	• Can be used to track changes in community composition[1] • Plays a critical role in effective conservation prioritization (e.g., designing reserve networks)[1] • Important for detecting changes in the fundamental processes[1]	• Many measures; no single best measure for all purposes[1] • Comparing measures across space, time and studies can be very difficult[1] • Scale-dependent (i.e., the size of the communities that are being included)[1]		
Occupancy[3]	Occupancy models[3]	• Closed to changes in occupancy[3] (abundance is constant)[4] • Sites and detections are independent[4] • The probability of occupancy and detection are constant across all sites	• Does not require individual identification[4] • Just requires detection/non-detection data for each site[1]	• Occupancy[3] only measures distribution; it may be a misleading indicator of changes in abundance[1] • Interpretation/communication of results may not be straightforward (if the scale	

Objective	Approach	Assumptions	Pros	Cons	References
		within a stratum or can be modelled using covariates[4] • Species are not misidentified[4]	• Relatively easy-to-use software exists for fitting models (PRESENCE, MARK, and the "unmarked" R package)[1] • "Open" models exist that allow for the estimation of site colonization and extinction rates[1,4] • Multi-species occupancy models[3] allow the inclusion of interactions among species while controlling for imperfect detection[1]	of movement is much larger than the camera spacing the results should be interpreted as "probability of use" rather than occupancy)[1]	[17] Chandler & Royle, 2013 [18] Borchers & Efford, 2008 [19] Efford, 2004 [20] Royle & Young, 2008 [21] Royle et al., 2009
Relative abundance indices	Poisson Zero-inflated Poisson (ZIP)[5] Negative binomial (NB)[6] Zero-inflated negative binomial (ZINB)[7] Hurdle models[8] Other	• Since used for many approaches, many assumptions exist[1]	• Simple to calculate and technically possible (even with small sample sizes when robust methods might fail)[1] • Relative abundance indices often do correlate with abundance[1] • Calibration with independent density estimates is possible[1]	• Difficult to draw inferences (a large number of assumptions); comparisons across space, time, species, and studies are difficult[1] • Requires stringent study design (e.g., random sampling, standardized methods)[1]	[22] O'Brien et al., 2011 [23] Doran-Myers, 2018 [24] Morin et al., 2022 [25] Green et al., 2020 [26] Parmenter et al., 2003 [27] Noss et al., 2012
Absolute abundance; Unmarked population	Royle-Nichols model[9,10]	• Individual detection probability is constant[1]	• Can relax assumption of constant abundance[1] • Abundance is a fundamental parameter in wildlife research and monitoring[1] • Can be applied to unmarked species[1] • Only requires detection/non-detection data for each site (not counts)[1] • May be used in models with relative abundance to control for imperfect detection[1]	• Assumes a relatively specific relationship between local abundance and species-level detection probability[1] • Depends on sampling area[1] • Requires all or some of a population to be marked[1] • No dedicated, simple software for this model (but can be implemented in MARK and the "unmarked" package in R)[1]	[28] Sollmann et al., 2013a [29] Sollmann et al., 2013b [30] Rich et al., 2014 [31] Whittington et al., 2018 [32] Efford et al., 2009b
Population size / Absolute abundance / vital rates /	Capture-recapture (CR) / capture-mark-recapture (CMR)[11,12]	• Demographically closed (i.e., no births or deaths)[1] • Geographically closed (i.e., no immigration or emigration)[1]	• May be used as a relative abundance index that controls for imperfect detection[1] • Easy-to-use software exists to implement (e.g., CAPTURE); MARK	• Requires that individuals are distinguishable.[1] (However, CR[11,12] has also been used to estimate abundance of species that lack natural markers but that have phenotypic	[33] Royle et al., 2014

Objective	Approach	Assumptions	Pros	Cons	References
Density; Marked population		• Each individual has at least some probability of being captured[2] • Overall sampled area should encompass full extent of individuals movements[2,11] • Activity centres are randomly dispersed and stationary[13]	Implements more complicated models with covariates (and must be used for mark-resight modelling)[1] • Can use the robust design with "open" models to obtain recruitment and survival rate estimates[1]	and/or environment-induced characteristics[2,,14,15] When the sample size is large enough to reliably estimate density with CR,[11,12] individuals are unlikely to have a unique marker[2,14,15]) • Dependent on the surveyed area, which is difficult to track and calculate[1] • Requires a minimum number of captures and recaptures[1] • Relatively stringent requirements for study design (e.g., no "holes" in the trapping grid)[1] • Geographic closure at the plot level, which is often unrealistic[16] • Assumes a specific relationship between abundance and detection[1] • Density cannot be explicitly estimated because the true area animals occupy is never measured (only approximated)[17]	[34] Augustine et al., 2019 [35] Burgar et al., 2018 [36] Sun et al., 2022 [37] Sollmann, 2018 [38] Augustine et al., 2018 [39] Davis et al., 2021 [40] Rowcliffe et al., 2008 [41] Rowcliffe et al., 2013 [42] Rowcliffe et al., 2014 [43] Rowcliffe et al., 2016
Density / population size; Marked population	Spatially explicit capture recapture (SECR)[18-21] (also referred to as Spatial capture-recapture [SCR])	• Individuals do not lose marks or are misidentified[1] • All animals have an equal probability of capture (or, for spatially explicit models, an equal probability of capture for a given distance from the centre of their home range)[1] • Captures of different individuals are independent[1] • No behavioural response to being trapped or marked[1] • Sampling occasions are independent[1] • Population is demographically closed (i.e., no births or deaths)[1] • For conventional models, geographically closed, i.e., no immigration or emigration)[1]	• Produces direct estimates of density or population size for explicit spatial regions[17] • Allows researchers to mark a subset of the population/to take advantage of natural markings[1] • Estimates are fully comparable across space, time, species and studies[1] • Density estimates obtained in a single model, fully incorporate spatial information of locations and individuals[1] • Both likelihood-based and Bayesian versions of the model have been implemented in relatively easy-to-use software (DENSITY and SPACECAP, respectively, as well as associated R packages)[1]	• Requires that individuals are identifiable[1] • Requires that a minimum number of individuals are trapped (each recaptured multiple times ideally)[1] • Requires that each individual is captured at a number of camera locations[1] • Multiple cameras per station may be required to identify individuals; difficult to implement at large spatial scales as it requires a high density of cameras[13,24] • May not be precise enough for long-term monitoring[25] • Cameras must be close enough that individuals come into contact with multiple cameras[1,17]	[44] Rowcliffe et al., 2011 [45] Cusack et al., 2015 [46] Nakashima et al., 2017 [47] Meek et al., 2016 [48] Anile & Devillard, 2016 [49] Huggard, 2018 [50] Becker et al., 2022 [51] Warbington & Boyce, 2020

Objective	Approach	Assumptions	Pros	Cons	References
		• Spatially explicit models have further assumption about animal movement.[1,18,21,22] These include: • Home ranges do not change during the survey[1] • Captures does not affect movement patterns[1] • Random placement with respect to the distribution and orientation of home ranges[1] • Distribution of home range centres follows a defined distribution (Poisson, or other, e.g.,)[1]	• Flexibility in study design (e.g., "holes" in the trapping grid)[1] • "Open" SECR[18-21] models exist that allow for estimation of recruitment and survival rates[1] • "Avoid ad-hoc definitions of study area and edge effects"[23] • SECR[18-21] accounts for variation in individual detection probability; can produce spatial variation in density; SECR[18-21] more sensitive "to detect moderate-to-major populations changes" (+/-20-80%)[13,24]	• ½ MMDM (Mean Maximum Distance Moved) will usually lead to an under - estimation of home range size and thus overestimation of density[1,26,27]	[52] Howe et al., 2017 [53] Palencia et al., 2021 [54] Gilbert et al., 2020 [55] Twining et al., 2022 [56] Bessone et al., 2020 [57] Moeller et al., 2018
Density; Marked population	Spatial mark-resight (SMR) (type of SCR model)[17,28,29]	• Demographic and geographic closure of the population during the survey[1] • Detections are independent[29] • Detection probability decays with increasing distance of the camera from the activity centre[29,30] • Animals have stable activity centres[30] • Individual marks are not lost (for maximum precision), but SMR[17,28,29] does allow for inclusion of marked but unidentified resighting detections[28,31] • The number of marked animals present is known before resightings[28,30] • Animals are ungrouped[29] • Counts of unmarked animals are modeled with a Poisson distribution[30] • Cameras randomly placed with respect to activity centres[28] • Marked animals are a random sample of the population with home ranges located inside the state space[29,30] • All animals have stable activity centres within home ranges where detection probability is greatest[28,32]	• Estimates are fully comparable to SECR[18-21] of marked species[1] • Can be applied to a broader range of species than SECR[18-21][1] • Allows researcher to take advantage of natural markings[1] • Allows researcher to mark a subset of the population (note - precision is dependent on number of marked individuals in a population)[1]	• Animals may have to be physically captured and marked if natural marks do not exist on enough individuals[1] • All individuals must be identifiable[1] • Allows for density estimation for a unmarked population, but the precision of the density estimates are likely to be very low value[1] • Remains poorly tested with camera data, although it offers promise[1] • Density estimates are likely less precise than with SECR[18-21] or REM, unless a large proportion of the population have marks[1] • Requires sampling points to be close enough that individuals encounter multiple cameras[1]	[58] Loonam et al., 2021 [59] Bridges & Noss, 2011 [60] Rovero & Zimmermann, 2016 [61] Borchers & Marques, 2017

Objective	Approach	Assumptions	Pros	Cons	References
Density; Unmarked population	Spatial count (SC) (type of SCR model)[17,33]	• Camera must be close enough together that animals are detected at multiple cameras[13,17] • Population closure[13,17] • Independence of detections[13,17] • Activity centres randomly dispersed[13,17] • Activity centres are stationary[13,17]	• Does not require individual identification[13]	• Produces imprecise estimates even under ideal circumstances unless it is supplemented with auxiliary data (e.g., telemetry)[17,23,28,29] • Precision decreases with an increasing number of individuals detected at a camera"[24] (as overlap of home ranges of individuals' increases)[13,34] • Not appropriate for low density or elusive species when recaptures too few to confidently infer the number and location of activity centres"[13,35] • Not appropriate for high-density populations with evenly spaced activity centres (camera[-specific] counts will be too similar and impair activity centre inference)"[13] • Ill-suited to populations that exhibit group-travelling behaviour"[13,36] • Study design (camera arrangement) can dramatically affect the accuracy and precision of density estimates"[13,37] • Cameras must be close enough that animals are detected at multiple camera locations (may be challenging to implement at large scales as many cameras are needed)"[13,17]	
Density / population size; Partially Marked population	Spatial Partial Identity Model (Categorical SPIM; catSPIM)[13,34,36] (Extension of SC model using animal traits (e.g. Sex Class, antler points) and model parameters)	• Same as SC[13,34,36] • Each categorical identifier (e.g., Sex Class, collar, etc) has fixed number of possibilities (e.g., male/female, collared/not collared)[36] • All possible values of categorical identifiers occur in the population with probabilities that can be estimated[13,34,36] • Every individual is assigned "full categorical identity" (i.e., "set of traits given all categorical identifiers and possibilities")[13,34]	• May produce more precise and less biased density estimates than SC with less information[13,36]	• Sensitive to non-independent movement (e.g., group-travel; can cause over-dispersion and bias estimates[13,36]); may limit application to solitary species only[13,36] • May produce be less reliable/accurate estimates for high-density populations[13,36] • To few categorical identifiers/ possibilities can result in mis-assignments and overestimating density[13,34,26]	

Objective	Approach	Assumptions	Pros	Cons	References
		• There is no change in an individual's identity trait during the survey period (e.g., antlers present/absent)[34]			
Density / population size; Partially Marked population	Spatial Partial Identity Model (2-flank SPIM)[13,38] (extension of SCR model augmented with data from partially-identifying images)	• Same as SCR[13,38] • Capture processes for left-side, right-side and both-side images are independent[13,38]	• Same as SCR[13,38] • Improved precision of density estimates relative to SCR[13,38,39] • Many study designs can be used (paired sample stations, single camera locations, and hybrids of both paired- and single camera locations[13,38,39] • Can be used with single-camera and hybrid sampling designs, and therefore requires fewer cameras (or sample more area) than SCR[13,38] • May be more robust to non-independence than SC[34,38]	• Computationally intensive[13,38] • Increased precision is less pronounced in high-density populations[13,38]	
Density; Unmarked	Random encounter models (REM)[40,41]	• Demographic and geographic closure[23,40] • Random with respect to animal movement[1,40] • Animal movement is not affected by the cameras[1,40] • Independent "contacts" between camera locations can be accurately counted[1,40] • Unbiased estimates of animal activity levels and animal speed can be obtained[1,42,43] • Camera's detection zone can be approximated well using a 2D cone shape, defined by the radius and angle parameters[44] • If activity and speed are to be estimated from camera data, two additional assumption: o All animals are active during the peak daily activity[42] o Animals moving quickly past a camera are not missed[43]	• Flexible study design (e.g., "holes" in grids allowed, camera spacing less important)[1] • Can be applied to unmarked species[1] • Allows community-wide density estimation[1] • Outputs also include informative parameter estimates (i.e., animal speed and activity levels, and detection zone parameters)[1] • Comparable estimates to SECR[18-21]1 • Does not require marked animals or identification of individuals[23,40] • Can use camera spacing without regard to population home range size[23,40] • Direct estimation of density; avoids ad-hoc definitions of study area[40]	• Requires relatively stringent study design, particularly (e.g., random sampling and use of bait or lure)[1] • Requires independent estimates of animal speed or measurement of animal speed within videos[1] • No dedicated, simple software[1] • Random relative to animal movement, grid preferred, avoid multiple captures of same individual, area coverage important for abundance estimation[2] • Possible sources of error include inaccurate measurement of detection zone and movement rate[41,45]	

Objective	Approach	Assumptions	Pros	Cons	References
Density; Unmarked	Random encounter and staying time (REST)[46]	• The population is closed (animal density is constant during the survey)[40] • The detection probability is perfect[1] (p = 1) unless otherwise modelled[46] • Camera locations are representative of the available habitat[46] • Cameras are randomly placement with respect to the spatial distribution of animals[46] • Animal movement and behaviour are not affected by cameras[46] • Observations are independent[46] • The observed distribution of staying time in the focal area fits the distribution of movement[46] • The observed staying time must follow a given parametric distribution[46]	• Provides unbiased estimates of animal density, even when animal movement speed varies, and animals travel in pairs[46]	• Attraction or aversion to cameras is exhibited in some species[47] and could affect the time within the detection zone and subsequently affect estimates of density[23] • Requires accurate measurements of the area of the camera detection zone, which has been a challenge in previous studies[23,44-46,48] • Mathematically challenging[45]	
Density; Unmarked	Time in front of the camera (TIFC)[49-51]	• Cameras are placed randomly, or representative relative to animal movement[50] • No influence of cameras on animal movement[50] • Reliable detection of animals in part of the camera's FOV (at least)[50]	• Does not require individual identification[51] • Makes no assumption about home range[51] • Comparable to estimates from SECR[18-21]51	• Requires careful calculation of the effective area of detection[51] • A high level of measurement error[50]	
Density; Unmarked	Distance sampling (DS)[52,61]	• Random or systematic random placements consistent with the assumption that points are placed independently of animal locations[52] • Placed randomly with respect to animal movement [53] • Certain detection at distance 0[53] • Certain detection at focal area[53] • Closed population[53] • Animal movement and behaviour not affected by the cameras[53]	• A shortcut to controlling for variation in detection distances by only counting individuals within a short distance with an unobstructed view, and well sampled across cameras and species[1] • Density estimates are unbiased by animal movement "since camera-animal distance is measured at a certain instant in time (intervals of duration *t* apart)"[13,52] • Can be applied to low-density populations[13,53]	• May require discarding a portion of the dataset (when the best fitting model truncates the dataset)[1] • Biased by movement speed[53] • Best suited to larger animals; the smaller the focal species, the lower [wildlife] cameras must be set, which reduces the depth of the viewshed, and thus sampling size and the flexibility of the model"[13,52] • Does not permit inference about spatial variation in abundance (unless using hierarchical distance which can model	

Objective	Approach	Assumptions	Pros	Cons	References
		• Animals detected at initial locations (e.g., they do not change course in response to the camera prior to detection)[53] • Distances are measured exactly (however if the data from different distances will be grouped ("binned") for analysis later, an accuracy of +/- 1m may suffice)[53] • Observations are independent events[53] • Snapshot moments selected independently of animal locations[53]	• Does not require individual identification[52]	spatial variation as a function of covariates)[13,54] • "Calculating camera-animal distances can be labour-intensive and time-consuming (However, recently developed techniques (e.g., Johanns et al., 2022) show promise for simplifying and automating the process)"[13] • Requires good understanding of the focal populations' activity patterns; density estimates can be biased (e.g., under-estimated) when regular periods of inactivity are not accounted for (using detection times to infer periods of activity may help overcome this limitation)"[13,52,53] • Tends to underestimate density[13,52,55] • Low population density and reactivity to cameras may be major sources of bias"[13,56]	
Density; Unmarked	Time-to-event (TTE) model[57]	• Demographic and geographic closure[57,58] • Locations randomly placed, systematic, systematic random[57] • Independent detections in space and time[57] • Spatial counts of animals (or counts in equal subsets of the landscape) are Poisson-distributed[58] • Accurate estimate of movement speed[58]	• Can be efficient for estimating abundance of common species (with a lot of images)[57]	• Requires independent estimates of movement rate (difficult to attain without telemetry data)[57] • Assumes that detection probability is 1 (or apply extension to account for imperfect detection)[57]	
Density; Unmarked	Space-to-event (STE) models[57]	• Demographic and geographic closure[57] • Locations randomly placed[v] • Independent detections in space and time[57] • Spatial counts of animals in a small area (or counts in equal subsets of the landscape) are Poisson-distributed[58]	• Can be efficient for estimating abundance of common species (with a lot of images)[57] • Does not require estimate of movement rate[57]	• Assumes that detection probability is 1[57]	

Objective	Approach	Assumptions	Pros	Cons	References
Density; Unmarked	Instantaneous sampling (IS)[57]	• Demographic and geographic closure[57] • Locations randomly placed[57] • Independent detections in space and time[57]	• Can be efficient for estimating abundance of common species (with a lot of images)[57] • Flexible assumption of animals' distribution[57]	• Requires accurate counts of animals[57] • Assumes that detection probability is 1[57] • Reduced precision[57]	
Behaviour (Diel activity patterns, mating, boldness, etc.)		• Assumptions vary depending on the behavioural metric[1] • For studies of activity patterns and temporal interactions of species: activity level is the only factor determining detection rates; animals are active when camera detection rate reaches its maximum in daily cycle[33,60]	• Can detect difficult to observe behaviours (i.e., boldness, or mating)[59] • Long-term data on behavioural changes that would be difficult to obtain otherwise (i.e., time-limited human observers, or costly GPS collars)[59] • Can monitor behaviour in response to specific locations (i.e., compost sites, which might be more difficult using GPS collars for example)[60] • Can evaluate interactions between species[60]	• Behavioural metrics may not reflect the behavioural state (inferred)[60] • Biases associated with equipment (i.e., presence of the camera itself may change behaviour studied)[60] • Difficult to consider individual variation[60]	

Table A2. Summary of appropriate study design, camera spacing, and survey effort (adapted from Wearn & Glover-Kapfer [2017] with additional references included) for various modelling approaches. Note – these are guidelines only, using best available information. There is uncertainty associated with each of the different approaches. To address this, the table contains 'minimum', 'ideal' and 'often' used values, as well as qualifiers.

Approach	Camera arrangement	Camera spacing	Number of cameras	Camera days per camera location	Total number of camera days	Survey duration	References
Species inventory	Targeted[1,2] Random if species poorly known[3]	No minimum[2,4] Ideally 1-2 km[2,4,5]	No minimum[4] Ideally ≥ 20[1,3]	No minimum Ideally ≥ 30; < 30 for highly detectable[4]	No minimum[1,3,4]	No maximum[1,4]	[1] Tobler et al., 2008 [2] Rovero et al., 2013 [3] Wearn et al., 2013 [4] Wearn & Glover-Kapfer, 2017 [5] Colyn et al., 2017 [6] O'Brien, 2010 [7] O'Connell & Bailey, 2011 [8] Cusack et al., 2015 [9] Ahumada et al., 2011 [10] Kinnaird & O'Brien, 2011 [11] Wearn et al., 2016 [12] Li et al., 2012 [13] Kays et al., 2020
Species diversity & richness	Ideally, random[2,4] Stratified, or Stratified random[4] Clustered[6,7]	Ideally ≥ 1 km, but closer may be justified[1,8] 1-2 km is often adequate (provided each camera is treated as an independent sample)[1,4,9,10]	Minimum 20; Ideally >=50; If stratified by habitat, 20-50 per stratum[4] 20-100 to reach species-accumulation asymptote[9,11,12] Commonly 30[9] 25-35, scale-dependent[13]	Ideally ≥ 30[4,9]	Generally, 600-1500; ≥ 1000[4]	Ideally < 6 months; 3-6 months for medium-large mammals[4]	
Occupancy models[14]	Ideally, random[7] Random or targeted[6,15-17] Clustered[7,18] Stratified random[4]	Ideally, larger than home range (minimum) or > 1 km if home range size unknown[4] ≥ 1 km is typical[4]	Minimum 40[4] Ideally ≥ 100[15-17] >60; species-dependent[2] <20 for common (occur at >75% of sites)[13]; ≤30 if occupancy > 0.8[17] >150 for rare (occur at <25% of sites)[13] 30-60 sites for less common[17]	≥ 30 for most[15-17] 80-100 if detection probability is low[17]	Species-dependent; >1200 for most[4] > 1,000 for most[6,15-17] > 5,000 for rare / hard to detect[17]	Species-dependent[16] Ideally < 6 months[6,15-17]	

Approach	Camera arrangement	Camera spacing	Number of cameras	Camera days per camera location	Total number of camera days	Survey duration	References
Relative abundance indices (RAI)	Ideally, random[4] Systematic random[4]	No minimum[4] Ideally, ≥ 1 km[3] 1-2 km[4]	As many as possible; Minimum of 20; Ideally ≥ 50[4,19] If stratified by covariates, 20-50 per covariate[4]	No minimum; Ideally ≥ 30; As many as possible[4]	Ideally > 2000[4] Enough to capture > 10 detections; Ideally >20 detections; Usually > 2,000 total for many carnivores / rare ungulates[4,19] >250 for common[4,19,20] 20,000 "hyper-rare" (caught 0.1% of the time)[4,6]	No maximum; Ideally < 12 months[3]	[14] MacKenzie et al., 2002 [15] Mackenzie & Royle, 2005 [16] Guillera-Arroita et al., 2010 [17] Shannon et al., 2014 [18] Pacifici et al., 2015 [19] Rowcliffe et al., 2008 [20] Rovero & Marshall, 2009 [21] Karanth & Nichols, 1998 [22] Karanth, 1995 [23] Sollmann et al., 2012 [24] Clarke et al., 2023 [25] Tobler & Powell, 2013 [26] Krebs et al., 2011 [27] Borchers & Efford, 2008 [28] Royle & Young, 2008 [29] Royle et al., 2009
Capture-recapture (CR) / Capture-mark-recapture (CMR)[21,22]	Ideally, paired[ii,1,2,4] or random[4] Targeted[iii,1,4,23] Targeted for carnivores[2] Systematic[24]	Spatially-dependent[iv,4] Species-dependent[v,2] (< home range size); >4 per home range[4] 2-4 per smallest home range[2] 1-4 km is typical[1,4,23]	At least 1 per smallest home range[2,21] At least enough to capture 10-30 individuals[2]	≥ 30 for all but the most detectable; >60 for reasonable precision for most; >60-120 if capture probability is low[4,25]	> 1,000 for most species; >1200 common[i] > 3,500 if the detection probability is low[4]	As short as possible[4] >60 recaptures[2] Species-dependent; Ideally < 3 months[1,23]	
Spatially explicit capture-recapture (SECR) / Spatial capture-recapture (SCR)[26-29]	Paired[2,4] Clustered[4,30] Systematic[24]	Species-dependent (< home range size); Ideally, 1/3 the home range radius[4,23,30] (~4-7 camera per home range)[4] Maximum of 0.8 times the home range radius[4,23,30]	At least enough to capture the home range of 5-10 individuals[4,25-26, 31] Enough to capture of >20 individuals[4,32] and ideally 20-50 total recaptures[4,31,33] **Recommendation:** Enough to recapture 10-30 individuals[4,34] **Recommendation:** If used suggested 4 camera per home range, 40-120 locations[4] 60-100 if detection probability is < 0.1[25]	≥ 30 for all but the most detectable; >60 for reasonable precision for most; >60-120 if capture probability is low[4,25]	Enough for 20-50 recaptures total[4,31,33]	Minimum of 30 days per survey (presuming multiple surveys will be completed; ideally > 12 months total; based on minimum requirements for running SCR models)[35,36]; Ideally 60-90 days (depending on time required to maximize detections while	

Approach	Camera arrangement	Camera spacing	Number of cameras	Camera days per camera location	Total number of camera days	Survey duration	References
Spatial mark-resight (SMR) (type of SCR model)[23,30,37]	Random with respect to activity centres[38] Systematic random or clustered[24]	1-3 sigma (related to home range size)[30]	Minimum of 30; 60 (but will depend on detection probability and resight data)[36,39]	Minimum 30 (precision is dependent on number of marked individuals in a population)[36,39]	360 days[36,39]	minimizing the violation of the "closed population" assumption)[35,36]	[30] Sun et al., 2014 [31] Noss et al., 2012 [32] Foster & Harmsen, 2011 [33] Efford, 2004 [34] Karanth et al., 2011 [35] Burgar et al., 2018 [36] Burgar, personal communication, April 23, 2023 [37] Chandler & Royle, 2013 [38] Sollmann et al., 2013b [39] Burgar, 2021 [40] Clark, 2019 [41] Sun et al., 2022 [42] Augustine et al., 2019 [43] Augustine et al., 2018 [44] Davis et al., 2021
Spatial count (SC)[37] (type of SCR model)	Systematic random or clustered may be best[24,30,40]	Close enough that individuals will be detected at multiple locations[24,29]	Minimum of 30; 60 (but will depend on detection probability and resight data)[35,41]	≥ 30 for all but the most detectable; >60 for reasonable precision for most; >60-120 if capture probability is low[4,25]	-		
Spatial Partial Identity Model (Categorical SPIM; catSPIM)[24,41,42]	Same as SC[24,30,41,42]	Similar to SC or with fewer cameras[41]	Similar to SC or less[24,30,41,42]	Similar to SC or less[24,30,41,42]	Similar to SC or less[24,30,41,42]	Similar to SC or less (such that no change in identity trait - e.g., antlers present/absent)[30]	
Spatial Partial Identity Model (2-flank SPIM)[24,43] (extension of SCR model augmented with data from partially identifying images)	Same as SCR[24,43] Flexible (can be used with paired-, single or hybrid camera configurations and single-or paired stations)[44] Regular, closely spaced cameras (relative to animal's home range sizes) ideal (more likely to capture both sides of animal)[43]	Fewer cameras than SCR (or same number of cameras but larger sampling area) Note - larger sampling areas preferred (less uncertainty associated with individual identification as fewer samples collected on the periphery of the camera array)[43]	Similar to SCR or less[24,43]	Similar to SCR or less[24,43]	Similar to SCR or less[24,43]	Similar to SCR or less[24,43]	

Approach	Camera arrangement	Camera spacing	Number of cameras	Camera days per camera location	Total number of camera days	Survey duration	References
Random encounter models (REM)[19,45]	Random with respect to movement[vi,2,4,45,46] Systematic[46] Systematic random[vii4] Stratified random[4] Stratified targeted[viii,4]	No minimum; Ideally ≥ 1 km[4] Spatially independent[45] > home range diameter; 1-2 km without home range size, closer if using mixed models[4]	Minimum of 20; ideally >50[4,19]; Dependent on species' density[4]	No minimum; ideally >30[4]	Minimum of 10 detections; Ideally > 20 detections; Often 2,000 total camera days[2,19] 1,000-10,000 for most, if activity & speed are to be estimated[47] >2000 for low-density carnivores / rare ungulates[4]	Ideally < 12 months[4] No maximum[19]	[45] Rowcliffe et al., 2013 [46] Loonam et al., 2021 [47] Rowcliffe et al., 2016 [48] Nakashima et al., 2018 [49] Moeller et al., 2023 [50] Becker et al., 2022 [51] Huggard, 2018 [52] Warbington et al., 2020 [53] Howe et al., 2017 [54] Moeller et al., 2018 [55] Ridout & Linkie, 2009 [56] Rowcliffe et al., 2014
Random encounter and staying time (REST)[48]	Same as REM[49,50]						
Time in front of the camera (TIFC)[50-52]	Random or stratified random (representative) with respect to movement[50]	Same as REM[49,50]					
Distance sampling (DS)[53]	Random with respect to movement, pointing in either random or consistent direction[24,46] Systematic[46] Random or targeted across known density gradient[49]	Dependent on spatial extent of interest[49]					

Approach	Camera arrangement	Camera spacing	Number of cameras	Camera days per camera location	Total number of camera days	Survey duration	References
Time-to-event (TTE) model[53]	Random with respect to movement[46] Systematic[46] Systematic random[46]	No minimum required if random sampling used[53]	Dependent on species density and distribution (e.g., more cameras with lower density and more clumped distribution)[53] Minimum of 20; ideally > 50[54]	No minimum[53]	Dependent on species density and distribution[54]	None required If demographic and geographic closure assumptions are not met (Appendix A - Table A1), the estimate will be the mean abundance or density in study area during the survey[54]	
Space-to-event (STE) model[53]		None (uses instantaneous snapshots)[54]					
Instantaneous sampling (IS)[53]							
Behaviour	Ideally, random; Stratified[4] Usually targeted[4]	Objective-dependent[4] Ideally, independant (larger than HR or > 1 km)[55,56]	Activity patterns: Enough to obtain > 100 detections[55,56] > 20 per stratum[4]	-	-	Dependent on behavioural metric (e.g., if it occurs during a certain period)[4]	

[i] **Spatially independent for species diversity and richness:** locations should be independent, meaning that any two locations do not sample the same community of animals. Note that this may be hard to achieve when considering the movement distances of some species, such as big cats, and in practice, a camera spacing of 1-2 km is often used (e.g., Tobler et al., 2008; Ahumada et al., 2011; Kinnaird & O'Brien, 2012)

[ii] **Paired design for CR:** higher chance of recognizing all individuals captured in a survey; using two cameras also decreases the chances of missing captures entirely (Tobler et al., 2008).

[iii] **Targeted design for CR:** This design is commonly used when estimating densities of marked populations (e.g., spatially explicit capture-recapture [SECR; Borchers & Efford, 2008; Efford, 2004; Royle & Young, 2008]) or behaviour studies. However, targeted sampling may impede the ability to draw inferences beyond the survey area.

[iv] **Spatially independent CR:** "camera locations should be sufficiently close to one another such that individuals are picked up across more than one location" (Wearn & Glover-Kapfer, 2017).

[v] **Species-dependent (home range size) for CR/CMR:** There is a trade-off between density and survey extent: 10-30 individuals exposed with a camera location density of at least 2-4 per smallest home range.

[vi] **Random design for REM models:** Note that species with very restricted distributions in a landscape are best sampled using a stratified design (Wearn & Glover-Kapfer, 2017).

[vii] **Systematic random design for REM**: to ensure a minimum separation between cameras (Wearn & Glover-Kapfer, 2017)

[viii] **Stratified targeted for REM:** species that are highly restricted in occurrence (Wearn & Glover-Kapfer, 2017)

Table A3. Example of camera settings and recommended camera settings options (Reconyx Camera Models).

Field name in Reconyx camera settings	Setting option - Reconyx PC800/PC900	Setting option - Reconyx HP2X	Field name in Remote Camera Survey Guidelines	Setting option Remote Camera Survey Guidelines	Recommended setting option
Trigger / **Motion**					
Motion Sensor	On / Off	On / Off	Trigger Mode(s)	Motion image / Time-lapse image / Video	On
Sensitivity	Low / Low/Medium / Med / Medium/High / High	Low / Low/Med / Med / Med/High / High / Very High	Trigger Sensitivity	Low / Low/Med / Med / Med/High / High / Very High / NULL	High
Pictures per Trigger	1 / 2 / 3 / 5 / 10	1 / 2 / 3 / 4 / 5 / 6 / 7 / 8 / 9 / 10	Photos Per Trigger	[numeric]	1
Picture Interval	RapidFire / 1 sec / 3 sec / 5 sec / 10 sec	RapidFire / 1 sec / 2 sec / 3 sec / 4 sec / 5 sec / 6 sec / 7 sec / 8 sec / 9 sec / 10 sec	Motion Image Interval (seconds)	[numeric; seconds; “NULL” if NA]	RapidFire
Quiet Period	No delay / 15 sec / 30 sec / 1 min / 3 min / 5 min	No Delay / 5 sec / 10 sec / 15 sec / 30 sec / 1 min / 2 min / 3 min / 5 min	Quiet Period (seconds)	[numeric; seconds; “NULL” if NA]	No delay
Motion videos	-	On / Off	Trigger Mode(s)	Motion image / Time-lapse image / Video	-
Video length	-	5 sec, 10 sec, Dynamic Length	*Video Length (seconds)	[numeric; seconds; “NULL” if NA]	-
External trigger images	On / Off; if applicable	On / Off	Trigger Mode(s)	Motion image / Time-lapse image / Video	-
External trigger videos	-	On / Off; if applicable	Trigger Mode(s)	Motion image / Time-lapse image / Video	-
Time-lapse					

Lapse Picture		On / Off	Trigger Mode(s)	Time-lapse images	On
Time-lapse interval	1 min, 5 min, 15 min, 30 min, 1 hour	1 min, 5 min, 15 min, 30 min, 1 hour	-	-	2 hours
Lapse Schedule	One hour increments	24 hr, Add Solar, Add Fixed	-	-	00:00 to 12:00
AM Period	On / Off	On / Off	-	-	On
PM Period	On / Off	On / Off	-	-	On
Time-lapse videos	-	On / Off	Trigger Mode(s)	Motion image / Time-lapse image / Video	-
Video length	-	5 sec, 10 sec, Dynamic Length	*Video Length (seconds)	[numeric; seconds; “NULL” if NA]	-
Night Mode / Day/Night					
Take pictures	Both / Day / Night	Both / Day / Night	-	-	Both
Take videos	-	Both / Day / Night	-	-	-
Infrared illuminator	On / Off	On / Off	-	-	-
Flash output	-	Low / Med / High / Off	-	-	-
Night Mode	Balance / High Quality / Fast Shutter / Max Range	Optimized / Fast shutter / Long Range	-	-	-
Other					
User label	[text field]	[text field]	-	-	[text field]
Minimum shutter speed	-	-	-	-	1/120th
Maximum ISO	-	-	-	-	ISO1600

Table A4. Recommended equipment for field deployments (checklist).

Category	Equipment
Safety	• Appropriate personal protective equipment for weather and safety (e.g., sunscreen, rain jacket, etc.) • Bear spray • First aid kit (ensure contents are complete) • A communication device (e.g., satellite phone, radio, etc.)
Navigation	• GPS unit (NAD83, decimal degrees) • Maps • Compass (set to appropriate declination; to document the Camera Direction (degrees))

Camera equipment	• Reconyx HP2X unit (or camera of your choice)
	• User manual for your Camera Make and Camera Model (for reference/troubleshooting)
	• Laptop case(s) (to protect the camera lens/detectors in transit)
	• AA lithium batteries (appropriate number make/model dependent)
	  ○ spare batteries
	  ○ Ziplock bags for old batteries and/or keep items dry
	• Sharpie for labelling
	• 1 SDHC memory card (16 GB or larger)
	  ○ spare SD cards
	• Cable lock with key (labelled with the Camera ID), with adjustable straps for support as needed
	  ○ extra key for cable lock (bolt cutter useful if lock jammed)
	• Bracket or security enclosure (e.g., lock box; optional but recommended to minimize risk of theft)
	• Desiccant packets
	• Lighter or de-icer (spray; for frozen locks in winter)

Camera Attachment	• Post or stake (to serve as an attachment point)
	• Mallet (to drive in post or stake)
	• Screws (for mounting cameras)
	  ○ Screwdrivers
	  ○ Phillips (crosshead)
	  ○ Robertson (square)
	  ○ Slotted (flathead)

Documentation	• Tablet, digital camera with SD card or a phone to view photos (if required) • Tablet or clipboard • Camera Deployment Field Datasheet (Rite-In-The-Rain paper with pencil, ideally). • Camera Service/Retrieval Field Datasheet (Rite-In-The-Rain paper with pencil, ideally). • Test Image Sheet or dry-erase board • Marker (to document deployment information in test images) • Measuring tape (to measure the camera height, etc.)
Deployment of lure	• Lure stakes & PVC pipes • Lure • Lure product Safety Data Sheet (SDS) • Nitrile gloves
Visibility	• Folding machete/saw/hatchet (to clear shrubs, tree branches and vegetation; gloves are also useful) • Conduit (1.3 m; painted with alternating swatches of high contrast paint [if required])

Table A5. Steps to deploy a remote camera.

Task	Instructions
Select camera locations	**1)** Locate the predetermined camera locations (e.g. based on study design and determined before camera set up; Appendix A - Table A2). **2)** Select a FOV Target Feature (if applicable) to maximize detection probability (e.g., wildlife trail). **3)** Identify a suitable attachment point in the vicinity of the target area (e.g., tree, fence post) that supports: • a detection zone ~3–5 m from the camera (~3–5 m from the FOV Target Feature), • a Field of View (FOV) at least 5 m wide and 10 m long (unobstructed by objects, shrubs or trees), and • the camera aimed perpendicular to the expected movement path of the Target Species. **4)** Trim vegetation as needed. ***Note:*** It may be necessary to bring a man-made attachment point (e.g., stake). The most suitable attachment point will depend on the camera height, angle, and direction because these choices will impact the Field of View (FOV).
Set camera	**5)** Before setting up the camera, record the Camera Make and Camera Model, Camera Serial Number, and optionally the Camera ID, SD Card ID, key ID (for python or cable lock), attachment and the equipment that will be used to secure the camera. **6)** Ensure the SD card is inserted, the batteries are fresh and turn the camera on. **7)** Check (and record) the camera settings (e.g., Trigger Mode(s), Video Length (seconds), Trigger Sensitivity, # of Photos Per Trigger, Motion Image Interval (seconds), Quiet Period (seconds) , etc.) to ensure they match the predetermined choices and that the date time is correct. Record the Deployment Start Date Time (in the format: "DD-MMM-YY HH:MM:SS")
Walktest	Perform a walktest to confirm that the Field of View (FOV) is satisfactory (see section 7.4.5). See the camera's user manual for instructions on how to perform the walktest for your particular Camera Make and Camera Model. **8)** Ensure the camera detects motion 5 m in front of the camera, at both 0 m and 0.5–1 m height. Trim vegetation as needed. **9)** Activate the walktest mode. **10)** Attach the camera at the desired camera height, angle, and direction. **11)** Walk in front of the camera to a specified distance (i.e., the "Walktest Distance," e.g., 5 m). **12)** Wave your hand in front of the camera (usually at ground level and at a chosen height [i.e., the "Walktest Height," e.g., 0.8 m]) to determine if the camera is activating. If the camera is set correctly (based on the user's criteria), an indicator light will flash to signal that the sensor is detecting heat and motion (thus indicating the camera's detection zone). **13)** Arm the camera or wait for the camera to arm itself (~2 minutes of inactivity).

Task	Instructions
	14) Note whether a walktest was performed on the field datasheets and if so, optionally record the Walktest Distance (m) and Walktest Height (m).
Attach and secure the camera	**15)** Attach and secure the camera to the tree/post (e.g., security box or bracket, cable lock and lock box, as needed). Security / lock boxes are recommended to avoid theft. • Cameras should be angled slightly downward. **16)** Record the camera height (m). • In general, cameras should be ~0.5–1 m from the base of the tree to the bottom of the camera lens. **17)** Record the Camera Direction (degrees). • Cameras should ideally face north (if not, south).
Test images	**18)** Write the deployment metadata (specifically, Sample Station ID, Camera Location ID, Deployment ID, Deployment Crew, and Deployment Start Date Time (in the format "DD-MMM-YYYY HH:MM:SS") on either a Test Image Sheet or a dry-erase board with a marker. This is important in case of the situation that the camera does not properly record the user label. **19)** Walk ~5 m in front of the camera. **20)** Face the Test Image Sheet/dry-erase board towards the camera, and slowly walk towards the camera. If the Test Image Sheet is laminated, tilt it slightly downward to avoid sun glare on the shiny surface. **21)** Allow the camera to take a series of images.
Document deployment metadata	Relevant deployment metadata should be documented each time a camera is **deployed** (see full list below). Each event should have its own Camera Deployment Field Datasheet. ***Note:*** If a camera is deployed for more than one survey, the field crews will need to revisit the camera location to "**service**" the camera and/or equipment (e.g., to refresh batteries or swap out SD cards. If the field crew visits the camera location to collect the camera and other equipment ("Service/Retrieval Crew"; i.e., the camera location will no longer be used and cameras, SD cards, and batteries are not replaced), this is referred to as a "**retrieval**." Whether the Service/Retrieval Crew services or retrieves a camera, additional metadata should be collected that is not included in the deployment metadata (see "service/retrieval metadata" below). Pertinent deployment metadata collection fields include [Camera Deployment Field Datasheet]: • Project ID • Sample Station ID • Camera Location ID • Latitude Camera Location OR Northing Camera Location • Longitude Camera Location OR Easting Camera Location • UTM Zone Camera Location (if applicable) • GPS Unit Accuracy (m) • *Access Method • Deployment Crew

Task	Instructions
	• Deployment Start Date Time (DD-MMM-YYYY HH:MM:SS) • Camera ID • Camera Make • Camera Model • Camera Serial Number • *SD Card ID • *Key ID • *Security • Trigger Mode(s) • *Video Length (seconds) • Trigger Sensitivity • Photos Per Trigger • Motion Image Interval (seconds) • Quiet Period (seconds) • Camera Height (m) • *Camera Direction (degrees) • *Camera Attachment • *Stake Distance (m) • FOV Target Feature • FOV Target Feature Distance (m) • Bait/lure Type • *Camera Location Characteristics • *Deployment Area Photos Taken • *Deployment Area Photos Numbers • *Test Image Taken • *Walktest Complete • *Walktest Distance (m) • *Walktest Height (m) • *Camera Active On Departure • *Camera Location Comments • *Deployment Comments
Camera service or retrieval	**22)** Approach the camera from the front so that the camera will collect images of the field crew, thus serving as backup documentation of the Deployment End Date Time (in the format "DD-MMM-YYYY HH:MM:SS") in case that field sheets are lost, destroyed, etc.
Document service/retrieval metadata	Relevant Service/Retrieval metadata should be collected each time a camera is **serviced** (e.g., revisited to refresh batteries or swap out SD cards) or **retrieved** (e.g., revisited to collect the camera and other equipment, i.e., the camera location will no longer be used and the camera, SD card, and batteries are not being replaced) if there have been any changes to camera location, sampling period, and/or setting type (e.g., not baited and then baited later) (see below for a full list). Whether the crew services or retrieves a camera, additional metadata fields should be collected that are not included in the deployment metadata. Each event should have its own Camera Service/Retrieval Field Datasheet.

Task	Instructions
	• Be sure to record the "Purpose Of Visit" (i.e., to service or retrieve the camera) as well as whether the camera was active or incurred damage, as this can provide context if there are no photos taken after a certain date. • If the camera was damaged/is not functioning - before setting up the camera, record the new Camera Make and Camera Model, new Camera Serial Number, and optionally the New Camera ID, Key ID, and/or SD Card ID (if applicable; if python or cable lock damaged). • Be sure to record whether the batteries were replaced (under "Batteries Replaced"). If using lithium batteries, the camera's battery level indicator may not decline evenly (but rather indicate full battery until a sudden drop-off). If you expect to leave your camera for a long period of time before checking it again, it is best to refresh the batteries. • Record other relevant metadata below. • Ensure you collect whatever material you used to attach the camera to the tree, post, etc. and any other equipment you brought with you. Pertinent service/retrieval metadata collection fields include [Camera Service/Retrieval Field Datasheet]: • Project ID • Sample Station ID • Camera Location ID • Purpose Of Visit (Service or Retrieve) • Service/Retrieval Crew or Deployment Crew • Deployment Start Date Time (DD-MMM-YYYY HH:MM:SS) (may also be the Deployment End Date Time (DD-MMM-YYYY HH:MM:SS) for a previous deployment) • *Camera Active On Arrival • *Camera Damaged • *Card Status (% full) • *# Of Images • *SD Card Replaced • *Remaining Battery (%) • *Batteries Replaced • New Camera ID • New Camera Make • New Camera Model • New Camera Serial Number • New SD Card ID • Bait/lure Type • *Deployment Area Photos Taken • *Deployment Area Photos Numbers • *Test Image Taken • *Walktest Complete • *Walktest Distance (m)

Task	Instructions
	• *Walktest Height (m) • *Camera Active On Departure • *Camera Location Comments • *Service/Retrieval Comments • Additional information may be collected as needed Data can be input into a tablet interface or recorded on a paper Camera Service/Retrieval Field Datasheet.

Notes: An asterisk (*) indicates the field is optional and not required by the AB Metadata Standards (RCSC, 2023) and B.C. Metadata Standards (RISC, 2019).

Visit metadata			
Project ID		**GPS Unit Accuracy (m)**	
Sample Station ID		***Access Method**	Foot / ATV / Argo / Truck / Snowmobile / Horse / Helicopter / Boat / NULL
Camera Location ID			
Latitude or Northing		**Deployment Crew** (list full names)	
Longitude or Easting			
UTM zone		**Deployment Start Date Time (24hr)**	DD-MMM-YYYY HH:MM:SS

Equipment information		Placement	
Camera ID		**Camera Height (m)** (0.5-1 m; record to the nearest 0.05 m)	
Camera Make		***Camera Direction (degrees)** (Ideally north, if other explain in comments)	
Camera Model			
Camera Serial Number		***Camera Attachment**	Tree / Post / Tree + Bungee/Strap / Tree + Screws / Post + Bungee/Strap / Post + Screws / Other†
***SD Card ID**	***Key ID**		
***Security**	Security Box / Bracket / Bracket + Screws / None	***Stake Distance (m)**	

Camera settings			
Trigger Mode(s) (circle all that apply)	Motion / Time-lapse / Video	**FOV Target Feature** (circle one)	Game Trail / Hiking Trail / Off-Highway Vehicle Trail / Paved Road / Dirt/Gravel Road / Road Crossing[1] / Railway / Cutline/Seismic Line / Transmission Line / Pipeline / Wellsite / Culvert / Beaver Dam / Burrow/Den / Nest / Carcass[2] / Natural Mineral Lick / Rub Post / Other† / None / NULL
***Video Length (seconds)**			
Trigger Sensitivity (circle one)	Low / Low/Med / Med / Med/High / High / Very High / NULL		
Photos Per Trigger		**FOV Target Feature Distance (m)** (to the nearest 0.05 m)	
Motion Image Interval (seconds)		**Bait/lure Type** (circle one)	Scent / Meal[3] / Bait Tree / Visual / Acoustic / Other‡ / None
Quiet Period (seconds)			

Site characteristics			
***Camera Location Characteristic(s)** (circle all that apply)	Trail / Road / Railway/Pipeline/Transmission Line / Cutline/Seismic Line / Wellsite / Clearcut / Building / Forest - Deciduous / Forest - Mixedwood / Forest - Conifer / Forest - Undefined / Meadow / Burn / Agriculture / Shrubland / Beaver Dam / Wetland / Lentic / Lotic / Other† / NULL	***Deployment Area Photos Taken** (circle one; photo order: datasheet, N, E, S, W)	Y / N
		***Deployment Area Photo Numbers** (list photo numbers)	

Equipment checks			
***Test Image Taken** (circle one; see Test Image Sheet next page)	Y / N	***Walktest Distance (m)** (to the nearest 0.05 m)	
		***Walktest Height (m)** (to the nearest 0.05 m)	
***Walktest Complete** (circle one)	Y / N	***Camera Active On Departure** (circle one)	Y / N

***Camera Location Comments**	
***Deployment Comments**	

* Optional and not required by the Wildlife Camera Metadata: Standards for Alberta (RCSC, 2022)
† The option should be described in the Camera Location Comments
‡ The option should be described in the Deployment Comments.
Notes: Abbreviations: Y = yes; N = no.

***Access Method:** record the method used to reach the camera location.
Bait/lure Type: record the type of bait or lure used at the camera location. If "Other," describe in the Deployment Comments.
[2]**Carcass [FOV Target Feature]:** not placed by the crew as bait/lure.
***Camera Active On Departure:** record whether a camera was functional upon departure.
***Camera Attachment:** record the method/tools used to attach the camera. If "Other," describe in Camera Location Comments.
***Camera Direction (degrees):** record the cardinal direction that a camera faces. Ideally, cameras should face north (N; i.e. "0" degrees), or south (S; i.e. "180" degrees) if north is not possible. The camera direction should be chosen to ensure the field of view (FOV) is of the original FOV target feature.
Camera Height (m): record the height from the ground (below snow) to the bottom of the lens (in metres to the nearest 0.05 m).
Camera ID: record the unique alphanumeric ID for the camera that distinguishes it from other cameras of the same make or model.
***Camera Location Characteristics:** record any significant features around the camera at the time of the visit. Camera Location Characteristics differ fom FOV Target Features in that Camera Location Characteristics could include those not in the camera's FOV. If "Other," describe in the Camera Location Comments.
***Camera Location Comments:** comments describing additional details about a camera location.
Camera Location ID: record the unique alphanumeric identifier for the location where a single camera was placed (e.g., "BH1").
Camera Make: record the make (i.e., the manufacturer) of the camera deployed (e.g., "Reconyx" or "Bushnell").
Camera Model: record the model number of the camera deployed (e.g., "PC900" or "Trophy Cam HD").
Coordinates: coordinates for the camera location should be taken from the GPS with five decimal places and in decimal degrees if using latitude/longitude or including UTM zone if using easting/northing.
Deployment Crew: record the first and last names of the individuals who collected data during the deployment visit.
***Deployment Area Photos Taken / Deployment Area Photo Numbers:** images of the area where the camera was deployed. Record the image numbers from a camera or phone. If not applicable, enter "NULL."
***Deployment Comments:** comments describing additional details about the deployment.
Deployment Start Date Time (DD-MMM-YYYY HH:MM:SS): the date and time that a camera was placed for a specific deployment.
FOV Target Feature: record the specific man-made or natural feature at which the camera is aimed to maximize the detection of wildlife species or to measure the use of that feature. If "Other," describe in the Camera Location Comments.
***FOV Target Feature Distance (m):** record the distance from the camera to the FOV Target Feature (in metres to the nearest 0.05 m). If not applicable, enter "NULL."
GPS Unit Accuracy (m): record the margin of error (in metres) of the GPS unit used to record spatial information (e.g., if the margin of error is +/- 3.5 m, record 3.5 m).
***Key ID:** record the unique ID for the key or set of keys used to lock/secure the camera to the post, tree, etc.
[3]***Meal [Bait/lure Type]:** including carcass placed by the crew.
Motion Image Interval (seconds): record the time (in seconds) between events (triggers) that occur due to motion, heat, or triggering of external trigger devices. If a Motion Image Interval was not set, enter "0" seconds (i.e., instantaneous).
Photos Per Trigger: record the number of photos taken each time the camera was triggered.
Project ID: record the unique alphanumeric identifier for the project (e.g., "UofA_WildEdmonton-Urban-Wildlife-Monitoring_2018").
Quiet Period (seconds): record the time (in seconds) between shutter "triggers"; that is, if the camera was programmed to pause between firing initially and firing a second time. If a Quiet Period was not specified, enter "0."
[1]**Road crossing [FOV Target Feature]:** e.g., overpass, underpass, or bridge.
Sample Station ID: record the sequential alphanumeric identifier given to each camera location within a grouping of two more non-independent camera locations when cameras are deployed in clusters, pairs or arrays (e.g., "SS1" in "SS1-BH1," "SS1-BH2," "SS1-BH3," and "SS1-BH4"). If not applicable, enter "NULL."
***SD card information / Battery %:** record the ID label on the SD card (e.g., "CMU-100"). Note the card status (% FULL) and remaining battery power. Toggle through options to find STATUS to record the # of photos (differs for different Camera Models).
***Security:** record the equipment used to secure the camera.
***Stake Distance (m):** record the distance from the camera to the stake (in metres to the nearest 0.05 m). If not applicable, enter "NULL."
***Test Image Taken:** record whether a test image (i.e., an image taken from a camera after it has been set up to provide a permanent record of the visit metadata) was taken. Arm the camera and walk towards the camera from ~5 m in front while holding the Test Image Sheet (see next page).
Trigger Mode(s): record the camera settings that determine how the camera will trigger: by motion ("Motion Image"), at set intervals ("Time-lapse image"), and/or by video ("Video"; possible with newer camera models, such as Reconyx HP2X).
Trigger Sensitivity: record how sensitive a camera is to activation ("triggering") via the infrared and/or heat sensors (if applicable). If the Trigger Mode is set to Time-lapse or if the camera does not have a sensitivity setting, circle "NULL."
***Video Length (seconds):** if recording video, note the video length selected in seconds. If not applicable, enter "NULL."
***Walktest Complete:** indicate whether a walktest was performed to ensure the Camera Height, tilt, etc., adequately captures the desired detection zone. Put the camera in "walktest" mode and move your hand along detection bands at ~5 m from the camera. Motion is detected when the red walktest light flashes.
***Walktest Distance (m):** record the horizontal distance at which the crew performs the walktest (in metres to the nearest 0.05 m). If not applicable, enter "NULL."
***Walktest Height (m):** record the vertical distance at which the crew performs the walktest (in metres to the nearest 0.05 m. If not applicable, enter "NULL."

Sample Station ID: ______________________________

Camera Location ID: __________________________

Crew: ________________________________

Deployment Start Date Time: ______________________

Visit metadata			
Project ID		**Service/Retrieval / Deployment Crew** (list full names)	
Sample Station ID			
Camera Location ID		**Deployment Start Date Time (24hr)**	DD-MMM-YYYY HH:MM:SS
Purpose Of Visit (circle one)	Service / Retrieve		
Equipment information		**Placement**	
***Camera active on arrival** (circle one)	Y / N	**Bait/lure Type** (circle one)	Scent / Meal[1] / Bait Tree / Visual / Acoustic / Other‡ / None
***Camera Damaged** (circle one)	Physical‡ / Mechanical‡ / None	**Site characteristics**	
SD Card ID	***Card status** (% full)	***Deployment Area Photos Taken** (circle one; photo order**:** datasheet, N, E, S, W)	Y / N
***# Of Images**	***SD Card Replaced** (circle one) Y / N	***Deployment Area Photo Numbers** (list photo numbers)	
***Remaining Battery (%)**	***Batteries Replaced** (circle one) Y / N	**Equipment checks**	
If camera replaced:		***Test Image Taken** (circle one; see Test Image Sheet next page)	Y / N
New Camera ID		***Walktest Complete**	Y / N
New Camera Make		***Walktest Distance (m)** (to the nearest 0.05 m)	
New Camera Model		***Walktest Height (m)** (to the nearest 0.05 m)	
New Camera Serial Number		***Camera Active On Departure**	Y / N
***Camera Location Comments**			
***Service/Retrieval Comments**			

Visit metadata			
Project ID		**Service/Retrieval / Deployment Crew** (list full names)	
Sample Station ID			
Camera Location ID		**Deployment Start Date Time (24hr)**	DD-MMM-YYYY HH:MM:SS
Purpose Of Visit (circle one)	Service / Retrieve		
Equipment information		**Placement**	
***Camera Active On Arrival** (circle one)	Y / N	**Bait/lure Type** (circle one)	Scent / Meal[1] / Bait Tree / Visual / Acoustic / Other‡ / None
***Camera Damaged** (circle one)	Physical‡ / Mechanical‡ / None	**Site characteristics**	
SD Card ID	***Card Status** (% full)	***Deployment Area Photos Taken** (circle one; photo order**:** datasheet, N, E, S, W)	Y / N
***# Of Images**	***SD Card Replaced** (circle one) Y / N	***Deployment Area Photo Numbers** (list photo numbers)	
***Remaining Battery (%)**	***Batteries Replaced** (circle one) Y / N	**Equipment checks**	
If camera replaced:		***Test Image Taken** (circle one; see Test Image Sheet next page)	Y / N
New Camera ID		***Walktest Complete**	Y / N
New Camera Make		***Walktest Distance (m)** (to the nearest 0.05 m)	
New Camera Model		***Walktest Height (m)** (to the nearest 0.05 m)	
New Camera Serial Number		***Camera Active On Departure**	Y / N
***Camera Location Comments**			
***Service/Retrieval Comments**			

* Optional and not required by the Wildlife Camera Metadata: Standards for Alberta (RCSC, 2022)

† The option should be described in the Camera Location Comments

‡ The option should be described in the Deployment Comments.

Notes: Abbreviations: Y = yes; N = no.

Bait/lure Type: record the type of bait or lure used at the camera location. If "Other," describe in the Deployment Comments.

***Camera Active On Arrival:** record whether the camera was functional upon arrival.

***Camera Damaged:** record whether there is any damage to the camera (physical or mechanical). If damage is present, describe the damage in the Service/Retrieval Comments.

Camera ID: record the unique alphanumeric ID for the camera that distinguishes it from other cameras of the same make or model.

***Camera Location Comments:** comments describing additional details about a camera location.

Camera Location ID: record the unique alphanumeric identifier for the location where a single camera was placed (e.g., "BH1").

Camera Make: record the make (i.e., the manufacturer) of the camera deployed (e.g., "Reconyx" or "Bushnell").

Camera Model: record the model number of the camera deployed (e.g., "PC900" or "Trophy Cam HD").

***Deployment Area Photos Taken / Deployment Area Photo Numbers:** images of the area where the camera was deployed. Record the image numbers from a camera or phone. If not applicable, enter "NULL."

Deployment Start Date Time (DD-MMM-YYYY HH:MM:SS): the date and time that a camera was placed for a specific deployment.

[1]***Meal [Bait/lure Type]:** including carcass placed by the crew.

Project ID: record the unique alphanumeric identifier for the project (e.g., "UofA_WildEdmonton-Urban-Wildlife-Monitoring_2018").

Purpose Of Visit: record the reason for visiting the camera location (i.e. to retrieve the camera ['retrieve'] or to change batteries/SD card or replace the camera ['service']).

Sample Station ID: record the sequential alphanumeric identifier given to each camera location within a grouping of two more non-independent camera locations when cameras are deployed in clusters, pairs or arrays (e.g., "SS1" in "SS1-BH1," "SS1-BH2," "SS1-BH3," and "SS1-BH4"). If not applicable, enter "NULL."

***SD card information / Battery %:** record the ID label on the SD card (e.g., "CMU-100"). Note the card status (% FULL) and remaining battery power. Toggle through options to find STATUS to record the # of photos (differs for different Camera Models).

***Service:** record whether the SD card has been swapped and the batteries replaced.

***Service/Retrieval Comments:** comments describing additional details about the service/retrieval.

Service/Retrieval / Deployment Crew: record the first and last names of the individuals who collected data during the service/retrieval visit.

***Test Image Taken:** record whether a test image (i.e., an image taken from a camera after it has been set up to provide a permanent record of the visit metadata) was taken. Arm the camera and walk towards the camera from ~5 m in front while holding the Test Image Sheet (see next page).

***Walktest Complete:** indicate whether a walktest was performed to ensure the Camera Height, tilt, etc., adequately captures the desired detection zone. Put the camera in "walktest" mode and move your hand along detection bands at ~5 m from the camera. Motion is detected when the red walktest light flashes.

***Walktest Distance (m):** record the horizontal distance at which the crew performs the walktest (in metres to the nearest 0.05 m). If not applicable, enter "NULL."

***Walktest Height (m):** record the vertical distance at which the crew performs the walktest (in metres to the nearest 0.05 m. If not applicable, enter "NULL."

12.0 Appendix B

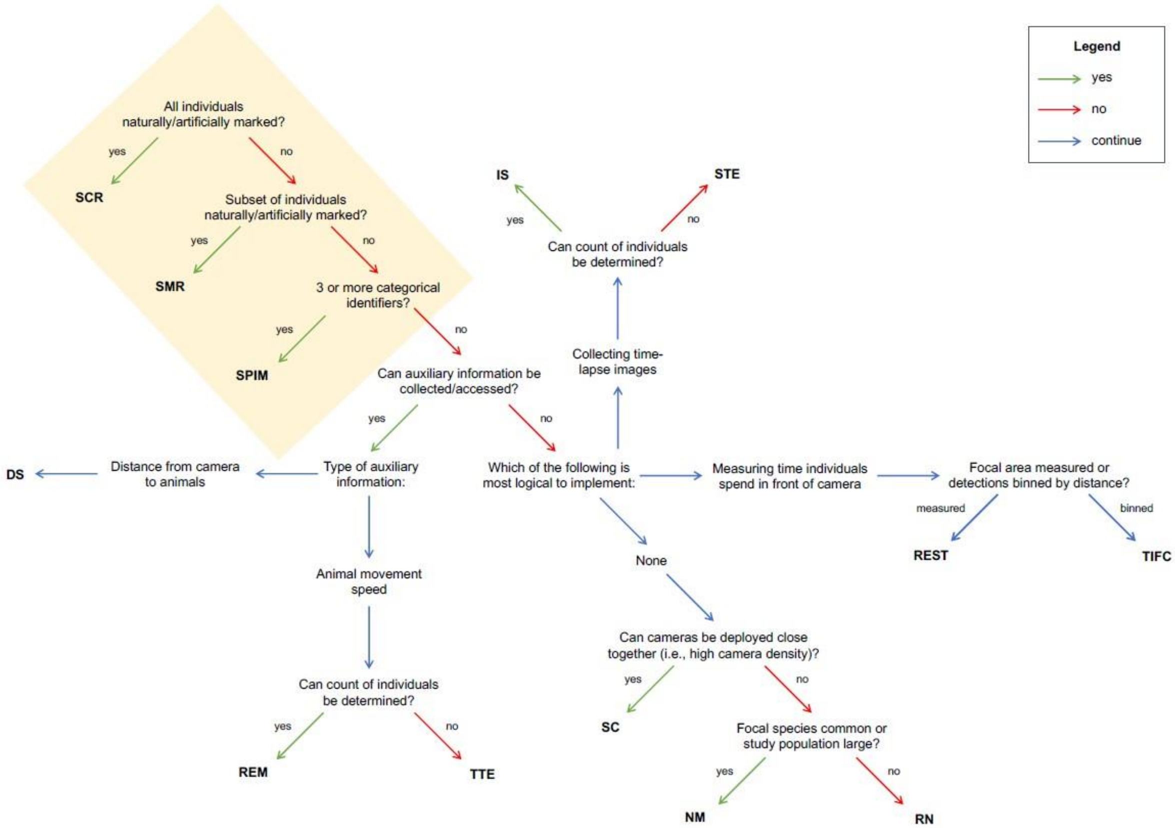

Figure B1. "Adapted from Gilbert et al. (2021) and Sun (unpublished). Decision tree for selecting camera trap density models. The models in the yellow rectangle are for marked and partially-marked populations; the remaining models are for unmarked populations. Note, the models in this decision tree are not necessarily ordered from strongest to weakest, but rather are organized by key features." (Clarke et al., 2022).