Brief Paper

Towards a Multispectral Airborne Light Field Dataset of Forest Animals

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Abstract:
Effective monitoring is crucial for conservation efforts, especially in forests, which cover a significant portion of the Earth's surface and are home to diverse ecosystems. Monitoring terrestrial animals often relies on indirect evidence or localized methods, such as camera traps, which provide limited data. Aerial methods, including drones and satellites, are increasingly used but face challenges in dense forest areas. Despite the existence of multiple public airborne wildlife datasets, the ecosystem forest is not addressed so far. For this reason, this work introduces a novel multispectral airborne dataset of forest animals, including spatial information. Like this, the dataset shall act as the foundation for the development of an automated wildlife detection process in forests using modern technologies such as airborne light-field sampling. The proposed dataset will consist of geo-referenced RGB and thermal video data from multiple drone flights over forests, wild animal gates, but also in animal parks with near-natural structured enclosures. So far, 1.62 TB of data (37.53 h footage) have been recorded between April 2022 and June 2023. The dataset mainly contains videos of species native to Austria such as red deer, chamois, roe deer and wild boar. Both the data recording and the labelling are still ongoing.

1 Introduction

The loss of biodiversity, alongside the pressing climate crisis, poses one of the most significant challenges humanity faces today [31, 36]. Earth's near-natural habitats and the associated diversity of life are currently under immense threat and rapidly declining, pushing us into the sixth major wave of species extinction [6]. Countless animal and plant species across the globe are in imminent danger of extinction, posing a risk to entire ecological networks [38]. To prevent such extinctions, accurate and reliable monitoring is essential. This enables us to precisely assess wildlife populations, detect potential declines, but also identify increases, such as those caused by invasive species [9], at an early stage. In turn, this allows implementing targeted management measures to address these changes [25].

On land, especially forests are of utmost importance, as they cover approximately 30.74% of the Earth's surface [13]. In Austria, this number is even higher, according to the Federal Forest Research Center; its habitat accounts for over four million hectares, or nearly 48% of Austria's national territory, making it one of the most densely forested countries in Europe [2]. However, alarming global trends were observed between 2000 and 2010, especially with tropical countries experiencing a net deforestation of 7 million hectares per year [15]. The same can be observed in Europe, with an increase in the harvested forest area of 49% between 2015 and 2020 [7]. This development has not stopped since then and is still ongoing, which highlights the urgent need for conservation efforts and sustainable land management practices to address the ongoing challenges in the ecosystem forest. Forests are crucial in preserving biodiversity and regulating the climate, playing key roles in these vital aspects. On a global scale, they serve as habitats for over half of all known species, thereby supporting and safeguarding a remarkable array of life forms. Additionally, forests offer a multitude of valuable ecosystem services that contribute to the overall well-being of our planet [1].

In the case of terrestrial animals, indirect evidence like footprints, tracks, or scat is analyzed to estimate population size and determine the status of a given population or habitat using statistical methods [28]. Additionally, direct methods such as camera traps are commonly employed, which automatically capture photos or short video sequences when an animal moves through the monitored area, allowing to get insights into the local animal population [5]. All these methods have the problem of being very localized and of providing very small sample sizes [37]. To overcome this issue, aerial methods utilizing (un-)crewed aerial vehicles or even satellites are used more frequently next to classic camera traps [39]. However, the dense vegetation in forested areas poses a significant challenge when it comes to observing and counting wildlife using aerial methods [39], as shown in Figure 1a and Figure 1c.

In contrast to classic visual airborne approaches, airborne light-field sampling (ALFS) [3] enables the identification and analysis of the forest floor, including the presence of wildlife, by uncovering the obstructing forest cover [23], as shown in Figure 1b and Figure 1d. In combination with periodic drone flights, ALFS allows the creation of a system that is capable of identifying and counting animals. In the near future, this should make it possible to monitor animal populations over a wide area. To automate this process, it is necessary to adapt methods from the field of artificial intelligence (AI), respectively computer vision (CV), such as convolutional neural networks or vision transformers, to this kind of visual data and the use case of wildlife detection. Next to the creation of suitable model architectures, datasets are of utmost importance, allowing to train appropriate model instances. Due to the novelty of ALFS, there are currently no such datasets publicly available. For this reason, a multispectral airborne-light-field dataset for the detection of forest animals is proposed in the present work. This dataset is not exclusively intended for ALFS-based systems and could also serve as a basis for other aerial monitoring methodologies.

2 State of the Art

The current state of monitoring wildlife populations using visual techniques, including camera traps, drones, and satellites, is discussed in this section. These tools provide valuable data on species presence and habitat changes. Additionally, airborne light field sampling is presented – an emerging methodology enabling detailed data extraction. This approach has the potential to enhance population estimation accuracy in forests by overcoming occlusion challenges.

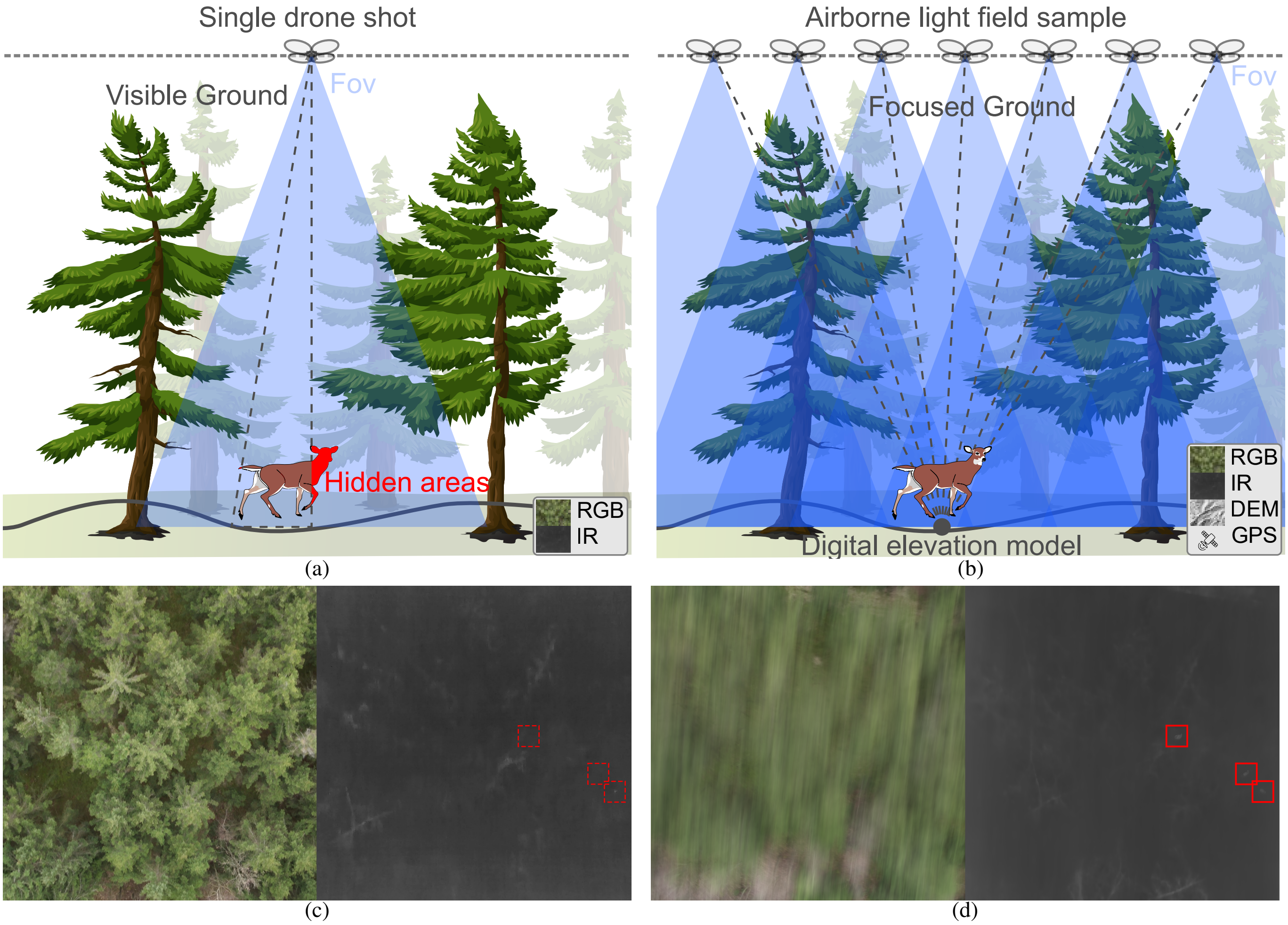


Fig. 1: (a) Uncrewed aerial vehicles equipped with RGB and infrared (IR) cameras can be used for monitoring wildlife, but face challenges in forested areas due to the dense vegetation. Like this, animals are only partially or not at all visible (marked with red, dashed bounding boxes) in respective recordings, as shown in (c). Combining multiple shots with exact spatial information (drone position and orientation, as well as a digital elevation model) using airborne light field sampling (b) allows changing the focus of the image to the forest ground instead of the treetop and, thus, revealing hidden subjects such as animals (marked with red bounding boxes) (d).

2.1 *Visual Wildlife Monitoring*

Next to footprint, track and scat analysis, also bioacoustic sensors [35] and especially visual methodologies are used for monitoring wildlife. The used techniques reach from manual observations by e.g. wildlife biologists, rangers or hunters, but also include citizen science projects such as *MammalNet* (`https://eu-citizen.science/project/226` (Accessed on 09.08.2023)), and go beyond to the utilization of highly advanced technology such as camera traps, (un-)crewed aerial vehicles and satellites. As discussed by Wang et al. [39] these surveying techniques show different (dis-)advantages, especially in the context of the observable area and animals, but also regarding the resulting costs. As outlined in Figure 2, uncrewed aerial vehicles (UAVs) are in the middle of this continuum. UAVs support the observation of rather big areas, with comparatively low costs. Furthermore, UAVs are applicable for observing rather small animals, due to their low distance to the ground.

In addition to these characteristics, the suitability of monitor techniques is use-case-specific. This is mostly the result of the typical operating distance between the observer, respectively the observing device, and the monitored area/animal, as well as the used imaging sensors. Especially in forest habitats, mostly camera traps and manual monitoring techniques are applied. Other techniques lead to highly unreliable animal population estimates, due to occlusion by vegetation, as for example discussed by Gonzalez et al. [16].

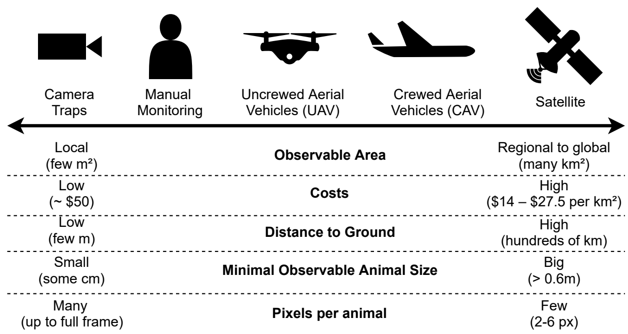


Fig. 2: Different visual survey techniques used for monitoring animals. They show different (dis-)advantages in the context of the observable area, the costs, the distance, and the minimal observable animal size, which is also related to the number of pixels and, thus, the level of detail that an animal will typically show within a recording as discussed by Wang et al. [39].

2.2 *Airborne Light Field Sampling*

ALFS utilizes light-field technology as its foundation [24] and has been successfully tested in the context of search and rescue missions [33]. Light fields represent a scene as rays that have an origin (spatial location) and a direction (two angles). ALFS recordings

Table 1 Overview of existing airborne wildlife datasets, animal species, animal annotations, habitats and recording modalities (based on [27]).

Data	Images (C/T/B)[1]	Species	Annotation			Habitat	Recording					
			Type	Count	Avg. Pixels		Country[2]	Year	Device[3]	Type	Altitude	Angle
[12]	561 (C)	Elephants, Zebra, Giraffe	Boxes	4305	50	Semi-arid grasslands, Savanna	KEN	2014, 2015	CAV	Manually	90 - 120 m	Tilted
[20]	541 (B)	Waterfowls (Siberian Crane)	Boxes	8976	7	Wetland	CHN	2018	UAV	Periodic Images	100 m	Nadir
[19]	40 (C)	Fake seabirds	Points	1560	17 - 275	Beach	AUS	2016	UAV	Several Images per altitude	30, 60, 90, and 120 m	Nadir
[32]	753 (C)	Penguins	Points	137365	30	Antarctic Islands	ATA	2013 - 2015	CAV	Periodic Images	Unknown	Nadir
[17]	1059 (T)	Turtles	Points	1902	10	Nearshore Pacific Ocean	CRI	2017	UAV	Periodic Images	90 m	Nadir
[29]	2074 (C)	Elephants	Points	1581	75	Semi-arid grasslands, Savanna	ZAF, BWA, NAM	2015 - 2018	CAV	Periodic Images	900 - 1200 m	Nadir
[40]	4653 (C)	Wading birds	Boxes	57000	35	Wetland	USA	2020	UAV	Periodic Images	76 - 91 m	Tilted
[41]	110667 (C)	Waterfowls (Goose, Gull, ...)	Points	631349	50	Izembek Lagoon	USA	2017 - 2019	CAV	At predetermined points	457 m	Nadir
[18]	3947 (C)	Albatross, Penguins	Boxes	44966	300	Coastlines	FLK	2018, 2019	UAV	Periodic Images	90 m, 60 m	Nadir
[34]	663 (C)	Cattle	Boxes	1919	90	Cattle pasture	JPN	2016	UAV	Periodic Images	50 m	Nadir
[30]	948 (C)	Sea Lion	Points	948	75	Aleutian Islands	RUS	Unknown	CAV, UAV	Unknown	Unknown	Unknown
[22]	11469 (C)	Whale	IDs	4542	1500	Open Sea	USA, CAN, ARG, BRA, ZAF, AUS, NZL	1970 - 2019	CAV, UAV	Unknown	Varying	Varying
[8]	44185 (B)	Seals	Boxes	14311	55	Coastline Alaska	USA	2019	Unknown	Unknown	Unknown	Unknown
[21]	1 (C) [Orthomosaic]	Pelicans, Terns, Gulls, Cormorant	Points	21516	30	Coastline	MRT to GIN (West Africa)	2019	UAV	Periodic Images	20 - 50 m	Nadir
[4]	61994 (T) [48 videos]	Human, Elephant, Giraffe, Lion, Dog	Boxes	166221	35	Semi-arid grasslands, Savanna	ZAF, MWI, ZWE	2020	UAV	Video	60 - 120 m	Tilted
[11]	88000 (C)	Crocodile	IDs	WIP	1000	Desert, Rivers, Ponds, Canals	IND	2022	UAV	Video	8 - 10 m	Nadir
[10]	633 (C)	Whale	Boxes	633	50	Open Sea	ARG	2006 - 2017	Satellite	Single Image	450 - 700 km	Nadir

[1] The datasets contain either colour/RGB images (C), thermal/IR images (T), or both (B).
[2] Countries are denoted in their ISO 3166 Alpha-3 notation.
[3] Used devices are uncrewed aerial vehicles (UAV), crewed aerial vehicles (CAV) and satellites.

allow visualization and processing beyond conventional imaging. For example, ALFS enables the possibility of creating an integral image with an arbitrarily parameterizable focus.

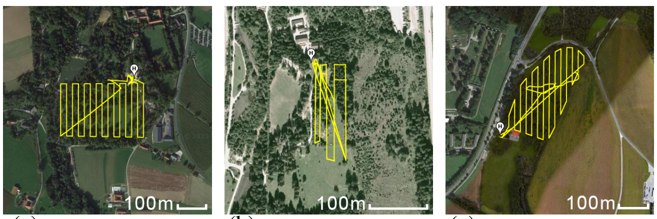
Light-field samples are typically created using specialized hardware, such as camera arrays or microlens-based cameras. Furthermore, one moving camera can also be used to record comparable data. In the case of a moving airborne vehicle equipped with one or multiple cameras, this is called airborne light-field sampling (ALFS). To create a light field sample with ALFS, a sequence of colour and infrared (IR) camera images captured from a UAV flight is merged with positional information from a global navigation satellite system such as the Global Positioning System (GPS) and a digital elevation model (DEM) (cf. Figure 1b) such as the global Aster dataset[14], allowing to create an integral image for the monitored area. In the context of wildlife monitoring in forested environments, this integration allows for changing the focus of the image from the treetops to the forest ground, thereby revealing hidden objects like animals, as shown in Figure 1d.

2.3 Airborne Wildlife Datasets

Multiple airborne wildlife datasets are publicly available, containing images of different animal species as listed in Table 1. These datasets are mostly created using (un-)crewed aerial vehicles such as drones and planes, but also contain images from satellites. The shown species range from small to big birds (e.g., terns or gulls, pelicans), mammals (such as dogs, cattle, zebras, elephants and even whales) and reptiles (e.g., crocodiles). The listed datasets show similar properties in the context of the recording type, using mostly periodic images that are created vertically to the ground (nadir) from a low altitude of a few dozen meters, but can also reach multiple hundreds and even thousands of meters distance to the ground. Concerning the monitored habitats, the available datasets address a tremendous variety of ecosystems, with one exception. To the best of the authors' knowledge, there is no airborne dataset of forests, respectively forest animals. This deficiency is probably related to the previously mentioned problem of dense vegetation heavily obscuring objects as well as the high effort and difficulty involved in detecting wildlife under the treetop.

3 Our Dataset

The dataset proposed in this work mainly contains videos of species native to Austria such as red deer, chamois, roe deer and wild boar. In order to be able to collect sufficient high-quality data for the training of AI models, regular flights are carried out over forests, wild animal gates, but also in animal parks, such as the one in the city of Haag or in Grünau im Almtal (Cumberland) with near-natural structured enclosures all around Austria (Tyrol, Upper Austria, Lower Austria, Carinthia). So far, the dataset consists of 37.53 hours of flight footage (1.62 TB of data) recorded from April 2022 to June 2023 (some examples are shown in Figure 3 and Figure 4). Recording happens with hunters and wildlife biologists, under the consent of the responsible individuals and the premise of not disturbing the animals.



(a) 48.09943, 14.557593 (b) 47.805976, 13.948753 (c) 46.653169, 14.288053

Fig. 3: A random selection of flights from the dataset with the associated take-off locations as WGS84 coordinates.

The recordings are created with multiple drones from the manufacturer DJI as listed in Table 2. While flying, the drone records a video at 29.97 frames per second. During recording, the drone is configured with a fixed orientation and avoids in-flight rotations and, thus, turn-artefacts which mostly result in motion blur. Additionally, the camera is always aligned vertically to the ground (nadir), resulting in orthophoto-like images. The drones fly automatically based on a given grid-like route with a side distance of 20 to 35 m between the

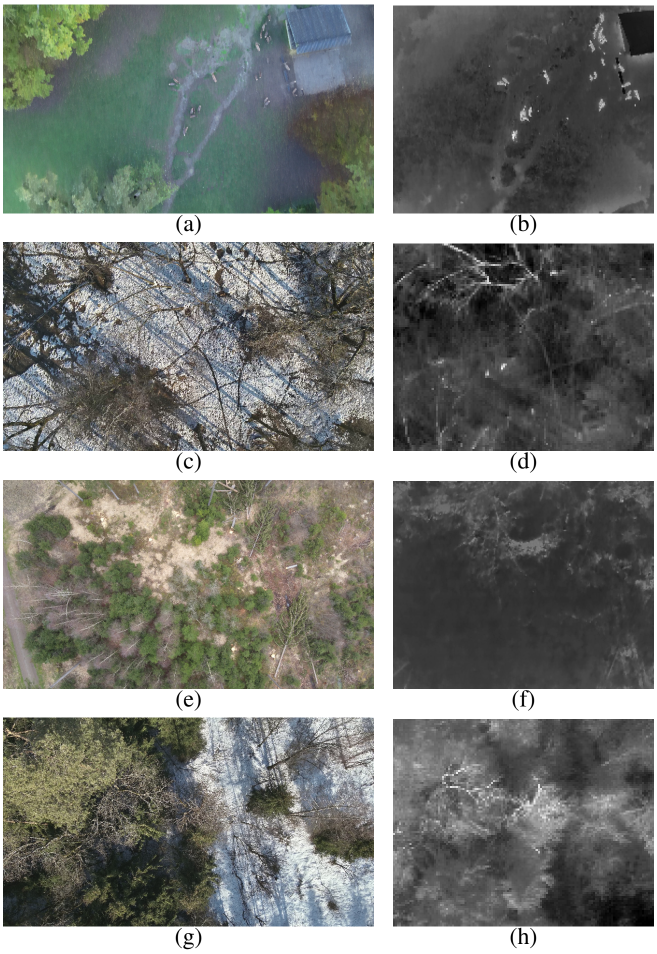


Fig. 4: Random selection of sample frames of the dataset, showing one RGB frame (left) next to the associated thermal frame (right). As shown, the dataset consists of recordings from different seasons with varying environmental conditions, but also diversity regarding the forest and forest-near habitats.

Table 2 Summary of drones, resolutions, and recorded videos in our dataset.

DJI Drone	Camera Resolution (px)		Recorded Video Pairs		
	RGB	Thermal	Count	Dur. (min)	Size (GB)
Mavic 2 Adv. Enterprise	1920 × 1080	640 × 512	79	132.98	86.52
Mavic 3 Enterprise	3840 × 2160	640 × 512	429	558.77	531.58
Matrice 30T	3840 × 2160	1280 × 1024*	612	1434.15	954.84
Matrice 300 +	3840 × 2160	640 × 512	59	126.29	45.95

* Super resolution from 640 × 512 px.
+ Applying the Zenmuse H20T camera.

grid's lines, a constant speed of 3 to 5 m/s and a steady altitude of 30–60 m, depending on the present tree height. Although some drones carry a gimbal system with three cameras (zoom, wide-angle and thermal) such as the DJI Matrice 30, Matrice 300 and Matrice 350, some systems only have two cameras (RGB and thermal). Therefore, we have unified the dataset into two channels and only use the wide-angle camera when two RGB cameras are available.

ALFS requires exact spatial information (global position and global orientation of drone, respectively camera) for the creation of the integral images. Every single used drone supports multiple Global Navigation Satellite Systems (GNSS) such as GPS or Galileo in combination with Real Time Kinematic (RTK) [26], allowing to have centimetre positional accuracy. The spatial information is recorded using DJI's subtitle feature as meta-information per video frame using the `.srt` file format. Since DJI's Pilot App V2, these files only contain spatial information with 5-digit accuracy, which is not precise enough for ALFS. However, the spatial information is also logged in an additional log file with a higher precision, which can be accessed using tools such as AirData (`www.airdata.com` (Accessed 09.08.2023)). This log file is only recorded with a 10 Hz update rate. Thus, a direct mapping of frames and positions is not possible and requires the combination of both the `.srt` file and the log file, allowing us to interpolate the required positions per frame.

Based on the drone recordings, animals are labelled in the multispectral data (RGB and thermal frames) by wildlife biologists. Every recording is associated with multiple labels of animals. As the data are videos, one animal will most likely occur in several frames of the video. Thus, we distinguish between labels per frame and a track of a single individual animal across several frames. Labels provide per-frame spatial information in the form of a boundary polygon, allowing the creation of segmentation masks and axis-aligned bounding boxes for classical object detection tasks. As we record data in forests, animals will be (partially) covered in some frames, every per-frame label, therefore, contains a visibility parameter indicating if the animal is entirely visible, partially obscured or hidden. Each animal track is associated with an identified animal species. For situations, where the animal species is not clearly recognizable, a confidence value for the species can be specified. Thus, frames with low-confidence labels/tracks can be removed in the training process. Furthermore, it is possible to store the age and gender of animals (i.e., the tracks) if known or recognizable. The age of an animal will be classified into unknown, juvenile, or mature; the gender into unknown, male, or female. Per-default age and gender are marked as unknown. Currently, the dataset consists of 4772 red deer, 4064 roe deer, 24 chamois, 329 wild boar, 336 rabbits and 356 fallow deer frame labels - gender and age are not included so far.

Next to the videos and labels, calibration parameters are also available for the used cameras. These are necessary, as the drones have different cameras (zoom, wide-angle, thermal) with various parameters (resolution, field of view, etc.). Through said distortion coefficients, it is possible to rectify individual frames and combine the RGB and thermal information into a multispectral image stack. The coefficients have been manually determined using calibration patterns and feature matching.

4 Conclusion and Outlook

As discussed in this work, the alarming decline of biodiversity on our planet requires suitable monitoring methodologies and strategies as a foundation for targeted management measures. While camera traps have been widely used for monitoring wildlife for many decades, airborne methodologies are used more and more frequently. However, this trend is mostly limited to non-forest habitats. With ALFS, a visual airborne approach has been developed that reveals animals on a ground level within forests; thus, for the first time, it enables the implementation of airborne wildlife monitoring systems for forests. This work proposes a novel multispectral airborne dataset of forest and forest-near environments, which may be used as the basis for ALFS-based wildlife detection. Currently, data is still being collected and labelled manually with the help of wildlife biologists. Once the recording and labelling process is complete, the entire dataset will be publicly available and periodically extended. Due to the novelty of ALFS, there are also no suitable annotation tools publicly available. The used software for the presented dataset will be open sourced on GitHub separately.

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