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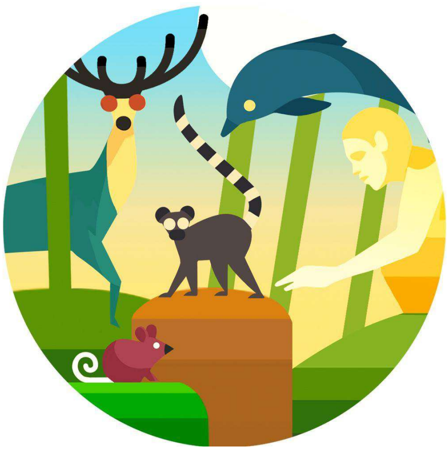

Assets for video monitoring terrestrial and aquatic wildlife

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ABSTRACT
This thesis aims to analyze the equipment used for video monitoring of wildlife. Depending on the environment and climatic context in which one must operate, the equipment used varies considerably to cope with the different conditions. The first part introduces camera traps in a terrestrial environment, such as European forests, providing a foundation for their use and their various functions. The main differences are between daytime and night-time observations, as the absence of light requires the use of infrared technology. Furthermore, the area that can be covered with a single camera is reduced at night. The second part focuses on cameras used in direct contact with water. These devices often must be placed on unstable terrain subject to constant shifts due to water movement. Furthermore, depending on the depth, the pressure they must withstand increases, requiring highly resistant insulation systems to prevent infiltration. In deeper waters, sunlight is completely or almost completely absorbed, making it necessary to use methods to allow the cameras to operate in the dark. In this case, infrared radiation cannot spread over a useful distance, making the use of artificial light sources essential. In conclusion: wildlife monitoring presents constant challenges, and different equipment can influence the results of observations or the animals themselves. It is essential to understand and take into account all the factors that can affect data acquisition and the potential influences that equipment may have on the animals.

INTRODUCTION

Effective wildlife conservation needs accurate monitoring methods capable of providing reliable information on animal species living in a specific area. Such information is fundamental for understanding ecosystem dynamics, assessing conservation status and supporting evidence-based management decisions (Caravaggi et al., 2017).

Among the available monitoring techniques, camera traps (CTs) have become one of the most widely adopted tools in wildlife research. By automatically recording images or videos in response to animal presence, they are considered a non-invasive approach that minimizes disturbance while allowing continuous monitoring over extended periods. As a result, camera traps have been successfully employed to investigate species occurrence, activity patterns, abundance, behavioural ecology and habitat use across a broad range of terrestrial, freshwater and marine ecosystems. Continuous technological developments, including improvements in trigger speed, image resolution and sensor detection capability, have considerably expanded the possible use of camera traps. Thus enable researchers to monitor species and environments that were previously difficult or impossible to study using conventional methods.

Despite these advantages, several methodological and practical challenges remain. The quality and reliability of the collected data can be influenced by multiple factors, including camera characteristics, deployment strategy, environment and target species. Furthermore, camera traps typically generate extremely large datasets that require considerable time and effort to process and analyse. Finally, many studies point out the lack of standardized protocols for data collection, management and sharing data.

CHAPTER 1: CAMERA TRAPS CHARACTERISTICS

1.1 Camera trap components

Camera traps are a versatile tool that can be modified and adapted depending on the situations and particular needs, but all share some common features.

Generally CT are made of a camera to register images or video, a memory to store the data recorded and a type of sensor to trigger the registration; alternatively cameras can have a time lapse feature. Some recent models are able to remotely send images via bluetooth, wifi, or GSM/GPRS telecommunications network (Campbell e Griffith,2015).

One of the first CT as we intend came onto the market at the end of 1980s. It used a camera connected to an infrared transmitter that shot pictures as soon as an animal interrupted the beam, then the film was automatically reloaded, ready for another shot (Trolliet et al., 2014). Nowadays, due to the rapid advance in technology and the popularity of this type of equipment, there is a great variety of camera traps models present on the market.

All of them have some parameters that define the CT itself and are important to take in consideration in order to correctly use the instrument avoiding biases (Trolliet et al., 2014).

Trigger speed: is the time delay necessary to the camera to shoot a picture once the sensor detects a change. Between camera models utilizing infrared beams there are substantial variations, ranging from less than 0.2 seconds to more than 4 seconds. Fast trigger speeds are essential for recording rapidly moving animals while slow trigger speeds may result in partial images or completely empty photographs (Trolliet et al., 2014).

Some softwares are able to modify the trigger speed in video records depending on the researcher's need. An example is MOTION: mostly used for videosurveillance, it compares the current image frames with the previous one, if it exceeds the number registered in the “threshold” parameter, the recording starts. Another parameter defines the length of a period without any motion detection to end a recording. Ultimately the “pre-capture” parameter defines the number of image frames to be included in the video before the detection of a motion event (L’Hoste et al.,2025).

Another alternative could be to set the camera to take pictures on a time lapse period, making it independent from the sensor .Also, to maximize detection events sensors, sensor and time lapse functions can be utilized simultaneously.

Detection zone and field of view: the detection zone corresponds to the area monitored by the infrared sensor. The field of view corresponds to the area actually recorded by the camera lens. (Figure 1.1)

A wider detection zone increases the likelihood of detecting fast-moving animals but may also generate empty images. Conversely, a narrower detection zone tends to produce better-centered photographs but may reduce the number of captures (Trolliet et al., 2014).
Recovery time: is the interval required before the camera can take another photograph after a trigger event (Trolliet et al., 2014).
Battery consumption: every function of the camera has an energy requirement like monitoring or processing pictures. This is particularly important in remote environments where maintenance is difficult. Some way to help extend the battery life could be the use of solar panels (Trolliet et al., 2014), increasing the number of batteries (Mouy, Xavier, et al.,2020), setting a minimum time interval between consequent registration (even tough risk to lose relevant data) and the improvement of efficiency of the electronic components reaching up duration of several months (Kalhor et al.,2024).
Picture resolution: it's expressed in megapixel (Mpx) and varies greatly between models. Again there is a compromise because low resolution images occupy less memory space, but have less detail and less precision, important in some cases like for individual recognition.
Furthermore there are other factors that influence the image quality like image sensor, the component housing the pixels. A sensor with an elevated pixel number, but a relatively small size, tends to have smaller pixels which are less sensitive to light, tend to produce more noise (unwanted signal) and have a narrower dynamic range (i.e. the range of light intensities being captured). (Trolliet et al., 2014)
Cost: camera trap cost can range from around $40 to thousands of dollars (Giddens et al., 2021) depending on the manufacturing process and their aim. The priciest cameras are the ones created to record data underwater. Even though there are some solutions that try to limit the cost to around some hundreds of dollars (Bilodeau et al., 2022), devices made to be attached to marine animals or explore the sea bottom are in the order of thousands of dollars (Tønnesen e Gero, 2024).
A wide range of taxa exhibit exclusive nocturnal behaviour so it's important to be able to record data even with dim or no light. There are two ways to gather visual data in a dark environment and both of them require illuminating the subject with a source of light (Trolliet et al., 2014).
The first is infrared light. Emitted by a series of Light Emitting Diodes (LEDs), it allows the camera to take black-and-white pictures while being hardly visible.
The second consists of an incandescent flash or a white light source that allows color pictures to be taken. Usually they have better resolution and quality. Those are fundamental features when a study requires animal identification by tags or natural marks, even though the light risks to scare the animals.

White light is also used underwater because infrared light is greatly attenuated (Humbert et al., 2023). For example, devices used at great depths where there's no light (Giddens et al., 2021) or equipment attached to deep diving animals like sperm whales often have a torch integrated (Tønnesen e Gero, 2024).

When thinking of camera traps one of the first devices that comes to mind is the trail camera: the classic off-the-shelf camera that can be attached to trees and will record the animals passing in front of it. In order to do so, the CT relies on the infrared sensors.

There are two types of them: active infrared (AIR) and passive infrared (PIR),(Brown and Gehrt, 2009).

The active infrared triggers when the receiver detects an object interrupting the path of the infra red light of a transmitter for a certain period of time. The detection zone is a straight line, which can span up to 150 feet, between the transmitter and the receiver. Thus the beam can be setted at specific height to exclude certain animal species. AIR are also relatively insensitive to changes in ambient temperature, including movement of sunlight, but can be triggered by any object interrupting the infrared beam, like moving leaves.

The passive infrared requires motion to trigger because it detects a rapid change in the amount of heat in comparison to the ground. Thus animals staying still in the detection area won't be detected. In some cases there is also the possibility to adjust the sensitivity of the PIR sensor; the user can set sensitivity high enough to detect even small amounts of change.

PIR systems are easy to set up and have low sensitivity to vegetative movement. Although they are also less sensitive to small animal movement due to the reduced body heat, and high ambient temperatures can reduce a system's sensitivity to the presence of large animals because there could be not enough difference between the animal body temperature and the background.

PIR sensors consist of a series of infrared lenses that divide the detection area into multiple zones and focus thermal radiation onto pyroelectric sensors. When an animal moves across these zones, changes in infrared energy generate electrical signals that activate the camera (Apps and McNut, 2018).

Animals moving towards or away from the camera are less likely to be detected because they could stay inside a single zone of the sensor without passing to another one, in this way the camera is not able to detect a change in temperature.(Figure 1.2)

In some cases infrared sensors are not suited for the type of equipment or study subject so we need to find alternatives.

A method could be having the camera always active, but this approach produces a large mole of data and rapidly consumes the battery. Thus it is preferred to set the camera to take pictures at

certain intervals to extend the battery life, even though there is the risk of losing meaningful data (Thompson et al., 2012).
Otherwise we can substitute the IR sensor with another triggering method that better suits the situation.
For example, investigating seals feeding behaviour, the cameras attached to the animal's head were triggered by a depth sensor and an accelerometer.The idea was to start recording videos only at a certain depth (400-800 meters) where the animal usually feeds and to catch the predatory attempts by detecting a burst in the head movement (Yoshino et al., 2020).
There are also plenty of animal species that lack detectable body heat and many of them live in aquatic environments where infrared radiation is attuned (Bilodeau et al., 2022).
Some alternatives can be far red light, but still attenuates in short distance, or acoustic images for species with a distinct morphology like sharks. These methods, alongside images taken with artificial white light illumination, need a considerable amount of energy that translate into a short battery life (scale of hours) or into the need of external power source.
The previously cited MOTION system was successfully applied on the surveillance of newts because it compares different frames to detect movement instead of relying on heat changes (L'Hoste et al.,2025).
Lastly, insects are small fast moving creatures that lack body heat so they are fairly complex to detect on camera.
Even if it's still in development, the use of Dynamic Vision Sensors (DVS), also known as event-based cameras, has shown some promising results.
Unlike conventional RGB cameras, DVS sensors do not continuously record images; instead, they register only changes in brightness at individual pixels. This allows rapid detection of moving objects even in highly dynamic environments while reducing data processing requirements and energy consumption (Gebauer et al., 2024).
The same is for ultra-lightweight convolutional neural networks (CNNs) (Gardiner et al., 2026). This model of artificial intelligence can be deployed directly on low-power microcontrollers to function as triggers for insect camera traps.
It was trained to perform binary classification (insect present or not present) resulting in low computational requirements while maintaining high detection performance (more than 80%). (Gardiner et al., 2026)

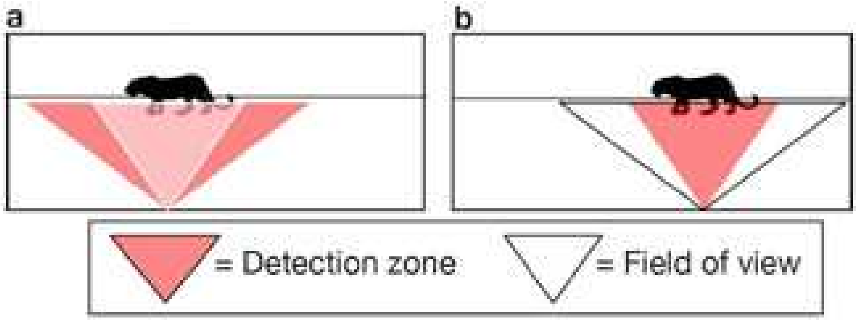

Figure 1.1 Diagram of the field of view of the detection zone of two type of camera traps (Trolliet et al., 2014)

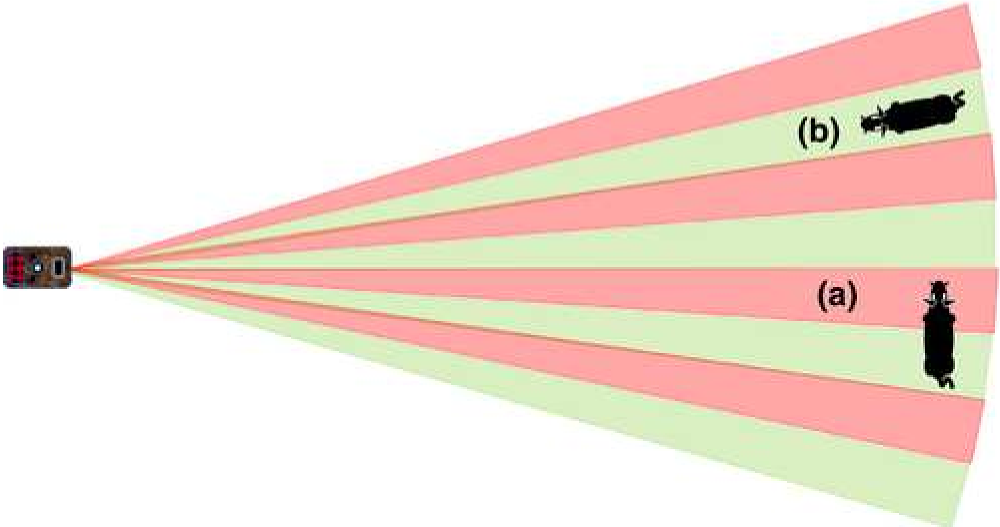

Figure 1.2 Different zones in the detection area of a PIR sensor (Apps and McNut, 2018)

1.2 Types of CTs and their limitations

CTs, almost in every scenario, require researchers to choose between compromises like a better quality of images against a shorter deployment time. Thus it is fundamental to know the characteristics of the equipment, consequently its limitations. Furthermore there are some factors that do not depend on the camera itself, but on how it is used and the environment around it.

We can divide camera traps in two broad categories: fixed cameras and animal borne cameras.

Fixed cameras are camera traps that are attached to trees, rocks with ropes or weighted down on the sea floor.

Those devices, like trail cameras (Figure 1.3), occupy the same spot throughout their entire deployment period that can be several months in some cases, therefore it is fundamental to place them correctly.

Small variations in camera height, angle, and orientation can substantially affect detection rates and lead to differences in survey outcomes that are unrelated to actual animal activity (Apps & McNutt, 2018).

It is important to consider the animal behaviour and morphology: paths, water sources, carcases, etc, are places that can influence animal detectability; different species have different dimensions, therefore require different camera height and angles.

A few centimeters can be very impactful, placing a camera higher the vegetation or slightly tilted in order to get a better perspective is determinant.

Usually a good method is to place the camera just below the target animal's shoulder height (Apps and McNut, 2018).

Environmental conditions surrounding the camera can further influence detection performance. Vegetation within the detection zone can obscure the camera or generate false triggers, direct sunlight and high ambient temperatures can reduce PIR sensitivity by decreasing the thermal contrast between animals and their surroundings and during rain season the lens window can get splashed with dirt by heavy rainfall if under 30 cm from the ground (Apps and McNut, 2018).

Slopes, background conformations must be taken into consideration because they could reduce the field of view of the camera especially if it is aimed horizontally, by offering hiding spots to the animals (Apps and McNut, 2018).

Animal borne cameras, on the other hand, are devices that are attached directly onto the animal body offering a spotlight on the behaviour of particular individuals.

These devices' biggest limitation is that they are strongly dependent on the animal's physical characteristics because they need to be carried without impairing the movement and behaviour of the host.

Most devices have a camera, a GPS unit, fundamental for the retrieval, and tri-axial accelerometer that registers data about the animal's movements. Although they usually have short autonomy: more power reservoir means more or bigger batteries that significantly increase the total weight of the apparatus. Some animal borne cameras have the possibility to remotely transmit the acquired data, but this feature further increases weight and energy consumption of the device.
Big terrestrial animals, like caribou, can be equipped with collars (Figure 1.4) of more than 1kg weight able to operate for around 9 months (Thompson et al., 2012).
On the other hand, birds, in accordance with international standards, need to wear equipment with total weight <3% of the animal body mass, in order to have minimal effect on the flight. This limits the battery life to just less than two hours of constant recording (Kane et al., 2014).
Even penguins fall under this restriction making it difficult to integrate into the equipment the light necessary to record video data in deep or dark water (Sato et al., 2025).
In large species of sharks, like tiger sharks (*galeocerdo cuvier*), the camera is fixed to the dorsal fin of the animal (Figure 1.5). The main body of the camera is secured to a stainless steel spring clap with a corrodible galvanic time release. In this way the tags will autonomously detach from the shark after 7-48 hours. Also the spring clap will detach from the shark due to a magnesium sleeve that dissolves in about 7 days (Andrzejaczek et al., 2019).
For whales and sea turtles, sensors and cameras are attached with suction cups (Figure 1.6), (Tønnesen e Gero, 2024 ; and Mullaney et al., 2024).
Especially for turtles, particular attention was given in creating a design as hydrodynamic as possible in order to limit disturbance to the animal locomotion (Agabiti et al., 2026).
All these devices to be applied require handling every single animal, and some ways are more stressful than others.
While on cetaceans capers are applied with a long pole that keeps distance of some meters (Tønnesen e Gero, 2024), other species like birds, sharks and sea turtles, need to be captured and restrained (Handley et al., 2018; Andrzejaczek et al., 2019; and Mullaney et al., 2024).

Figure 1.3 Trail camera representation (Apps and McNut, 2018)

Figure 1.4 GPS camera collar unit (Thompson et al., 2012)

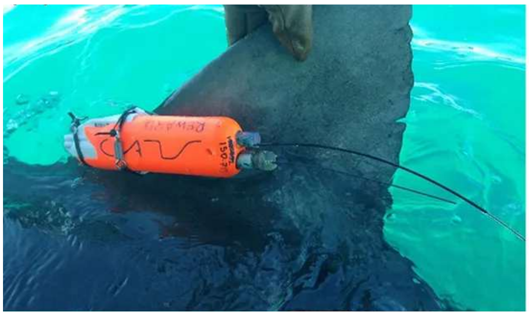

Figure 1.5 Camera tag clapped to the dorsal fin of a shark (Andrzejaczek et al., 2019)

Figure 1.6 Camera affixed to a sea turtle with suction cups (Mullaney et al., 2024)

CHAPTER 2: CAMERA TRAPS APPLICATIONS

The versatility of camera traps not only resigns their adaptability to the most various situations, but also in their applications. Having an almost undetected monitoring system offers data otherwise impossible to obtain and opens up new possibilities for animal studies.

These data, still images or videos, can comprehend an individual or a group of individuals, of one or more species, and can be linked with additional information like date, time and location (Caravaggi et al., 2017).

Here are some of the most relevant or recent CT applications.

2.1 Monitor activity patterns and behaviour

Understanding animal behaviour is fundamental for effective conservation.

Behavioural studies offer insights on species' habitat requirement, dispersal or migration and on the effects of climate change and habitat fragmentation. They are also an important indicator regarding the effectiveness of conservation plans (Caravaggi et al., 2017).

However, direct observation of wildlife is frequently limited by observer disturbance, logistical constraints, and the elusive nature of many species.

Fixed camera traps provide a non-invasive alternative capable of collecting behavioural data over long periods with minimal human interference.

They are well suited for ethological studies, providing detailed sampling of wild animal behaviour repertoires. Even for species once considered too elusive to be studied, hopping mice (*Notomys aquilo*) for example, it is now possible to study complex behaviours like burrowing. Generally these types of studies are curiosity driven, but nevertheless rich in conservation value (Caravaggi et al., 2017).

The vast majority of field based behavioural studies have used radio (VHF) or satellite telemetry, activity sensors and/or biologgers (Caravaggi et al., 2017), but the confrontation between camera traps and radio-tags has given similar results in deriving activity patterns (Edwards et al., 2021).

Radio-tags allow a continuous and long term sampling period of activity pattern, giving a measure of the movement rates of individuals throughout the day derived from the calculation of distances between consecutive spatial data points.

On the other hand, CTs have the potential to collect temporal data from the entire population or animal community within their field of view (Edwards et al., 2021).

Edwards et al. (2021) compare the data acquired from CT placed in different points of interest for on brown hyaena (*Parahyaena brunnea*), like latrines or dens sites, and GPS collars attached on 6

hyaenas. The activity curve produced by the combined camera traps and those produced by the activity sensor and movement rates overlap for more than 80%.
Even though the strong overlap, there are lots of variables that may have influenced the experiments, like period of the year or camera placement or the fact that almost all GPS collars were on female individuals. The two methods, CT and GPS collars, are both valid, but they need to be considered more an integration of each other that provides a more complete pool of data (Edwards et al., 2021).
There are at least three ways which behaviour research can benefit conservation: identify anthropogenic impacts, show effect of behaviour-based management and identify behavioural indicators that suggest changes in population or environment (Caravaggi et al., 2017).
Anthropogenic impacts
Animal behaviour is greatly influenced by anthropogenic stressors, like habitat fragmentation, disturbance or alien species. For example, animals can have both negative, increasing warriness, and positive, increased occupancy, behaviours in areas near human activity (Caravaggi et al., 2017).
CTs can document behavioural responses to fragmentation, the separation of large, connected habitats into small, isolated fragments, and the dispersal behaviour, to monitor changes in genetic diversity and structure of isolated populations (Caravaggi et al., 2017).
Behaviour-based management and behavioural modification are ways for ethology to influence the active management of conservation.
CT surveys can inform behaviour-sensitive management and help design reserves and corridors, plan species reintroduction or translocation based on animal behaviour.
They can also give insights useful to exploit animal behavior by changing or preserving it within a focal population (Caravaggi et al., 2017).
Social Network Analysis (SNA) provides useful data on the relationship between individuals and groups (Caravaggi et al., 2017). Even though they need the recognition of individuals, it has potential to be relevant: it increases our understanding of disease or pathogen transmission and it is necessary in understanding social dynamics for successful reintroduction programs.
Behavioural indicators are used to “assess the state of animals and the environment they inhabit”(Caravaggi et al., 2017). They are a signal of issues like population decline or habitat degradation, even before the consequences are evident.
An important behaviour that can be measured by CT is the giving up density (GUD)(Caravaggi et al., 2017). It consists of the quantity of food left behind from a known quantity.
This value is used to study different aspects like predation risk, competition, energy cost etc.
The other instrument to monitor animal behaviour is an animal borne camera.

Many studies utilizing them focus on investigating elusive behaviour, often registering data otherwise impossible to obtain.

Thompson et al. (2012) observed the feeding behaviour of caribou throughout the year, while Kane et al. (2014) studied the predatory behaviour of falcons. Similar studies were conducted on penguins (Sato et al., 2025), sharks (Andrzejaczek et al., 2019).

Mullaney et al. (2024) studied marine turtles focusing on social interactions, habitat use, and behavioural responses to anthropogenic structures in an urban marine environment. The results uncovered interaction between individuals and active use of some anthropogenic elements, like metal structure, by rubbing on them.

2.2 Abundance estimation

Measuring the population abundance and density pattern and changes is fundamental for conservation decision making.

Capture-recapture (Silver et al., 2004) methods are statistically robust ways to estimate population density.

The fundamental assumption is that individuals can be identified and jaguar, with their unique individual fur pattern, are an optimal example. This method also does not tolerate variation in population, like birth, death or migration. Also all individuals in the sample area should be detectable.

Cameras can be placed in focal points, like trails or water sources, to maximize the detection probability.

While capture–recapture methods provide robust estimates for species with individually recognizable markings, many species lack distinctive natural features, making individual identification impossible. Consequently, alternative approaches have been developed to estimate the abundance or density of unmarked populations using camera-trap data (Gilbert et al., 2021).

There are different viable methods, but each of them is better applied to a specific situation dictated by the ecology of the target species, the sampling design, and the quality of the available data.

Site-Structured Models (Gilbert et al., 2021) use “replicated survey periods at independent locations”(Gilbert et al., 2021).

The abundance is estimated at each camera location, but, due to animals moving out the detection zone of the CT, each camera is considered to have a larger and unknown effecting area than the actual one. Those areas should be distant enough to avoid overlapping between each other.

Model assumptions: population closure (no individuals enter or leave the population); equal detection probability for all individuals; no false-positive detections; and

independent detections of individual animals at a camera. This implies that, during the survey period, animals are unlikely to leave or enter by any means the population and to be detected a second time.
Those assumptions should be strictly followed otherwise the data obtained will be biased.
A great advantage is that the model does not require random camera placement, meaning that is viable for study that exploit trail or baited locations.
Unmarked Spatial Capture-Recapture (USCR) (Gilbert et al., 2021) is a spatial capture-recapture model that considers where and when animals are detected.
It calculates density by modelling the number and distribution of animal activity centers.
In this case, cameras should be spatially correlated, meaning they should allow animals to be detected by multiple CTs, but not contemporally.
Model assumptions: activity centers are fixed, not attractive or repulsive towards animals; animals are less likely to be detected further from their activity center; the sampling frame comprehends all activity centers of the studied animals.
Although even this model is very sensible to assumption violations.
Random Encounter Model (REM) (Gilbert et al., 2021) considers animals like the particles of an ideal gas, thus calculating their density based on animal movement speed and camera detection zone and encounter rate (photos per unit).
Model assumptions: random placement; population closure, do not vary during survey period; animals move independently from each other, otherwise the average group size is needed; each photo is an independent contact between the animal and the camera.
An extension of this model is the random encounter staging time (REST) which, instead of the animal movement speed, relies on an easier to obtain measure: the animal staying time. This data represents the amount of time the animal stays in the camera field of view.
Time-to-Event Model (TTE) (Gilbert et al., 2021) estimates density inside the collective field of view of cameras by utilizing detection rate and animal movement data, intended as time until the first detection of an animal.
Model assumptions: population closure; random camera placement; detection independence in space and time, no animal resting in front of camera; detection needs to be perfect.
Space-to-Event Model (STE) and Instantaneous Sampling Model (IS) (Gilbert et al., 2021)
The STE model is an extension of the TTE model that utilized time-lapse photos whether or not animal presence in them. The IS model counts animals in view of each photo. Those models can rely on the total field of view of the camera, not just the detection zone of the sensors.
The assumptions are the same as the TTE model.

By utilizing time-lapse photos, density estimates can be considered independent from animal movement because each detection is a defined moment in time.
Those models produce reliable results, but are not suited for rare species that risk to not be detected at all.
Distance Sampling (DS) (Gilbert et al., 2021) consists in surveying transects or points at an estimated distance. To the animal observed in the area is applied a function that takes in account the distance of the animal and their probability to be detected in order to estimate the number of undetected animals.
While in traditional DS surveys the observer moves in relation to the animal, the camera traps offer a fixed point of view.
Model assumptions: detectors are randomly located; animals at a closed defined distance are perfectly detected; animals are detected at their initial location; distances measured accurately; detections are independent in space and time.
To ensure independent detection of individuals a minimum interval between CT acquisitions is set, but it does not have a fixed value and its variation may influence data analysis.
Da Silva et al. (2026) compared different time-to-independence filters (the minimum time between consecutive records of the same species at a camera station considered to represent independent records) effect detection, estimated richness, abundance and composition of medium and large mammals.
They applied filters of 30 min, 60 min, 12 h, and 24 h costating that estimated species richness remains consistent. On the other hand, abundance and composition varied a lot, especially for species rarely detected that would be considered commonly present while utilizing larger time intervals.
Applying abundance estimation models in an aquatic environment is challenging. Most of the time is difficult to respect the model assumptions of independence of sampling, because capturing and handling a fish is often invasive and may influence consequent capture; then waiting for the animal to recover ensure independence between samplings, but risk to violate the population closure assumption (Coggins et al., 2014).
A solution to avoid violation in the previously cited model assumption, is to compare the results given by the simultaneous deployment of cage traps and camera traps. This opens the possibility to generate replicate samples that are used to compensate for the incomplete and variable detection for marine fish (Coggins et al., 2014).

Coggins et al. (2014) used a site-structured model, but at the end the results were biased by violating the assumption of independent detection between individuals. This could be due to clustering behaviour of fishes or a too short interval between image acquisitions.

2.3 Disease prevention/monitoring

Camera traps are not able to make virology tests or physically block the spread of diseases, but offer a powerful surveillance tool that helps prevent disease spread and coordinate management actions (Barroso et al., 2023).

Transmissible pathogens influence animal health, public health, wildlife management, and biodiversity conservation, therefore insight on their epidemiology are crucial.

Camera traps offer the possibility to make social network analysis, estimate population abundance of different species simultaneously and spot key species for disease transmission (Barroso et al., 2023).

Animals can interact between each other or pass through areas where other individuals have been before in a time period where a pathogen is able to survive in the environment (Barroso et al., 2023). By analyzing those data, it is possible to make a plot with all the interactions relevant for the transmission of a pathogen.

Also CTs link these data to a specific location, thus creating a geographical overview of animal movement and aggregation sites and, consequently, of the pathogen dense areas.

A positive health indicator is biodiversity (Barroso et al., 2023): it is more difficult for a pathogen to encounter a designated and weak host in species rich communities.

Wild boars and red deer are examples of key species for disease monitoring (Barroso et al., 2023). Areas with high density or frequent interaction between them are linked to more overall pathogens detected.

Another way CTs can monitor diseases is by identifying infected animals. Pathogens can leave clear and easy to identify symptoms like the mite sarcoptes scabies, responsible for the sarcoptic mage (Barroso et al., 2024).

This mite burrows into the host’s epidermis (Barroso et al., 2024) producing various clinical signs, like alopecia which is particularly evident on animals, that could lead to severe declines in certain populations. It constitutes an important concern for wildlife conservation, welfare and management due to its ability to affect a wide range of domestic and wild mammal species, including humans.

Red fox (*Vulpes vulpes*) is one of the principal hosts due to their dispersal habits and variable daily range that help the pathogen spread (Barroso et al., 2024).

Barroso et al. (2024) divided the images, taken with camera traps containing foxes, by the degree of mite infestation and body condition of the animal. Those data paired with environmental and population related variables, suggested two significant high-risk hotspots in the study area and a correlation between sarcoptic mage and environmental factors such as altitude or humidity.

2.4 Other applications

The ability of some cameras to send pictures via SMS or other long distance manners can be exploited to monitor cage traps.

Cages are often used in those situations where it is necessary to get closer to dangerous or elusive animals, like for sedation in order to deploy GPS collars (Edwards et al., 2021).

This practice is really stressful for the animal so it is crucial to intervene in the minimum time possible, but for an animal to approach the cage it has to be left alone for an indefinite period of time.

A CT can be placed in front of the cage and set up to periodically send a picture, better if the interval is of half the time that is considered ethical to keep the animal trapped (Campbell and Griffith, 2015). CTs also have movement sensors that can detect individuals entering the cage and triggering the tap's door (Figure 2.1).

In this way an operator needs to check the cage less frequently and by knowing in real time when an animal is trapped the intervention time is minimized.

There are magnetic locks that notify when the cage door closes, but the CT offers a more complete and reliable feedback on the situation (Campbell and Griffith, 2015).

It is possible that remote areas have little or no signal that makes the sending of SMS delayed or impossible (Campbell and Griffith, 2015), thus it is fundamental to always check the correct functioning of the apparatus and act consequently.

CTs do not have to focus only on animals, potentially they can monitor any subject offering conservation relevant insight.

Pan et al. (2022) utilized CTs to analyze detached macrophytes, detached seagrasses and drifting macroalgae , deposition and movement as beach wrack. Usually this process is done by in person operation and CTs offer a valid alternative able to underline aspects, like tide, wind and season influences, otherwise impossible to detect.

Figure 2.1 Two successive images. In (a) the cat is seen entering the trap, in (b) the door of the trap is closed with the cat inside (Campbell and Griffith, 2015)

CHAPTER 3: APPLICATIONS OF ARTIFICIAL INTELLIGENCE

One of the biggest flaws of CT is due to some of their most appreciated qualities: their long deployment period and the possibility to be autonomously triggered.

Those characteristics result in a huge quantity of images or video data that need to be analyzed and sorted into useful data and false trigger or unuseful material.

It is time consuming and in some cases, like individual recognition, the operator needs to undergo long training sessions.

AI is one of the most recent and fast developing tools and its application in CT shows surprisingly accurate results, thus reducing the need to analyze images by hand and speeding up the process.

One of its first uses is to sort images recognizing the presence of animals and their species with an accuracy of over 95% (Tabak et al., 2020).

The major limitation in using machine learning to analyze CT images (Tabak et al., 2020) is that the model trains on the whole images using the background as a reference, this means that it could perform poorly in different locations limiting its versatility.

Another obstacle is that to enhance a model performance usually is needed a substantial dataset (20 thousand to 5.5 million images) (Park et al., 2024).

In fact the model created by Magaldi et al.(2025) was trained on a dataset of 2.775.671 photographs and 221.982 videos and is the first deep learning algorithm able to process both photos and videos.

It can be also used offline, with low computational requirements and without the need of programming knowledge.

“However, human effort is still needed to validate predictions for species of particular interest” (Magaldi et al., 2025).

The image processing can be also finalized to the application of abundance estimation models (Zampetti et al., 2024). Due to the imperfect detection of camera traps, imperfect detection of machine learning algorithms in DS and REM models do not have a drastic influence on the final results, but the effects of those error propagation have yet to be analyzed (Zampetti et al., 2024).

As previously discussed, AI can assist in the detection of images. Recognizing insects rapidly in an energy efficient way shows the potential of this new technology that can be applied to recognize other fast moving animals (Gardiner et al., 2026).

CHAPTER 4: WEAK POINTS

4.1 Interferences with wildlife

Many research papers consider camera trapping a non-invasive method and do not even mention the possible concerns for animal welfare regarding the equipment utilized.

Trail cameras avoid stressful animal-human interaction, like in the capture recapture methods, and can be a cost effective and resource efficient way to observe animal behaviours.

Despite the great improvements that this technology offers compared to other methods, it is important to consider and analyze the possible impact of a camera on wildlife.

Shape, colour, odors, flash or sounds may all influence the animal behaviour towards the equipment resulting in changes in the data acquisition and giving biased data analysis (Nogues et al., 2025).

There is evidence of species showing behavioral responses to cameras (Nogues et al., 2025).

Avoidance or attraction can be triggered by many factors (Nogues et al., 2025): white flash usually produces a flight response; the odour left by human contact can attract animals to the CT area causing bias in population estimates.

As previously discussed, photography in dark environments is really useful to monitor nocturnal and elusive species, but we have to keep in mind that observing something means interacting with it in some way.

Some cameras may have a subtle red glow coming from LED light in the infrared emitters that animals can see (Trolliet et al., 2014) and some species can even detect the infrared flash illumination (Nogues et al., 2025).

In the deep ocean, where infrared light is absorbed, bright white light is used to observe animals, but this method can damage eyes and disrupt normal behaviours (Giddens et al., 2021; Humbert et al., 2023 and Widder et al., 2005).

While there is no evidence of absence of species due to artificial illumination (Widder et al., 2005), it is good to take in consideration some alternatives to lessen the impact of human explorations on the local fauna.

The light of animal borne camera tags on sperm whales seems to not have consequence on their general behaviour, but is hypothesized to deter the prey due to the fewer prey capture attempts observed (Tønnesen e Gero, 2024).

Another study on sperm whales compared the diving parameters like depth, duration and speed, looking for differences in behaviour caused by the light of the animal borne cameras. Although the data gathered weren't enough to prove a correlation with certainty (Aoki et al., 2015).

Widder et al. (2005) compares the presence of sablefish (*Anoplopoma fimbria*) under white light and red light.

The experiment was carried out with a baited camera where cycles of red and white illumination were alternated. The results showed a higher presence under the red light and suggested some degree of adaptation to the white light after a while.

Furthermore, being consistent with light intensity between observations helps avoid bias in data (Giddens et al., 2021).

Another deterrent could be the type of bait if it uses animals of the same species that were intended to observe (Giddens et al., 2021).

Sato et al. (2025) taken in consideration the effect of red light with king penguins (*Aptenodytes patagonic*) and myctophids for behaviour studying in deep water.

Red light has a wavelength of 600-700 nm and the three classes of cones in the eyes of Humboldt penguins lack the capacity of absorbing light over 600 nm (Sato et al., 2025). Then the genomic sequence of retinal opsins of king penguins revealed that it senses colors with three classes of cones (Sato et al., 2025). Also an experiment on Adélie penguins with devices of various colors to their backs reported a significantly lower number of disturbances with red and black devices (Sato et al., 2025). Those data supported the conclusion that red LED light had no significant impact on the foraging behaviour observed.

Regarding the Myctophidae family, prey item of penguins, the maximum absorbance of their pigments is reported to be between 480 nm and 492 nm (Sato et al., 2025). This excluded interference also with the penguin's hunting behaviour.

Heaslip and Hooker (2008) investigate red light interference on Antarctic fur seals (*Arctocephalus gazella*) by comparing the diving behaviour with and without the flashes of the camera.

Previous studies on seals have revealed that some species possess a vision shifted through shorter light wavelengths, while other's vision is more similar to terrestrial animals able to perceive longer wavelengths (Heaslip and Hooker, 2008).

Although differences in behaviour were observed, they were not significant enough to cause ethical concern.

A considerable effect was due to the presence or absence of the camera itself, instead. The data obtained revealed an increase in the dive duration, time spent at the bottom and ascending to surface with the camera equipped (Heaslip and Hooker, 2008).

Animal borne cameras are the devices that more influence behavior, other than producing light in some cases, they are directly attached to the animal's body.

Size, weight, buoyancy, drag force are all factors that can modify the movement capability of an animal, consequently scientists need to follow restrictions in the camera design based on the animal species they intend to study.

Additionally most of the animals need to be handled in order to place the monitoring devices on them. This procedure can cause stress and changes in behaviour.
To investigate those effects Robinson et al. (2024) observed green sea turtle's movement with and without an animal borne camera on them.
Some individuals were captured and the camera was attached with epoxy resin, while other turtles were observed via unoccupied aerial vehicles (UAV) avoiding any interaction.
The comparison of the behavior of the two groups revealed that, during the first 30 minutes after release, turtles spent significant time swimming, probably to get away from what they perceived as a treat. After 90 to 120 minutes the proportion of time spent swimming returned to what can be considered a normal parameter.
This suggests that consequences of handling persist for some time and need to be investigated in order to avoid collecting biased data, especially in the first period of registration.

4.2 Camera theft and vandalism

Camera theft and vandalism are issues globally present that add considerable cost, via equipment loss and theft prevention, and influence survey design and data acquisition (Meek et al., 2019).
The negative impacts of this phenomenon are multiple (Meek et al., 2019): the loss of data, in the first place, can be irreplaceable, particularly for studies that compare consequent situations or focus on specific time of the year; although replaceable, the equipment itself has a cost in term of money and labour needed to find a replacement and set it up again; there are also psychological and experimental effects like the need of modifying the survey design or repercussion on the relationship with project partner and the public.
There are different methods to deter human interference, some more effective than others.
Signs are used most of the time for protecting the privacy of the public, but can deter interference (Meek et al., 2019). The overly polite ones seem to work better. Cts can also be placed away from human activity or camouflaged.
The last one is to secure the equipment in the attempt to discourage theft. There are security housing designed to protect the camera, but sometimes even them are enough (Meek et al., 2019).

4.3 Privacy and legal concerns

It is common for camera traps, trail cameras in particular, to record human images containing all sorts of behaviour, from innocuous actions to serious crimes.
This poses an ethical dilemma for researchers that need to respect individual privacy and at the same time report illegal activity.

The use of unauthorized CT images has social and legal consequences, therefore researchers have to be aware of the local laws in order to avoid being legally actionable.
Furthermore, not properly managed CT use could disrupt delicate relationships built on trust and transparency between various societal groups (Sharma et al., 2020).
There are guidelines that offer useful information regarding image handling (Franchini et al., 2022). For example high resolution images are great for demographic information, but can contain clearly recognizable people's faces. A solution can be the use of automated image classification to sort out or blur those images (Franchini et al., 2022).
Anyway researchers and managers need to agree in advance on detailed procedures to determine what to do with images containing people (Sharma et al., 2020).
Sharma et al. (2020) suggest a list of ethical and pragmatic good practice:
Permission: Camera trapping must be initiated only after obtaining all necessary permissions from legal authorities and local communities if needed.
Purpose limitation: clearly identified in the project documentation The purpose of setting up camera traps, what the data acquired represent and how they are gonna be used.
Disclosure: make aware local communities and stakeholders of the setting up of camera traps and their duration and purpose. Consultations, meetings, presentations, the use of signages that indicate a camera trapping area and the periodical share of results are great ways to maintain transparency.
Legality: researchers must be aware of the applicable laws in the study area and respect them.
Privacy: protect the privacy of individuals inadvertently photographed by locating and blurring (there are AI tools able to do so). If the law requires researchers to report illegal activities captured on camera traps, it must be declared a priori to the communities and other local stakeholders.
Participation: encouraging voluntary participation of stakeholders such as local communities.
Sharing: explain the functioning, use and limitations of camera traps with the local community in order to address any misinformation.

4.4 Standardized methodology

Many CT studies reflect the need for standardized ways to collect and share data.
One of the first attempts to organize the mole of data produced is the Camera Trap Metadata Standard (CTMS) (Forrester et al., 2016): a common data format to facilitate data storage and sharing. IT categorizes CT data in four hierarchical levels (Forrester et al., 2016): project, deployment, image sequence (all images taken in a single acquisition event), and image.
Other programs organized data in a program specific way and stored it locally, consequently not available for the public. CTMS, instead, provides a way to share data through web service.

However, CTMS has several technical shortcomings and limited adoption and failed to be widely used, but is an important first step (Wieczorek et al., 2023).
Based on its blueprint and after long consultations between main existing camera trap data management platforms and some major experts in camera trapping, Wieczorek et al. (2023) developed a new data exchange format called Camera Trap Data Package (Camtrap DP).
Camtrap DP is developed openly and collaboratively and is designed to allow easy and interoperable data exchange.
It provides a standardized and machine-readable structure that enables researchers to store both metadata and biological observations in a consistent format while ensuring compatibility with modern data-processing pipelines.
Camtrap DP structure (Wieczorek et al., 2023) consists of a descriptor file (datapackage.json) containing project metadata and dataset specifications, together with three relational data tables stored as comma-separated values (CSV) files: Deployments(CT placement and settings), Media(information on photo or video recorded), and Observations(informations derived from media files).
In this way researchers can always add information and incorporate new tables while maintaining a structure easy to read by people and computer programs (Wieczorek et al., 2023).
Now, focusing on data acquisition, there is a standardized protocol emerging recently. It’s called Snapshot and is designed to coordinate camera-trap surveys across multiple research groups and countries (Fukasawa et al., 2025).
The idea is to adopt identical sampling procedures in different ecosystems so data can be collected in a single monitoring framework, allowing robust large-scale ecological analyses.
Those procedures consist in organizing camera traps into arrays where the distance between them is within the range of 200 m and 5 km (Fukasawa et al., 2025). Each array is defined by a combination of setting (Urban, Suburban, Rural, Wild) and habitat (Forest, Grassland, Desert, Anthropogenic, Other) and should have more than eight camera traps in it (Fukasawa et al., 2025).
The devices are fixed 50cm off the ground, with horizontal orientation and set up to acquire images both day and night.
No food bait or scent lure is used, but positioning on trails or water features is permitted (Fukasawa et al., 2025).

CONCLUSION

Camera traps are one of the most widespread and versatile tools in wildlife research.
Understanding the functioning of this technology is a key aspect to correctly apply it in conservation studies.
There are many different factors that influence data acquisition, ranging from how the equipment interacts with animals to its technical characteristics. All those elements have to be put in relation with the condition to the model applied in the study.
The camera trapping study field is constantly evolving and changing especially with the development of new technologies.
The great mole of data produced by years of study can now be analyzed by AI tools that are constantly updated and refined.
Are emerging standardized protocols to coordinate research effort on an international level and help to publish results in accessible ways.
These are still novel approaches, but nevertheless have achieved promising results opening up future possibilities.
Another fundamental aspect that is rarely shown in studies report is the legal implication and the related privacy concern. Every country, region has his specific set of rules, but simply following them could not be enough.
Institutions and communities can be tedious to deal with, but they shouldn’t be seen as an obstacle, rather a starting point to promote open dialogue and collaboration between researchers and the public.
I believe that the creation of a strong relation with local communities can also mitigate the problems related to vandalism and theft of camera traps.

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