Technological advancements: A global review of the use of camera technology in wildlife research

Ingrid L. Pollet[1], Alexa Arnyek[1], Julia E. Baak[2,3], Rikki Clark[1], Jacob Comeau-Ouellette[1], Asha C. Grewal[1], Sarah E. Gutowsky[1,4], Kristine E. Hanifen[1], Emilie J. Knighton[1], Mark L. Maddox[1], Nola Morey[1], Kiirsti C. Owen[1,5], Katie R. Ryder[1], Alexis Saulnier[1], Ruby Schweighardt[1], Jordan Takkiruq[1], Jessica Wilson[1], Mark L. Mallory[1]

1 Acadia University, Biology Department, Wolfville NS B4P 2R6, Canada
2 Environment and Climate Change Canada, Iqaluit, NU X0A 3H0, Canada
3 Department of Natural Resource Sciences, McGill University, Sainte Anne-de-Bellevue, QC H9X 3V9, Canada
4 Environment and Climate Change Canada, Ottawa, ON, K1A 0H3, Canada
5 University of New Brunswick, Forestry and Environmental Management, Fredericton, New Brunswick, E3B 5A3

Corresponding author: Ingrid L. Pollet (email: ipollet@yahoo.com)

ILP: ORCID: 0000-0001-7207-8294
JEB: ORCID: 0000-0003-3284-4833
SEG:ORCID: 0000-0003-1711-4744
KEH:ORCID: 0009-0003-6651-0767
MLM:ORCID: 0009-0002-6971-2789
MLM: ORCID: 0000-0003-2744-3437
EJK: ORCID: 0009-0004-2713-8779

Abstract

Cameras have become widely used tools in wildlife research, providing new insights into the behavior, population dynamics, and habitat preference of species across a wide range of taxa. In this study, we conducted a systematic literature review to explore the use camera technology, both still and video, in wildlife research over time. We analyzed 2,472 peer-reviewed articles published between 2010 and 2023 from around the world that incorporated cameras into wildlife studies. Our review reveals a sharp increase in the number of English-language publications using cameras after 2018, which may be attributed in part to the increasing availability of drones and to the development of machine-learning algorithms for processing large datasets. Mammals (75%) and birds (19%) were the most studied organisms, and camera traps were the most used camera device type. Research topics were equally divided between behavioral studies, population dynamics, and species presence/absence monitoring. Despite the global spread of studies using camera technologies, geographic gaps remain, particularly in central Asia, northern Africa, and Greenland. Our findings highlight the increasing role of camera technology in studying wildlife. However, despite these technological advancements, we suggest that it is essential not to lose the direct connection with nature and the species being studied. We emphasize that time in the field remains important for ecologists to gain a deeper understanding of ecological processes and to foster a meaningful connection to the research.

Keywords: surveillance, imagery, camera trap, monitoring, ecology, remote wildlife sensing

Introduction

Historical context and early use of cameras in wildlife research

Cameras have been used to record wildlife information since the 1890s (Webb, 2020) but have recently become an indispensable tool in scientific research, particularly in wildlife monitoring and conservation (Bassing et al. 2023; Kinnaird et al. 2003). The widespread use of still and video cameras (i.e.: remote wildlife sensing) has revolutionized our ability to gather data on species presence/absence, population dynamics, behavior, and habitat use across a diverse range of ecosystems such as underwater (Neidig et al. 2024), grassland (Muthoka et al. 2022), tree canopy (Haysom et al. 2021), or remote Arctic and Antarctic environments (Huffeldt and Merkel 2013; Southwell and Emmerson 2015). For example, underwater cameras and image analysis algorithms present an autonomous, long-term solution for monitoring benthic fauna in the extreme conditions of Antarctic coastal waters (Marini et al. 2022), and satellite imagery has been successfully used to conduct global censuses of several penguin species, revealing previously undetected breeding pairs (LaRue et al. 2022). Remote wildlife sensing now provides researchers with a non-invasive and highly efficient means of collecting observational data in the field, allowing for improved documentation of cryptic species and behaviours. (Fig. 1; Loonam et al. 2021; Bruce et al. 2025) For instance, camera traps have been used in combination with capture-recapture analysis to estimate the population size of nocturnal, elusive wildlife (Trolle and Kéry 2003), and the deployment of video cameras has permitted researchers to record complex behavioral interactions between co-occurring species (Rasool et al. 2021). Remote wildlife sensing offers advantages over human observers by providing objective, continuous, long-term data collection while reducing disturbance to the animals being studied (but see Meek et al. 2015). It additionally allows for the collection of multimodal information relevant to a wide range of empirical inquiries, thus enhancing the versatility and depth of research findings. As a result, remote wildlife sensing – ranging from standard visual cameras to infrared sensors – is now widely employed across disciplines, contributing valuable insights into everything from species conservation efforts to ecosystem monitoring and behavioral studies.

Technological advancements and increased accessibility

Technological advancements in cameras, notably trail cameras, have occurred rapidly and regularly since the 1980s when they were first produced in a price and utility range suitable for sport hunters, leading to increased demand (Webb 2020). As well, by 1999, high resolution digital single lens reflex cameras became available and affordable (Galal 2016). Concomitantly, cameras allowed scientists and wildlife managers to conduct long-term studies which were previously logistically or financially challenging. For example, in remote areas such as polar regions, year-round deployment of cameras allows for continuous monitoring of wildlife populations, even when human presence is not feasible (Black et al. 2017). Long-term observations such as these have enabled scientists to track trends over time, detecting changes in wildlife species or their habitats that may otherwise go unnoticed (Hanya et al. 2018; Rostro-García et al. 2024).

Ecological and conservation applications of camera-based monitoring

Indeed, long-term, continuously collected data on species' behaviour (Caravaggi et al. 2017), population dynamics (Karanth et al. 2006), habitat preferences (Rovero et al. 2014), and more can be used to inform conservation, management, and policy for these species and their habitats. For example, the use of camera traps in Bangladesh wildlife sanctuaries has enhanced the patrol team's ability to detect and investigate illegal harvesting (Hossain et al. 2016). Camera studies also support the early detection of environmental change, such as shifts in breeding phenology (Hofmeester et al. 2020), migration patterns (Jachowski et al. 2015), or habitat use (Bowkett et al. 2007), which can facilitate more prompt responses to these issues. Finally, the use of remote wildlife sensing can inform habitat restoration for species at risk (Tattersall et al. 2020).

Public engagement and citizen science through camera imagery

Images from cameras provide a valuable source of data but also act as a bridge between researchers and the public or stakeholders. These images act as a tangible connection to the research and its findings - something that is often lacking in many empirical studies (Lavers and Bond 2024). They can provide an image of a problem, habitat, or species that the public may struggle to imagine or may not otherwise have an opportunity to see, which can make research and science more accessible to those within and outside the scientific community (Schwarz 2013). Through citizen science apps such as iNaturalist (https://inaturalist.org/), eBird (https://ebird.org), or SIKU (https://siku.org), the public can aid in research by contributing to the creation of data-rich sources that might not have been possible otherwise due to limited resources and time (Grégoire Taillefer et al. 2024). The plethora of images now available to scientists can also be handled via Artificial Intelligence (AI) and machine-learning (ML), with the possible drawback of being disconnected from the study species (Barnas and Fisher 2024).

Scope and objectives of this review

While previous reviews focused on a single type of camera system (Burton et al. 2015, Blount et al. 2021, Bruce et al. 2025), or a single habitat type (Zwerts et al. 2021), we aimed to describe how remote sensing imagery has been used globally to monitor wildlife since 2010. Notably, we strived to highlight both the advantages and the potential downfalls of relying on camera technology to understand ecological study systems. We assessed trends in camera use over time, as well as their use in a diverse range of research topics (e.g., behaviour or population dynamics) and applications (e.g., conservation or management). We also characterized and evaluated the use of various camera types for wildlife research. We anticipated a continuous increase in the number of papers published using camera-acquired data, particularly during or following the COVID-19 pandemic, as many scientists were prevented from working in the field and thus could focus on writing some of their existing work (e.g., Else, 2020). Finally, we commented on the future of remote wildlife sensing and the potential disconnect between researchers and the studied species as artificial intelligence and machine-learning tools are increasingly performing tasks previously done by researchers themselves.

Methods

We performed a literature search for peer-reviewed articles using cameras to study wildlife. We used the Scopus search engine on January 29, 2024, with the following terms: (wildlife) AND (video* OR camera* OR photo OR photography OR drone). We limited our search to 2010 and later. Before deciding on our final search string, we tested several other terms that we ultimately deemed unsuitable. For example, the term "photo*" in lieu of "photo" and "photography" greatly increased the number of irrelevant results (e.g., titles including "photosynthesis" or "photochemistry"). Similarly, we tried including several taxa-specific terms alongside "wildlife" such as "bird," "mammal", and "reptile" but this greatly increased our search results (>14,000 results) with the majority being lab-based research that was not applicable to our study. Consequently, the term "wildlife" was included in our search, which may have excluded papers that only used taxa-specific terms. All references were manually screened to exclude articles that were reviews, methods papers, focused on photo-based artificial intelligence (AI) training, or using animals in captivity. We then manually extracted the following variables from the selected publications (Table 1): publication year, country, habitat, taxa group, research topic, and application. The categorizations for research topic and application were based on the primary focus, objectives, and applied context of each article. Where an article overlapped categories, it was assigned according to its dominant theme. The camera type, image type, number of camera units, and whether the authors used community science was also recorded. We determined use of thermal cameras by screening articles that mentioned "thermal" in the title, abstract, or keywords. We also screened the title, abstract, and keywords of the selected publications for "artificial intelligence" and "machine learning". We subsequently tallied the categories of each variable by year. To examine a change in the distribution of the different categories, chi-square tests of independence were conducted to examine the relationship between each variable and publication year. We also note that by limiting our search to English publications, articles from predominantly non-English regions may be underrepresented. (Amano et al. 2021).

Recent patterns in use of cameras in wildlife research

A total of 2472 articles out of an original 4475 met the selection criteria. The number of articles increased progressively from 2010 (n = 34) to 2018 (n = 154, average publication per year until 2018 = 80 ± 44), with a drastic increase in publication quantity after 2018 (average publication per year post 2018 = 300 ± 38; Fig. 2). Articles published in 2024 at the time of our search (n = 36) were removed from the dataset to have only full years of data at the time of our analysis, resulting in n = 2436 articles.

Geographic distribution

Studies were distributed globally, except for northern Africa (the Maghreb and greater Sahara regions), central Asia (Kazakhstan, Uzbekistan and Turkmenistan), and Greenland (Fig. 3). Over 20% of the study sites were in the United States of America (n = 487), followed by China (n = 206), Australia (n = 146), and Canada (n = 108).

Focal taxa

Most studies focused on mammals (75 %; Fig. 2A), followed by birds (19 %), with no change in proportion over time (χ^2 = 88.23, df = 91, p = 0.56). Camera traps were the most used camera type in the articles we reviewed (83.4%; Fig. 2B), and were used primarily for studies on mammals (n = 1711) or birds (n = 381; Fig. 4). Studies used mean = 83 ± 194 SD and median = 30 cameras per study, excluding social media studies. 2% (n = 43) of studies used thermal cameras. There was no change in the proportion of studies using photographs (80 %) and studies using videos (20%) over time (χ^2 = 14.73, df = 13, p = 0.32). Interestingly, we noted that almost all wildlife groups were represented by at least one study using animal-borne cameras (Fig. 4). Given that attached units generally need to be 2-5% of the animal's body mass (e.g., https://ccac.ca/Documents/Standards/Guidelines/CCAC_Guidelines-Wildlife.pdf), the progress of studies across taxa attests to the miniaturization of this technology in recent years. For example, cameras weighing less than 0.3 g have been deployed on beetles (Iyer et al. 2020).

Focal topics

Research topics were almost equally divided between behavioural occurrence (31%), population dynamics (29%), and species occurrence (presence/absence; 29%; Fig. 2E) within the entire timeframe selected for this review. However, the division of research topic prevalence in each year showed a significant change of distribution over time (χ^2 = 74.88, df = 52, p = 0.020). This difference over time was non-directional as significant differences were driven by a higher proportion of presence/absence studies in 2010 and 2020 and lower proportion of presence/absence studies in 2015 and 2022. Applications were divided among management (38%), conservation (33%), and fundamental research (28%; Fig. 2F), with no change in the proportion over time (χ^2 = 69.71, df = 65, p = 0.32).

Why has the use of cameras changed?

We observed a marked rise in publications using camera-acquired data after 2018, but the reasons for the timing of this increase are unclear (Fig. 2). We speculate that it may in part be attributable to the increase in the use of drones in wildlife research, as highlighted in Figure 2B (see also Brisson-Curadeau et al. 2024). However, this alone is not enough to explain the significant leap in the number of studies between 2018 and 2019. During this period, the adoption of ML algorithms and computer-automated detection tools to process large volumes of images became more widespread (Fig. 5A; Chabot and Francis 2016; Dujon et al. 2021; Yang et al. 2021). These technological advancements allowed researchers to analyze large image datasets more efficiently (Meek et al. 2020), likely encouraging the broader use of camera equipment in research projects and contributing to the sharp increase in related publications. In addition, advances in other remote sensing technologies such as LiDAR (Light Detection and Ranging) and high-resolution satellite imagery, coupled with improved GIS-based analytical tools, have expanded the possibilities for integrating camera data with detailed spatial and structural information (Robold and Huettmann 2021; Cosgrove et al. 2024). The overall quality and accessibility of remote sensing data beyond drones has increased significantly, allowing for richer datasets and more comprehensive ecological analysis. When algorithms are not used to process large datasets of images, researchers can benefit from the public through different citizen science platforms (e.g., zooniverse.org; Edney et al. 2024; Fig. 5B). Such platforms can increase public engagement in conservation issues and are becoming increasingly popular.

The COVID-19 effect?

Our expectation that the COVID-19 pandemic would be followed by a pulse of papers on camera work was not well supported. In 2020, a year marked by the onset of the COVID-19 pandemic, we observed the highest number of publications involving camera use in any year. COVID-19 forced governments to restrict human movement and contact, establishing guidelines which mandated lockdowns and social distancing. While we know that this led to an increase in publications in almost all scientific disciplines (Else 2020) including ecology (Fox and Meyer 2021), the peak of camera-use papers in 2020 meant that most of those manuscripts were actually in review prior to the pandemic, given an optimistic expectation of ~ 1 year for writing, submission, review, and publication. However, we suspect there were some related “benefits”. For example, though most of humanity’s everyday life, including many types of science, was put on hold, camera traps offered researchers the ability to continue projects while under lockdown. Fortunately, COVID-19 happened to coincide with a time when cameras themselves were more affordable than ever, and camera technology had reached a technical stage (memory storage, resolution, size) that was applicable for many types of work (Blount et al. 2021). The technological advancements have continued; for example, some camera battery systems may last more than a year (or can be continuously solar-charged), some systems have images that can be transmitted instantaneously to a smartphone, and, in many cases, recovered images can be automatically classified via ML software (Blount et al. 2021).

While camera traps allowed researchers to continue projects throughout COVID-19, the pandemic and its lockdowns also provided the unique opportunity to investigate ripples in nature as a result of unprecedented low human activity. For example, in an exploratory camera trap study, Silva-Rodríguez et al. (2021) documented novel records of four native carnivores in Chilean cities in 2020, none of which had been previously linked to urban areas. Collectively, these factors may explain why numbers of camera-related publications have remained high since the pandemic, despite a return to "normal" work patterns for most researchers.

Surprisingly, we expected a continued increase in papers produced annually using camera-acquired data, but after the peak in 2020, the number of papers produced each year declined and stabilized (Fig. 2). Bruce et al. (2025) found a similar pattern in Australian camera-trap studies, after expecting a pattern of exponential increase. They conducted interviews of researchers and consequently argued that the "plateau" in publication output was caused by scientists reaching their current capacity for the time it takes to sample, process/analyse images, and write papers. They conclude that the number of publications will start to increase again as researchers adopt AI and/or ML approaches (e.g., Meek et al. 2020). We agree with this explanation and expect it should apply globally.

Drivers of camera use

The jump in camera-related publications in 2019 may also be attributable to a more practical, economic factor: cost. Webb (2020) showed that in 2016, there was a clear increase in interest and demand for cellular trail cameras as prices had declined and newer models had come into the market - the start of a predictable economic pattern. We therefore suspect that many studies which may have been previously limited due to costs were liberated in 2016 and 2017, which could lead to publications based on one or two years of data coming out in 2019 and 2020.

Another contributing factor to the marked increase in camera-related publications is likely the popularization of unmanned aerial vehicles (UAVs, or drones; see reviews in Chabot 2018; Wang et al. 2021). Their use in wildlife research comes with diverse applications and advantages, but also many caveats (Table 2). Remote sensing imagery, obtained via drones, aircraft, or even high-resolution satellite sensors, allows researchers to monitor remote locations with greater speed and ease than traditional ground-based methods or handheld aerial cameras (Schad and Fischer 2023). Remote sensing imagery has a wide range of uses in wildlife research, including population monitoring of mammals (Vermeulen et al. 2013), seabirds (Rush et al. 2018), and reptiles (Sykora-Bodie et al. 2017), as well as the study of their movement and habitat usage (Strandburg-Peshkin et al. 2017). Drones provide high-resolution images (e.g., Fig.1A) and cover large areas quickly while also minimizing the need for direct human presence, which can disturb wildlife and their breeding habitats (Schad and Fischer 2023). However, as with all techniques, researchers must consider animal welfare when using drones. Studies have shown that drone flights can cause stress, alarm responses, or even abandonment of nests, particularly in sensitive species (Borrelle and Fletcher 2017; Cantu De Leija et al. 2023). Factors such as the drone’s altitude, noise level, and flight speed can all influence how wildlife react, and careful planning is necessary to minimize these impacts (Schad and Fischer 2023). Additionally, behavioral changes induced by drone presence, such as altered feeding patterns or aggression (Brisson-Curadeau et al. 2024), may bias the data collected and negatively affect wildlife at the breeding site (Edney et al. 2023). Behavior change is not just observed with the use of drones. Camera traps, while generally considered non-invasive, can also alter the behavior of animals (Sequin et al. 2003; Schipper 2007; Wegge et al. 2004). Certain species may become aware of the camera's presence, especially if the device emits light (Wegge et al. 2004), which can lead to avoidance behavior, attraction to the equipment, changes in activity patterns, or increased predation upon the studied species (Henden et al. 2025). It is crucial to remember that these factors can introduce bias in the data collected when planning studies relying on the use of cameras.

Regardless of the diverse options that camera technology offers for studying wildlife, the most commonly used combinations remain relatively limited. Camera traps in particular are predominantly used for studying mammals and birds (Fig. 4). This reflects the strengths of camera traps in monitoring terrestrial species (Fig. 2D) that are active both during the day and at night, are of suitable size and speed to be detected (e.g., Swann et al. 2004, Bruce et al. 2025), and are potentially in remote or difficult-to-access locations. Furthermore, many behaviors can be studied from camera traps (Caravaggi et al. 2017). Mammals and birds are prime targets because of their ecological significance, larger body sizes, and the fact that many are charismatic species or species of conservation concern. While camera traps have proven their utility in detecting species presence, estimating population sizes, and studying behavior, their application in other taxonomic groups or ecosystems, such as aquatic environments or for studying smaller organisms, remains limited (Fig. 4). This suggests that, while the potential of camera technology is vast with broad applications from conservation and management to fundamental research (Fig. 2F), its application has so far been concentrated on specific taxa and research contexts. Expanding these tools to other wildlife groups could further unlock insights across a broader range of species and habitats (Bjerge et al. 2023).

Despite being more affordable with passing time, cameras of all types can still pose relatively high costs to a project, especially considering typical numbers required for deployment, and this can limit researchers' ability to use them in studies. While there has been an increase in published research using drones, handheld cameras, and animal-borne cameras, these expensive camera types which require specialized skills or training to use remain relatively uncommon tools in ecology research. The dominant application of camera traps is likely in part due to ease of use, as units are readily available off-the-shelf from many retailers and are designed to be user-friendly for layperson applications. However, camera trap study designs often require building extensive camera networks within a research area. If we consider using a robust, higher quality trail camera, designed to withstand a range of environmental conditions, it can cost up to ~ $600 CAD per camera. Once we include additional equipment for installment, data storage, power, and protection of the camera from wildlife and theft, each camera deployment can cost between $650 to $700 CAD. Importantly, this does not include field expenses associated with deployment and recovery of camera traps. Of course, there are many options available for seasonal use in less extreme conditions (e.g., many trail cameras designed for hunters), and these are roughly half the cost. As camera technology has become more accessible and affordable, it is increasingly being integrated into research studies. However, cost remains a barrier—particularly for large-scale landscape projects that require a significant number of cameras.

Why are some wildlife taxa underrepresented in camera studies?

Compared to mammals and birds, cameras are used far less frequently to study other animal groups, including invertebrates, fish, amphibians, and reptiles. One possible reason for this disparity is that camera traps, commonly equipped with a passive infrared (PIR) sensor, are designed to detect animals based on both heat and motion. While this reliance on thermal radiation lends itself well to monitoring of endothermic mammals and birds, PIR sensors do not reliably detect ectotherms, i.e., invertebrates, fish, amphibians, and reptiles (Hobbs and Brehme 2017). Additionally, size and shape of the detection zone varies considerably across camera trap models, and few are optimized to detect smaller-bodied animals (Meek et al. 2015; Swann et al. 2004; Ortmann and Johnson 2021). Monitoring fish with cameras presents unique challenges stemming from their complex environment and the organisms themselves, such as fluctuations in water turbidity and lighting, optical distortion, similarity between fish colour and background, and colour-changing fish (Yang et al. 2021). Insects are particularly challenging to detect and identify in imagery given their small body size and extensive diversity (Bjerge et al. 2023). However, automated detection algorithms capable of recognizing various insect species against complex backgrounds have recently been developed (Bjerge et al. 2023). These advances, combined with ongoing increases in sensor resolution, will likely help to facilitate efficient, non-invasive monitoring of invertebrates in the field (Ärje et al. 2020; Bjerge et al. 2023). Finally, we note that our results likely reflect the taxonomic bias in biodiversity and conservation research towards more charismatic animal groups, particularly mammals and birds (Titley et al. 2017).

Anticipated future developments

As camera use in wildlife research becomes more widespread, we expect that camera technology and applicability will continue to improve. While thermal cameras currently represent a small proportion of camera use, infrared sensors offer unique advantages, particularly in detecting species with cryptic colouration or behaviour (e.g., nocturnal; Fig.1B; Psiroukis et al. 2021). As technology advances, prices for cameras and memory storage are decreasing (McCallum 2024) and simpler integration is expected to drive greater adoption of thermal cameras among researchers. Another area of interest for future improvement is the integration of AI. Camera trapping is a cost-effective method of monitoring multiple species over long periods; however, such projects often generate vast amounts of data which incur significant processing costs and can be highly time-consuming (Vélez et al. 2023). By using AI as a tool to streamline data processing, long-term monitoring projects with limited capacity for manual image or video processing will become more feasible and accessible (Petroni et al. 2024). This is particularly valuable for detecting and explaining temporal variation in ecological processes. Depending on project goals, researchers may adopt fully or partially automated systems (Vélez et al. 2023). Fully automated systems are ideal for continuous, large-scale data collection or real-time applications; one example is the AI-enabled tiger-monitoring cameras in India and Nepal, which send alerts to mitigate human-wildlife conflict and prevent poaching (Dertien et al. 2023). Semi-automated systems can filter out blank images, categorize data, or highlight specific image features, like placing bounding boxes around small or cryptic animals (Vélez et al. 2023). While there are several AI models available for species identification and image processing, current models may be biased by unbalanced training sets (Schneider et al. 2020). To date, camera trap studies have most often been used for terrestrial-based, charismatic animal groups like mammals and birds, which can lead to uneven species representation and geographically-limited datasets (Titley et al. 2017; Bruce et al. 2025). As camera monitoring expands to understudied taxa and locations, these biases may be reduced.

What do we potentially lose using cameras?

As a cautionary note, also raised by Barnas and Fisher (2025), we believe it is worth recognizing that while advances in camera technology, such as camera traps and drones, have revolutionized the way we study wildlife, they may also have unintended, socio-ecological effects, perhaps analogous to ecological grief (Cunsolo and Ellis 2018). The ease of remote monitoring and the increasing reliance on post-field data analysis can inadvertently lead to a disconnect between researchers and the ecosystems they study (Watson 2011; Kiggel 2021). Immersive time in nature remains invaluable for the body and the mind (Keniger et al. 2013), and it allows scientists to observe behaviors and environmental nuances, including the importance of non-visual cues like scent, that may not be captured by still frame shots alone or by video capturing only part of the 360° story (Schleper 2021). Spending time immersed in the study system fosters a deeper understanding of species interactions and environmental changes, which are essential for conservation efforts. As Mantegna (2024) stressed, the joy and value of field research lie in direct engagement with nature, where researchers can gain a more profound understanding of ecological processes. Rafiq et al. (2024) similarly highlighted the importance of the value of field research in academia: direct engagement with study species enhances not only the quality of research but also the researchers' connection to their work. This personal engagement can inspire more meaningful insights and a greater sense of stewardship toward wildlife and their ecosystems, reminding us that fieldwork is an irreplaceable part of ecological research.

Future developments in AI and thermal imaging should improve the effectiveness and accessibility of camera-based research, allowing for wider applicability across taxa and ecosystems. However, it is important to remember the socio-ecological effects of these technologies as we adopt them. Cameras and automated systems may encourage a disengagement from field immersion, which could lead to a loss of the nuanced understanding that comes from close interaction with nature. Immersion in nature is essential to the development and maintenance of reciprocal relationships between scientists and study organisms, and the understanding that these beings provide humans with a multitude of gifts we must reciprocate with our care and protection is essential to lasting conservation and sustainability (Kimmerer 2018). The time-saving benefits of using AI tools must not come at the cost of scientists losing their emotional connection with wildlife (Barnas and Fisher 2025). Balancing technological innovation with traditional fieldwork practices will ensure that wildlife research not only advances our scientific knowledge but also strengthens our connection to the ecosystems we strive to conserve. In other words, having human "boots and eyes on the ground" is irreplaceable.

Conclusion

Cameras have emerged as a vital instrument for wildlife research. Technological developments and associated ease of use, decreasing costs, and a growing demand for minimally disruptive techniques have contributed to their widespread acceptance. The capacity of camera traps to track terrestrial species in isolated or challenging-to-reach areas is especially appreciated as it yields vital information on species presence, behaviour, and population dynamics. By providing high-resolution imagery with little disturbance to the animals, drones and other remote sensing technologies have greatly increased our ability to study wildlife in a variety of ecosystems. However, these technologies do have certain limits. For drones and specialised equipment, the costs can still be high and the required technological skills continue to be obstacles to their mainstream use. Furthermore, the taxa under study exhibit biases, favouring larger, charismatic creatures, and monitoring smaller or ectothermic species continues to be difficult due to sensor constraints. Additional factors to take into account include biases in AI-based data processing and possible stress or behavioural changes brought on by the presence of cameras. We expect that the diverse applications of cameras in wildlife research will increase, especially with advancements in the ease and speed of data processing and analysis that come with AI and ML approaches. Indeed, it is likely that we are entering the golden age of camera use in wildlife studies, and we hope that the approach remains anchored with traditional field practices that maintain researcher connections with the organisms they study.

Competing interests

The authors declare there are no competing interests.

Data availability

Data for this manuscript consist of the publications metadata from the literature search and the information extracted from the papers that met the selection criteria. Data can be obtained upon request.

Acknowledgement

We thank two anonymous reviewers for their valuable feedback that greatly improved the manuscript.

References

Amano, T., Berdejo-Espinola, V., Christie, A.P., Willott, K., Akasaka, M., Báldi, A., Berthinussen, A., Bertolino, S., Bladon, A.J., Chen, M., Choi, C.-Y., Bou Dagher Kharrat, M., De Oliveira, L.G., Farhat, P., Golivets, M., Hidalgo Aranzamendi, N., Jantke, K., Kajzer-Bonk, J., Kemahlı Aytekin, M.Ç., Khorozyan, I., Kito, K., Konno, K., Lin, D.-L., Littlewood, N., Liu, Yang, Liu, Yifan, Loretto, M.-C., Marconi, V., Martin, P.A., Morgan, W.H., Narváez-Gómez, J.P., Negret, P.J., Nourani, E., Ochoa Quintero, J.M., Ockendon, N., Oh, R.R.Y., Petrovan, S.O., Piovezan-Borges, A.C., Pollet, I.L., Ramos, D.L., Reboredo Segovia, A.L., Rivera-Villanueva, A.N., Rocha, R., Rouyer, M.-M., Sainsbury, K.A., Schuster, R., Schwab, D., Şekercioğlu, Ç.H., Seo, H.-M., Shackelford, G., Shinoda, Y., Smith, R.K., Tao, S., Tsai, M., Tyler, E.H.M., Vajna, F., Valdebenito, J.O., Vozykova, S., Waryszak, P., Zamora-Gutierrez, V., Zenni, R.D., Zhou, W., and Sutherland, W.J. 2021. Tapping into non-English-language science for the conservation of global biodiversity. PLoS Biol **19**: e3001296. https://doi.org/10.1371/journal.pbio.3001296

Ärje, J., Melvad, C., Jeppesen, M.R., Madsen, S.A., Raitoharju, J., Rasmussen, M.S., Iosifidis, A., Tirronen, V., Gabbouj, M., Meissner, K., and Høye, T.T. 2020. Automatic image-based identification and biomass estimation of invertebrates. Methods Ecol. Evol. **11**(8): 922-931. https://doi.org/10.1111/2041/210X.13428

Barnas, A. F., and Fisher, J. T. 2024. Will using artificial intelligence to review camera trap images reduce human connection to wildlife research? Wildl. Soc. Bull. 49(2): e1588. https://doi.org/10.1002/wsb.1588

Bassing, S.B., DeVivo, M., Ganz, T.R., Kertson, B.N., Prugh, L.R., Roussin, T., Satterfield, L., Windell, R.M., Wirsing, A.J., and Gardner, B. 2023. Are we telling the same story? Comparing inferences made from camera trap and telemetry data for wildlife monitoring. Ecol. Appl. **33**(1): e2745. https://doi.org/10.1002/eap.2745

Bjerge, K., Alison, J., Dyrmann, M., Frigaard, C.E., Mann, H.M.R., and Høye, T.T. 2023. Accurate detection and identification of insects from camera trap images with deep learning. PLoS Sustain Transform **2**: e0000051. https://doi.org/10.1371/journal.pstr.0000051

Black, C., Rey, A.R., and Hart, T. 2017. Peeking into the bleak midwinter: Investigating nonbreeding strategies of Gentoopeenguins using a camera network. Auk **134**(3): 520-529. https://doi.org/10.1642/AUK-16-69.1

Blount, J.D., Chynoweth, M.H., Green, A.M., and Şekercioğlu, Ç.H. 2021. Review: COVID-19 highlights the importance of camera traps for wildlife conservation research and management. Biol. Conserv. **256**: 108984. https://doi.org/10.1016/j.biocon.2021.108984

Borrelle, S.B., and Fletcher, A.T. 2017. Will drones reduce investigator disturbance to surface-nesting birds? Mar. Ornithol. **45**(1): 89–94.

Bowkett, A.E., Rovero, F., and Marshall, A.R. 2007. The use of camera-trap data to model habitat use by antelope species in the Udzungwa Mountain forests, Tanzania. Afr. J. Ecol. **46**(4): 479-487

Brisson-Curadeau, É., Lacombe, R., Gousy-Leblanc, M., Poirier, V., Jackson, L., Petalas, C., Miranda, E., Eby, A., Baak, J., Léandri-Breton, D., Choy, E., Legros, J., Tranze-Drabinia, E., and Elliott, K.H. 2024. A meta-analysis of the impact of drones on birds. Front. Ecol. Environ. **e2809**. https://doi.org/10.1002/fee.2809

Bruce, T., Amir, Z., Allen, B.L., Alting, B.F., Amos, M., Augusteyn, J., Ballard, G.-A., Behrendorff, L.M., Bell, K., Bengsen, A.J., Bennett, A., Benshemesh, J.S., Bentley, J., Blackmore, C.J., Boscarino-Gaetano, R., Bourke, L.A., Brewster, R., Brook, B.W., Broughton, C., Buettel, J.C., Carter, A., Chiu-Werner, A., Claridge, A.W., Comer, S., Comte, S., Connolly, R.M., Cowan, M.A., Cross, S.L., Cunningham, C.X., Dalziell, A.H., Davies, H.F., Davis, J., Dawson, S.J., Stefano, J.D., Dickman, C.R., Dillon, M.L., Doherty, T.S., Driessen, M.M., Driscoll, D.A., Dundas, S.J., Eichholtzer, A.C., Elliott, T.F., Elsworth, P., Fancourt, B.A., Fardell, L.L., Faris, J., Fawcett, A., Fisher, D.O., Fleming, P.J.S., Forsyth, D.M., Garza-Garcia, A.D., Geary, W.L., Gillespie, G., Giumelli, P.J., Gracanin, A., Grantham, H.S., Greenville, A.C., Griffiths, S.R., Groffen, H. Hamilton, D.G., Harriott, L., Hayward, M.W., Heard, G., Heiniger, J., Helgen, K.M., Henderson, T.J., Hernandez-Santin, L., Herrera, C., Hirsch, B.T., Hohnen, R., Hollings, T.A., Hoskin, C.J., Hradsky, B.A., Humphrey, J.E., Jennings, P.R., Jones, M.E., Jordan, N.R., Kelly, C.L., Kennedy, M.S., Knipler, M.L., Kreplins, T.L., L'Herpiniere, K.L., Laurance, W.F., Lavery, T.H., Le Pla, M., Leahy, L., Leedman, A., Legge, S., Leitao, A.V., Letnic, M., Liddell, M.J., Lieb, Z.E., Linley, G.D., Lisle, A.T., Lohr, C.A., Maitz, N., Marshall, K.D., Mason, R.T., Matheus-Holland, D.F, McComb, L.B., McDonald, P.J., McGregor, H., McKnight, D.T., Meek, P.D., Menon, V., Michael, D.R., Mills, C.H., Miritis, V., Moore, H.A., Morgan, H.R., Murphy, B.P., Murray, A.J., Natusch, D.J.D., Neilly, H., Nevill, P., Newman, P., Mewsome, T.M., Nimmo, D.G., Nordberg, E.J., O'Dwyer, T.W., O'Neill, S., Old, J.M., Oxenham, K., Pauza, M.D., Pestell, A.J.L., Pitcher, B.J., Pocknee, C.A., Possingham, H.P., Raiter, K.G., Rand, J.S., Rees, M.W., Rendall, A.R., Renwick, J., Reside, A., Rew-Duffy, M., Ritchie, E.G., Roach, C.P., Robley, A., Rog, S.M., Rout, T.M., Schlacher, T.A., Scomparin, C.R., Sitters, H., Smith, D.A., Somaweera, S., Spencer, E.E., Spindler, R.E., Stobo-Wilson, A.M., Stokeld, D., Streeting, L.M., Sutherland, D.R., Taggart, P.L., Teixeira, D., Thompson, G.G., Thompson, S.A., Thorpe, M.O., Todd, S.J., Towerton, A.L., Vernes, K., Waller, G., Wardle, G.M., Watchorn, D.J., Watson, A.W.T., Welbergen, J.A., Weston, M.A., Wijas, B.J., Williams, S.E., Woodford, L.P., Wooster, E.I.F., Znidersic, E., and Luskin, M.S. 2025. Large-scale and long-term wildlife research and monitoring using camera traps: a continental synthesis. Biol. Rev. https://doi.org/10.1111/brv.13152

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

Cantu De Leija, A., Mirzadi, R., Randall, J., Portmann, M., Mueller, E., and Gawlik, D. 2023. A meta-analysis of disturbance caused by drones on nesting birds. J. Field Ornithol. **94**(2): 3. https://doi.org/10.5751/JFO-00259-940203

Caravaggi, A., Banks, P.B., Burton, A.C., Finlay, C.M.V., Haswell, P.M., Hayward, M.W., Rowcliffe, M.J., and Wood, M.D. 2017. A review of camera trapping for conservation behaviour research. Remote Sens. Ecol. Conserv. **3**(3): 109–122. https://doi.org/10.1002/rse2.48

Chabot, D. 2018. Trends in drone research and applications as the Journal of Unmanned Vehicle Systems turns five. J. Unmanned Veh. Syst. **6**: vi-xv.

Chabot, D., and Francis, C.M. 2016. Computer-automated bird detection and counts in high-resolution aerial images: a review. J. Field Ornithol. **87**(4): 343–359. https://doi.org/10.1111/jofo.12171

Cosgrove, C.F., Coops, N.C., and Martin, T.G. 2024. Using the full potential of Airborne Laser Scanning (aerial LiDAR) in wildlife research. Wildl. Soc. Bull. **48**:e1532. https://doi.org/10.1002/wsb.1532

Cunsolo, A. and Ellis, N.R. 2018. Ecological grief as a mental health response to climate change-related loss. Nat. Clim. Change **8**: 275-281.

Dertien, J.S., Negi, H., Dinerstein, E., Krishnamurthy, R., Negi, H.S., Gopal, R., Gulick, S., Pathak, S.K., Kapoor, M., Yadav, P., Benitez, M., Ferreira, M., Wijnveen, A.J., Lee, A.T.L., Wright, B., and Baldwin, R.F. 2023. Mitigating human–wildlife conflict and monitoring endangered tigers using a real-time camera-based alert system. BioScience, **73**(10): 748–757. https://doi.org/10.1093/biosci/biad076

Dujon, A.M., Ierodiaconou, D., Geeson, J.J., Arnould, J.P.Y., Allan, B.M., Katselidis, K.A., and Schofield, G. 2021. Machine learning to detect marine animals in UAV imagery: effect of morphology, spacing, behaviour and habitat. Remote Sens. Ecol. Conserv. **7**(3): 341–354. https://doi.org/10.1002/rse2.205

Edney, A.J., Danielsen, J., Descamps, S., Jónsson, J.E., Owen, E., Merkel, F., Stefánsson, R.A., Wood, M.J., Jessopp, M.J., and Hart, T. 2024. Using citizen science image analysis to measure seabird phenology. Ibis **167**(1): 56-72. https://doi.org/10.1111/ibi.13317

Edney, A.J., Hart, T., Jessopp, M.J., Banks, A., Clarke, L.E., Cugnière, L., Elliott, K.H., Martinez, I.J., Kilcoyne, A., Murphy, M., Nager, R.G., Ratcliffe, N., Thompson, D.L., Ward, R.M., and Wood, M.J. 2023. Best practices for using drones in seabirds monitoring and research. Mar. Ornithol. **51**(2): 265-280. https://doi.org/10.5038/2074-1235.51.2.1544

Else, H. 2020. How a Torrent of COVID Science Changed Research Publishing—In Seven Charts. Nature **588**: 553. https://doi.org/10.1038/d41586-020-03564-y

Fox, C.W. and Meyer, J. 2021. The influence of the global COVID-19 pandemic on manuscript submissions and editor and reviewer performance at six ecology journals. Funct. Ecol. **35**: 4-10.

Galal, A.M., 2016. An analytical study on the modern history of digital photography. Intern. Design J. **6**: 203-215.

Grégoire Taillefer, A., Larrivée, M., Mlynarek, J. J., Petawabano, H., and Giroux, M. 2024. Nunavik Sentinels: documenting northern insect biodiversity and supporting Indigenous youth leadership through participatory research and education. Can. Entomol. **156**: 1-16. https://doi.org/10.4039/tce.2024.2

Hanya, G., Otani, Y., Hongo, S., Honda, T., Okamura, H., and Higo, Y. 2018. Activity of wild Japanese macaques in Yakushima revealed by camera trapping: Patterns with respect to season, daily period and rainfall. PLoS ONE **13**: e0190631. https://doi.org/10.1371/journal.pone.0190631

Haysom, J.K., Deere, N.J., Wearn, O.R., Mahyudin, A., Jami, J.B., Reynolds, G., and Struebig, M.J. 2021. Life in the Canopy: Using Camera-Traps to Inventory Arboreal Rainforest Mammals in Borneo. Front. For. Glob. Change **4**: 673071. https://doi.org/10.3389/ffgc.2021.673071

Henden, J.-A., Ims, R. A., and Strømeng, M. A. 2025. Trail cameras can greatly inflate nest predation rates. J. Widl. Manag. 89:e22684. https://doi.org/10.1002/jwmg.22684

Hobbs, M.T., and Brehme, C.S. 2017. An improved camera trap for amphibians, reptiles, small mammals, and large invertebrates. PLoS ONE **12**: e0185026. https://doi.org/10.1371/journal.pone.0185026

Hofmeester, T.R., Young, S., Juthberg, S., Singh, N.J., Widemo, F., Andrén, H., Linnell, J.D. C., and Cromsigt, J.P.G.M. 2020. Using by-catch data from wildlife surveys to quantify climatic parameters and timing of phenology for plants and animals using camera traps. Remote Sen. Ecol. Conserv. **6**(2): 129-140

Hossain, A.N.M., Barlow, A., Greenwood Barlow, C., Lynan, A.J., Chakma, S., and Savini, T. 2016. Assessing the efficacy of camera trapping as a tool for increasing detection rates of wildlife crime in tropical protected areas. Biol. Conserv. **201**: 314-319

Huffeldt, N.P., and Merkel, F.R. 2013. Remote time-lapse photography as a monitoring tool for colonial breeding seabirds: A case study using thick-billed murres (*Uria lomvia*). Waterbirds **36**(3):330-341. https://doi.org/10.1675/063.036.0310

Iyer, V., Najafi, A., James, J., Fuller, S., and Gollakota, S. 2020. Wireless steerable vision for live insects and insect-scale robots. Sci. Robot. 5:eabb0839. https://doi.org/10.1126/scirobotics.abb0839

Jachowski, D.S., Katzner, T., Rodrigue, J.L., and Ford, W.M. 2015. Monitoring landscape-level distribution and migration phenology of raptors using a volunteer camera-trap network. Wildl. Soc. Bull. **39**(3): 553-563. https://doii.org/10.1002/wsb.571

Karanth, K.U., Nichols, J.D., Kumar, N.S., and Hines, J.E. 2006. Assessing tiger population dynamics using photographic capture-recapture sampling. Ecology **87**(11): 2925-2937.

Keniger, L., Gaston, K., Irvine, K., and Fuller, R. 2013. What are the benefits of interacting with nature? Int. J. Environ. Res. Public Health **10**(3): 913-935. https://doi.org/10.3390/ijerph10030913

Kiggel, T. 2021. Monitoring extinction: defaunation, technology and the biopolitics of conservation in the Atlantic Forest, Brazil. J. Political Ecol. **28**(1): 845-863

Kimmerer, Robin Wall. "Mishkos Kenomagwen, the lessons of grass: restoring reciprocity with the good green earth." Traditional ecological knowledge: Learning from Indigenous practices for environmental sustainability (2018): 27-56.

Kinnaird, M.F., Sanderson, E.W., O'Brien, T.G., Wibisono, H.T., and Woolmer, G. 2003. Deforestation Trends in a Tropical Landscape and Implications for Endangered Large Mammals. Conserv. Biol. **17**(1): 245–257. https://doi.org/10.1046/j.1523-1739.2003.02040.x

LaRue, M., Brooks, C., Wege, M., Salas, L., and Gardiner, N. 2022. High-resolution satellite imagery meets the challenge of monitoring remote marine protected areas in the Antarctic and beyond. Conserv. Lett. **15**: e12884. https://doi.org/10.1111/conl.12884

Lavers, J.L., and Bond, A.L. 2024. Plastic pollution as a canvas for change: fostering collaboration for environmental solutions and actions through art and science. Ecol. Soc. **29**(4): 7. https://doi.org/10.5751/ES-15521-290407

Loonam, K.E., Ausband, D.E., Lukacs, P.M., Mitchell, M.S., and Robinson, H.S. 2021. Estimating Abundance of an Unmarked, Low-Density Species using Cameras. J. Wildl. Manag. **85**(1): 87–96. https://doi.org/10.1002/jwmg.21950

Marini, S., Bonofigliio, F., Corgnati, L.P., Bordone, A., Schiiaparellii, S., and Peirano, A. 2022. Long-term automated visual monitoring of Antarctic benthic fauna. Methods Ecol. Evol. **13**(8): 1746-1764. https://doi.org/10.1111/2041-210X.13898

Massicotte, P. 2023. rnaturalearth: World Map Data from Natural Earth. R package version 1.0.1, https://CRAN.R-project.org/package=rnaturalearth

McCallum, J. C. 2024. U.S. Bureau of Labor Statistics (2024) - https://jcmit.net/memoryprice.htm Accessed on June 10, 2025.

Meek, P. D., Ballard, G.-A., and Fleming, P. J. S. 2015. The pitfalls of wildlife camera trapping as a survey tool in Australia. Aust. Mammal. **37**(1): 13-22. https://doi.org/10.1071/AM14023

Meek, P.D., Ballard, G., Falzon, G., Williamson, J., Milne, H., Farrell, R., Stover, J., Mather-Zardain, A.T., Bishop, J. C., Ka-Wai Cheung, E., Lawson, C.K., Munezero, A.M., Schneider, D., Johnston, B.E., Kiani, E., Shahinfar, S., Sadgrove, E.J., and Fleming, P.J.S. 2020. Camera trapping technology and related advances: into the new millennium. Aust. Zool. **40**(3): 392-403. https://doi.org/10.7882/AZ.2019.035

Muthoka, J.M., Antonarakis, A.S., Vrieling, A., Fava, F., Salakpi, E.E., and Rowhani, P. 2022. Assessing drivers of intra-seasonal grassland dynamics in a Kenyan savannah using digital repeat photography. Ecol. Indic. **142**: 109223. https://doi.org/10.1016/j.ecolind.2022.109223

Neidig, C., Lee, M., Patrick, G., and Schloesser, R. 2024. Employing an innovative underwater camera to improve electronic monitoring in the commercial Gulf of Mexico reef fish fishery. PLoS ONE **19**: e0298588. https://doi.org/10.1371/journal.pone.0298588

Ortmann, C.R. and Johnson, S.D. 2021. How reliable are motion-triggered camera traps for detecting small mammals and birds in ecological studies? J. Zool. **313**: 202-207.

Petroni, L., Natucci, L., and Massolo., A. 2024. An ecologist-friendly R workflow for expediting species-level classification of camera trap images. Ecol. Evol. **14**(12): e70544. https://doi.rg/10.1002/ece3.70544

Psiroukis, V., Malounas, I., Mylonas, N., Griivakis, K.-E., Fountas, S., and Hadjigeorgiou, I. 2021. Monitoring of free-range rabbits using aerial thermal imaging. Smart Agr. Technol. **1**:100002. https://doi.org/10.1016/j.atech.2021.100002

Rafiq, K., Jordan, N.R., McNutt, J.W., Neelo, J., Attias, N., Boersma, D., Palmer, M S., Ruesink, J., and Abrahms, B. 2024. The value of field research in academia. Science **384**: 855-856. https://doi.org/10.1126/science.ado6937

Rasool, M.A., Zhang, X., Hassan, M.A., Hussain, T., Lu, C., Zeng, Q., Peng, B., Wen, L., and Lei, G. 2021. Construct social-behavioral association network to study management impact on waterbirds community ecology using digital video recording cameras. Ecol. Evol. **11**(5): 2321–2335. https://doi.org/10.1002/ece3.7200

Robold, R.B., and Huettmann, F. 2021. High-resolution prediction of American red squirrel in Interior Alaska: a role model for conservation using open access data, machine learning, GIS and LIDAR. PeerJ **9**:e11830. https://doi.org/10.7717/peerj.11830

Rostro-García, S., Kamler, J.F., Sollmann, R., Balme, G., Sukmasuang, R., Godfrey, A., Saosoong, S., Siripattaranukul, K., Suksavate, S., Thomas, W., Crouthers, R., In, V., Prum, S., Clements, G.R., Kadir, A., Liang, S. H., Avriandy, R., Gunaryadi, D., Kholiq, N. Pinondang, I., Surahman, M., Astaras, C., and Macdonald, D.W. 2024. Leopards on the edge: Assessing population status, habitat use, and threats in Southeast Asia. Biol. Conserv. **299**: 110810. https://doi.org/10.1016/j.biocon.2024.110810

Rovero, F., Martin, E., Rosa, M., Ahumada, J.A., and Spitale, D. 2014. Estimating species richness and modelling habitat preferences of tropical forest mammals from camera traps data. PLoS ONE **9**: e103300. https://doi.org/10.1371/journal.pone.0103300

Rush, G.P., Clarke, L.E., Stone, M., and Wood, M.J. 2018. Can drones count gulls? Minimal disturbance and semiautomated image processing with an unmanned aerial vehicle for colony-nesting seabirds. Ecol. Evol. **8**(24): 12322-12334. https://doi.org/10.1002/ece3.4495

Schad, L., and Fischer, J. 2023. Opportunities and risks in the use of drones for studying animal behaviour. Methods Ecol. Evol. **14**(8): 1864–1872. https://doi.org/10.1111/2041-210X.13922

Schipper, J. 2007. Camera-trap avoidance by Kinkajous Potos flavus: rethinking the “non-invasive” paradigm. Small Carniv. Conserv. **36**: 38-41

Schleper, S. 2021. Airplanes, cameras, computers, wildebeests: The technological mediation of spaces for humans and wildlife in the Serengeti since 1950. EPE: Nature and Space **5**: 740-761. https://doi.org/10.1177/25148486211005659

Schneider, S., Greenberg, S., Taylor, G.W., and Kremer, S.C. 2020. Three critical factors affecting automated image species recognition performance for camera traps. Ecol. Evol. **10**(7): 3503–3517. https://doi.org/10.1002/ece3.6147

Schwarz, E.A.G. 2013. Visualizing the Chesapeake Bay watershed debate. Environmental Communications **7**(2): 169-190. http:dx.doi.org/10.1080/17524032.2013.781516

Sequin, S.E., Jaeger, M.M., Brussard, P.F., and Barrett, R.H. 2003. Wariness of coyotes to camera traps relative to social status and territory boundaries. Can. J. Zool. **81**(12): 2015-2025

Silva-Rodríguez, E.A., Gálvez, N., Swan, G.J., Cusack, J.J., and Moreira-Arce, D. 2021. Urban wildlife in times of COVID-19: What can we infer from novel carnivore records in urban areas? Sci. Total Environ. **765**: 142713. https://doi.org/10.1016/j.scitotenv.2020.142713

Southwell, C., and Emmerson, L. 2015. Remotely-operating camera network expands Antarctic seabird observations of key breeding parameters for ecosystems monitoring and management. J. Nat. Conserv. **23**: 1-8. http://dx.doi.org/10.1016/j.jnc.2014.11.002

Strandburg-Peshkin, A., Farine, D.R., Crofoot, M.C., and Cousin, I.D. 2017. Habitat and social factors shape individual decisions and emergent group structure during baboon collective movement. eLife **6**: e19505. https://doi.org/10.7554/eLife.19505

Swann, D.E., Hass, C.C., Dalton, D.C. and Wolf, S.A. 2004. Infrared-triggered cameras for detecting wildlife: an evaluation and review. Wildl. Soc. Bull. **32**(2): 357-365.

Sykora-Bodie, S.T., Bezy, V., Johnston, D.W., Newton, E., and Lohmann, K.J. 2017. Quantifying nearshore sea turtle densities: applications of unmanned aerial systems for population assessments. Sci. Rep. **7**: 17690. https://doi.org/10.1038/s41598-017-17719-x

Tattersall, E.R., Burgar, J.M. Fisher, J.T., and Burton, A.C. 2020. Mammal seismic line use varies with restoration: Applying habitat restoration to species at risk conservation in a working landscape. Biol. Conserv. **241**: 108295. https://doi.org/10.1016/j.biocon.2019.108295

Titley, M.A., Snaddon, JL., and Turner, E.C. 2017. Scientific research on animal biodiversity is systematically biased towards vertebrates and temperate regions. PLoS ONE **12**(12): e0189577. https://doi.org/10.1371/journal.pone.0189577

Trolle, M., and Kéry, M. 2003. Estimation of ocelot density in the Pantanal using capture-recapture analysis of camera-trapping data. J. Mammal. **84**(2): 607-614.

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

Vermeulen, C., Lejeune, P., Lisein, J., Sawadogo, P., and Bouché, P. 2013. Unmanned aerial survey of elephants. PLoS ONE **8**: e54700. https://doi.org/10.1371/journal.pone.0054700

Wang, J., Wang, S., Zou, D., Chen, H., Zhong, R., Li, H., Zhou, W. and Yan, K. 2021. Social network and bibliometric analysis of unmanned aerial vehicle remote sensing applications from 2010 to 2021. Remote Sens. **13**(15): 2912. https://doi.org/10.3390/rs13152912

Watson, G.P.L. 2011. Field birding and digital objects: immaterial technologies and their implications for one practice of coming to know the more-than-human. Environ. Educ. Res. **17**(6): 789-799

Webb, G.K. 2020. Price and performance trends for cellular trail cameras explained with a time trend, Google keyword trends, and a case of suburban deer management. Issues in Information Systems **21**(2): 196-205.

Wegge, P., Pokheral, C.Pd., and Jnawali, S.R. 2004. Effects of trapping effort and trap shyness on estimates of tiger abundance from camera trap studies. Anim. Conserv. **7**(3): 251–256. https://doi.org/10.1017/S1367943004001441

Yang, L., Liu, Y., Yu, H., Fang, X., Song, L., Li, D., and Chen, Y. 2020. Computer vision models in intelligent aquaculture with emphasis on fish detection and behavior analysis: A review. Arch. Comput. Methods Eng. **28**: 2785-2816. https://doi.org/10.1007/s11831-020-09486-2

Yang, D.Q., Ren, G.P., Tan, K., Huang, Z.P., Li, D.P., Li, X.W., Wang, J.M., Chen, B.H., and Xiao, W. 2021. An adaptive automatic approach to filtering empty images from camera traps using a deep learning model. Wildl. Soc. Bull. **45**(2): 230-236. https://doi.org/10.1002/wsb.1176

Zwerts, J.A., Stephenson, P.J., Maisels, F., Rowcliffe, M., Astaras, C., Jansen, P.A., van der Waarde, J., Sterck, L.E.H.M., Verweij, P.A., Bruce, T., Brittain, S., and van Kuijk, M. 2021. Methods for wildlife monitoring in tropical forests: Comparing human observations, camera traps, and passive acoustic sensors. Conserv. Sci. Pract. **3**(12): e568. https://doi.org/10.1111/csp2.568

Table 1. Information selected to characterize publications using cameras on wildlife

Variable	**Description**
Publication year	Year when the article was published
Location	Country or Ocean/Sea where the study took place
Habitat	Aquatic Marine Terrestrial
Taxa group	Amphibians Birds Fish Invertebrates Mammals Reptiles Wildlife
Research topic	Behavioural interactions Behavioural occurrence Education Human opinion Population dynamics Presence/absence Technology Unknown
Application	Conservation Fundamental research Management Monitoring Population dynamics
Image	Photo Video
Camera unit	Number of cameras used
Community science	Yes/No

792 Table 2. Pros and cons of each camera type.

793

Camera Type	**Pros**	**Cons**
Video camera	Continuous Better record of behaviour than photographs Increased probability of identifying species in area of high forest/grass coverage than photographs Records sound	Analysis is time-consuming Battery life constraints Requires increased storage capacity compared to photographs
Vehicle mounted	Cover large distances in short amount of time with capability to obtain detailed, close up images	Constrained by vehicular access
Smartphone	Often no additional cost Option for both video and photograph	Typically opportunistic use must be accounted for in analysis Image quality may be lower
Security camera	Continuous and consistent coverage of a single area No concerns about battery life	Analysis is time-consuming Typically low resolution Only one field of view means presence/absence or records of behaviours can be easily missed
Remote aerial camera	Large area covered Reduced cost compared to manned aerial camera	Noise disturbance Often low image resolution when zooming in
Nest camera	Continuous monitoring of nesting behaviour	Camera installation or maintenance may disturb nesting Battery life constraints

		Requires high storage capacity Analysis is time-consuming
Identification catalogues	Allows for long-term tracking of individuals Can be used for population modeling (?) Frequently involves citizen science (low cost of data collection for vast data sets)	Analysis is time-consuming Large data sets require high computing power Must be cognisant of biases introduced by use of citizen science data (eg/ lots of data collected on eco-tours introduces geographic and temporal bias based on times and locations of tours)
Handheld camera	Portable Records what is seen by “boots and eyes on the ground”	Can be time intensive Equipment can be sensitive or fragile
Gopro	Durable Portable Good battery life	Resolution is low when zooming in on an image
Drone	Can be autonomous Large area covered in less time compared to handheld cameras Repeatable	Noise disturbance Limited battery life Need to be cautious of drone no-fly zones and other drone-related laws
Dashboard camera	Less costly Can cover larger distances	Constrained by vehicular access Typically poor image quality Time consuming to analyze video
Camera trap	Autonomous Repeatable Motion trigger increases battery life	Analysis is time-consuming Requires large storage capacity Animals may steal cameras
Blimp-mounted	Large area covered	Weather restrictions for flight more

camera	Reduced noise disturbance Hovering capability to focus on specific locations Reduced vibrations make for better quality images	prohibitive than drones or fixed-wing aircraft
Animal-borne camera	Unique “animal’s eye view” Record of behaviours, movements, and encounters with environment and other animals	Impacts on individual wearing device (can impact survival, reproduction, etc) Installation is stressful and invasive for individual Recapture required for most devices Limited battery life on some devices Can be costly Can be time-intensive to capture and tag individuals
Aerial camera	Large area covered	Noise disturbance Animals may learn to avoid aircraft (skews data) Costly

Figure captions.

Figure 1. Different applications of cameras in modern wildlife research, including: a) drone survey image captures wetland habitat characteristics (note also eight countable Canada geese *Branta canadensis*); b) thermal camera image locates the cryptic nest of a Nelson's sparrow (*Ammospiza nelsoni*); c) handheld digital single lens reflex camera image records a common tern (*Sterna hirundo*) with a prey item for dietary study; and d) remote camera trap image captures a satellite-collared American black bear (*Ursus americanus*) moving at night, a ground-truthing of satellite data. Photographs a, b and c taken by the authors; photograph d provided by Jason Power of Nova Scotia Department of Natural Resources.

Figure 2. Temporal distribution of the screened published papers on camera use in wildlife studies, summarized by: A: Animal group; B: Camera type and average number of unit per study excepting social media studies (black line); C: Image type; D: Habitat type; E: Research topic; F: Application.

Figure 3. Geographical distribution of the screened published articles using cameras in the wild to address animal ecology questions. Land-based studies were assigned to the country in which they took place (or multiple countries where appropriate), while marine-based studies were assigned to an ocean or sea, with the number of studies indicated by the label colour. Map was created using the Natural Earth countries polygons from the rnaturalearth package (Massicotte 2023) as a base layer, with the WGS84 geographic coordinates system.

Figure 4. Heat map of camera types used for the different animal groups. The greatest number of studies were undertaken using camera traps on mammals followed by camera traps on birds.

Figure 5. Percentage of screened published articles mentioning “artificial intelligence” or “machine learning” (top panel) and “citizen science", community science", or “social media” (bottom panel) in either their title, abstract, or keywords .

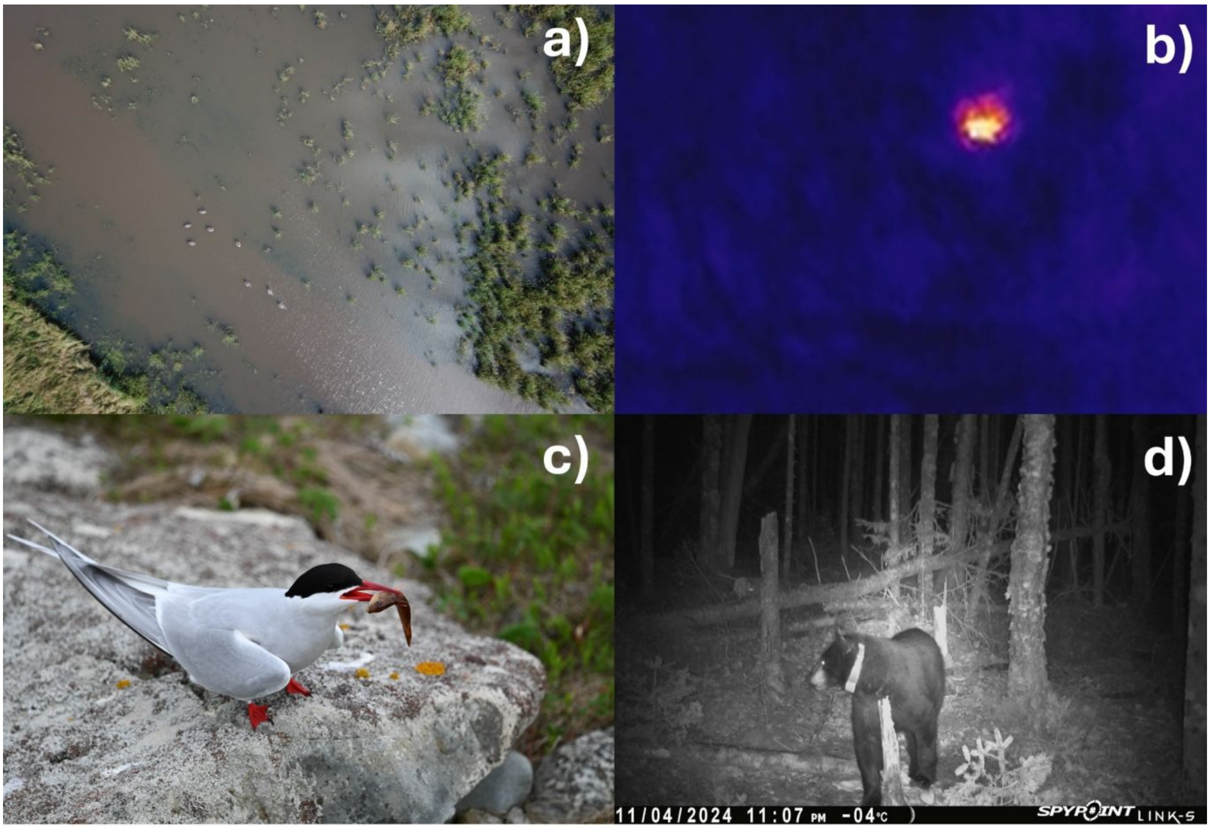

Figure 1. Different applications of cameras in modern wildlife research, including: a) drone survey image captures wetland habitat characteristics (note also eight countable Canada geese *Branta canadensis*); b) thermal camera image locates the cryptic nest of a Nelson's sparrow (*Ammospiza nelsoni*); c) handheld digital single lens reflex camera image records a common tern (*Sterna hirundo*) with a prey item for dietary study; and d) remote camera trap image captures a satellite-collared American black bear (*Ursus americanus*) moving at night, a ground-truthing of satellite data. Photographs a, b and c taken by the authors; photograph d provided by Jason Power of Nova Scotia Department of Natural Resources.

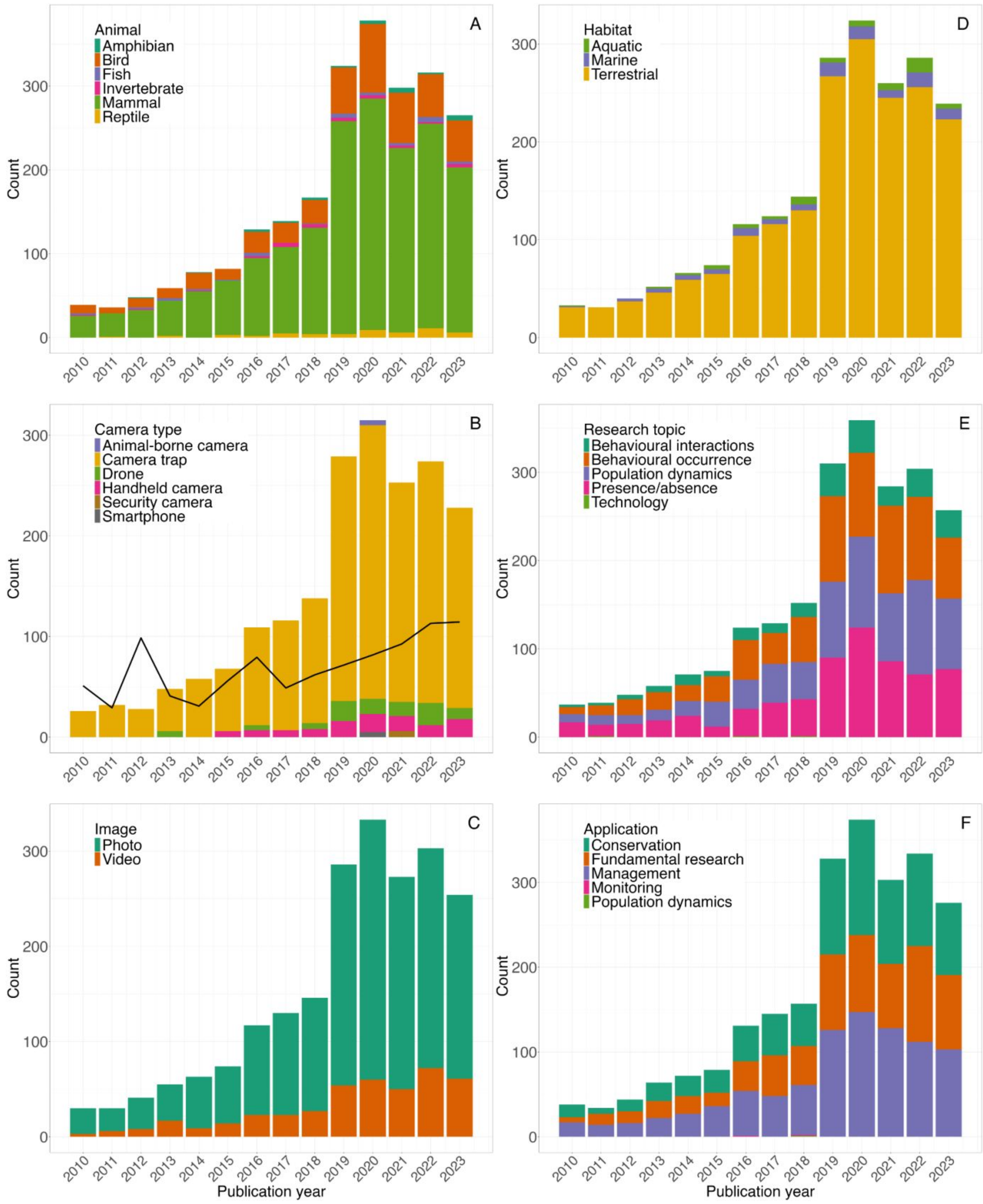

Figure 2. Temporal distribution of the screened published papers on camera use in wildlife studies, summarized by: A: Animal group; B: Camera type and average number of units per study excepting social media studies (black line); C: Image type; D: Habitat type; E: Research topic; F: Application.

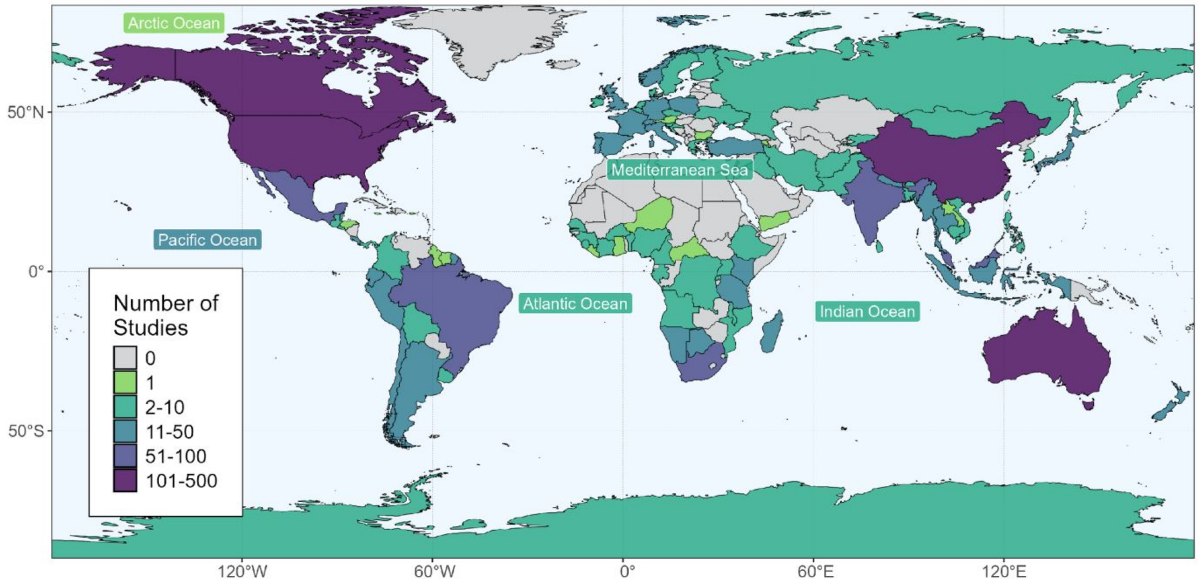

Figure 3. Geographical distribution of the screened published articles using cameras in the wild to address animal ecology questions. Land-based studies were assigned to the country in which they took place (or multiple countries where appropriate), while marine-based studies were assigned to an ocean or sea, with the number of studies indicated by the label colour. Map was created using the Natural Earth countries polygons from the rnaturalearth package (Massicotte 2023) as a base layer, with the WGS84 geographic coordinates system.

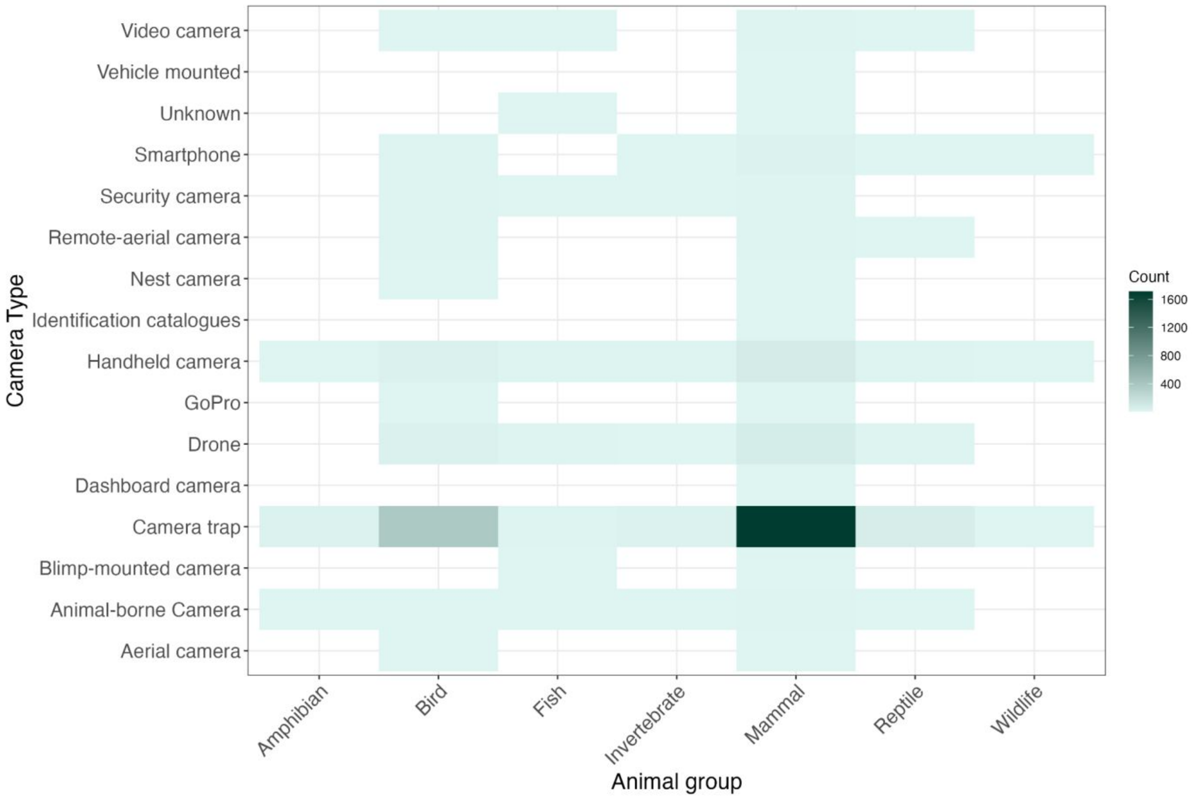

Figure 4. Heat map of camera types used for the different animal groups. The greatest number of studies were undertaken using camera traps on mammals followed by camera traps on birds.

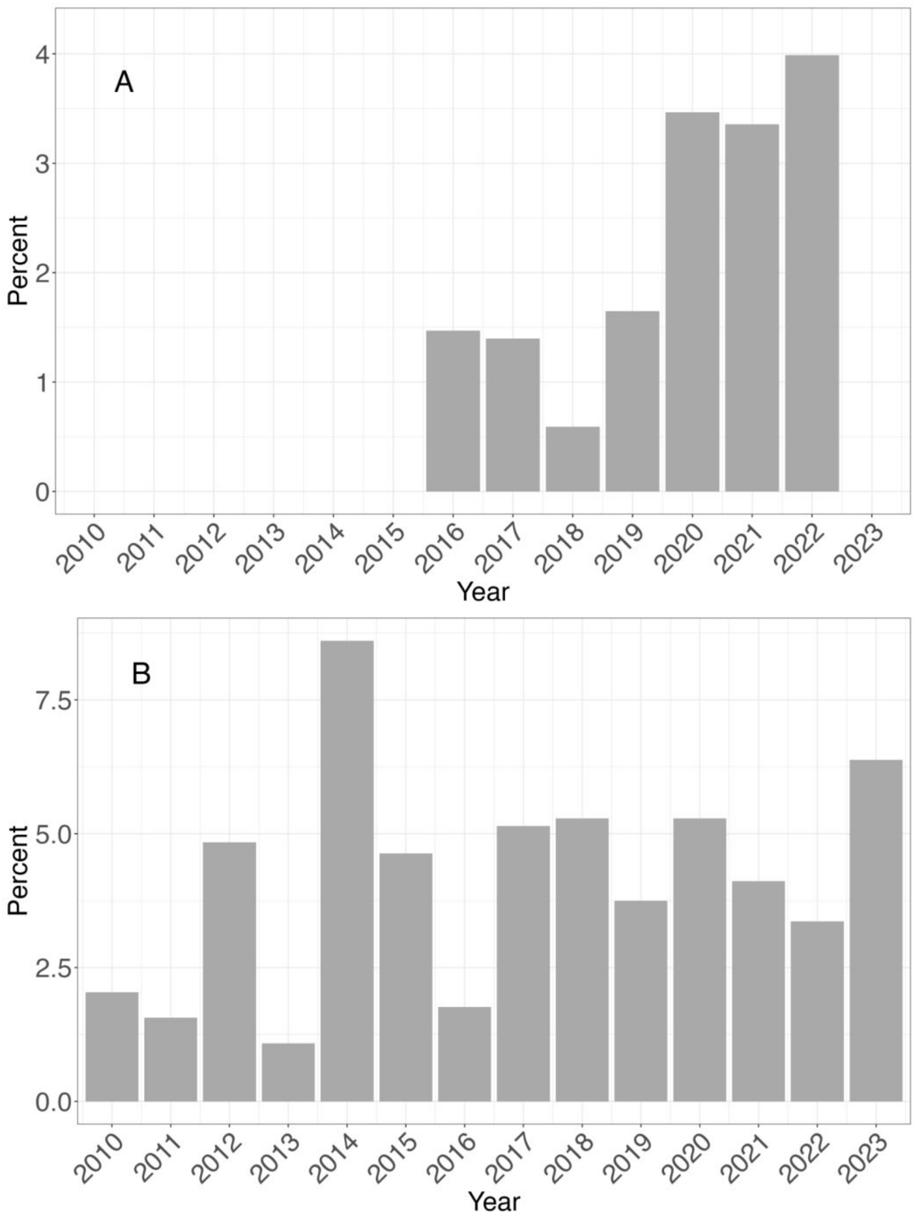

Figure 5. Percentage of screened published articles (post-validation) mentioning “artificial intelligence” or “machine learning” (top panel) and “citizen science", community science", or “social media” (bottom panel) in either their title, abstract, or keywords.