



# WILDDRONE

## D1.1 – Technological Requirements for Digital Conservation Missions

WP1, T1.1 Initial methods and field experiments for DCs 1-4 & 8

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**Authors:** Blair Costelloe (MPG); Elena Iannino (MPG); Kasper Hlebowicz (WU);  
Camille Rondeau Saint-Jean (SDU); Lucie Laporte-Dewylder (WIP)



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# Executive Summary

The objective of this report is to identify and summarize the technical needs of DC projects in Theme 1 that can potentially be addressed by DC projects in Themes 2 and 3. For each new technology to be developed in Themes 2 and 3, we have described the current approaches in wildlife ecology and conservation and the limitations to these approaches. We have then laid out the tasks to be undertaken in Theme 1 that would be aided by the new technologies and, where applicable, provided information regarding the requirements of these technologies. New tools that address these requirements will be transformative not only to Theme 1 DC projects, but to drone-based wildlife ecology and conservation in general.

**Keywords:** fieldwork, conservation, wildlife monitoring, drone operations, animal behavior



# 1. Introduction

## 1.1. Purpose, scope, and target group

The purpose of this report is to identify the technical needs of the DC projects in Theme 1 that may be fulfilled by technologies developed by DC projects in Themes 2 and 3. This information can be used to establish collaborations between students across themes and direct Theme 2 and 3 projects to be maximally transformative for wildlife conservation end-users. The technical needs are based off of the anticipated goals and methods of Theme 1 projects, the prior field experiences of the report authors, and their reviews of the existing literature relevant to their projects. The target group for this report is WildDrones DC candidates and supervisors in Theme 2 and 3.

## 1.2. Contributing partners

Table 1: Contribution of partners

Partner	Contribution
Syddansk Universitet (SDU)	Camille Rondeau Saint-Jean - contributing ideas and use cases
Max-Planck-Gesellschaft zur Förderung der de Wissenschaften EV (MPG)	Blair Costelloe - report writing Elena Iannino - contributing ideas and use cases
WIPSEA (WIP)	Lucie Laporte-Devyllder - contributing ideas and use cases
Wageningen University (WU)	Kasper Hlebowicz - contributing ideas and use cases

## 1.3. Relation to other activities in the project

Table 2: Relation to other activities in the project

Task	Description
Task 3.3	Input to Deliverable 3.3

## 1.4. Delays and obstacles

This report was intended to be informed by the experiences of the Theme 1 Doctoral Candidates during their initial field excursions. However, delays in permitting for wildlife research in Kenya have resulted in delays of the Kenyan fieldwork components. Thus, this report is informed by the initial fieldwork conducted in Europe by DC4 and DC8, and by



the background knowledge and expectations of all Theme 1 Doctoral Candidates established during their project development.

Additionally, the candidate originally recruited for DC2 resigned his position prior to the preparation of this report. Therefore, this report does not incorporate insights from DC2.

### **1.5. Potential for dissemination, exploitation, and communication activities**

This report is intended to inform the directions of projects in Theme 2 and Theme 3. It is possible that objectives that are laid out here but not completed in the course of the project could be presented to the broader research community as goals for future research and development. However, the primary purpose of the report in its current form is for internal use.

### **1.6. Ethical and security considerations**

No ethical or security issues were encountered in preparing this report.





## 2. Technical Requirements for Theme 2 and Theme 3 DC Projects

Below we address the potential innovations in each Theme 2 and Theme 3 DC project that would benefit Theme 1 DC projects, or other drone-based wildlife research that uses similar approaches and methodologies to Theme 1 projects. Table 2-1 lists the Theme 2 and 3 DC projects and indicates their relevance to each of the Theme 1 DC projects. Note that DC2 is not addressed in this report since re-recruitment for that position is currently underway.

Table 2-1: List of technological advances pursued in Theme 2 and Theme 3 PhD projects, and their applicability to Theme 1 PhD projects.

	Technology	DC1	DC2	DC3	DC4	DC8
DC5	Unobtrusive noise profiles and flight paths	X		X	X	X
DC6	Automated planning of multi-drone missions	X		X	X	X
DC7	Flexible deployment for BVLOS operations	X		X	X	X
DC13	Mutualistic drones for multi viewpoint capture			X	X	X
DC9	Individual detection, tracking and metrics	X		X	X	X
DC10	Landscape reconstruction	X		X		
DC11	Interactive census	X			X	X
DC12	Adaptive tracking			X	X	

### 2.1. DC5 - VTOL drone noise profile optimization and its impact on animal behaviour

#### 2.1.1. Current approach and limitations

The potential of drones to disturb animals is a key consideration surrounding the use of drones for wildlife conservation purposes. Many studies have demonstrated the potential of drones to cause disturbance, but have also identified flight parameters that avoid negative behavioural reactions. Reactions appear to be species-specific, with birds generally being more sensitive than mammals, and birds responding negatively to both the visual appearance and sound of drones and mammals appearing to be affected by the noise only (although many exceptions exist; for example, pinnipeds that are vulnerable to aerial predators may be sensitive to the visual appearance of drones) (Álvarez-González et al., 2023). However, it is difficult to predict how animals a given species will respond to drone activity given the wide range of drone appearances and



noise profiles, and our limited understanding of the auditory capabilities of most animal species (Duporge et al., 2021).

For some wildlife species, previous studies can help predict how the animals will react to drones and what flight parameters are likely to be tolerated. However, current best practice is to a) choose drone models and accessories (such as propellers) that minimize the noise produced by the drone and b) incorporate a pilot phase into any drone-based wildlife study where the reactions of the specific species and population of interest are gauged and flight parameters are adjusted to avoid negative impacts on wildlife.

### 2.1.2. Technical requirements for innovation

In the absence of information regarding the auditory capabilities of species of interest, developments in drone noise profiles should focus on reducing the overall noise output of drones (while maintaining sufficient noise output to avoid potential ill-use of silent or near-silent drones). Table 2-2 gives the species of interest for Theme 1 projects, along with expected flight parameters (altitude and angle from the drone to the animal) to be used in studying these species. Although DC4 will also work with humpback whales, this species is not included on the table because prior studies suggest that drones flying at least 10m above the water's surface cause little auditory disturbance to large whales (Christiansen et al., 2016).

Table 2-2: Primary species of interest for Theme 1 DC projects.

Species	Latin name	DC	Distance range	Angle(s)
Lion	<i>Panthera leo</i>	1, 3	20-120m	Nadir, oblique
Burchell's zebra	<i>Equus burchelli</i>	3, 4	30-120m	Nadir, horizontal
Impala	<i>Aepyceros melampus</i>	3	50-120m	Nadir
Cattle	<i>Bos taurus</i>	1, 3	50-100m	Nadir
Black rhinoceros	<i>Diceros bicornis</i>	8	50-120m	Nadir, oblique
Harbour porpoise	<i>Phocoena phocoena</i>	8	50-120m	Nadir
Grey seal	<i>Halichoerus grypus</i>	8	50-120m	Nadir, oblique

To avoid disturbance to wildlife, automated flight operations should be responsive to negative reactions by wildlife to drones. Although some reactions may be physiological and therefore not detectable by visual means (Ditmer et al., 2015), often reactions entail behaviors indicative of stress (e.g. vigilance toward the drone), avoidance behaviors (fleeing or hiding), or aggression toward the drone (e.g. tail or fin slap). Typical reactions of each target species toward drones will be noted by each DC in Theme 1 and relayed to DC5.



## 2.2. DC6 - Automated planning of safe, multi-drone nature conservation missions

### 2.2.1. Current approach and limitations

Autonomous multi-drone missions and operations involving coordination between drones and other entities have a variety of potentially transformative applications to wildlife monitoring and conservation. Current multi-drone operations are extremely limited in wildlife conservation due to the lack of commercially-available automated solutions and the risk and challenge of manually piloting multiple drones at once. However, multiple drones have been used in a relay system to extend the duration of behavioural observations beyond the duration of a single drone battery (Koger et al., 2023), and at least one study entails flying three drones simultaneously in a triangular formation such that the cameras' fields of view overlap, allowing continuous coverage of a large ground area (Akanksha Rathore, personal communication). Wildlife Drones has developed a drone system that interfaces with on-animal tracking devices, but this system uses the drone as an elevated and mobile platform from which to locate on-animal tags and download geolocation data from tags, rather than using the on-animal geolocators to position the drone for further data (e.g. image, video) collection (Saunders et al., 2022).

### 2.2.2. Technical requirements for innovation

The following are generic templates of multi-drone or multi-device use cases that would be of use to Theme 1 projects.

#### 2.2.2.1. Drone relays

Relevant DCs: 3, 4. Flying two drones in overlapping relays can enable continuous recordings of subject animals that exceed the duration of a single drone battery (Koger et al., 2023). Currently, such maneuvers are performed manually, which is inefficient and prone to human error. The manual operation described in Koger et al. (2023) proceeds as follows:

- 1) The remaining flight duration of an active drone is monitored and a replacement is deployed once the battery capacity is approximately 30%.
- 2) The replacement drone ascends to an altitude 10 meters above the active drone, and is flown to the location of the active drone.
- 3) The field of view of the replacement drone is rotated until it approximately matches the field of view of the active drone. The replacement drone's camera begins recording.
- 4) The "Return to Home" function is activated on the active drone.
- 5) The replacement drone descends 10 meters.

#### 2.2.2.2. Extended footprint

Relevant DCs: 1, 3, 4. The spatial area captured by a drone-based camera depends on the distance between the drone and the subject. In the case of nadir recordings, this distance is the flight altitude. Operational ceilings limit the maximum permitted flight



altitude, which limits the area that can be monitored by a single camera. Many behavioural processes, e.g. predator hunting behaviour, or collective behaviours of groups of animals, occur over larger spatial scales than can be monitored by a single camera. For instance, in marine environments, tracks left on the surface of the water are transient but can potentially remain for several minutes while the animal swims away, making it difficult to keep the same animal and its tracks in the field of view of a single camera. Flying multiple drones simultaneously in configurations that allow the cameras' fields of view to overlap would allow for easier study of these phenomena with lower risk of human error than manual flying. This use case could be entirely autonomous, or one "lead" drone could be piloted manually, with peripheral drones automatically adjusting their position relative to the lead drone to maintain the degree of image overlap desired by the user.

#### 2.2.2.3. *Multi Viewpoint*

See also Section 2.8.

Relevant DCs: 1, 4, 8. Many data collection activities would benefit from the ability to collect multiple viewpoints of the same subject or scene simultaneously. For example, a researcher studying groups of animals may wish to collect close-up imagery of a single individual while continuing to record the entire group, or a researcher may wish to collect multiple orthogonal viewpoints in order to facilitate 3D reconstruction of an animal or a behavioural sequence. In some cases, multi-view requirements could be satisfied by enabling simultaneous recording by two different cameras mounted on the same drone. In other cases, two drones engaged in coordinated flight would be necessary. In the context of DC1, the simultaneous use of multiple drones would allow the study of predator-prey interactions. One drone could be deployed to detect and track a predator while supplementary coordinated drones could scan the surroundings to detect prey species and record their reactions to the predator.

#### 2.2.2.4. *GPS collar coordination*

Relevant DCs: 1, 3. A major potential application of drone technologies in wildlife conservation is using drones to collect image or video data of animals fitted with geolocators ("GPS collars"). Coordination between on-animal devices and drones would facilitate repeated observations of known individuals by helping researchers efficiently locate collared animals in the field with the drone, and to facilitate tracking the animal with the drone, to ensure that the animal stays within the camera's field of view. Locating collared animals in the field can be very challenging, especially for elusive, cryptic or nocturnal species with large home ranges, such as lions. The drone's aerial position is superior to a ground-level search because VHF signals are easier to detect from above (Saunders et al., 2022), and the animals themselves may also be easier to see from an elevated position.

#### 2.2.2.5. *Field vehicle coordination*

Relevant DCs: 1, 3, 4, 8. In nature conservation missions, drone operations must often be conducted from a vehicle such as a boat or truck. Dynamic coordination that accounts for the mobility of field vehicles, for example by updating the "Return to Home" location to



match the vehicle's current location, would greatly increase flexibility and safety of operations. When operating from a moving boat, erroneously initiating a Return to Home manoeuvre that would target the boat's previous (but not current) location is potentially disastrous. In both marine and terrestrial environments, dynamic coordination with field vehicles would extend the area accessible by VLOS operations, reduce risk of human error, and facilitate extended observations of highly mobile species.

### **2.3. DC7 - Safe BVLOS operations of drones for nature conservation**

#### 2.3.1. Current approach and limitations

Visual line of sight (VLOS) requirements can severely limit data collection for wildlife missions. For example, to maintain direct visual contact with the drone during a large-scale wildlife survey mission, researchers may need to operate the drone from within the area to be surveyed, where their presence or activity may disturb wildlife and thereby skew survey results. Maintaining VLOS with drones while filming mobile animal groups can require continuous repositioning of operators and equipment, complicating flight logistics and increasing the risk of human error or disturbance of wildlife. Also, in many environments, such as marine and coastal settings, windows of flying opportunity can be limited and unpredictable. In these settings, BVLOS operations would allow the drone to be deployed quickly from shore to monitor distant animals or large areas, without requiring that a boat be staffed and deployed in order to approach within VLOS distances.

#### 2.3.2. Technical requirements for innovation

Safe BVLOS operations requires that drone systems be capable of detecting and responding to common hazards encountered in wildlife operations. Example hazards include attacks by large birds, encounters with manned aircraft, and sudden changes in weather conditions. Drone systems should also be equipped with features that facilitate rescue and recovery operations in case of equipment loss, to reduce data loss, environmental pollution, and hazards to humans or animals. For marine operations, it is particularly critical that the drone be able to autonomously return to the operator's current location (rather than the launch location) in the event of an emergency (see also section 2.2.2.5)

### **2.4. DC9 - Detecting posture, metrics and biometrics of animals from drone data**

#### 2.4.1. Current approach and limitations

A common task in wildlife conservation and ecology is assessing the identity, health, physical condition, and behaviour of individual animals. These are challenging tasks that are conventionally performed by human researchers directly observing animals in the field. There is thus significant potential for streamlining these tasks through the use of drone- and computer vision-based approaches.



Several projects have developed tools to identify individual animals from imagery using pattern or facial recognition algorithms (Berger-Wolf et al., 2017; Blount et al., 2022; Clapham et al., 2020). However, automated individual identification appears to be rarely conducted using drone imagery, despite the fact that, particularly for marine mammal species, drones are now commonly being used to capture photos used for manual individual identification (Degollada et al., 2023; Landeo-Yauri SS et al., 2020; Ryan et al., 2022).

Health and physical condition of wildlife are typically assessed based on visual characteristics of the animal, including the quality of the pelage, the degree of emaciation, and presence or number of external parasites. For marine mammals, it is increasingly common to assess size and body condition using photogrammetric analysis of drone imagery (Christiansen et al., 2019). Similar approaches are uncommon for terrestrial species.

Inferring behavioural state from imagery is a developing area of research. Posture tracking is an increasingly common approach for estimating animal pose (Graving et al., 2019; Mathis et al., 2018). In some cases, behavioural states can be inferred directly from animal postures, but very often this is not possible, because similar postures are used in many different behavioural sequences (Chen et al., 2023). Deep learning-based methods for detecting animal behavioural state without pose tracking offer some promise (Chen et al., 2023; Eric Price et al., 2023), but challenges in training these models and adapting them across species and video types have so far largely prevented their adoption.

#### 2.4.2. Technical requirements for innovation

In Theme 1, multiple tasks will require inspection of individual animals for determining individual identification, behavioural state, and body condition. Specific tasks for each DC project are given below. In all cases, manual performance of the task is technically possible, but automation will massively reduce the amount of time and effort needed to perform the task, and thus allow much faster production of final results.

##### 2.4.2.1. DC1

African lions and their prey will be detected in drone imagery and identified to species and, for lions, to individual if possible. Lion and prey behavioural states will also be classified from imagery. For lions, behavioural classification will be used to assess lion reactions to drone operations. Posture tracking will be used to determine head and body orientation. For prey, behavioural state will be classified from thermal imagery to characterize the prey's awareness of and response to the presence of the lion.

##### 2.4.2.2. DC3

Plains zebras will be individually identified in drone imagery by their stripe patterns. Impala will be classified by sex (male/female) and age classes. For both species, behavioural state (vigilant/non-vigilant) will also be determined from drone imagery.





### 2.4.2.3. DC4

Vigilance states will be determined for plains zebras to assess their behavioural response to approaches by drones. For marine mammals, individual metrics such as species and body size will also be determined from drone imagery.

### 2.4.2.4. DC8

A main goal of this project is to identify individual animals from features detectable in drone imagery. The species of interest are grey seals, harbour porpoises and black rhinoceros. For harbour porpoises and seals, key features will likely be natural patterns of coloration and scarring. For black rhinoceros, features may include horn shape, scars, skin folds, ear notches, body size, and sex.

## 2.5. DC10 - Reconstructing natural habitats from multimodal drone measurements

### 2.5.1. Current approach and limitations

3D landscape reconstructions can provide valuable context for animal movement, behaviour and environmental interactions. Currently, 3D landscape models are typically created by flying a fixed-wing or multirotor drone in parallel transect paths over an area of interest, and using photogrammetry software (e.g. Pix4D) to create point clouds and triangular mesh models (Strandburg-Peshkin et al., 2017). Models can also be created from video frames directly extracted from footage collected during animal observation flights (Koger et al., 2023), but the linear nature of animal movements (and, thus, drone flight paths following animal movements) can reduce model accuracy e.g. by causing “doming” and other distortions (Tournadre et al., 2015). Even when parallel transect paths are used, the resulting imagery does not capture elements of the landscape or vegetation that are obscured, for example by tree canopies. This results in models that are distorted and unrealistic below canopy level, which is arguably the most relevant area for most terrestrial animals.

### 2.5.2. Technical requirements for innovation

Key directions for improvement of landscape modelling approaches depend on the ultimate application of the model. For some use cases higher quality models are needed, particularly below tree canopies or in other areas relevant to the focal animal species. This might be accomplished by incorporating low-altitude flights, re-flying of transect paths using different camera angles, or incorporating imagery collected via ground-level sensors. In other use cases, a low-resolution model is sufficient but dedicated flights to collect landscape imagery are not feasible or easy. In this case, innovation would involve incorporating image collection for landscape modelling into flight protocols for behavioural observation. For example, at the end of an observation, the drone’s flight path could be planned to maximize revisits to locations along the animals’ route to generate additional viewpoints. As these return flights would be longer than a straight-line flight to the launch point, the energy required for the return flight would need to be accounted for in estimates of the drone’s remaining flight time.



Anticipated uses of landscape models in Theme 1 DC projects include calculating bush density; reconstructing animals' visual fields or calculating sight lines between animals and objects of interest in the environment; quantifying potential escape routes of fleeing animals; and defining accurate and fine-scale elevation models. Beyond 3D reconstruction, landscape imagery may also be used for segmentation or classification tasks such as quantifying tree species diversity and distribution or detecting networks of animal-created trails.

## **2.6. DC11 - Interactive census monitoring: the accurate, the generic, and the rare**

### 2.6.1. Current approach and limitations

Aerial surveys of animal populations are a central component of wildlife management and the key means by which estimates of wildlife population sizes and trends are derived. Conventionally, these surveys are conducted from manned aircraft flying pre-determined transect routes. On board, human observers count the number of animals of each species that are visible from each side of the aircraft, sometimes also noting their distance from the aircraft's path. Image-based methods are increasingly being incorporated into census missions: rather than having human observers directly count animals in real time, researchers take photos of animal groups, or cameras mounted on the aircraft - either manned aircraft or, increasingly, unmanned aircraft - record images continuously throughout the survey flight. The use of images instead of direct human counts of animals typically increases count accuracy and allows counts to be independently validated. However, manual processing of images is typically extremely time- and resource-intensive. Therefore, there is strong interest in automating the processing of such imagery using deep learning-based detection models.

Well-trained models can detect animals in aerial survey photos very effectively, leading to more rapid and accurate estimates of population sizes. When combined with drones, which can be deployed more flexibly and inexpensively than manned aircraft, detection models have massive potential to revolutionize monitoring of wildlife populations by increasing the frequency and accuracy of wildlife censuses. However, training models to new scenarios is a major barrier to the uptake of these approaches. Generating sufficient training data for a model is time- and labour-intensive, and models trained for one application often do not generalize to other applications. Thus, models trained to detect wildlife at Conservancy A, where a particular set of animal species exist in particular relative abundances and vegetation and terrestrial substrates have a certain appearance, is unlikely to perform well at Conservancy B where these conditions differ. Furthermore, retraining a model initially trained on conditions at Conservancy A to perform well at Conservancy B will result in loss of performance on data from Conservancy A, a phenomenon known as "catastrophic forgetting".

### 2.6.2. Technical requirements for innovation

To promote the uptake of automated image processing methods for census applications, we need tools that significantly reduce the burden of training models to new situations,





including not just new conservancies or field sites, but also diverse conditions within a given field site (e.g. changes in vegetation appearance or landscape “greenness” due to seasonality, changes in sea state and water turbidity), or diverse image types (e.g. RGB versus thermal imagery).

Models that can extract finer-grain information (e.g. species; sex, age or reproductive classes; or even individual identities) would also be extremely useful as this information can help parameterize population models for improved predictions of future population trends.

Specific needs of DC1 are detection of large African mammalian carnivores and herbivores and classification of these animals to species, sex and age classes in both RGB and thermal imagery. Imagery will be collected across a range of habitat types, including dense and open bushland, grasslands and riverine forests.

Specific needs of DC4 are detection and classification of marine mammal species under weather and sea conditions that result in different sea colours and turbidity, where animals vary in their visibility and appearance due to their depth beneath the surface and body orientation. Challenging conditions also include imagery featuring abundant false positives (waves, sun reflection, corals, boats) and imagery where only part of the animal (fins, flukes) or indirect evidence of the animal (blow, fluke prints) are visible. Both RGB and thermal/infrared cameras will be used, so comparing ease of detection in these image types would also be of interest.

## **2.7. DC12 - Adaptive tracking for detection and identification**

### 2.7.1. Current approach and limitations

Studies of wildlife behaviour or movement require the subject animal(s) to be followed and continuously recorded to capture behavioural sequences over an observation period (Koger et al., 2023). Autonomous tracking is already integrated into many commercial drone models, for example DJI’s “ActiveTrack” and “Follow Me” modes. However, these are typically not useful for wildlife applications, likely because the detection models are not trained on appropriate targets. Therefore, drones are currently piloted manually to keep the subject animal(s) in frame. This includes adjusting the drone’s horizontal position and/or camera angle to track the animal as it moves across the landscape, and adjusting the drone’s altitude and/or camera zoom level to keep multiple focal animals in frame. Altitude adjustments are limited by the ground sampling distance (GSD) required for later processing, as well as operational limitations: increasing altitude beyond a certain point may result in too-low resolution of target animals or violate operational regulations. When multiple animals are of interest, the pilot must decide which individuals or sub-groups to follow if the group splits up or becomes too spatially dispersed to keep all animals within the video frame.

The decisions required of the drone operator and the challenges of keeping track of multiple potentially small and cryptic animals on a small display screen can result in errors and loss of data. Animals may leave the screen without the operator noticing, or the operator may be unable to keep track of a specific focal animal within a larger group and



thus not know which individual to track. Manual flight can also result in inefficient or unnecessary drone movements, which can reduce flight duration and disturb animals.

### 2.7.2. Technical requirements for innovation

An autonomous drone-based wildlife tracking tool must, at a minimum, be capable of consistently detecting an animal of interest and adapting its position and/or camera to keep the animal within the field of view. Often drones are deployed when animals of interest have already been detected by researchers from ground- or sea-level, but it would be useful if the drone could also undertake this initial task of finding the animals of interest. The drone's aerial viewpoint is generally superior for this task, but manually-piloted searches are inefficient. An optimal procedure would be for the researchers to launch the drone in a "search mode", in which the drone would systematically search the surrounding area for potential tracking targets. Upon locating a potential target, the drone would seek confirmation from the researcher that the target is suitable and, if confirmed, enter a "tracking mode" to maintain the target in the camera's field of view.

In cases where multiple potential targets are detected, the tool should be a) responsive to real-time user input (e.g. the user clicking on the desired target on the controller's display) to identify the desired target and/or b) programmed to make decisions about which target to track or prioritize. Programmed decision rules could be established prior to flight, for example by the user designating a species of interest (e.g. "follow zebras") or rank species in order of priority (e.g. "follow lions and maximize the number of zebras in view where possible, but when the zebras run away stay with the lions"). These decision rules would require that the drone's software be able to distinguish between different animal species. In cases where a group of animals is the subject of interest, decision rules might dictate that the drone maintain as many animals as possible in the field of view, such that if the group splits up, the drone follows the larger sub-group.

Automated tracking decisions should also adhere to user-defined limitations. For example, a drone can increase its field of view by increasing its altitude or distance from the subject, but unless limits are imposed this could result in the drone ascending beyond permitted operational altitudes or capturing imagery in which the animals are too small for further analysis.

In both terrestrial and marine environments, animals of interest often become temporarily occluded during filming. For example, terrestrial animals pass under trees, and marine mammals submerge between breathing events. It is important that a tracking tool be robust to such temporary occlusions. At a minimum this would mean the drone should maintain its position for some time while waiting for the animal to re-appear. A more advanced solution would predict the animal's location based on its prior trajectory and proactively adjust the drone's position to resume tracking once the animal reappears.

An important consideration in using drones to study wildlife is ensuring that the drones do not disturb or elicit unwanted behavioural responses from the animals (Bennitt et al., 2019; Ditmer et al., 2015). An autonomous tracking tool would thus ideally be responsive to the behavioural state of the animal and adjust its flight path or behaviour accordingly. For example, if animals flee from the drone they should generally not be pursued as this



can cause unnecessary stress and negative impacts on the animals. In the case of behavioural studies, subtler responses, such as increased frequency of vigilance scans, may have negligible negative impacts on the animals themselves, but can bias behavioural data. Tools that reliably recognize unwanted reactions and dynamically adjust or abort missions in response would be desirable.

## **2.8. DC13 - Mutualistic drones for multi-viewpoint capture**

### 2.8.1. Current approach and limitations

Obtaining multiple viewpoints of the same animals or scene has many valuable applications for wildlife conservation. Multiple viewpoints can potentially increase count and species-identification accuracy in wildlife census missions, facilitate 3D reconstruction of individuals or landscapes, or allow collection of fine-scale (“zoomed in”) data simultaneously with broader-scale (“wide angle”) contextual data. Current solutions for obtaining multiple simultaneous viewpoints require the use of multiple manually piloted drones. As such, we are not aware of any use of multiple viewpoints in wildlife ecology to date, beyond flying multiple drones in sequential overlapping “relays” to extend continuous observation time beyond the duration of a single battery (Koger et al., 2023).

### 2.8.2. Technical requirements for innovation

Potential applications of a multi-viewpoint system in Theme 1 DC projects are as follows:

#### 2.8.2.1. DC1

A system of two coordinated drones would be useful for observing foraging lions or other predators: one drone could follow the focal predator, and the other drone could perform systematic survey flights to capture information on prey animals present in the surrounding area.

#### 2.8.2.2. DC3

Multiple viewpoints could allow for concurrent observations of predators and prey during hunts, with one drone following the predator and additional drones following potential prey. Additionally, in observations of zebras and other herbivores, simultaneous wide-angle and zoomed in views would allow for the identification of individual animals from close-up imagery without sacrificing video observations of the entire herd.

#### 2.8.2.3. DC4

Multiple viewpoints would enable the collection of a visual dataset that would enable 3D reconstruction of animal vigilance postures. In marine mammal monitoring, there is a strong interest in combining large-scale detection and behavioural observations from high altitudes or long distances with simultaneous close-up side view of focal animals for identification based on dorsal fin or fluke characteristics.



#### 2.8.2.4. DC8

Multiple viewpoints are critical for individual identification where photos from multiple angles are necessary to capture characteristics of interest. In marine and terrestrial environments, combining wide-angle views for detection and zoomed-in views for individual identification would greatly facilitate the monitoring of wild animals on an individual scale.



### 3. Conclusions

This report gives the technical requirements for new drone and computer vision technologies for wildlife conservation applications. The report focuses on the needs of the DC projects in Theme 1, but given the diversity of approaches in Theme 1, the potential developments described here will also significantly advance drone-based conservation approaches as a whole.



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