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Methods in Ecology and Evolution

REVIEW

Studying collective animal behaviour with drones and computer vision

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Abstract

1. Drones are increasingly popular for collecting behaviour data of group-living animals, offering inexpensive and minimally disruptive observation methods. Imagery collected by drones can be rapidly analysed using computer vision techniques to extract information, including behaviour classification, habitat analysis and identification of individual animals. While computer vision techniques can rapidly analyse drone-collected data, the success of these analyses often depends on careful mission planning that considers downstream computational requirements—a critical factor frequently overlooked in current studies.
2. We present a comprehensive summary of research in the growing AI-driven animal ecology (ADAE) field, which integrates data collection with automated computational analysis focused on aerial imagery for collective animal behaviour studies. We systematically analyse current methodologies, technical challenges and emerging solutions in this field, from drone mission planning to behavioural inference. We illustrate computer vision pipelines that infer behaviour from drone imagery and present the computer vision tasks used for each step. We map specific computational tasks to their ecological applications, providing a framework for future research design.
3. Our analysis reveals AI-driven animal ecology studies for collective animal behaviour using drone imagery focus on detection and classification computer vision tasks. While convolutional neural networks (CNNs) remain dominant for detection and classification tasks, newer architectures like transformer-based models and specialized video analysis networks (e.g. X3D, I3D, SlowFast) designed for temporal pattern recognition are gaining traction for pose estimation and behaviour inference. However, reported model accuracy varies widely by computer

vision task, species, habitats and evaluation metrics, complicating meaningful comparisons between studies.
4. Based on current trends, we conclude semi-autonomous drone missions will be increasingly used to study collective animal behaviour. While manual drone operation remains prevalent, autonomous drone manoeuvrers, powered by edge AI, can scale and standardise collective animal behavioural studies while reducing the risk of disturbance and improving data quality. We propose guidelines for AI-driven animal ecology drone studies adaptable to various computer vision tasks, species and habitats. This approach aims to collect high-quality behaviour data while minimising disruption to the ecosystem.

KEYWORDS
AI-driven animal ecology, animals, collective animal behaviour, computer vision, drone, edge AI

1 | INTRODUCTION

Traditionally, studies of animal behaviour rely on data collected by experts making careful observations of individuals in the wild (Altmann, 1974). Behaviour data may include fine-grained individual behaviour observations, collective behaviour observations, social interactions or individual and group movement data (Bateson & Martin, 2021). Social behaviour and context are vital for understanding the decisions of group-living animals in the context of their social and environmental conditions. Social context may include the behaviours exhibited by other animals nearby and the demographic categories of the animals, including species, age and sex. Environmental context includes habitat characteristics, weather and time of day. Social behaviours involve interactions among group members and often reflect social relationships, such as kinship or group hierarchies. Fine-scale movements, such as individual positions, velocity and turning angles, provide additional description and context to social and individual behaviours (Hughey et al., 2018). Posture, or pose, can determine individual behaviour (Koger et al., 2023). Adding the temporal element to animal presence produces movement data (Koger et al., 2023; Ozog'any et al., 2023). Movement throughout the landscape is studied within the context of its social factors and habitat (Aben et al., 2018; Davies et al., 2016).

Ethograms are lists of behavioural elements experts use to conduct field observations of collective group behaviours and individual actions using scan or focal sampling, respectively (Altmann, 1974). Focal sampling has the advantage of gathering detailed behaviour information of one observed individual but lacks the social context of the other individuals' concurrent behaviours. Scan sampling periodically samples the behaviour of each individual in the group, capturing social context, but it may miss fine-scale details or rare behaviours captured by focal sampling. Activity budgets are calculated as the percentage of time estimated to be spent on each behaviour in the ethogram. They are tools for comparing overall behavioural patterns as a function of species, demographic makeup, habitation, time of day, etc. Ecologists use ethograms as a foundation for behaviour studies, and as the species is studied more closely, more behaviours can be added to the ethogram (Kholiavchenko, Kline, Kukushkin, et al., 2024).

Analysing animal behaviour within the social and environmental context in which it occurs is crucial to understanding the complex dynamics of group-living organisms (Hughey et al., 2018). Animal behaviour data serves as a key indicator of individual, species and population-level health. As such, it is essential for conservation efforts, as behaviour indicates individual, population and ecosystem health (Besson et al., 2022). Understanding the complex dynamics of animal behaviour is critical to determining whether animals change behaviour in response to changing environmental conditions, especially in response to acute disturbances from climate change (Besson et al., 2022). Gathering data on the individual and collective behaviour of group-living animals is challenging, as it requires fine-scale observations of multiple animals simultaneously with minimal interruptions (Hughey et al., 2018). Analysing the behaviour data of group-living species is also challenging because it simultaneously tracks three levels of a complex system. This system includes (1) individual behaviours, (2) interactions among individuals and (3) the behaviour of the group as a whole, which is an emergent property of individual behaviours and interactions, illustrated in Figure 1. We provide a glossary of terms related to studying collective animal behaviour with drones and computer vision to facilitate interdisciplinary research (Table 1). This review focuses on techniques for studying the behaviour of group-living animals. Still, these principles may also be applied to studying solitary species and individuals using drones and computer vision.

2 | WHY USE DRONES AND COMPUTER VISION TO STUDY COLLECTIVE ANIMAL BEHAVIOUR?

Researchers are developing new ways to observe collective animal behaviour in the wild by combining drone-based video acquisition

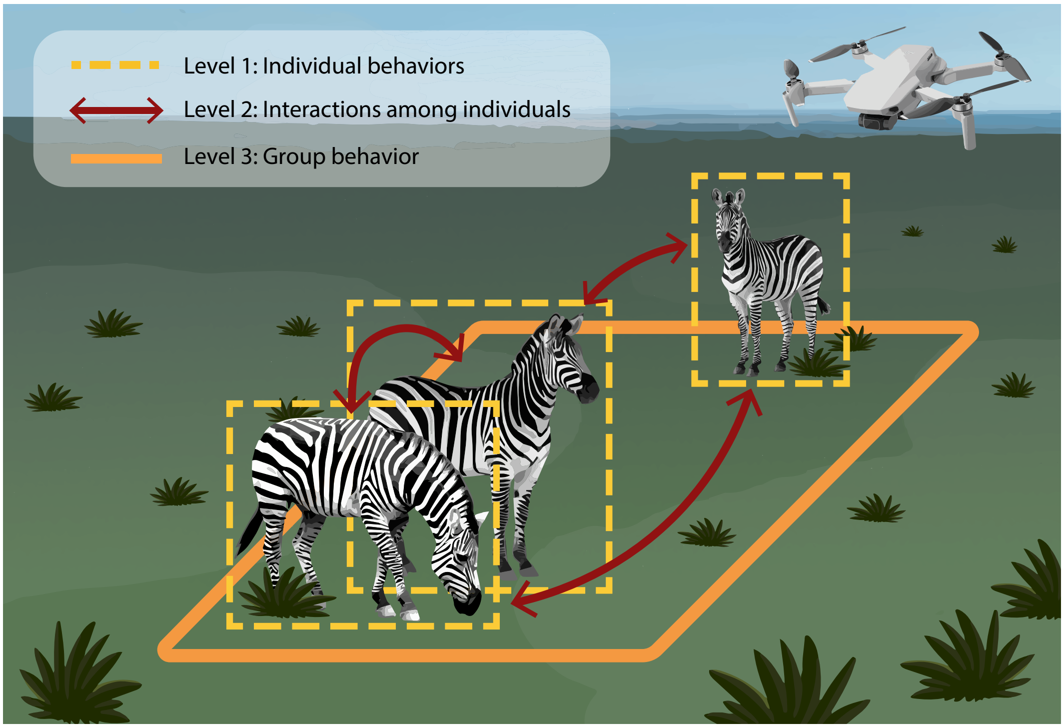

FIGURE 1 Levels of group-living animal behaviours: (1) individual behaviours, (2) interactions among individuals and (3) the group as a whole, which is an emergent behaviour of individual behaviours and interactions.

TABLE 1 Glossary of terms related to studying collective animal behaviour with drones and computer vision.

Term	Definition
Collective animal behaviour	The coordinated behaviour of animal groups emerge from individual actions and interactions between individuals
Drone	An unmanned aerial system (UAS) capable of autonomous or remote-controlled flight. A UAS includes sensors, such as IMU and camera, ground-control-station, such as remote controller or laptop, and flight components, including rotor blades, batteries and motors
Artificial intelligence (AI)	The field of computer science focused on creating systems that can perform tasks typically requiring human intelligence, including learning, reasoning and problem-solving
Machine learning (ML)	A subset of AI that enables systems to learn and improve from experience without explicit programming, using statistical techniques to find patterns in data
Inference request	The process of querying a trained model to generate predictions or outputs based on input data. For example, a computer vision model analysing an image to return a class prediction
Latency	The time interval between collecting and analysing the image
Edge computing	A distributed computing paradigm that brings computation closer to data sources, reducing latency and bandwidth usage (Cao et al., 2020)
Edge AI	The deployment of AI algorithms directly on edge devices for real-time processing and decision-making without cloud dependency (Singh & Gill, 2023)
Fog device	Devices used to augment compute resources on the edge. Examples: GPU laptop, RaspberryPi (Cao et al., 2020)
AI-driven animal ecology (ADAE)	The application of AI techniques to study animal populations, behaviour and ecosystems using automated, adaptive data collection and analysis (Kline, O'Quinn, et al., 2024).
Surface-of-Interest (SI)	The part of the animal that contains data required to answer the ecological question, see Figure 6 (Rolland, Grøntved, Laporte-Devylder, et al., 2024)
Computer vision	A field of AI that enables computers to understand and process visual information from the world, mimicking human visual perception.
Computer vision pipeline	The sequence of processing steps that transform raw visual data into meaningful information, including pre-processing, feature extraction and analysis

with computer vision techniques (Pedrazzi et al., 2025). Drone data, analysed using computer vision, allow ecologists to collect new types of aerial vision data and extract insights in multilevel animal societies promptly (Maeda & Yamamoto, 2023). Drone videos can be analysed to extract continuous, simultaneous time series of the behavioural states of multiple individuals (Kline, Zhong, Kholiavchenko, et al., 2025; Maeda & Yamamoto, 2023; Smith & Pinter-Wollman, 2021). This task is impossible with traditional manual data collection methods, such as scan and focal sampling (Altmann, 1974). Drones are increasingly used for research as they can quickly obtain detailed behaviour data of group-living animals (Besson et al., 2022; Corcoran, Winsen, et al., 2021), such as the studies illustrated in Figure 2. Camera sensors are becoming smaller and smaller, allowing for more possibilities in terms of drone payloads. These technological advances have enabled ambitious animal machine vision-based studies, including species identification (Corcoran, Winsen, et al., 2021; Delplanque et al., 2022; Petso, Jamisola, Mpoeleng, Bennitt, & Mmereki, 2021; Petso, Jamisola, Mpoeleng, & Mmereki, 2021), behaviour (Kholiavchenko, Kline, Ramirez, et al., 2024; Koger et al., 2023) and population counts (Brack et al., 2018; Brown et al., 2022). Between 2015 and 2020, drone imagery was used in 19 automated animal detection studies alone (Corcoran, Winsen, et al., 2021) (Table 2).

Drones can collect videos and images with sufficient granularity to infer fine-grained behaviour and social interactions (Koger et al., 2023). Drones may adjust their trajectories to follow animals as they move through their habitat, providing richer spatiotemporal context to behaviour compared to static methods such as camera traps or acoustic sensors (Kline, Berger-Wolf, et al., 2024; Luo et al., 2024). Drones extend the sensing capacity of experts compared to ground-based observations (Smith & Pinter-Wollman, 2021). A study of whale behaviour found that drones provided three times more observational capacity than boat-based observations, including novel foraging tactics (Torres et al., 2018). Drones are especially promising for animal behaviour studies that require tracking wildlife over vast, remote regions that are difficult for experts to access (Hughey et al., 2018; Kholiavchenko, Kline, Ramirez, et al., 2024; Ozog'any et al., 2023; Schad & Fischer, 2023). Drone platforms are quickly becoming the preferred platform for aerial population counts (Eikelboom et al., 2019; Elmore et al., 2023; Lamprey, Pope, et al., 2020).

Analysing aerial videos of animal behaviour combines the advantages of both focal and scan sampling by capturing the fine-scale behaviour of each individual in the group concurrently, providing the social context (Aben et al., 2018; King & Jensen, 2023; Ozog'any et al., 2023; Russo et al., 2023). Drone footage can be analysed to determine habitat conditions, including vegetation and weather (Koger et al., 2023; Schad & Fischer, 2023), providing insight into the influences of habitat and landscape on behaviour (Russo et al., 2023). Aerial imagery obtained from satellites provides sufficient granularity to conduct population counts for some large species (Duporge, Isupova, et al., 2021; Guirado et al., 2019; LaRue et al., 2015; Wang et al., 2019). However, animal monitoring with satellite imagery is limited due to the timing of satellite overpasses and varying weather conditions, limiting their applicability for collective animal behaviour studies.

Computer vision streamlines data analysis, facilitating researchers' ability to extract biological insight from aerial datasets (Kholiavchenko, Kline, Kukushkin, et al., 2024; Kline, O'Quinn, et al., 2024; Tuia et al., 2022; Valletta et al., 2017). Unlike manual surveys, drone imagery analysed with computer vision may be less biased for detection tasks (Corcoran, Denman, et al., 2021). Computer vision models are often used in sequence to analyse data and extract ecological insights, (Kholiavchenko, Kline, Ramirez, et al., 2024; Koger et al., 2023; McNutt et al., 2024; Price et al., 2018; Shukla et al., 2024). These sequences of computer vision tasks are called *pipelines*, illustrated in Figure 3. However, these pipelines are often developed for post-processing and do not support real-time analysis in the field. Further, pipelines that infer complex ecological traits require images with prescribed pixel resolution, angles, timing and data quality factors determined at runtime. Images with low resolution or occlusions require expert analysis to decipher insights or must be discarded altogether.

Autonomous drones are a potential solution to overcoming the drawbacks of manual missions for collective behaviour studies (Kline et al., 2023; Luo et al., 2024; Rolland et al., 2025). Most behavioural studies using drones rely on manual missions, which are difficult to standardize and scale to enable reproducible experiments. Autonomous drones can respond to their environment in real-time, using computer vision and edge AI. Edge AI is an emerging area of research in distributed computing, where autonomous systems are designed to process sensor data and make real-time decisions directly on far-edge devices, such as drones, without relying on cloud connectivity. Studies applying AI in real-time to enable adaptive data collection are known as *AI-driven animal ecology* (ADAE) studies (Kline, O'Quinn, et al., 2024). Adaptive sampling allows ecologists to optimize data collection over time, which is particularly important effectively for monitoring dynamic systems, such as group-living animals (Yang et al., 2020). Applying an ADAE approach to automate drone missions allows for fast reactions to dynamic environments and more reliable operations in the field. Autonomous missions can be programmed with flight parameters to optimize data collection for downstream computer vision analysis. Further, safety parameters can be pre-programmed into flight plans to minimize the risk of disturbing the animals. Drone flight parameters influencing animal behaviour include approach distance, altitude, velocity and flight frequency (Pinel-Ramos et al., 2024). Autonomous drones, powered by Edge AI, can scale and standardize collective animal behavioural studies while reducing the risk of disturbance and improving data quality.

3 | COMPUTER VISION TO INFER COLLECTIVE ANIMAL BEHAVIOUR FROM DRONE IMAGERY

3.1 | Computer vision pipelines

Automating the analysis of vast volumes of drone footage using AI techniques, specifically computer vision tasks, allows for the timely analysis of collective animal behaviour (Gonzalez et al., 2016). Pipelines of computer tasks assist in automating image analysis by cleaning and processing the data with limited manual intervention. Inferring animal

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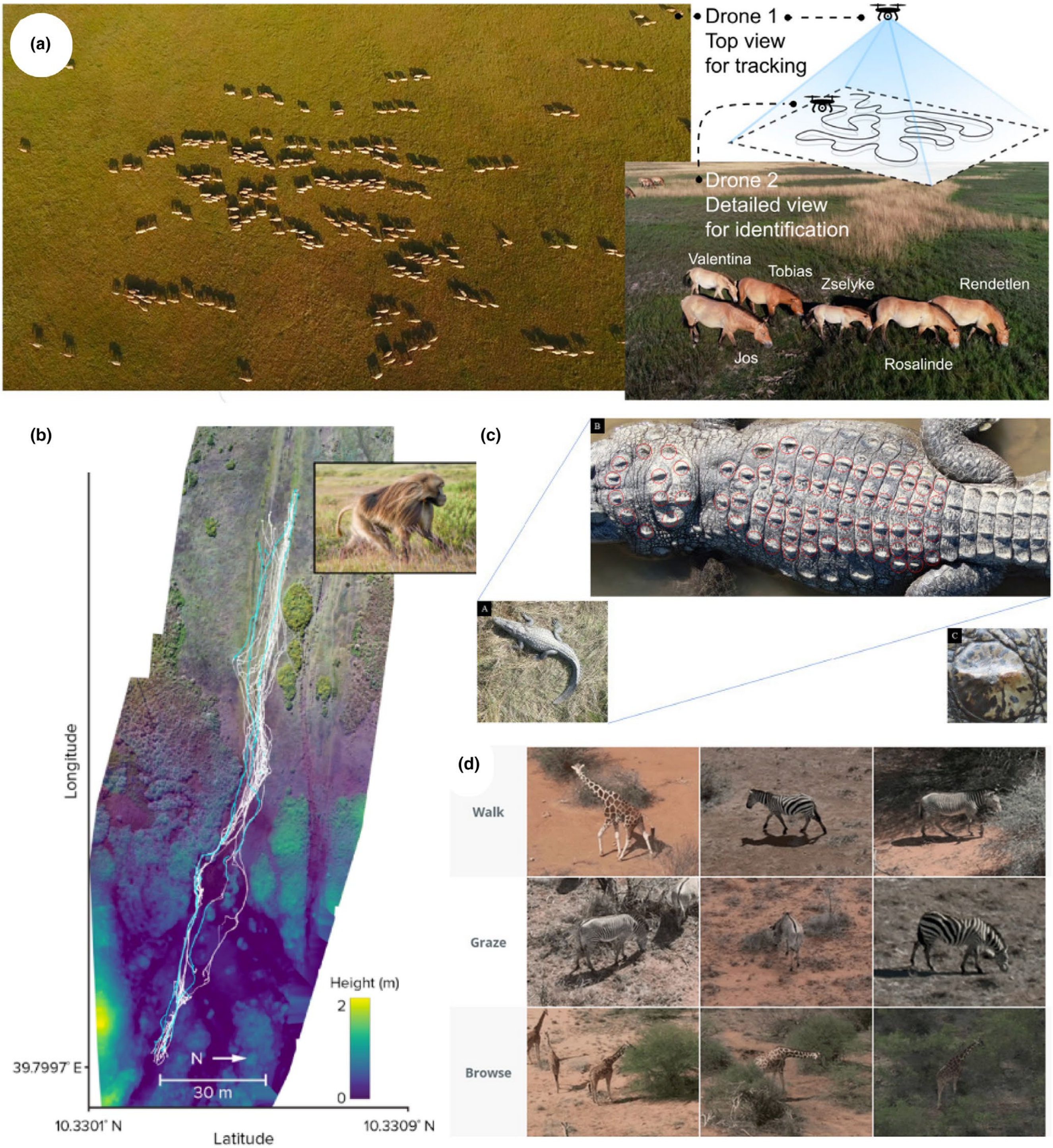

FIGURE 2 Computer vision tasks from drone imagery for collective animal behaviour studies: (a) Tracking and individual identification of Przewalski's horses with swarm (Ozog'any et al., 2023), (b) Tracking Gelada baboon movement through landscape (Koger et al., 2023), (c) Individual identification of mugger crocodiles (Desai et al., 2022), (d) behaviour of giraffes and zebras from video (Kholiavchenko, Kline, Ramirez, et al., 2024).

behaviour from drone imagery requires numerous computer vision pre-processing tasks (Hughey et al., 2018; Tuia et al., 2022; Valletta et al., 2017). We illustrate how computer vision tasks create pipelines to extract ecological insights in Figure 3. We summarize our review of studies performing one or more computer visions tasks required to infer behaviour from drone imagery in Table 2.

3.1.1 | Translating biological questions to computer vision tasks

Translating biological questions to computer vision tasks is challenging due to the different terminology used by ecological and computer science communities (Rolnick et al., 2024; Tuia et al., 2022). To

TABLE 2 Summary of animal ecology studies using computer vision and drones.

CV task	Model(s)	Accuracy	Species	RTP	Study
D, C	CNN, OBIA, Supervised and unsupervised pixel-based image classification, Detection moving wild animals (DWA) algorithm, Support vector machine, Spectral thresholding	32%–100%	Various		Corcoran, Winsen, et al. (2021)
D, C	RetinaNet	90%–95%	Elephant, zebra, giraffe		Eikelboom et al. (2019)
D, C	Libra-R-CNN	73% MAP	Topis, buffalo, elephant, kob, warthog, waterbuck		Delplanque et al. (2022)
D, C	HerdNet	85% F1	Elephant, buffalo, topi, Uganda kob, waterbuck, warthog, giant forest hog, hippopotamus, crocodile, cow, sheep, goat		Delplanque, Lamprey, et al. (2023)
D, C	YOLO	70.45% mAP	Northwestern Serbian deer		Rančić et al. (2023)
D, C	YOLO	95% F1	Antarctic shags		Cusick et al. (2024)
D, C	YOLO	77%–99% mAP	White-tailed deer, domestic cow and horse		Krishnan et al. (2023)
D, C, P	CNN, MorphoMetrix	98%	Humpback, minke, blue whales		Gray et al. (2019)
D, C	CNN	75%–94%	Seals, sea birds, sea turtle		Dujon et al. (2021)
D, C	CNN	87%–98%	Albatross, penguin		Hayes et al. (2021)
D, C	R-CNN, R-FCN, SSD, RetinaNet, YOLO	54%–96% AP	Birds		Hong et al. (2019)
D, C	Faster R-CNN, RetinaNet	63%–68% MAP	Waterbird species		Kabra et al. (2022)
D, C	YOLO	95%	Crane		Chen, Jacob, et al. (2023)
D, C	Tensorflow, YOLO	28%–94% (D), 96% (C)	Elephant, giraffe, rhinoceros, wildebeest, zebra		Petso, Jamisola, Mpoeleng, Bennitt, and Mmereki (2021)
D, C	Tensorflow, YOLO	28%–94% (D), 96% (C)	Elephant, giraffe, white rhinoceros, wildebeest, zebra		Petso, Jamisola, Mpoeleng, Bennitt, and Mmereki (2021)
D, C	Deep CNN	80%–88% Recall	Dugong		Maire et al. (2015)
D, C	R-CNN	15%–57% Recall	Various	✓	Bondi et al. (2018)
D, C	Faster-R-CNN	83% Recall	Rhinoceros		Chalmers et al. (2021)
D, C	Faster-R-CNN	83% mAP	Rhinoceros	✓	Chalmers et al. (2019)
C	ANN, CNN	85% F1	Cow, horse, deer, goat		McCraine et al. (2024)
D, C, T, P	CNN	75%–94% Rec.	Seal, sea turtle, gannet		Dujon et al. (2021)
D, C	Faster-R-CNN	80%	Caribou		Lenzi et al. (2023)
D, C	YOLO	92%, 85% F1	Swamp deer	✓	Tripathi et al. (2025)
C	Photogrammetry	Match ground-truth long-term monitoring ($p > 0.1$)	Bottlenose dolphin		Vivier et al. (2024)
IID	Hotspotter	95%–100%	Zebra, giraffe, jaguar, lionfish		Crall et al. (2013)
IID	ALFRE-ID	82% Top-1	Saimaa Ringed Seals, whale shark		Nepovinnykh et al. (2024)
IID	CNN (YOLO, Inception-v3)	90%	Crocodile		Desai et al. (2022)

TABLE 2 (Continued)

CV task	Model(s)	Accuracy	Species	RTP	Study
D, C, T	Faster-R-CNN	72%–100% Recall	Zebra, impala, buffalo, waterbuck, gelada		Koger et al. (2023)
D, C, T	YOLO (D,C), BoT-SORT (T)	85% (YOLO), 48% BoT-SORT	Turtle		Noguchi et al. (2025)
D, C, T	YOLO (D, C), KF (T)	93% (YOLO), 61% (KF) mAP	Przewalski's gazelle	✓	Luo, Li, et al. (2023)
D, C, T	YOLO (D, C)	93% (YOLO), 61% (KF) mAP	Tibetan antelope	✓	Luo, Zhao, et al. (2023)
D, C, T	YOLO (D, C), Deep-SORT (T)	95% mAP (YOLO), 79% MOTP Deep-SORT	Przewalski's gazelle		Zhang et al. (2024)
D, T, Re-ID	YOLO (D), BoT-SORT (T)	62% mAP, 54% HOTA	Blackbuck antelopes		Naik et al. (2024)
D, C, T	CNN, KF	83%–97% TP	Antelope, Wasp		Rathore, Sharma, et al. (2023)
P	YOLO-NAS-Pose	81 mAP	Elephant		McNutt et al. (2024)
P	Stacked DenseNet	0.35 PMA	Mice, flies, zebra		Graving et al. (2019)
P	DeepLabCut	5.21 pixel ATE	Mice, flies		Mathis et al. (2018)
B	X3D	62% (micro), 87% (macro) Top-1	Zebra, giraffe		Kholiavchenko, Kline, Ramirez, et al. (2024)
B	X3D-L, I3D, SlowFast	66%, 65%, 66% Overall mAP	Zebra, giraffe		Kholiavchenko, Kukushkin, Brookes, et al. (2024)
B	YOLO-Behaviour	70%–91%	Sparrow, jays, pigeon, zebra, giraffes		Hang Chan et al. (2024)
B	D-CNN	81%	Zebra		Price et al. (2023)

Note: Computer Vision (CV) Tasks: D: detection, C: classification, T: tracking, P: posture/pose, B: Behaviour, IID: individual identification. Performance: Performance reported in terms of accuracy unless otherwise stated.

Abbreviations: AP, average precision; ATE, average test error; HOTA, higher-order tracking accuracy; KF, Kalman filter; MAP, mean average precision; MOTP, multiple object tracking precision; PMA, posterior mean accuracy; Rec, Recall; RTP, real-time processing; TP, true positive.

assist in alleviating this challenge, we illustrate each computer task and its dependencies and provide examples of biological questions that may be answered at each stage in Figure 3 (Tuia et al., 2022; Xu, Zhang, et al., 2024). We focus on computer vision tasks commonly used when executing drone missions and analysing aerial imagery for behaviour studies. Table 3 provides definitions for the computer vision tasks. We refer readers to (Weinstein, 2018) and (Valletta et al., 2017) for detailed reviews on computer vision for animal ecology and machine learning for animal behaviour, respectively. Xu, Wang, et al. (2024) provides an overview of machine learning techniques applied to remotely sensed data, including aerial and satellite images, for detecting and monitoring animal populations.

Computer vision tasks, including detection, localization, individual identification and posture, are illustrated in Figure 4, reproduced from Tuia et al. (2022). Most computer vision tasks, except tracking, may be performed on individual images. Before computer vision tasks can be performed, individual frames from the video stream must be extracted for analysis. The frame's sampling rate depends on the drone's camera parameters and the latency requirements established, as discussed in Section 4.1. Detection and localization tasks are performed to determine if an animal is in the frame and, if so, where it is located, shown in Figure 3a2. Detection results are often recorded as bounding boxes, which draw a rectangular outline around the region of pixels where the object appears in the frame, illustrated in Figure 5.

Next, classification is performed to determine the animal's species, shown in Figure 3a3. Depending on the study, additional classification tasks may be performed to determine the animal's demographic class, such as age and sex. Detection and classification tasks are often performed using convolution neural networks (CNNs) to reduce manual annotation efforts (Bowley et al., 2018; Chalmers et al., 2021; Delplanque, Foucher, et al., 2023; Han et al., 2019; Kellenberger et al., 2018; Torney et al., 2019). The YOLO CNN models are the most popular neural network architecture for detection and classification tasks (Kholiavchenko, Kline, Ramirez, et al., 2024; Kline et al., 2023; Redmon et al., 2016; Xu, Wang, et al., 2024). If multiple frames of the same animal are available, it can be tracked, adding a temporal element to its location, as shown in Figure 3a4. As shown in Figure 3a6, posture or pose is determined by the relative location of the key points on the animal's body. Finally, behaviour can be automatically inferred from tracked video clips or the animal's posture, as shown in Figure 3a5. If the animal has distinctive morphological markings, it may be individually identified using a tool such as WildBook (ConservationXLabs) (Figure 3a7).

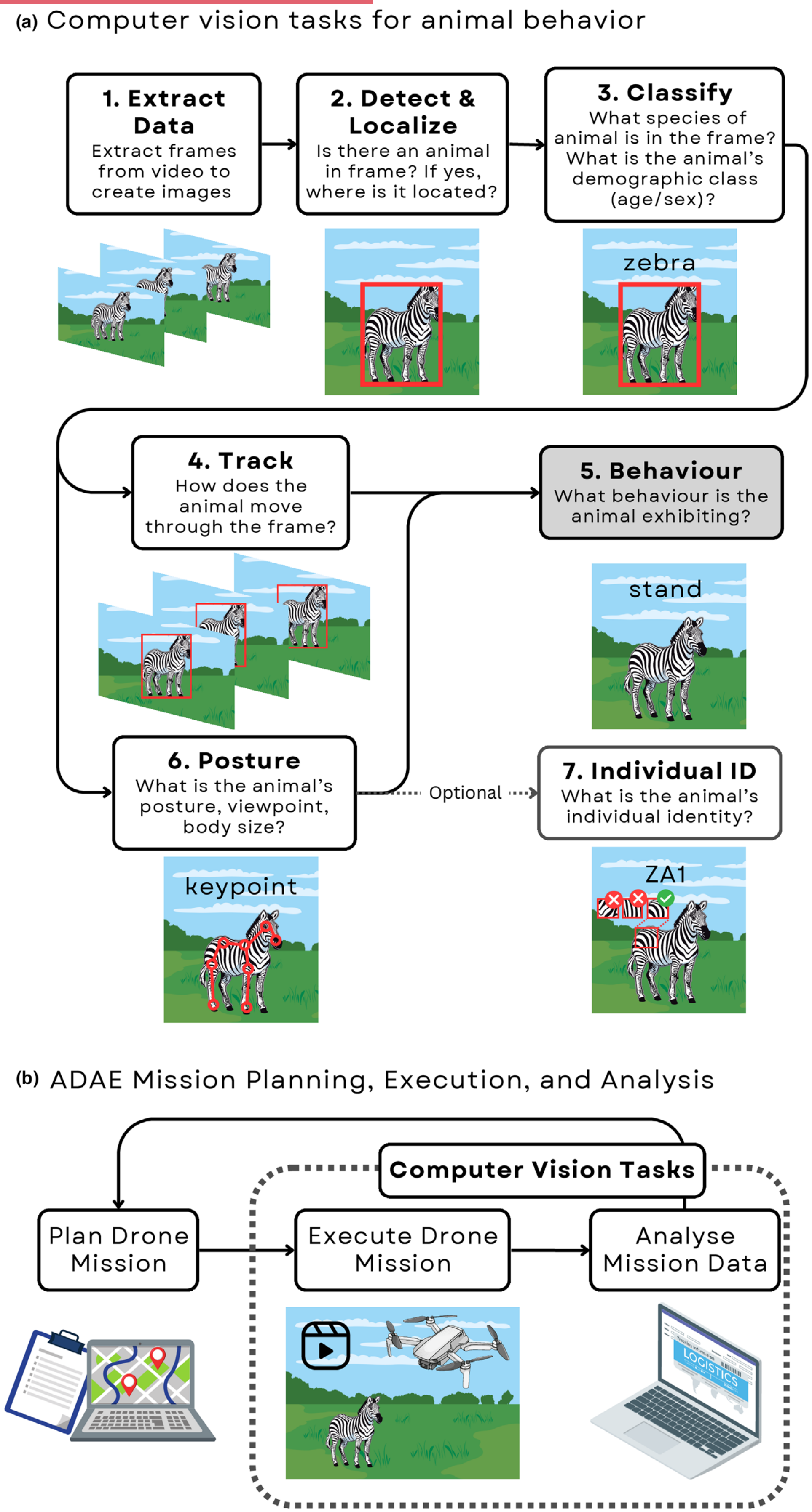

FIGURE 3 (a) Computer vision tasks for animal behaviour may be included in the execution or analysis phase of drone missions. (b) AI-driven animal ecology (ADAE) drone mission phases: Planning, execution and analysis, detailed in Section 4.

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TABLE 3 Computer vision tasks for collective animal behaviour studies.

Computer vision task	Definition
Detection	Identifying the presence of objects (e.g. animals) in an image or video frame
Location	Determining the precise spatial position of detected objects, often using bounding boxes or coordinates
Classification	Categorizing detected objects into predefined classes (e.g. species identification)
Tracking	Following the movement of objects across consecutive video frames while maintaining their identity
Behaviour	Recognizing and categorizing specific actions or patterns of movement exhibited by animals
Individual identification	Distinguishing individual animals within a species based on unique visual characteristics

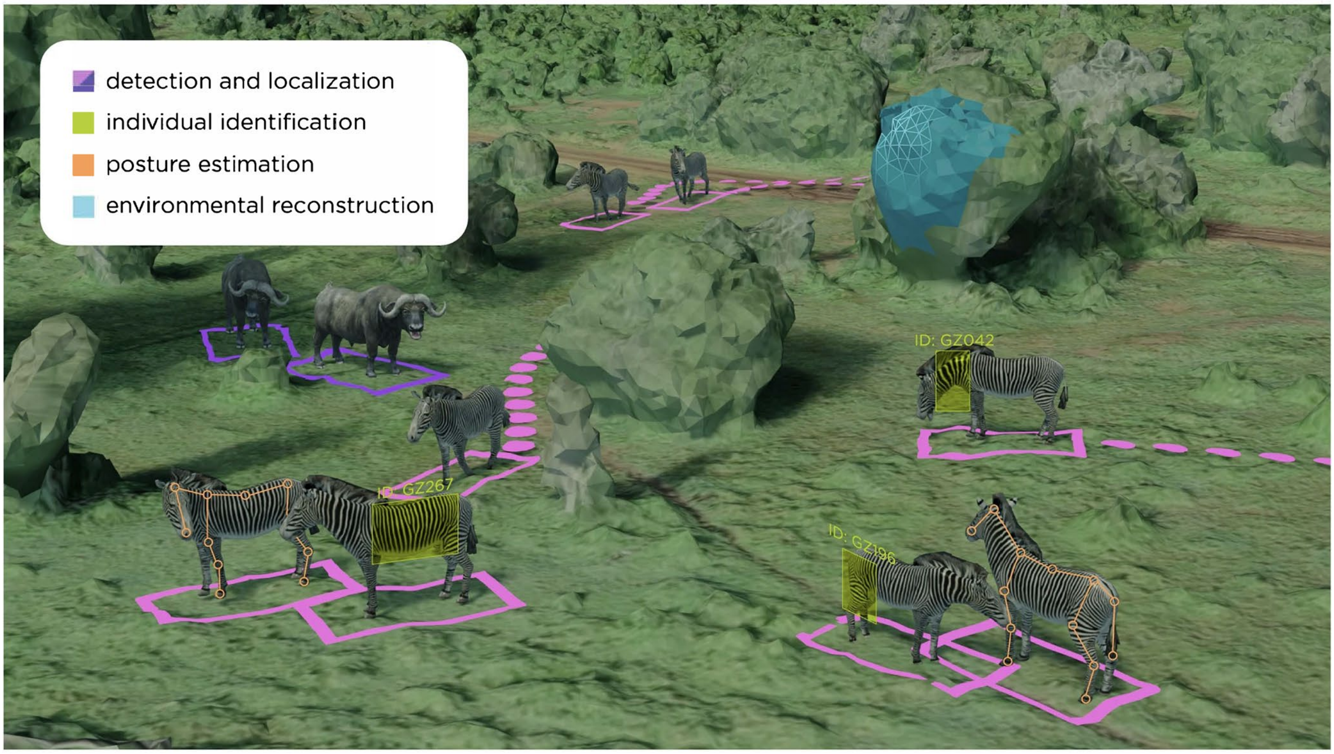

FIGURE 4 Setting a common vocabulary for computer science and ecology: Mapping computer vision tasks to ecological questions (Tuia et al., 2022).

3.1.2 | Annotation for computer vision tasks

Annotated data is a requirement for training and fine-tuning computer vision models to complete tasks to infer behaviour automatically. Data annotation completed manually by experts is the gold standard for dataset creation, though it represents one of the most significant bottlenecks in deploying computer vision pipelines for wildlife monitoring (Samiappan et al., 2024). The time investment for annotation varies considerably by task complexity, with simple detection tasks requiring less effort than complex behavioural annotations with temporal tracking. Multiple annotators working in a team can accelerate data labelling, but cross-validation protocols are essential to ensure consistency between annotators and maintain annotation quality (Samiappan et al., 2024). Inter-annotator agreement metrics should be established early in the annotation process to identify and resolve discrepancies in labelling criteria. Fine- tuning existing models on custom datasets is typically faster and less computationally expensive than training from scratch, making it the preferred approach when suitable pre-trained models are available (Kline, Stevens, Maalouf, et al., 2025).

Several specialized tools have been developed to streamline the annotation process for wildlife data. The Aerial Wildlife Image Repository (AWIR) (Samiappan et al., 2024) provides a centralized repository for curating wildlife drone datasets, offering standardized annotation guidelines to ensure consistency and quality while addressing common challenges such as ambiguity, occlusions and annotation bias. The kabr-tools package (Kline, Zhong, Kholiavchenko, et al., 2025) provides scripts for calculating time budget analysis from drone videos. It includes instructions for using the Computer Vision Annotation Tool (CVAT) (CVAT.ai Corporation, 2023) to generate annotations of animals from drone footage. This tool was developed to create the Kenyan Animal Behaviour Recognition (KABR) dataset and has since been used to develop the BaboonLand (Duporge et al., 2024) and Multi-Environment, Multi-Species, Low-Altitude Drone (MMLA)

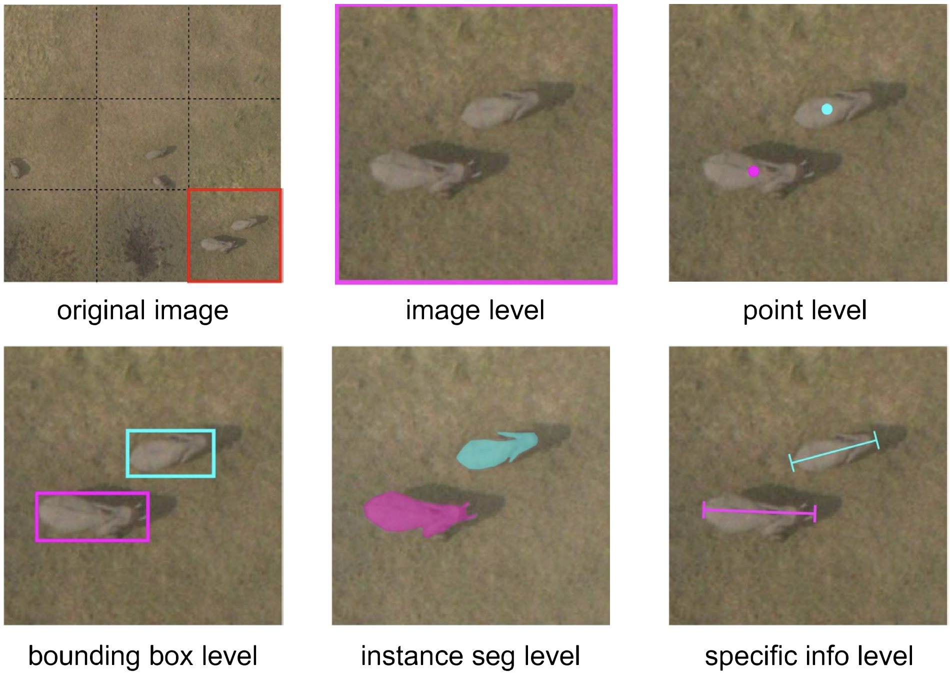

FIGURE 5 Detection and localization techniques applied to aerial elephant drone imagery (Xu, Wang, et al., 2024).

(Kline, Stevens, Maalouf, et al., 2025) datasets. SmarterLabelMe (Price & Ahmad, 2023) offers a novel annotation method to reduce temporal drift between frames, a significant challenge in drone datasets where both the camera and animals move simultaneously. This tool has been successfully used to generate large volumes of annotated behavioural data from video (Price et al., 2023). Conservation AI provides an online service to automatically process drone footage for animal detection and species classification using AI (Fergus et al., 2024).

Different computer vision tasks require distinct annotation approaches, as illustrated in Figure 5. For population-level estimates captured from high-altitude flights, point-level annotations are common (May et al., 2024), as they are faster to complete and sufficient for counting tasks where precise bounding boxes are not required. Species classification and behaviour recognition typically rely on bounding box annotations (Hang Chan et al., 2024; Kholiavchenko, Kline, Ramirez, et al., 2024), which provide spatial context while maintaining reasonable annotation speed. For video datasets intended for movement and behaviour studies, temporal tracking annotations that maintain individual identity across frames are essential, though these represent the most time-intensive annotation category (Kholiavchenko, Kline, Ramirez, et al., 2024; Naik et al., 2024).

3.2 | Computer vision tasks

The current research landscape in AI-driven animal ecology, summarized in Table 2, demonstrates a pronounced emphasis on detection and classification tasks. Detection and classification collectively constitute approximately 75% of all documented studies, with combined detection/classification approaches representing the predominant methodological framework. Convolutional Neural Networks (CNNs) maintain architectural dominance across the field, manifesting through diverse implementations including YOLO variants (Cusick et al., 2024; Krishnan et al., 2023; Rančić et al., 2023), Faster R-CNN configurations (Chalmers et al., 2019, 2021; Lenzi et al., 2023), RetinaNet architectures (Eikelboom et al., 2019; Kabra et al., 2022) and specialized CNN implementations (Dujon et al., 2021; Gray et al., 2019; Hayes et al., 2021), representing approximately 90% of all surveyed studies. Conversely, transformer-based architectures, such as X3D models (Kholiavchenko, Kline, Kukushkin, et al., 2024), remain substantially under-represented, appearing exclusively in behaviour analysis applications and constituting fewer than 5% of total studies, indicating limited adoption of contemporary deep learning paradigms despite their demonstrated efficacy in broader computer vision contexts. Tracking methodologies account for approximately 15% of research efforts (Koger et al., 2023; Luo, Li, et al., 2023; Noguchi et al., 2025), while specialized applications including individual identification (Crall et al., 2013; Desai et al., 2022; Nepovinnykh et al., 2024), pose estimation (Graving et al., 2019; Mathis et al., 2018; McNutt et al., 2024) and behaviour analysis (Hang Chan et al., 2024; Kholiavchenko, Kline, Ramirez, et al., 2024; Price et al., 2023) each represent less than 10% of documented studies. Performance metrics exhibit considerable variability across taxonomic groups and computational tasks, with detection and classification studies typically achieving accuracies ranging from 70% to 95%, while more sophisticated behavioural inference tasks demonstrate more modest performance ranges of 62%–87%. Critically, real-time processing capabilities are implemented in merely 15% of surveyed studies, underscoring a substantial disparity between laboratory-based analytical capabilities and practical field deployment requirements for autonomous ecological monitoring systems

(Bondi et al., 2018; Chalmers et al., 2019; Luo, Li, et al., 2023; Luo, Zhao, et al., 2023; Tripathi et al., 2025).

3.2.1 | Detection and localization

Detection, shown in Figure 3a2, is the first step in a computer vision image-processing pipeline and involves annotating the image to indicate the presence of animals (Brown et al., 2022; Xu, Wang, et al., 2024). Localization is often combined with detection using bounding boxes to indicate the presence and location of the animals in the frame in one step, as shown in fig. 5 from Xu, Wang, et al. (2024). Detection and localization of animals from drone videos have been used to study both wildlife (Lamprey, Ochanda, et al., 2020), and livestock (Andrew et al., 2017; Barbedo et al., 2020; Brown et al., 2022; Han et al., 2019). For animals that tend to group closely, distinguishing individuals is challenging (May et al., 2024). Density maps have been proposed to individually localize animals that tend to group closely, such as penguins (Qian et al., 2023), sea lions and elephants (Padubidri et al., 2021). Using density maps for localization performs well on aerial drone imagery, mainly when the animals are small, or the photos are low resolution.

An excellent review of detection studies from drone imagery is provided in (Corcoran, Winsen, et al., 2021). This thorough review includes 19 studies published between 2015 and 2021 that use computer vision methods to detect animals from drone imagery automatically. Various drone platforms were used: 10 from multi-rotor drone platforms, 5 from fixed-wing platforms and 1 from a blimp. The probability of detection ranged from 30% to 100%. Nine studies used RGB sensors, four used infrared and three used a combination of both. Flight height above the ground ranged from 20 to 300 m, with an average of approximately 70 m and ground resolution varies from 0.01 to 13.7 cm/pixels. Various habitats were reported, including grasslands, wildlife enclosures, beaches, lakes and rivers, with canopy coverage ranging from none to moderate.

Terrestrial mammals constitute the largest category of animals studied using automated drone detection, with spatial resolutions ranging from 26 to 530 cm. Birds and marine mammals constitute the second-largest categories, with spatial resolutions of 31–137 and 80–2000 cm, respectively. Fish, reptiles and insects have also been detected using remote aerial imaging, although these categories occur with much less frequency (Xu, Wang, et al., 2024). The maximum spatial resolution of multi-rotor drones is 1 cm; for satellites, it is 30–50 cm (Xu, Wang, et al., 2024). Detection tasks using machine learning models are performed at different levels of detail depending on the chosen annotation method and granularity of the image data. These machine learning models perform best on drone image datasets that contain consistent backgrounds in open, flat habitats with limited occlusion from vegetation (Corcoran, Winsen, et al., 2021). A strong contrast between the animals of interest and the background for RGB drone datasets yields the best detection results (Corcoran, Winsen, et al., 2021). For cryptic species living in closed habitats with vegetation, drones equipped with thermal cameras are more effective for detection tasks than RGB cameras (B'arbulo Barrios et al., 2024; Corcoran et al., 2019; Kays et al., 2019; Longmore et al., 2017; Ulhaq et al., 2021).

3.2.2 | Species and demographic classification

Classification typically refers to species-level labelling and categorizing demographic features, such as age and sex, as shown in Figure 3a3. Species classification is commonly performed using AI models trained to categorize species based on their distinguishing morphologies, such as BioClip (Stevens et al., 2024). Classification is essential for calculating accurate population estimates from images containing multiple species, such as those collected with aerial surveys (Ulhaq et al., 2021). Aerial imagery datasets from satellites and drones may replace manned aerial population counts since unmanned surveys are less expensive and risky and may produce more accurate population counts, as demonstrated in (Eikelboom et al., 2019; Lamprey, Pope, et al., 2020; Wu et al., 2023). For marine animals, computer vision models have been used to classify several species of whales (Gray et al., 2019), seals, sea birds and sea turtles from drone images (Dujon et al., 2021). The aerial imagery of whales was further analysed to determine the size and length of whales (Gray et al., 2019). Photogrammetry measurements using drones have been used to measure the body length of bottlenose dolphins to identify the juveniles and assess the age-structure of critically endangered populations (Vivier et al., 2024). Drone imagery annotated using AI models to perform classification tasks has been effective in estimating populations of large bird colonies, which are difficult-to-count manually (Chen, Jacob, et al., 2023; Hayes et al., 2021; Hong et al., 2019; Kabra et al., 2022). Species can also be categorized based on their distinctive behaviour and movement patterns instead of their distinguishing morphology. Petso, Jamisola, Mpoeleng, Bennitt, and Mmereki (2021) proposed a technique to automatically classify species based on the characteristic behaviours exhibited by the herd using point pattern analysis. This technique of categorizing species based on their movement is accurate even at high altitudes, where convolutional neural network (CNN) object detectors such as YOLO (Redmon et al., 2016) frequently fail due to the small number of pixels per individual animal. Other work has demonstrated the feasibility of detecting and classifying animal species using CNNs based on their hyperspectral imagery. CNNs perform well at detection and classification tasks even when the animals are obscured by vegetation (McCraine et al., 2024). Demographic information may be automatically inferred from the drone imagery, such as determining juveniles based on their smaller stature or distinguishing marks (Dujon et al., 2021). Sexual dimorphism of a species and young appearing different than mature adults may cause CNN classifiers to mislabel individuals (Dujon et al., 2021). In this case, creating separate categories for different demographic classes is often helpful to improve the classifier's accuracy. Demographic labelling may be included in classification tasks, such as labelling animals as adults or juveniles, such as (Lenzi et al., 2023), distinguishing adult and calf caribou from drone imagery. In addition to improving classification accuracy, demographic information provides valuable behavioural context for group-living animals.

Demographic data allows biologists to determine patterns in individual behaviours as a function of various factors such as sex, age and relationship to other individuals in the group (Ozog'any et al., 2023).

3.2.3 | Tracking and movement

Tracking follows an animal moving through concurrent video frames or images, adding a temporal element to the localization annotation to create tracks. If sufficient temporal data is available, behaviour may be inferred by tracking individuals' movements across the landscape. Tracking data may infer basic behavioural states from the animal's velocity, such as walking versus standing. However, this level of temporal granularity is usually not collected for population count drone missions, which capture the presence of animals at a single point in time. Tracking data provides valuable insight into the social structure of group-living animals (Ozog'any et al., 2023), including how individuals and groups make decisions and interact with the landscape, as shown in Figure 2a. Drones have been successfully used to conduct tracking studies of group-living animals, including gelada monkeys, Grevy's zebras (Koger et al., 2023), Przewalski's horses (Ozog'any et al., 2023) and antelope (Rathore, Vadavalli, et al., 2023). MOTHe (multi-object tracking in heterogeneous environments) for animal video recording has been successfully used to track both blackbuck antelope and wasps using CNNs for detection and Kalman filter for tracking (Rathore, Sharma, et al., 2023). Tracking becomes very challenging if features in the environment occlude the animals. For example, a study tracking sea turtles at the surface with the BoT-SORT model had a 100% success rate, but only 46% of underwater turtles could be tracked (Noguchi et al., 2025).

Recently, approaches using computer vision to track group-living animals through the landscape autonomously have been proposed. Kline et al. (2023) proposes an autonomous tracking system using YOLO for a track-by-detection approach for herds of zebras. Similarly, region-of-interest (ROI)-to- centroid tracking technology used to reduce the processing cost of motion interpolation for identifying and tracking injured antelope (Luo, Zhao, et al., 2023). An autonomous drone navigation model using YOLO, paired with a long and short-term memory (LSTM) Kalman filter (KF) has been deployed to track ante- lope (Luo, Li, et al., 2023). This approach has been expanded multi-object tracking of individuals using DeepSORT (Zhang et al., 2024), which achieved a 79% multiple object tracking precision (MOTP) performance.

3.2.4 | Inferring pose, actions and behaviour

Behaviour may be inferred directly from video-based behaviour tracking or still image-based posture and pose categorization (Saad Saoud et al., 2024). Behaviour can be classified automatically from video using machine learning techniques, including YOLO-Behaviour (Hang Chan et al., 2024), X3D, I3D or SlowFast (Kholiavchenko, Kline, Kukushkin, et al., 2024) models. KABR proposes a computer vision pipeline to automatically infer behaviour from drone videos of zebras and giraffes, as shown in Figure 2d. Computer vision pipelines such as KABR (Kholiavchenko, Kline, Ramirez, et al., 2024) and Smart-LabelMe (Price et al., 2023) decrease the amount of manual effort required to train automatic behaviour recognition models leveraging computer vision techniques to clean the video data. Pipelines have been proposed to automatically infer behaviour from camera trap videos, such as (Brookes et al., 2023), which automatically detects and classifies the behaviour of great apes. Alternatively, behaviour may also be inferred from the animal's posture/pose using tools like DeepEthogram (Bohnslav et al., 2021), DeepLabCut (Mathis et al., 2018) and DeepPoseKit (Graving et al., 2019). Once the species is known, the key points on the animal's body can be mapped to determine its posture, which can be used to infer behaviour.

3.2.5 | Individual identification

Once the animal species is known, its unique markings or morphology may be used to visually identify the individual animal captured in the drone image using tools such as WildBook (ConservationXLabs). Wild-Book offers platforms for individually identifying over 50 species, including zebras, giraffes, sharks and whales. Nepovinnykh et al. (2024) proposes a computer vision pipeline for re-identification for species-agnostic patterned animals with small datasets using deep local feature aggregation. Drone imagery of individual animals must have sufficient pixels for individual estimation tasks. For tools such as HotSpotter, which identifies individual animals based on their unique patterns, at least 700 pixels is typically required to perform individual identification tasks successfully (Crall et al., 2013; Kline et al., 2023). Autonomous drones have been used to identify cattle based on their unique markings individually (Andrew et al., 2017, 2018). Mugger crocodiles have been individually identified from drone imagery using a CNN trained to detect their unique dorsal scute patterns visible on their backs (Desai et al., 2022), as shown in Figure 2c. Individual identification provides rich insight into the dynamics of group-living animals (Ozog'any et al., 2023) when combined with behaviour.

3.3 | Hardware and latency requirements for computer vision models

Computer vision models have minimum hardware requirements for compute, memory and storage. These requirements are particularly important to consider if computer vision tasks must be performed in real-time, such as the studies described in Chalmers et al. (2021) and Bondi et al. (2018). Animal ecology studies which process computer vision tasks in the field in real-time are indicated with a ✓ in the RTP column of Table 2. Edge devices, such as Raspberry Pis, Jetson Nanos or laptops, may augment a drone's computer hardware. Sufficiently robust edge devices are vital to meet an autonomous navigation system's latency requirements, which rely on computer vision models' output speed.

Latency refers to the time interval between collecting and analysing the image. Each instance of a computer vision model analysing an image is called an *inference request*. Computing capability may be provided by a central processing unit (CPU), a graphic processing unit (GPU) or both. Compute is measured by the number of cores, and CPU may also be measured by clock speed (GHz). Storage is where the data is kept long-term, whereas random access memory (RAM) stores data temporarily that the CPU needs to access quickly. For example, Ultralytics recommends a system with a CUDA-compatible GPU, at least 8 GB of RAM and at least 50 GB of free disk space for dataset storage and model training for YOLO models (Jocher et al., 2023). Ultralytics also provides specific YOLO models optimized for inference on edge devices, like NVIDIA Jetson (Jocher et al., 2023). Table 4 summarizes compute and memory specifications for popular edge devices.

The latency requirements for a particular study depend on how quickly the animals move in the frame and what the inference request is used for in the system. In this step, the data arrival rate is dictated by the behaviour of the species of interest and its interactions with the drone hardware. If the system uses an inference request to inform a navigation decision, such as YOLO for autonomous vision-based tracking (Kline et al., 2023), the latency requirements should be sufficient to keep the animal in view.

Latency requirements depend on the average speed of the species of interest or how fast the drone must move to keep the animals in view. For example, the required latency may change throughout the mission if the animals increase or decrease in velocity, such as when they go from running to grazing. Some computer vision model inference requests may not be a component of the control system component but still provide the practitioners with helpful information. For example, Meier et al. (2024) calculates the approximate distance between a drone and an animal in real-time. This gives the ecologist information about wildlife but is not a component of the navigation policy. The latency requirements for such studies should be less strict than those for model components of the control system.

4 | BEST PRACTICES FOR DRONE MISSION PLANNING, EXECUTION AND ANALYSIS

Our review shows that most drone-based animal ecology behaviour studies leverage AI as a critical component, indicating that such studies will continue to take an AI-driven approach. We recommend that experts carefully consider the possible computer vision pipelines required to analyse the data when designing and deploying drone-based AI-driven animal ecology (ADAE) studies. An ADAE study using drones comprises three phases: planning, execution and analysis, illustrated in Figure 3b. Aerial imagery may be gathered manually and analysed with computer vision post hoc. However, we recommend implementing AI into the deployment phase, if possible, to support autonomous missions, as illustrated in Figure 3. Recent advancements in edge AI system design make it possible to support inference requests in the field for real-time analytics and autonomous flight, such as those implemented in (Bondi et al., 2018; Chalmers et al., 2021). Edge computing brings computation and storage closer to the data source, near the network's *edge*, instead of relying on a centralized cloud data centre. Processing data locally on *edge*, for example, drones, or *fog* devices, for example, laptops, reduces latency and enables real-time decision-making. ADAE studies control remote sensing systems at runtime, filtering images, adjusting angles and changing camera or drone positions to improve data quality (Luo et al., 2024). AI-driven animal ecology workflows are unlike traditional field ecological studies because they require computational resources provisioned at the edge. Like traditional studies, AI-driven animal ecology studies can fail if the data collected is inadequate to evaluate the hypothesis. However, AI-driven animal ecology studies only succeed if the edge platform can quickly adapt runtime to capture high-quality visual data. Drones are innately adaptive if they are piloted well. Edge AI can reduce the burden on pilots, allowing ADAE studies to employ multiple drones and capture data from vast areas (Bala et al., 2023; Boubin et al., 2022; Kholiavchenko, Kline, Ramirez, et al., 2024; Luo et al., 2024). Edge AI can reduce reliance on a manual approach, promote reproducible data collection methodologies and improve data quality.

With edge AI supporting real-time inference in the field, ADAE studies can use computer vision models to build adaptivity and autonomy into the data collection process. Taking an AI-driven approach to animal ecology studies aid in overcoming challenges associated with computer vision performance, potential disturbance to the animals and navigation, as discussed in Section 5. Drones must capture imagery with sufficient resolution to complete each computer vision task. These minimum resolution requirements may be integrated into the control software to increase the percentage yield of usable data, such as ensuring a minimum distance from the

TABLE 4 Summary of common edge devices: Jetson Nano (NVIDIA, 2025), RaspberryPi (RaspberryPi) and a generic GPU-enabled laptop (Buzzi, 2024).

Device	GPU	CPU	Memory	Storage	Price (USD)
Jetson Nano	NVIDIA Maxwell architecture with 128 NVIDIA CUDA® cores	Quad-core ARM Cortex-A57 MPCore processor	4 GB 64-bit LPDDR4, 1600 MHz 25.6 GB/s	16 GB	$ 99
RaspberryPi 5	VideoCore VII GPU	Broadcom BCM2712 2.4 GHz quad-core 64-bit Arm Cortex-A76 CPU	LPDDR4X-4267 SDRAM	2 GB, 4 GB, 8 GB	$140
Laptop	GPU 8 GB	Intel® Core™ Processor	32 GB	1 TB	$2000

animals of interest (Meier et al., 2024). Safety features may be programmed into the autonomous control system to minimize the possibility of spooking the animals. This can used to automate the altitude guidelines recommended for a specific species (Afridi et al., 2024; Bennitt et al., 2019; Bevan et al., 2018; Duporge, Spiegel, et al., 2021; Hodgson & Koh, 2016; Mulero-P'azm'any et al., 2017; Schad & Fischer, 2023; Weston et al., 2020). Automating flight components reduces the pilot's cognitive burden and increases the reproducibility of drone datasets.

4.1 | Planning

The planning phase consists of establishing the study objective and study parameters. ADAE studies ideally are interdisciplinary collaborations with experts in animal ecology, computer vision, robotics and edge systems. When working with interdisciplinary teams, it is crucial to establish shared vocabulary and objectives (Rolnick et al., 2024). The planning checklist contains three main components: (1) the ADAE research question, (2) the aerial system characteristics and (3) legal and ethical considerations.

4.1.1 | AI-driven animal ecology research questions

Two main components of AI-driven animal ecology studies are (1) the ecological research question and (2) the computer vision model used to answer the research question. At a high level, the ecological research question will include the species studied, the habitat and the *surface-of-interest* (SI) (Rolland, Grøntved, Laporte-Devylder, et al., 2024). The SI refers to the part of the animal that contains data required to answer the ecological question. For example, an ADAE study seeking to identify whales individually would define the SI as the fluke (Rolland, Grøntved, Laporte-Devylder, et al., 2024). In contrast, a survey of zebra behaviour would want to capture the side-view of the animals (Kholiavchenko, Kline, Ramirez, et al., 2024), illustrated in Figure 6.

The computer vision models capture and analyse the SI to answer the ecological research question. At the planning step, it is decided which components of the computer vision pipeline will be run in real-time during data collection and which will be used to analyse the data post hoc. Once the list of computer vision tasks in the AI pipeline is determined, practitioners must select which models will perform each task. Details on the performance of specific models for these tasks are discussed in Section 3. Practitioners should establish latency and hardware requirements for the computer vision models, which will inform the characteristics of the aerial system. Latency requirements refer to the average time the system takes to complete an inference request, that is, to run a computer vision model to make a prediction. Hardware requirements include the compute and memory required to run and store an AI model. See Section 3 for details.

4.1.2 | Aerial system characteristics

Aerial system characteristics include the type and quantity of drones used, the compute sources available, the network characteristics and the navigation technique. The type of drone influences its battery life and mission range, while the navigation technique determines the level of autonomy. The drone model should fit the parameters established by the ADAE study research question, which considers ecological factors and computer vision tasks. For example, studies seeking to count a herd of animals over a large area are well-suited to fixed-wing drones, as they can quickly cover extensive landscapes. In addition, detection tasks may be performed on lower-resolution data collected at higher altitudes. In contrast, behavioural studies requiring high-resolution oblique imagery are better suited to multi-rotor drones. Their hovering capabilities make them ideal for monitoring animals, as they can easily transition between different static monitoring positions. Additionally, their mobility in three-dimensional space is less constrained by flight characteristics than that of fixed-wing drones, allowing for more flexible path planning and deployment. Depending on the computer vision tasks and models chosen to run in real-time, additional compute resources may be needed in the field to meet latency requirements. Compute resources are commonly additional laptops or RaspberryPis (Jolles, 2021). Devices used to augment compute resources in the system are called *fog devices* (Cao et al., 2020). The network communication bandwidth between the drones and fog resources should also be considered, as this impacts the system's ability to meet its latency requirements (Kline, O'Quinn, et al., 2024).

Finally, the navigation technique may be manual, automatic, semi-autonomous, or fully autonomous, as summarized in Table 5. Manual missions rely on human pilots to direct the drone. Semi-autonomous systems utilize real-time inference from computer vision models to guide the drone while requiring human oversight to ensure safety and allow for manual control. Fully autonomous missions coordinate the mission from start to end under human supervision. Automatic geo-fencing may assist human pilots in deploying multiple drones simultaneously, that is, swarm missions, to prevent collisions. For most missions, varying degrees of semi-autonomy with human oversight are preferred to comply with safety regulations.

4.1.3 | Legal and ethical considerations

Potential impacts to both humans and animals should be carefully considered when planning ADAE missions. The noise produced by drones may disturb animals, so the navigation process should be designed to minimize the possibility of disturbance (Afridi et al., 2025; Bennitt et al., 2019; Schad & Fischer, 2023). Gruber (2023) provides a framework for the ethical assessments of studying animal behaviour concerning disturbance and invasiveness, including drones. Drones flying at lower altitudes may induce vigilance behaviour (Bennitt et al., 2019). Fast flight speed is associated with increased

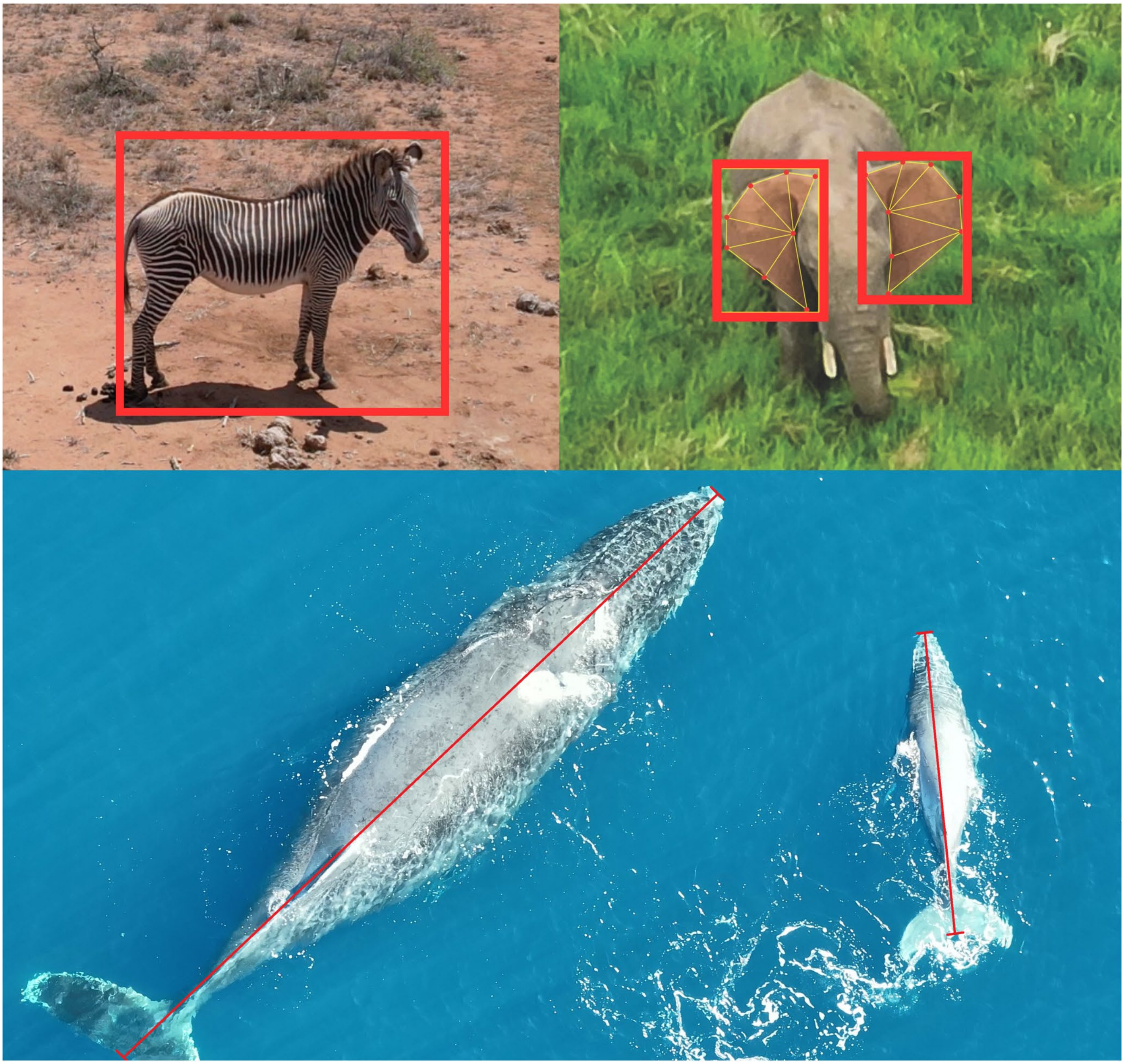

FIGURE 6 Examples of surfaces-of-interest (SI) shown in red for different species and ADAE missions. From top-left: Behaviour for Grevy's zebra (Kholiavchenko, Kline, Ramirez, et al., 2024); Individual identification of elephants (Rolland, Grøntved, Laporte-Devylder, et al., 2024); Demographic classification of whales (Laporte-Devylder, 2024).

noise levels, which may trigger animal responses, while slower speeds and gradual approaches may produce less intense responses (Bennitt et al., 2019; Mesquita et al., 2022). The approach distance, horizontal and vertical, also influences behaviour responses (Hodgson & Koh, 2016; Mulero-P'azm'any et al., 2017). The flight frequency influences the degree to which the animals may become habituated to the drone's presence (Pinel-Ramos et al., 2024). The background anthropogenic noise in the environment also impacts species' tolerance to the presence of drones and may influence the habituation process (Schad & Fischer, 2023). It is vital to obtain the proper operational permits before conducting drone operations in order to comply with regulations and manage risk appropriately (Maalouf et al., 2025). Drone safety entails minimizing ground risk and air risk. Ground risk includes the potential for a drone to fall and cause fatalities. Air risk includes the possibility of colliding with a manned aircraft. Ongoing work, such as developing risk assessment frameworks like the Specific Operations Risk Assessment (SORA) methodology, aims to quantify and mitigate these hazards (Joint Authorities for Rulemaking on Unmanned Systems (JARUS), 2024). Regulations around autonomous missions may not be established, so a manual pilot should oversee the mission to ensure safety and maintain airspace situational awareness. Maintaining reliable airspace situational awareness remains challenging, particularly in Beyond Visual Line of Sight (BVLOS) and autonomous missions (Maalouf et al., 2025). This challenge is due to the inherent constraints of current detection technologies and the complexities of integrating diverse cooperative and non-cooperative data sources. These issues require further systematic testing to enable accurate intruder detection and early conflict resolution (Maalouf et al., 2024). Regulations vary by region and country and may be restricted or banned in wildlife conservation parks. Common rules mandate that flights remain within Visual Line of Sight (VLOS), typically within 500 m from the pilot and up to 400 feet Above Ground Level (AGL). Operators must hold appropriate certification, avoid overflying crowds and densely populated areas, and obtain special permits for any deviations from these guidelines. As a general rule, drone missions are not permitted near airports. Practitioners should also consider the ethical considerations of using drones to study animal behaviour and the potential impact on both people and animals, both positive and negative. Working with animals may require the Institutional Animal Care and Use Committee (IACUC) permit to conduct research in the United States or an equivalent institution in other countries. The social impact of drone studies should also be considered. Surveillance technologies such as drones may inadvertently capture humans, causing privacy concerns. Engaging with populations that drone studies may impact is an important component of conducting socially responsible science (Sandbrook et al., 2021).

4.2 | Mission execution

4.2.1 | Computer vision tasks

The first execution phase includes collecting imagery data with drones of the animals of interest or focal species and extracting the collected frames for analysis, shown in Figure 3a1. Next, detection and localization tasks are performed, shown in Figure 3a2. Detection and localization answer the following questions: Is there an animal in this frame? If so, where is the animal located in the frame? If an animal is detected, classification may be performed on the image region containing the animal, Figure 3a3 to determine species, sex or other demographic category. Once classification is complete, additional tasks may be performed, including tracking, posture, behaviour and individual identification (Figure 3a4–7). These computer vision tasks may inform runtime adaptations as long as the upstream dependencies are also performed and the latency requirements for the navigation policy are met. Runtime adaptations include relocating drones, adjusting the sampling duration and updating the edge resource management to respond to workload demands.

4.2.2 | Navigation

Drone studies typically utilize one of four navigation methods: manual, automatic, autonomous or hybrid, summarized in Table 5. Manual piloted missions offer flexibility, allowing pilots to adjust trajectories in real-time based on environmental conditions or animal behaviour (Ryan et al., 2022; Stein & Georgiadis, 2006). However, this approach raises concerns about reproducibility, places a heavy burden on pilots and limits the scope to small areas and short durations. The data collected manually is insufficient for long-term wildlife behaviour studies and is costly and time-consuming (Kholiavchenko, Kline, Ramirez, et al., 2024; Kline, Berger-Wolf, et al., 2024). Additionally, these missions require extensively skilled operators in the fields of animal behaviour, environmental analysis and piloting Ryan et al. (2022). Consequently, relying on a limited operator workforce is not a sustainable solution for large-scale data collection.

Automatic flight, which uses path-planning tools that allow a drone to follow a set of specified GPS waypoints, can reduce the burden on the pilot and generate suitable drone behaviours for

TABLE 5 Comparison of drone navigation methods for animal behaviour studies.

Method	Advantages	Disadvantages	Best use cases
Manual	• Flexibility in real-time adjustments • Adaptable to environmental conditions • Responsive to animal behaviour	• Poor reproducibility • Heavy burden on pilots • Limited to small areas • Limited duration • Requires extensively skilled operators	• Situations requiring immediate human judgement • Complex, short-duration missions
Automatic	• Reduced pilot burden • Follows pre-planned GPS waypoints • Efficient for systematic surveys	• Inflexible once launched • Unable to adapt to dynamic features • Predefined flight path limitations	• Population counts • Environmental mapping • Static feature surveys
Autonomous	• On-board decision-making • Dynamic trajectory planning • Leverages AI capabilities • Addresses operator shortage	• Complexity of implementation • Requires sophisticated AI systems	• ADAE studies • Wildlife monitoring • Dynamic feature tracking
Hybrid	• Combines autonomous capabilities • Maintains human oversight • Balances automation with manual control	• More complex system architecture • Requires both AI systems and skilled operators	• Complex missions requiring both automation and human judgement • Situations where reliability and adaptability are crucial

con- ducting ADAE studies. This methodology efficiently performs population counts or environmental mapping (Hodgson et al., 2018; Wood et al., 2021). However, this approach is unsuitable for adaptive tracking of dynamic features, such as animals in an environment: the flight path is defined before taking off. Autonomous drone solutions represent a promising approach for ADAE studies, offering standardized data collection for AI-powered wildlife monitoring while addressing the shortage of skilled operators. These drones leverage on board decision-making capabilities and computer vision models to dynamically adjust their flight paths in response to environmental conditions (Faessler et al., 2016; Rolland, Grøntved, Christensen, et al., 2024).

Missions conducted using commercially available UAS typically use a hybrid approach, a combination of manual and automatic capabilities. Manual missions may still use real-time computer vision models to inform the pilot's decisions, such as distance estimates (Meier et al., 2024). Manual missions are straightforward to execute with commercially available drones but require specialized expertise in a particular species and habitat to collect data (Hughey et al., 2018; Kholiavchenko, Kline, Ramirez, et al., 2024; Ozog'any et al., 2023). For an automatic mission, the drone executes pre-programmed logic that does not require direct human intervention. Common examples of automatic manoeuvres available on commercial UAS include automatic launch, automatic return-to-home, flying to predetermined waypoints and automatic tracking of people or vehicles (Hadidi et al., 2021). Autonomous or semi-autonomous methods use computer vision models as an input into the control system, such as the tracking-by-detection methods (Kline et al., 2023; Luo et al., 2024), illustrated in Figure 7a.

4.3 | Data analysis and management

4.3.1 | Short-term data management

Managing the storage, transfer and analysis of the large video files produced by drone missions in remote field sites is inherently challenging. During the Kenyan Animal Behaviour Recognition (KABR) project, which captured behaviour 4K video data of zebras and giraffes, each flight generated 20.5 GB of footage. The team flew roughly six missions per day for 3 weeks, yielding approximately 1 TB of total data, mainly video, plus telemetry files, photos and field notes (Kholiavchenko, Kline, Ramirez, et al., 2024; Kline, Kholiavchenko, et al., 2024).

A practical workflow for managing such extensive data in resource-constrained field environments begins by downsampling the live video feed to 1080p (Kline, Zhong, Irizarry, et al., 2025). A ground-control laptop equipped with a modest GPU (at least 4 GB VRAM) and 16–32 GB RAM can then display telemetry and execute lightweight CNN models in real time to support autonomous operations. The native 4K or 5K footage is simultaneously written to the drone's SD card for later, fine-grained analysis. To prevent I/O bottlenecks during data offloading, the laptop should reserve ample free disk space for temporary files. Immediately after each flight, or, at minimum, at day's end, the SD card and accompanying telemetry logs should be duplicated to an external solid-state drive (recommended minimum of 1 TB). This onsite redundancy markedly reduces the risk of data loss while preserving the full-resolution archive for subsequent processing. Once a stable connection is available, the data is synchronized to cloud storage (25 megabits per second of sustained bandwidth for uncompressed 4K video, much less for stills or compressed clips). This staged *stream-low, store-high, sync-when-able* strategy minimizes bandwidth bottlenecks, preserves data fidelity and ensures that downstream pipelines, whether local, cloud or HPC, receive a complete, versioned archive of data collected in the field.

4.3.2 | Post hoc data analysis

Once the drone mission is complete, the imagery data will be analysed to answer the ADAE study's research question. Computer vision models that require more compute, memory or processing time than is practical to support in the field or are not required for navigation should be implemented post hoc. In addition to the imagery data, the telemetry data should be analysed to determine how future missions may be improved. Telemetry data captures the drone's status during the mission, including altitude, GPS location, battery level, heading and gimbal position. For example, determining whether sufficient pixels were collected to infer behaviour or if the SI of each individual was collected with adequate granularity (Rolland, Grøntved, Laporte-Devylder, et al., 2024). Kline, Berger-Wolf, et al. (2024) analysed the KABR telemetry dataset to determine the optimal altitude, speed and bounding box size to infer behaviour from oblique aerial videos. Integrating this insight into the autonomous tracking model improved navigation performance by 18%.

4.3.3 | Long-term data storage and accessibility

Large datasets generated by ADAE studies require systematic organization and post-processing protocols to ensure efficient analysis workflows, building upon established Imageomics best practices (Balk et al., 2024). Kline, Zhong, Kholiavchenko, et al. (2025) provides guidelines for managing large video datasets throughout the annotation process, including systematic metadata embedding in filenames following the format `YYYYMMDD-species-location-videoidXX.mp4` to facilitate dataset organization and automated processing workflows. For sharing datasets with the broader research community, preferred hosting solutions for machine learning-ready ecological datasets include Harvard Dataverse, Kaggle, Hugging Face and OpenML platforms. Following open-source dataset best practices, data contributors should provide comprehensive documentation, including dataset cards, version control mechanisms, standardized train/validation/test splits and clear licensing information with a preference for permissive licences that facilitate reuse while respecting ethical considerations for wildlife data. Annotation platform optimization requires strategic resolution management to balance computational efficiency with analytical accuracy (Kline, Zhong, Kholiavchenko, et al., 2025). High-resolution drone footage (4K-5K) presents processing challenges in annotation platforms such as CVAT (CVAT.ai Corporation, 2023), including extended buffering times and memory limitations. Downscaling raw video files to lower resolution before uploading significantly improves platform responsiveness while preserving sufficient detail for accurate manual annotation. However, coordinate transformations must be carefully managed when scaling annotations back to the original resolution for subsequent processing steps. Large-scale video datasets often exceed single-system storage capacity, necessitating distributed storage strategies. CVAT instances require a minimum of 20% free memory to maintain stable operation, often necessitating separation of raw data storage from annotation processing environments. Research-optimized data transfer tools such as Globus (Foster, 2011) provide robust solutions for moving large video datasets between storage systems with secure, high-throughput transfers and data integrity verification. This distributed storage approach enables resource optimization while aligning with modular workflow design principles (Balk et al., 2024).

4.4 | Example ADAE drone missions

Real-world ADAE missions (Figure 7; Table 6) succeed only when *planning*, *execution* and *analysis* are tightly integrated.

- *Kenyan Animal Behaviour Project (KABR)*. The fine-scale behaviour analysis of zebras and giraffes necessitated fully manual, expert piloting at low altitude, with no edge compute available during flights. The entire 4K RGB stream (~10 GB per mission) was offloaded daily and later trimmed to focus on individual animals for automatic behaviour labelling with the X3D model. The full videos, cropped scenes, telemetry and field notes are retained for future mission refinement and made publicly available.
- *SPOT*. Anti-poaching operations demand low latency and low bandwidth. Every 720p/25 fps thermal frame is processed at ~5 fps by Faster R-CNN, either locally on a K40 GPU or remotely on AzureBasic/AzureAdvanced GPU VMs, with 100% of incoming video frames analysed in the field. The videos are retained for further detection model refinement, but are not made publicly available due to security and privacy concerns.
- *WildWing*. Autonomous herd-centroid tracking was deployed on cost-effective hardware, a Parrot Anafi and GPU laptop, downsampling 1080p video at 1 fps during mission execution. Keyframes are processed on a field laptop to update the navigation in real time. The full videos, cropped scenes, telemetry and field notes are retained for future mission refinement, and made publicly available.
- *WildLive*. Near real-time 4K multi-animal tracking directly on a Jetson Orin AGX edge device in the field. The full-resolution frames enter a SAHI sampler, YOLOv-based detect/segment and finally a sparse optical-flow tracker at 7.5 fps (4K) or 17.8 fps (HD).

These four ADAE missions illustrate how each study's specific SI and species requirements determined at the planning stage cascade through navigation autonomy and edge-compute choices to dictate (1) how much of the video stream is processed in the field and (2) how much is preserved for reproducibility. Making both layers explicit helps new ADAE practitioner's budget storage, bandwidth and annotation resources more realistically. For example, the KABR project's planning focus on detailed behavioural analysis of specific species necessitated manual expert piloting during execution

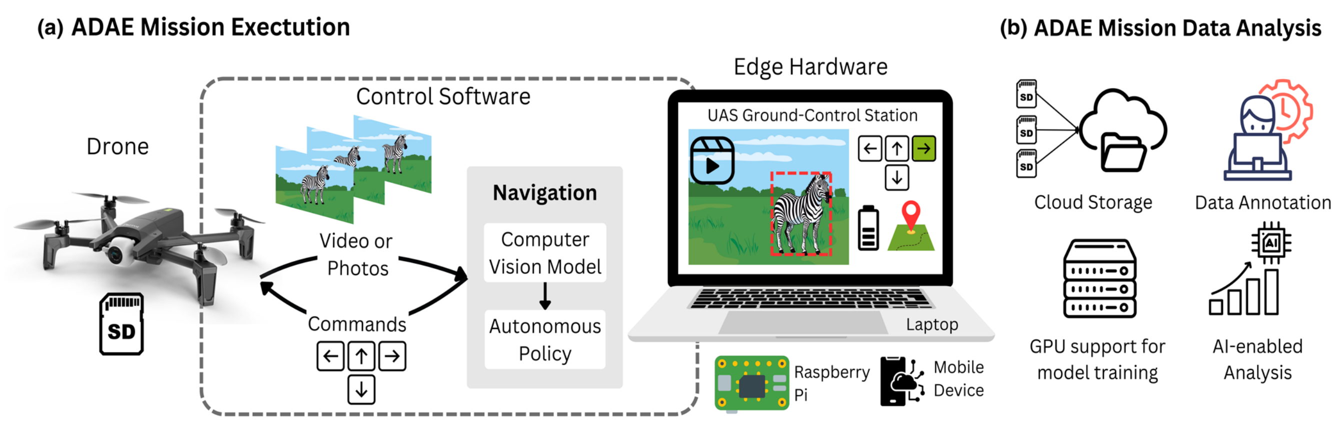

FIGURE 7 ADAE Drone Mission Deployment and Execution. (a) Unmanned Aerial System (UAS) Field Deployment adapted from WildWing (Kline, Zhong, Irizarry, et al., 2025). The UAS consists of three components: Drone(s), control software and ground-control station, typically a laptop equipped with GPU. The control software connects the drone to the autonomous navigation policy and allows users to monitor the system during deployment. The navigation policy analyses video frames using computer vision models and determines the next commands to send to the drone. The control software is hosted on the laptop, where the users can also monitor the UAS status. (b) Analysis tasks performed after the mission is completed include storing data in the cloud, data annotation, model training and AI-enabled analysis.

TABLE 6 Examples of real-world ADAE drone missions.

Project	Planning: Species/Habitat • Surface-of-Interest (SI) • Aerial System • Data & Schema Plan	Execution: Navigation • CV tasks • Real-time Pipeline • In-field Storage/Backup	Analysis: Post hoc AI tasks • Curation • Long-term Storage/Sharing
KABR (Kholiavchenko, Kline, Ramirez, et al., 2024)	Zebra, Giraffe (Kenya) • Lateral flank behaviour • DJI Air 2S • *Data plan*: 4K @ 30 fps RGB → 10 GB/mission, daily off-load schedule, CSV + EXIF metadata template	***Manual*** piloting • Detection → ID → Behaviour (offline) • No edge compute • SD card mirror to rugged hard drive at day-end; field notebook logs IDs of cards/devices	Two-stage annotation (CVAT) → X3D/I3D behavioural models • Cluster post-proc, versioned by DVC • Dataset (1 TB) stored on Ohio Supercomputer; Processed portion of dataset and code + models public via Zenodo DOI
SPOT (Bondi et al., 2018)	Poachers + Wildlife (Botswana) • Human/animal thermal signatures • Matrice + FLIR • *Data plan*: 720 p/25 fps thermal stream, 7-day on-board ring buffer, JSON alert schema	***Semi-autonomous*** patrol with live-stream dashboard for manual supervision • *Real-time*: Faster R-CNN @ 5 fps on K40 GPU (field laptop) *or* Azure-Basic NC-6 (Tesla K80) via SFTP + Python; AzureAdvanced TensorFlow-Serving cluster (NC-6, Kubernetes, 4-thread client, ProtoBuf) batches frames and returns lightweight annotations to minimize bandwidth	Post hoc detection model refinement • Training/test videos • Limited sharing due to privacy and security concerns
WildWing (Kline, Zhong, Irizarry, et al., 2025)	Grevy's Zebra, Giraffe, Przewalski's Horse (Ohio) • Herd centroid • Parrot Anafi + GPU laptop • *Data plan*: 1080 p RGB, 1 fps key-frame extraction, flight mission metadata, projected 20 GB/mission	***Autonomous*** herd tracking • *Real-time*: YOLOv5su detect/-track → waypoint update • Frames, telemetry and videos saved to external hard drive, auto-sync to field laptop nightly	Automated pipeline → Telemetry alignment, behaviour classification • Moderate volume (200 GB total) • Final dataset and code + models public via Zenodo DOI
WildLive (Dat et al., 2025)	Zebra, Giraffe, Elephant in Ol Pejeta (Kenya) • Individual ID + trajectories • DJI Mavic 3 E/Pro + custom quad, Jetson Orin AGX • *Data plan*: 4K/30 fps RGB (3 GB per 3 min); per-frame bounding box annotations (JSON)	*Operator-assisted* flight • *Near real-time*: SAHI sampling + YOLO detect/segment → LK sparse optical-flow tracking @ 17.8 fps (HD)/7.5 fps (4K) • Stores cropped detections + point trajectories	Tracklet smoothing, benchmark vs SOTA tracking methods • WildLive Dataset: 22 videos, 19,139 frames, 215,800 boxes + masks (250 GB) • Versioned with DVC, Final dataset and code + models to be made public via Zenodo DOI
Cross-project challenges	Manual flight variability, behaviour annotation complexity	Night operations, human/animal classification, autonomous navigation	Limited labelled data, processing speed, data storage scaling

Note: These studies reveal that successful ADAE deployment requires careful integration across all three phases, with planning decisions (species, hardware, surface-of-interest (SI)) directly constraining execution methods (navigation autonomy, real-time processing) and analysis capabilities (data storage, processing pipelines). Early planning decisions (data rates, schema, storage budgets) constrain in-field capture and backup strategies, which in turn shape post hoc analysis pipelines and long-term archiving. DVC = Data Versioning Control, this allows researchers to reproduce experiments exactly, roll back to previous versions of data and track how data changes over time.

Abbreviations: fps, frames per second; SOTA, state-of-the-art. SAHI, Slicing Aided Hyper Inference.

and computationally intensive post-processing with specialized behaviour models, while SPOT's anti-poaching mission requirements led to semi-autonomous patrol routes with thermal imaging and minimal data storage optimized for real-time alerts. Similarly, WildWing's planning goal of standardized herd tracking informed the choice of autonomous navigation with cost-effective hardware, enabling automated data pipelines, whereas WildLive's emphasis on high-resolution individual tracking required powerful on-board processing during execution and large-scale dataset management during analysis.

5 | CHALLENGES AND SOLUTIONS FOR STUDYING COLLECTIVE ANIMAL BEHAVIOUR WITH DRONES AND COMPUTER VISION

5.1 | Computer vision challenges and solutions

Drones must capture photos or videos at sufficient granularity to perform each computer vision task in the pipeline for inferring behaviour, as shown in Figure 3. If there are insufficient pixels to detect the animals or classify the species, the behaviour is unlikely to be determined manually or using computer vision models. Petso, Jamisola, Mpoeleng, Bennitt, and Mmereki (2021) found that environmental factors such as camouflage, occlusion, shadows and seasonal vegetation changes reduce wildlife detection accuracy by obscuring distinguishing features, with additional variability introduced by sun position and background elements like clouds and non-target animals. Inconsistent behaviour and differing backgrounds or habitats adversely affect the performance of ML models in performing computer vision tasks (Dujon et al., 2021). Species classifiers may struggle with populations that exhibit sexual dimorphism or are young and appear different from adults (Dujon et al., 2021). Open habitats with little occlusion from vegetation and consistent background perform best for detecting large animals from fixed-wing drones and drones equipped with RGB sensors (Brown et al., 2022). Drones equipped with hyperspectral imagery sensors also detect animals partially occluded by vegetation (Longmore et al., 2017; McCraine et al., 2024). In habitats with more vegetation coverage or occlusion, infrared (thermal) and multi-rotor best detect animals, particularly if the animals are small (Brown et al., 2022), or occluded by shadows in low-light conditions (Krishnan et al., 2023). Fine-tuning existing models on curated wildlife drone datasets improves accuracy and generalizability across habitats (Kline, Stevens, Maalouf, et al., 2025).

Animal behavioural studies using machine learning techniques often suffer from the *long-tailed distribution problem*. Rare species or behaviours may infrequently occur in the dataset, causing a *long tail* in which most of the samples used in training are of common categories (Blair et al., 2024; Kholiavchenko, Kline, Ramirez, et al., 2024; Kline, Stevens, Maalouf, et al., 2025). Machine learning models trained on such unbalanced datasets struggle to categorize rare categories accurately. This challenge is reflected in the accuracy results from KABR (Kholiavchenko, Kline, Ramirez, et al., 2024), which reported an 87% accuracy per instance in predicting behaviour but a 61% Top-1 accuracy per class accuracy. MammalNet reported a Top-1 accuracy of 51% for animal behaviour classification from video (Chen, Hu, et al., 2023). This issue is addressed in (Zheng et al., 2021), which offers a solution for improving the accuracy of rare species classifications from drone videos using a self-supervised pretraining technique. Synthetic data produced by generative AI may augment sparse datasets to increase the training sets of rare species or difficult-to-capture behaviours (Bonetto & Ahmad, 2024). Beyond data augmentation, generative AI shows promise for extending observations of ecological patterns and increasing the accessibility of ecological data, potentially transforming how ecologists approach data-scarce research questions (Rafiq et al., 2025).

Digital twin approaches are emerging as another powerful tool for precision biodiversity monitoring, creating virtual representations of ecosystems that can integrate real-time data from multiple sources, including drone surveys (Sharef et al., 2022). These digital twins enable continuous biodiversity projection modelling and facilitate incremental learning while reducing uncertainties from the complex factors contributing to biodiversity declines. Realistic simulation environments also accelerate the development and validation of autonomous navigation approaches by providing controlled testing conditions that would be impractical or risky to replicate in the field (Grushchak, Kline, Pianini, & Farabegoli, 2024). These virtual environments enable rapid iteration of flight parameters, obstacle avoidance algorithms and animal tracking behaviours without the ethical concerns of repeated wildlife disturbance or the logistical constraints of field deployments. By testing and refining autonomous drone systems in simulation first, researchers can ensure safer and more effective field operations while reducing the time and cost associated with iterative field testing.

5.2 | Infrastructure and navigation challenges and solutions

Automatic and semi-autonomous navigation policies offer significant advantages over manual flights, as discussed in Section 4.2.2. However, these missions are difficult to implement in the field due to infrastructure and navigation challenges. Most computer vision models are initially developed to be run on powerful supercomputers. This limits the deployment of autonomous aerial systems reliant on computer vision models since running large, powerful models in the field on edge devices is challenging. Further, designing navigation approaches with sufficient flexibility to be generalizable across multiple settings to be effective on different populations, species and habitats is challenging.

Autonomous drones have proven reliable when deployed in domains such as digital agriculture and search and rescue, but little guidance exists on drone navigation policies for animal behaviour studies. Automatic manoeuvres, such as pre-programming a drone to fly to a set of specified GPS waypoints, may reduce the burden on manual pilots and aid in experimental replicability. However, automatic or pre-programmed UAS are often unsuitable for collecting data on multiple moving targets, such as animals, without disturbing them. Automatic manoeuvres are not well-suited to complex, dynamic scenes required for surreptitiously conducting surveillance missions on multiple moving targets. The behaviour and movements of the multiple moving animals are often not known before the mission begins. As such, pre-programmed routes are ineffective for long-term tracking required for animal ecology studies.

Drone navigation policies should aim to be non-disruptive and not induce the animals to alter their behaviour. Autonomous, non-disruptive drone navigation policies have been proposed for more general settings, but more research is required to apply these approaches to animal ecology missions. Previously proposed covert surveillance of moving objects formulate the problem as adversarial (Kouzeghar et al., 2023; Zhou et al., 2022), which may not be applicable to animal studies. For example, one drone performing evasive manoeuvres to follow a moving vehicle undetected (Huang et al., 2022). Covert surveillance has been explored (Hu et al., 2021), but the problem is formulated as a single drone following a single subject, limiting its usefulness in capturing group behaviours. Such an approach does not consider the undesirable noise produced from these evasive manoeuvrers or the group dynamics of multiple moving targets.

The ability to track moving targets with multiple drones, that is, swarms, has been explored (Bandarupalli et al., 2023; Parker & Emmons, 1997). Multiple drones working collectively in a swarm can collect data from various angles, providing better coverage of the animals (Naik et al., 2024; Rolland et al., 2025). Multiple views of the subject(s) increase the likelihood of collecting valuable biological behaviour data, such as rare behaviours like fighting or mating. Commercially available drones are usually limited to 30 minutes of flight time, which decreases in the presence of wind. Swarms overcome drone hardware constraints, namely limited power and computing, to extend mission time and throughput. However, swarms may produce excess noise and may require more edge infrastructure to support the navigation system's compute requirements.

Drones equipped with on-board GPUs, such as those incorporating a Jetson Nano as in the WildLive project Dat et al. (2025), enable low-latency execution of computer vision models directly on the aircraft, bypassing the need to transmit data to an external edge device for inference. This capability is essential for time-sensitive ecological monitoring tasks or field sites with limited or unreliable communication infrastructure (Kline, O'Quinn, et al., 2024). However, the inclusion of GPU hardware and high-capacity batteries significantly increases payload weight, necessitating the use of larger UAV platforms that demand specialized operator training and regulatory clearance. These heavier-class drones also tend to be more costly and acoustically disruptive, which may constrain their suitability for monitoring noise-sensitive species or conducting unobtrusive behavioural studies.

5.3 | Potential disturbance from drones

Ecologists have increasingly expressed concerns regarding the potential risks posed by drone disturbances to wildlife (Schaul et al., 2015). Edge-enabled autonomous navigation equipped with safeguards could reduce the disturbance. The mere presence of drones can artificially induce animal behaviours, resulting in biased datasets (Afridi et al., 2025). Variability in reactions to drones is noted across species, demographic classes and habitats, with some studies detailing these differential responses (Bevan et al., 2018; Brisson-Curadeau et al., 2025; Schad & Fischer, 2023). Comprehensive research investigating terrestrial mammals' responses to drones reveals that animal behaviour is highly dependent on the drone's distance and altitude relative to the species in question and their habitat (Bennitt et al., 2019). Studies consistently show that flight altitude, approach distance, flight speed and drone noise levels significantly affect wildlife responses (Mesquita et al., 2022). General guidelines suggest maintaining minimum distances of 30–100 m depending on species, with birds typically showing minimal reactions when drones maintain distances over 40 m during take-off (Weston et al., 2020). Larger mammals like elephants and giraffes become more vigilant at 50–80 m, respectively (Bennitt et al., 2019), while marine mammals such as bottlenose dolphins display behavioural changes primarily at lower altitudes with responses intensified by longer hovering times (Fettermann et al., 2019; Giles et al., 2021).

Flight patterns, engine types and drone size also influence animal responses (Mulero-P'azm'any et al., 2017). Species sensitivity to drone noise depends on frequency and intensity, characterized by audiograms, which can help provide a basis for determining optimal drone flight altitudes to minimize disturbance (Duporge, Spiegel, et al., 2021). These findings highlight the need for species-specific flight altitude considerations to minimize wildlife disturbances from drones. However, flying at higher altitudes may also limit the ability to detect animals and accurately classify their species and behaviour (Petso, Jamisola, Mpoeleng, & Mmereki, 2021). For instance, an analysis of the KABR data found that drone missions conducted at altitudes between 10 and 30 m generated the best data for inferring zebra behaviour Kline, Berger-Wolf, et al. (2024), which is lower than the altitudes recommended in other reviews of zebra responses to drones (Bennitt et al., 2019; Petso, Jamisola, Mpoeleng, & Mmereki, 2021). Therefore, mission planning should carefully weigh these parameters to strike a balance between achieving the necessary accuracy and minimizing disturbance to wildlife (Hodgson & Koh, 2016; Schad & Fischer, 2023).

6 | FUTURE TRENDS

6.1 | Edge AI for real-time processing

Traditionally, animal ecology behaviour studies have relied heavily on offline data processing. However, recent research has begun exploring the potential for more immediate data analysis with Edge AI. As shown in Table 2, we identified five studies using real-time computer vision inference to collect drone data from 2018 to the present. Edge AI systems perform computations at the edge near the source of the data, as opposed to sending data to a centralized cloud server (Singh & Gill, 2023). Edge AI requires massive amounts of data and computing capacity. Still, recent advancements in sensors, hardware and communication technology like 5G and 6G networks (Jolles, 2021; Singh & Gill, 2023) have made this possible on the edge in remote regions. Ongoing improvements in the performance of edge processors will enable the deployment of more sophisticated computer vision on edge devices in the future. Researchers are exploring using various mobile computing devices, such as ruggedized laptops, tablets or custom-built portable units, to augment in situ processing capabilities. Such devices can serve as intermediate processing nodes, bridging the gap between data collection points and cloud infrastructure. Techniques such as model pruning, quantization and knowledge distillation are being explored to run complex models on resource-constrained edge devices (Eccles et al., 2024; Giovannesi et al., 2024; Kline, O'Quinn, et al., 2024; O'Quinn et al., 2025). These approaches show promise for deploying advanced algorithms on edge devices with limited resources, though their effectiveness in ecological field studies needs further research (Jolles, 2021; Whytock et al., 2023).

6.2 | Computer vision for the edge

Edge computing and computer vision are increasingly applied to AI-driven animal ecology studies, enabling new data collection and analysis approaches. This convergence of technologies has the potential to enable real-time analysis of aerial data gathered from drones using computer vision. As the volume and complexity of ecological data continue to grow, efficient computing approaches are needed to handle the unique challenges posed by aerial monitoring of animals in remote environments. Drones equipped with on-board GPU are increasingly available, enabling real-time, on-board processing for autonomous navigation policies (Andrew et al., 2019; Dat et al., 2025; Kline, Berger-Wolf, et al., 2024; Luo et al., 2024). Currently, applications of drone imagery to study animals are dominated by detection studies, consisting 75% of studies (Table 2). A recent review of deep learning for animal detection in drone imagery identified 200 studies on this topic (Axford et al., 2024).

As edge computing becomes more widely adopted, we predict more studies traversing 'further down the pipeline' to tracking and behaviour detection computer vision tasks. Tasks including individual identification, pose estimation and behavioural analysis constitute less than 10% of documented studies, representing a significant opportunity for research contributions in this area. Latency-aware autonomous tracking models (Luo, Li, et al., 2023) and fine-tuned YOLO models designed for edge deployments such as WildARe-YOLO (Bakana et al., 2024) and WilDect-YOLO (Roy et al., 2023) may be tuned for ADAE. At the same time, we anticipate an increasing number of tasks to be done in real-time at the edge, as has been done for detection and classification tasks (Bondi et al., 2018; Chalmers et al., 2019, 2021; Meier et al., 2024; Tripathi et al., 2025). As noted in (2025), numerous AI models exist for terrestrial biodiversity monitoring, but technological advancements are needed in robotics platforms, sensors, power sources and data handling to fully deploy them in robotics and autonomous systems.

Aerial imagery collected with drones poses new challenges for the computer science community. Meeting these challenges will require innovation in both collecting higher-quality datasets with automation and computer vision models tailored for deployment on the edge. For example, Lee et al. (2021) proposes an algorithm to quickly detect animals from drone imagery without training data, and Zhang (2023) proposes a specialized version of YOLO for detection from drone imagery. Such datasets will enable more sophisticated computer vision models to be trained for detection, localization and classification tasks for animal ecology applications, such as (Chappidi & Sundaram, 2024; Jiang & Wu, 2024). Kellenberger et al. (2019) proposes a novel active learning strategy to reuse CNNs across different domains so models can be used to analyse datasets collected in distinct habitats at other times. Ma et al. (2022) proposes a technique for counting herbivores in drone imagery as detecting small targets by optimizing Faster-R-CNN for these tasks. The development of such models relies on the availability of high-quality datasets to train on, such as the Wildlife Aerial Images from Drone (WAID) (Mou et al., 2023) and the Multi-Environment, Multi-Species, Low-Altitude Drone (MMLA) datasets (Kline, Stevens, Maalouf, et al., 2025).

6.3 | Autonomous drone swarms

Video datasets with multiple viewpoints can lead to more accurate behavioural studies. Multiple drones can be used to monitor large groups of animals to capture emergent behaviours, as in the approach used to study the mating ecology of a lek-breeding antelope (Sridhar et al., 2024). Multiple views of a herd reduce the likelihood of encountering occlusions from vegetation or other animals and provide more usable pixels for inferring behaviour. Multi-view datasets make it easier to identify and localize the animals within the landscape individually. Drone swarms collecting data from an oblique angle, or non-nadir, may produce higher-quality classification results, as this angle provides additional angles of the animal as shown in Figure 8. In addition to providing multiple views of the herd, swarms may be deployed to cover larger areas than is possible to monitor by a single drone alone (Boubin et al., 2022).

However, flying multiple drones is difficult or impossible to manage manually. Autonomous drone missions are known to be safer, less expensive and more reliable than manual missions flown by human pilots (Boubin et al., 2023). Reliability and consistency are critical when data is analysed through computer vision pipelines. An analysis of the KABR dataset found that behaviour was best captured during missions flown at low speeds and altitudes between 10 and 30 m (Kline et al., 2023). However, training human pilots to conduct specialized animal behaviour missions tailored to specific species, habitats and demographics is difficult and time-consuming and may produce inconsistent datasets between pilots. The altitude of missions is known to impact the accuracy of classification of individual animals and herds (Petso, Jamisola, Mpoeleng, Bennitt, & Mmereki, 2021) and behaviour (Kholiavchenko, Kline, Ramirez, et al., 2024). Automating flights with pre-defined parameters, such as speed and altitude, to collect optimal data is a promising solution for scaling up behavioural studies with drones across large geographical areas repeatedly. Drone swarms may be deployed to optimize coverage of group-living animals (Grushchak, Kline, Pianini, Farabegoli, Aguzzi, et al., 2024) or capture the desired SI (Rolland et al., 2025). Autonomous drones can be programmed to automatically track a herd of animals using the *herd tracking* algorithm proposed in Kline, Berger-Wolf, et al. (2024). This technique uses the bounding box annotations for each animal produced by YOLO (Redmon et al., 2016) to calculate the centroid of the herd dynamically. It directs the drone to keep this centroid in view of the camera, allowing it to automatically follow most of the herd as it moves through the landscape. Deploying

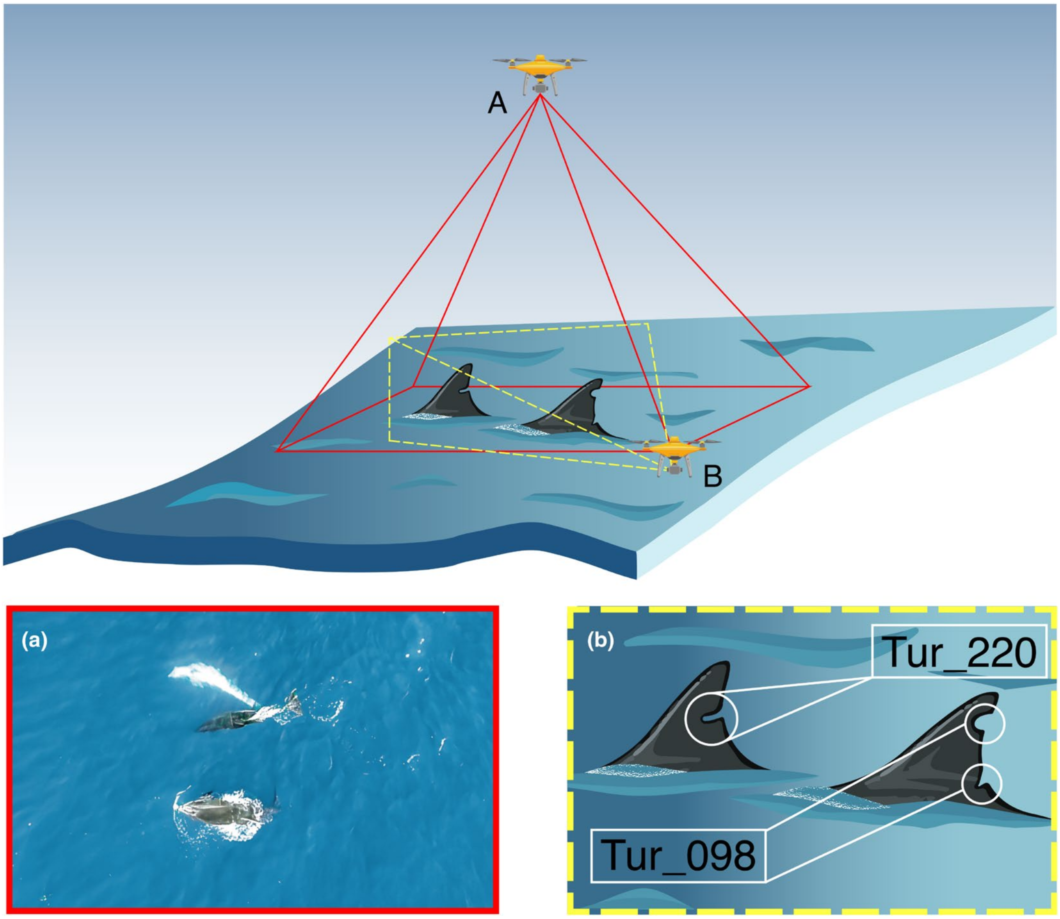

FIGURE 8 Drones performing (a) vertical and (b) horizontal monitoring of a pod of Tursiops (Rolland, Grøntved, Laporte-Devylder, et al., 2024).

this herd tracking technique improved the yield of usable data for behavioural studies from 66% to 87% (Kline, Zhong, Irizarry, et al., 2025).

The deployment of autonomous drone swarms has generated significant interest in the environmental monitoring community due to their scalability and high error resistance. Swarms are well-suited for operation in large and harsh environments (Parker, 1994; Rolland et al., 2025; Schranz et al., 2021). By distributing different monitoring tasks among various agents, drone swarms can leverage the capabilities of single-drone missions. For instance, they can conduct landscape coverage missions more quickly and enable multi-perspective monitoring of wildlife (Grøntved et al., 2023; Rolland, Grøntved, Laporte-Devylder, et al., 2024). Drone swarms have been successfully deployed using automation to control several drones concurrently for agriculture applications (Boubin et al., 2022).

Multi-perspective data collection is a growing area of interest for ADAE studies as well. Drone swarms can extend the duration of monitoring, allowing for the collection of rare animal behaviours (e.g. fighting or mating) while also providing better perspective coverage of different species. While the challenge of tracking moving targets with multiple drones has been addressed in several studies, few have applied drone swarms to real-life wildlife monitoring (Bandarupalli et al., 2023; Parker & Emmons, 1997). Rolland et al. (2025) demonstrated an early version of a three-agent drone swarm capable of autonomously collecting multi-perspective data on zebra herds (Figure 9). Their system accounted for wildlife-specific constraints, such as minimizing animal disturbance and ensuring sufficient view quality for behavioural analysis and individual identification, using an optimization-based centralized controller. While promising, this initial implementation highlighted areas for further development, such as enhancing the swarm's responsiveness to dynamic animal movement and reducing reliance on manual animal detection to achieve full autonomy. However, before swarm applications can be widely adopted for wildlife monitoring, significant research gaps must be addressed to make the technology accessible to non-robotic experts. These include the development of commercially available drone platforms tailored for field deployment in harsh conditions, and the creation of user-friendly interfaces that meet end-users' needs for controlling the swarm (Abdelkader et al., 2021).

7 | CONCLUSIONS

Drones and computer vision have the potential to scale animal behaviour studies to enable real-time monitoring of ecosystems over large spatiotemporal scales. Adapting drone navigation and

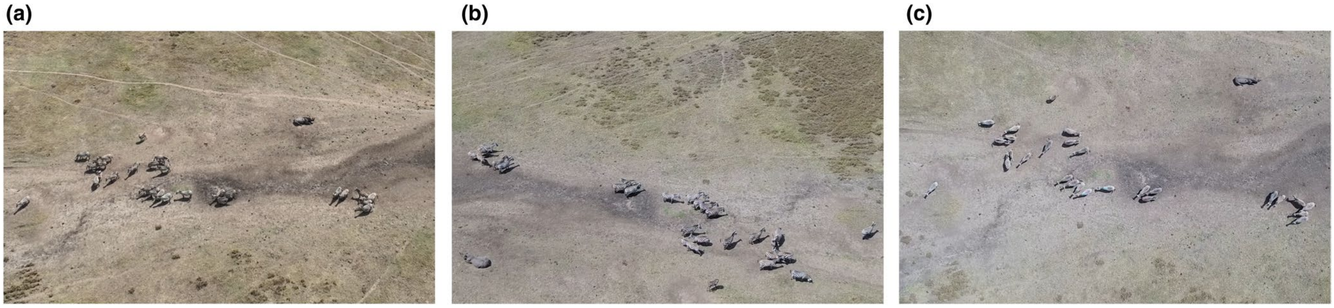

FIGURE 9 Example of multi-perspective wildlife drone imagery from Rolland et al. (2025). (a) Drone 1, (b) Drone 2, (c) Drone 3.

computer vision techniques to answer ecological questions presents challenges that offer opportunities to innovate in robotic sensing, edge computing and animal ecology. Existing techniques may be adapted for challenging drone datasets, improving the state-of-the-art in both computer science and biology (Rolnick et al., 2024). The deployment of autonomous drones can scale up the generation of new models to complete detection, localization and classification tasks on aerial imagery, on edge, in real-time for optimal monitoring. Autonomous aerial systems equipped with Edge AI can enhance and standardize large-scale animal behaviour studies, minimizing disturbance and boosting data accuracy. Automating drone swarms to conduct animal behaviour studies enables real-time monitoring of ecosystems. Real-time monitoring is essential for conservation applications, such as detecting poachers in protected wildlife zones (Bondi et al., 2018). Fast, real-time animal detection from imagery requires innovation in edge computing techniques and models optimized for fast inference with low computing and memory resources on the edge. Smart drones, equipped with computation resources on board, have been used to automatically detect black rhinos and giraffes at a low cost, with low communication bandwidth in real-time (Hua et al., 2022). Autonomous drones can be programmed to maintain a safety zone between the animals of interest and the drone to minimize the possibility of artificially inducing behaviour from the data collection process while automatically tracking the group simultaneously.

Integrating drones and computer vision is revolutionizing how researchers study and interpret animal behaviour in the wild, with recent studies highlighting how biological systems can inform increasingly sophisticated technological approaches. As highlighted by recent research, AI applications in conservation extend from species recognition to predictive modelling of biodiversity loss (Reynolds et al., 2024), while animal-inspired robotics provide innovative solutions for studying elusive species in their natural habitats without disruption (Afzal et al., 2025). Particularly promising is the development of adaptive intelligence systems that draw inspiration from the inherent flexibility of biological intelligence, where animals continuously adjust their behaviours based on environmental feedback (Mathis, 2024). This biomimetic approach to AI development, combined with advances in robotics and computer vision, offers a powerful framework for creating more sophisticated and responsive conservation tools. By learning from nature's solutions while working to protect it, researchers are establishing a reciprocal relationship between biological and artificial intelligence that could revolutionize our understanding of animal behaviour and enhance our capacity for effective conservation.

AUTHOR CONTRIBUTIONS

Jenna Kline and Tanya Berger-Wolf conceived the original idea; Jenna Kline conducted the literature review and led the writing of the manuscript; Saadia Afridi contributed noise considerations and potential disturbance analysis; Edouard G. A. Rolland provided mission planning for autonomous drone aerial ecology and autonomous drone control; Guy Maalouf contributed mission planning for safety; Lucie Laporte-Devylder provided field biology best practices and extensive drone deployment experience; Christopher Stewart contributed autonomous drone deployment and edge AI expertise; Margaret Crofoot provided critical feedback on drones for ecology; Charles V. Stewart contributed computer vision expertise; Daniel I. Rubenstein provided expertise on group-living animals and drone-based study methods; Tanya Berger-Wolf provided original conception and advisory guidance. All authors contributed critically to the drafts and gave final approval for publication.

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CONFLICT OF INTEREST STATEMENT

The authors declare no conflict of interest.

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This paper does not contain any data or code.

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