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Development of a cost-efficient automated wildlife camera network in a European Natura 2000 site☆

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ABSTRACT

Modern approaches with advanced technology can automate and expand the extent and resolution of biodiversity monitoring. We present the development of an innovative system for automated wildlife monitoring in a coastal Natura 2000 nature reserve of the Netherlands with 65 wireless 4G wildlife cameras which are deployed autonomously in the field with 12 V/2A solar panels, i.e. without the need to replace batteries or manually retrieve SD cards. The cameras transmit images automatically (through a mobile network) to a sensor portal, which contains a PostgreSQL database and functionalities for automated task scheduling and data management, allowing scientists and site managers via a web interface to view images and remotely monitor sensor performance (e.g. number of uploaded files, battery status and SD card storage of cameras). The camera trap sampling design combines a grid-based sampling stratified by major habitats with the camera placement along a traditional monitoring route, and with an experimental set-up inside and outside large herbivore exclosures. This provides opportunities for studying the distribution, habitat use, activity, phenology, population structure and community composition of wildlife species and allows comparison of traditional with novel monitoring approaches. Images are transferred via application programming interfaces to external services for automated species identification and long-term data storage. A deep learning model for species identification was tested and showed promising results for identifying focal species. Furthermore, a detailed cost analysis revealed that establishment costs of the automated system are higher but the annual operating costs much lower than those for traditional camera trapping, resulting in the automated system being >40 % more cost-efficient. The developed end-to-end data pipeline demonstrates that continuous monitoring with automated wildlife camera networks is feasible and cost-efficient, with multiple benefits for extending the current monitoring methods. The system can be applied in open habitats of other nature reserves with mobile network coverage.

Introduction

The Kunming-Montreal Global Biodiversity Framework adopted in December 2022 highlights the need for developing a global biodiversity observing system (Gonzalez et al., 2023). This requires effective and cost-efficient monitoring techniques and a dramatic increase in the spatial, temporal, and taxonomic extent of biodiversity monitoring (Besson et al., 2022; Kissling et al., 2018; Wearn & Glover-Kapfer, 2019). To achieve this, advanced technologies such as low-power digital sensors, wireless communication technology, and automated approaches are important tools to collect, store, transfer and process data about species and ecological communities (Besson et al., 2022; Glover-Kapfer et al., 2019; Wägele et al., 2022). Digital sensors such as cameras and microphones can provide high-frequency species observations without observer disturbance, allow sampling in remote areas, and obtain observations at times that are otherwise not feasible (Kissling et al., 2018).

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Moreover, sensors with wireless functionality allow for automated data streams and near-real-time biodiversity monitoring (Porter et al., 2005). However, this requires innovations in automated data transmission, efficient data handling, big data storage, and machine learning for automated species identification (Steenweg et al., 2017; Tuia et al., 2022; Wägele et al., 2022).

Recent technological advances have resulted in wildlife cameras that can be operated autonomously, e.g. wildlife cameras with solar panels that do not require manual replacement of batteries, and with functionalities for automated data transmission (e.g. through mobile networks or satellite links) that avoid the need for manual retrieval of SD cards (Wearn & Glover-Kapfer, 2017). Deploying such cameras depends upon good light conditions and stable on-site telecommunication networks for automated data pipelines from sensors to a computational infrastructure. Moreover, data pipelines and storage need to be established (Scotson et al., 2017), and web interfaces are needed to visualize and monitor the data streams (Ahumada et al., 2020). Artificial intelligence (AI) such as machine learning and deep learning algorithms for automated species identification (Norouzzadeh et al., 2018; Tuia et al., 2022) can also allow for near-real-time and cost-efficient species classification, but also requires investments into image labelling and model development (Chalmers et al., 2023). Various online platforms have recently emerged to facilitate the processing of camera-trap images with AI (Tuia et al., 2022; Vélez et al., 2023), but the volume, variety, velocity and security of data remains a challenge for using AI models in operational biodiversity monitoring systems.

Setting-up a new wildlife camera network is typically done in several phases, including the collection of pilot data with sensors under field conditions, development of sampling designs, establishment of data handling and processing pipelines, and implementation and maintenance of the system (Dyo et al., 2012; Wearn & Glover-Kapfer, 2017). Sampling designs should have a clearly defined aim, use a standardized methodology for data collection, and consider basic principles such as randomisation, replication and stratification (Wearn & Glover-Kapfer, 2017). Recommendations for standardized sampling designs with camera traps include the use of high-quality cameras without bait, usually at a height of 30–50 cm, and avoiding microsites with major obstructions (Wearn & Glover-Kapfer, 2017). For monitoring larger areas, camera traps can be assembled in networks using systematic grids or stratified-random designs (e.g. outside well-established trails; Wearn & Glover-Kapfer, 2017). Species detection with different camera deployments (e.g. at different heights or in different habitat types) can be tested during pilot studies and preliminary analyses can show at which rates data accumulate and how well species are detected (Kays et al., 2020). Recommendations for camera trap sampling designs suggest using 40–60 camera traps per site, but 20–30 cameras can already be sufficient to estimate the occupancy of common species and the species richness of sites in temperate regions (Kays et al., 2020). Sampling designs can also include comparisons with traditional sampling methods (Wearn & Glover-Kapfer, 2019) or experimental designs such as herbivore exclosures in rewilding projects (Bakker & Svenning, 2018).

Here, we describe the development of an automated wildlife camera network in a 34 km^2 dune ecosystem west of Amsterdam at the coast of the Netherlands. The network aims to expand current monitoring approaches and should allow to study the distribution, habitat use, activity, phenology, population structure and community composition of ground-dwelling mammals and birds in an efficient way. We used pilot studies to test the autonomous deployment of wireless 4G wildlife cameras with solar panels and automated data transmission, with different deployment heights, camera lens types and an analysis of focal species detection (rabbits, deer, foxes). We then developed a sampling design, implemented a network of 65 cameras and tested an AI model for species identification and human detection in wildlife camera monitoring workflows. To understand whether the system is cost-efficient, we calculated the full economic costs of the automated camera network (including establishment and annual operation costs over a 5- and 10-year time period, respectively) and compared it to the costs of a manual system with traditional camera traps. Our work contributes to operationalising modern approaches for biodiversity monitoring using sensor networks, wireless data transmission, and automated processes for data streams and species identification with AI.

Materials and methods

Study area

The Amsterdam Water Supply Dunes (AWD) are a 34 km^2 dune ecosystem west of Amsterdam, located just south of the resort Zandvoort (southwest of Haarlem) and stretching 8 km along the Dutch North Sea coast with a width varying from 1.5 to 5 km. The area is an important nature reserve and part of the European Natura 2000 site Kennemerland-Zuid (site code NL1000012), which includes two other dune areas (Nationaal Park Zuid-Kennemerland and Noordwijkse Noordduinen). The AWD are owned by the Municipality of Amsterdam and managed by Waternet, a water company for Amsterdam and the surrounding area. The management of the area accommodates four functions: 1) production of drinking water, 2) nature conservation, 3) recreation, and 4) sea defence.

The study area has been used for the production of drinking water since 1853. Infiltration canals have been made in part of the area for drinking water purification. The extensive area is dominated by various dune habitats, including shifting white dunes, fixed coastal dunes with herbaceous vegetation, dunes with sea-buckthorn formations, wooded dunes and humid dune slacks (EU habitat type codes 2120, 2130, 2160, 2180 and 2190, respectively). Vegetation is dominated by grasses (46 %), but also includes large parts of scrublands (22 %) and forests (21 %), and smaller areas of sand (6 %) and other low vegetation (Appendix A). The landscape is important for a variety of vertebrates, vascular plants and invertebrates. Nearby urbanization also renders the study area an important recreational area, with over 1 million visitors annually as much of the study area is accessible for hiking and nature-orientated recreation. The first 100 m from the shoreline are strictly managed for sea defence.

As in other Dutch coastal dunes, grazing mammals such as the European rabbit (*Oryctolagus cuniculus*) and the European fallow deer (*Dama dama*) are key species in the study area because they slow down the rate of natural succession and alter plant species composition and vegetation structure through their grazing and digging. To study ecosystem recovery after high-intensity grazing by fallow deer, a total of 16 fenced exclosures ranging in size from 0.5 to 7.2 ha were established in the winter of 2019–2020. Moreover, several traditional survey methods are already used to monitor wildlife in the study area. For rabbits, a 23.5 km long monitoring route is surveyed each year in spring (March–April) and autumn (September–October) to examine breeding success and winter mortality (van Strien et al., 2011). Surveys are done from a car driving along the monitoring route in the evening 1 h after sunset, with high beam headlights and a speed of about 20 km per hour, counting all rabbits that appear in the beam of the car light. Other mammals such as red fox (*Vulpes vulpes*), European hare (*Lepus europaeus*) and roe deer (*Capreolus capreolus*) are also registered, but data are insufficient for monitoring those species. For fallow deer, the whole study area is surveyed once per year at the end of winter (end of March, beginning of April) by subdividing it into eleven counting sectors, each counted simultaneously by a separate counting team with at least two counters. Counting is done from a car using a standardized sampling protocol (https://www.fbezh.nl/telrapporten/) and each count consists of three consecutive counting sessions with 2.5 h in the evening, morning and evening twilight hours, respectively.

Wildlife cameras

To expand current monitoring, we used camera traps with wireless functionality and solar panels (Fig. 1). The cameras are triggered by a passive infrared sensor (PIR) and use an infrared flash at night, comparable with other widely used wildlife cameras (see comparison in Table B.1 in Appendix B). A key difference to other cameras on the European market is that they allow setting up an automated sensor network because (1) they can be deployed autonomously for long time periods using a 12 V/2A solar panel, (2) they can automatically transmit images (and a daily report) via 4G using MMS, email or an FTP server, and (3) allow users to define SIM card plans and the end point of the images. Details on camera settings can be found in the supplement (Appendix B: Fig. B.1). Cameras and solar panels were mounted with security cages on wooden poles at 30–50 cm height (Fig. 1B), installed off-trail, facing north, without bait, at microsites without major obstructions, and not facing towards trails or steep upward angles, taking best practices for camera trap studies into account (Wearn & Glover-Kapfer, 2017).

Pilots

We conducted three pilots with 2–6 wildlife cameras each between summer 2021 and spring 2023 (details in Table C.1 of Appendix C) to test (1) the autonomous deployment (with solar panels, no battery replacement and no SD card retrieval), (2) wireless data transmission (with SIM cards and 4G via a telecommunication network), (3) data accumulation of images over time, and (4) differences in the detection of focal species (rabbit, fallow deer and the red fox as top predator) inside and outside exclosures and between regular lens (52°) and wide lens (100°) cameras. For comparing lens angles, two cameras with different lenses were installed as pairs at the same locations and the same time, allowing a direct comparison of detection rates. Observations for this lens angle comparison were defined within sequences of images taken within 120 s. A total of 47,597 images from these three pilots were manually checked (Appendix C). Data were compared in terms of data accumulation over time, number of detected individuals of focal species, total species richness, and differences in detection rates with different lens angles (regular vs. wide lens). For the latter, we fitted occupancy models (details in Appendix C) to estimate the effect of lens angle (regular vs. wide) and location on the probability of detection for two species with sufficient sample sizes (rabbit and fallow deer). The R code for the occupancy analysis is available on GitHub (https://gist.github.com/jevansbio/b6d76371e79eb68b7b8f6c2b6c32dfbd) and the collected data are described in a data paper (Evans, Zilber, & Kissling, 2024).

Sampling design of camera network

The overall sampling design of the camera network was guided by three research questions (Table 1). This resulted in an integrated sampling design, combining a grid-based sampling approach with the monitoring along a traditional survey route and with the paired sampling inside/outside deer exclosures. For the grid-based sampling, a 1 × 1 km^2 grid was put over the study area and camera placement was stratified by major habitat types (Appendix D), using a digital vegetation map of the study area (Appendix A: Fig. A.1). Along the traditional survey route for rabbit monitoring, cameras were placed approximately 1 km apart and within a buffer of up to 20 m from the route, taking locations of grid camera placements into account. For the exclosures, a paired sampling design was used, with exclosure cameras inside

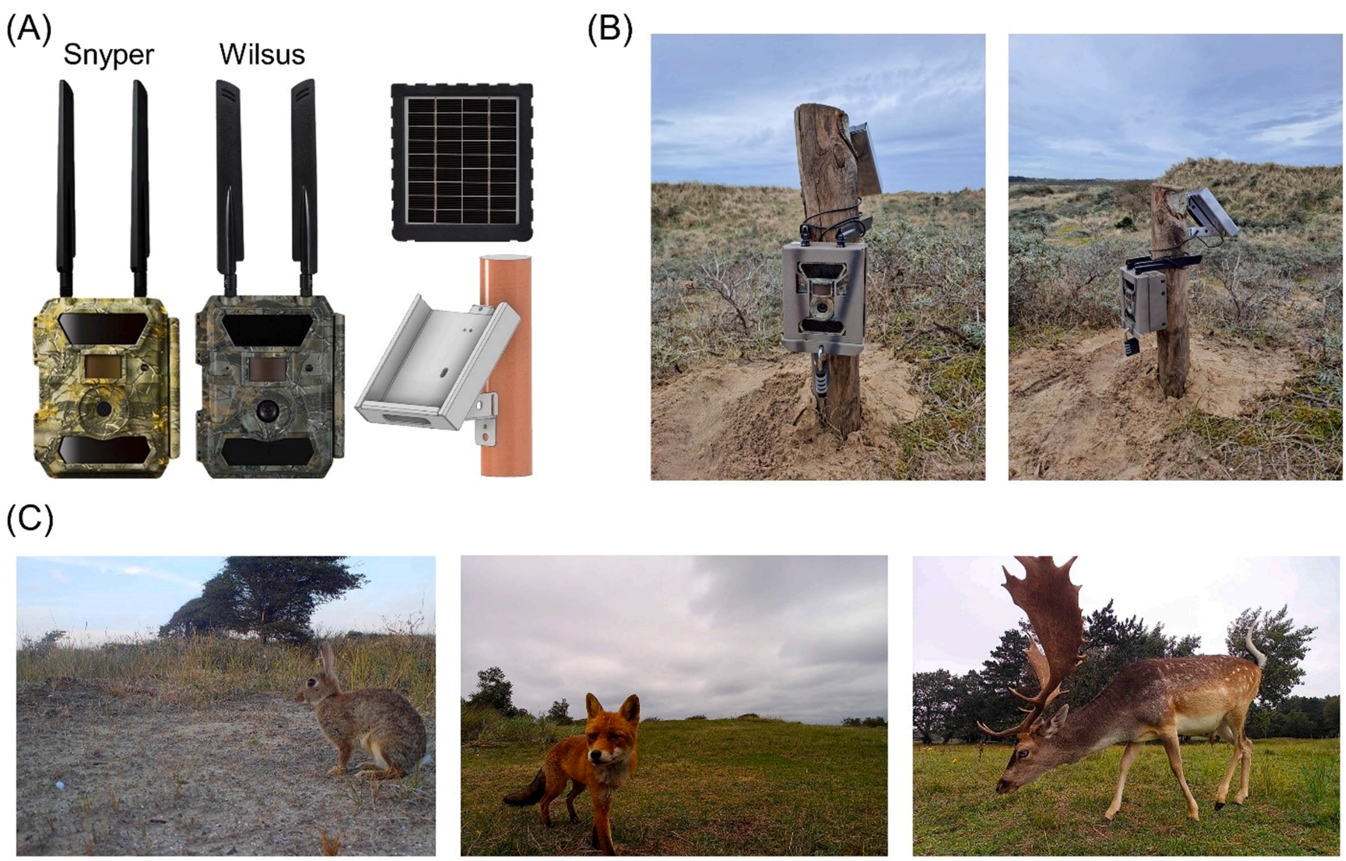


Fig. 1. Wildlife camera deployment in the Dutch coastal dunes. (A) The Snyper Commander 4G Wireless and its successor the Wilsus Tradenda 4G Wireless, with a 12 V/2A solar panel and its custom-designed solar panel bracket. (B) Camera mounted on a wooden pole, with metal cage and lock around the camera, and with a solar panel in a custom-designed bracket. (C) Camera trap images of focal species. Left: European rabbit (*Oryctolagus cuniculus*); Middle: red fox (*Vulpes vulpes*); Right: European fallow deer (*Dama dama*). A story map is available online (https://arcg.is/1OPb1X).

Table 1
Sampling designs for implementing a wildlife camera network in the Amsterdam Water Supply Dunes of the Netherlands. Each type of sampling is guided by a specific research question.

Type	Design criteria	Research question
Grid-based sampling	One camera per 1 × 1 km^2 grid cell, stratified by major habitats (grass, scrubland, forest, sand, other low vegetation)	How does the diversity and community composition of wildlife and the occupancy of mammalian herbivores (e.g. rabbits, hare, fallow deer, roe deer) and top predators (red fox) change over space and time?
Rabbit monitoring route	Approximately one camera per kilometre along the 23.5 km traditional survey route, within a 20 m buffer of the edge of the route	How do population trends of rabbits derived from traditional monitoring (i.e. transect counts) compare to trends derived from wildlife cameras?
Exclosures	One camera inside and one outside exclosures ($n = 16$), each pair placed in same habitat	How does the diversity and occupancy of wildlife differ inside and outside large herbivore exclosures?

exclosures and control cameras outside (placed in a buffer 200–300 m away from the exclosure boundary). All geospatial analyses such as grid placement and distance or buffer calculations were done in ArcGIS Pro 3.0 (Appendix D).

Data handling

Data handling was done with a sensor portal that was developed for the monitoring demonstration sites of the large-scale research infrastructure project ARISE (https://www.arise-biodiversity.nl/teammonitoringdemonstration). The sensor portal was built with open source software such as Django, Celery, Podman, PostgreSQL and PostGIS (Appendix E) and uses Python as the main programming language (50 %), but also Java (25 %), CSS (15 %) and HTML (10 %). A first shareable version of the source code is on GitHub (https://github.com/jevansbio/ARISE-MDS-sensor-portal) and will be further expanded to make it more portable, reusable and generalisable. Several system security and data protection considerations have been taken into account (Appendix E). The data pipeline automatically imports the images and daily reports from the cameras (transmitted over 4G to an external landing zone) into the sensor portal. The sensor portal allows managing and remotely monitoring the cameras, and includes local data storage, a PostgreSQL database, and functionalities for automated task management and application programming interfaces (APIs; Appendix E). From the sensor portal, images are securely transferred via APIs to external platforms for automated species identification. Images are archived (as TAR files) on long-term cold storage of the Dutch national IT infrastructure SURF (Appendix E).

Automated species identification

We tested the automated species identification with a deep learning model from Conservation AI that uses the Faster R-CNN architecture (based on ResNet101) to detect and classify species from camera trap images (Chalmers et al., 2023; Fergus et al., 2023). We fine-tuned the learned parameters of this deep learning model and added additional training data to support our focal species (Appendix F). Performance of the trained model was assessed by comparing its results with a manual classification of 4058 images from 46 cameras deployed mainly from August–October 2023. Results were summarized into a confusion matrix (Table F.1 in Appendix F). In the main text, we mainly refer to the balanced accuracy (i.e. the sum of sensitivity and specificity divided by 2) and the recall (= sensitivity) of five classes (rabbit, fallow deer, fox, person, blank). Additional performance metrics are reported in the supplement (Table F.2 in Appendix F).

Cost estimation

To estimate whether an automated camera network is cost-efficient compared to traditional camera traps, we calculated the total costs of both networks with 65 cameras each, using the sampling design and focal species of our study area. The total costs covered all establishment costs and all annual operating costs of the implemented system over either a 5-year or a 10-year time span (see Appendix G: Fig. G.1). This included materials (e.g. cameras, batteries, SIM cards, fuel, data transmission, data storage) and staff time (technicians, researchers) for data collection, workflow and administration (Table 2). Costs were derived from the pilots, standard market sale prices, official reimbursement rates, standard salary rates, and our own experience (Appendix G). For traditional camera traps, we included costs for cameras with batteries and SD cards, manual data collection and battery replacement, manual upload and external hard drive storage, and species identification by humans (assuming support through an online system). For the automated camera network, we calculated costs for wireless cameras with solar panels and 4G data transmission, data pipelines for automated data handling and archiving, and automated AI species identification (extension of the existing deep learning model). Cost efficiency (the relative costs of generating an identical dataset) was calculated as the difference in costs between the two camera networks.

Results

Pilots

The autonomous deployment of wildlife cameras with solar panels did not require any battery replacement or SD card retrieval, thereby reducing the need for regular site visits. This also applied to the three cameras of pilot 1 which were deployed over a total of 746 days (> 2 years). Wireless data transmission with 4G and SIM cards over the Dutch KPN telecommunication network worked well in the coastal dunes. In 47,597 manually annotated images over ~500 days of deploying three cameras of pilot 1 (placed in exclosures), a total of 20 species were detected (Table C.2 of Appendix C). The rabbit was the most commonly detected species in pilot 1 (Fig. 2A), with >1500 observations per year (Fig. 2B). The accumulated number of rabbit observations was 8 times higher per year than that of foxes (Fig. 2B), and the number of blank images (including daily report images and false triggers) was two times higher than that of rabbit observations (Fig. 2B). Rabbits were also the most often detected species in pilot 2, whereas fallow deer were detected only in pilot 3 (outside exclosures; Fig. 2C). Foxes were detected in low numbers in all pilots (Fig. 2C). Comparisons of different lens angles (in pilots 2 and 3) showed that a wide lens can detect 1.5–2.5 times more individuals of the same species than a regular lens (Fig. 2C). However, while the total number of detections differed between lens angles (Fig. 2C), the detection rate of both species showed no statistically significant difference between wide and regular lens (Fig. 2D, Appendix C: Table C.3). This suggested that species which occupy and inhabit a particular site can be equally detected by both lens angles. However, pilot 2 and 3 also showed that rare or less frequently visiting species such as mice (genus *Apodemus*), polecats (*Mustela putorius*) and various bird species (e.g. *Parus major, Scolopax rusticola, Fringilla coelebs*) often remained undetected by a regular lens, resulting in 2–6 times more species detected with a wide lens than with a regular lens (Fig. 2E).

Sampling design of camera network

The vegetation distribution in the study area (Fig. 3A) together with the integrated sampling design (Table 1) defined the locations of the 65 wildlife cameras (Fig. 3B,C) which were installed during July–November 2023. Based on the pilot results, we opted for an installation at

Table 2
Overview of how costs were calculated. See Appendix G for additional details.

Cost categories and cost items	Description	Automated camera network	Traditional camera trapping
Establishment costs			
Materials for data collection*	The full supplier costs of all materials used for data collection, plus fuel costs for setting-up the cameras	Cameras**, memory cards**, batteries**, security enclosures, poles, solar panels** & mount. Site set-up fuel costs (9 visits at 95.82 km)	Cameras**, memory cards**, batteries**, security enclosures, poles. Site set-up fuel costs (9 visits at 95.82 km)
Staff for camera set-up	The initial labour required to set-up the cameras.	Camera set-up (10 days total), assembly and configuration (4 days) and quality control (2 days)	Camera set-up (10 days total), assembly and configuration (2 days) and quality control (2 days)
Materials for workflow	The initial material costs required to set-up the data pipeline.	SIM cards	Multi SD-card reader
Staff for workflow set-up	The initial labour required to set-up the data pipeline from camera to database	Two months time of a data scientist, plus time for making high-quality labels (with bounding boxes) to develop a training dataset (14 s/image, 2000 images/species)	
Annual operating costs			
Fuel for maintenance of data collection	Annual fuel costs for camera maintenance	Charged at 0.21 EUR/km (reimbursement rate at the University of Amsterdam), assuming 72.4 km round trips to the site and within-site travel spanning 23.42 km for each visit (total 95.82 km/trip).	
Material losses of data collection	The costs of replacing cameras that are damaged or stolen	Assumes two cameras per year and fuel costs to set them up and replace them.	
Staff for annual data collection	Annual pro-rata costs of technicians conducting field maintenance, based on estimates from the pilots (2021–2023).	Time for four physical maintenance visits per year. Time to set up and reinstall two lost cameras per year.	Changing batteries and memory cards (4 days every three weeks), plus travel time for site visits and time for recharging batteries. Collectively 34 person days per year. Time to set up and reinstall two lost cameras per year.
Workflow costs for data transmission*	Annual costs of data transmission from SIM cards by the wireless 4G wildlife cameras	Data transmission (1.78 EUR/ camera/ month based on an average of 40 images, each 0.47 MB, transmitted daily at 2.5 EUR/ GB) FTP server (6.05 EUR/month) and virtual machine (80 EUR/month).	NA
Workflow costs for data storage	Annual costs of storing data generated from the sampling network.	Each camera generates an average of 572 MB/month of data per month at 0.061 EUR/GB/ month (rates of SURF Data Archive). This is cumulative, i.e. the value increases by the same amount each year (a 10 year average is presented).	Two 5 TB external hard drives (one as a primary storage and the other for backup) at €149.5 each (incl. VAT).
Staff for workflow maintenance	Annual pro-rata costs of a technician involved in the workflow, based on estimates from the pilots (2021–2023)	Remotely monitoring the performance and automated data upload of cameras (2 hrs/month).	Memory card extraction and download (0.25 hrs/camera/visit).
Staff for species identification	Annual costs of species identification, based on estimates from the pilots, Conservation AI, and camera trapping projects	Automated species identification with Conservation AI platform at cost of 0.02 EUR per 18,000 images, and 10 % manual validation per year (of which 90 % for manual validation and 10 % for new labelling) with ~6 s or 0.0017 hrs per image.	Manual identification of all images, with 2 s or 0.00056 hrs per image, assuming the use of an online platform for easy and efficient tagging of species in sequences of images.
Administration (staff)	Annual costs of a part time administrator to lead the project.	Based on a single administrator at the level of an academic non-scientific employee working at 20 % FTE.	

*VAT at 21 % (Netherlands standard rate) is applied to items in this category.
**These items are replaced every 5 years and ~2 cameras per year are assumed to need replacing due to damage or theft, with associated travel (1 visit), labor and material costs.

~35 cm height and using cameras with a wide lens. A total of 41 cameras (one per 1 × 1 km^2 grid cell) were implemented for the grid-based design (Fig. 3B). Of those, 27 were shared with either the rabbit monitoring route (n = 14), the exclosure control (n = 10), or both (n = 3). Two additional cameras were installed in forest habitat (Fig. 3B). A total of 20 cameras were placed along the rabbit monitoring route (Fig. 3B). For the paired exclosure design, 32 cameras (= 16 × 2) were installed (Fig. 3C). Camera locations were approximately stratified according to the proportion of habitat types in the study area (Fig. 3E,F).

Data handling

The images (~0.5 MB per file) are sent from the 4G wildlife cameras (within max. 60 s after triggering) to an external landing zone (FTP server; Fig. 4A). The sensor portal then imports the data every 15 min and handles them automatically (Fig. 4A). The sensor portal includes a web graphical user interface (GUI) to view the collected images in near-real time via a file browser (Fig. 4B). It further provides several ways of remotely monitoring the performance of the cameras, including the number of files uploaded per camera and per day, battery status and available space for SD card storage (Fig. 4C).

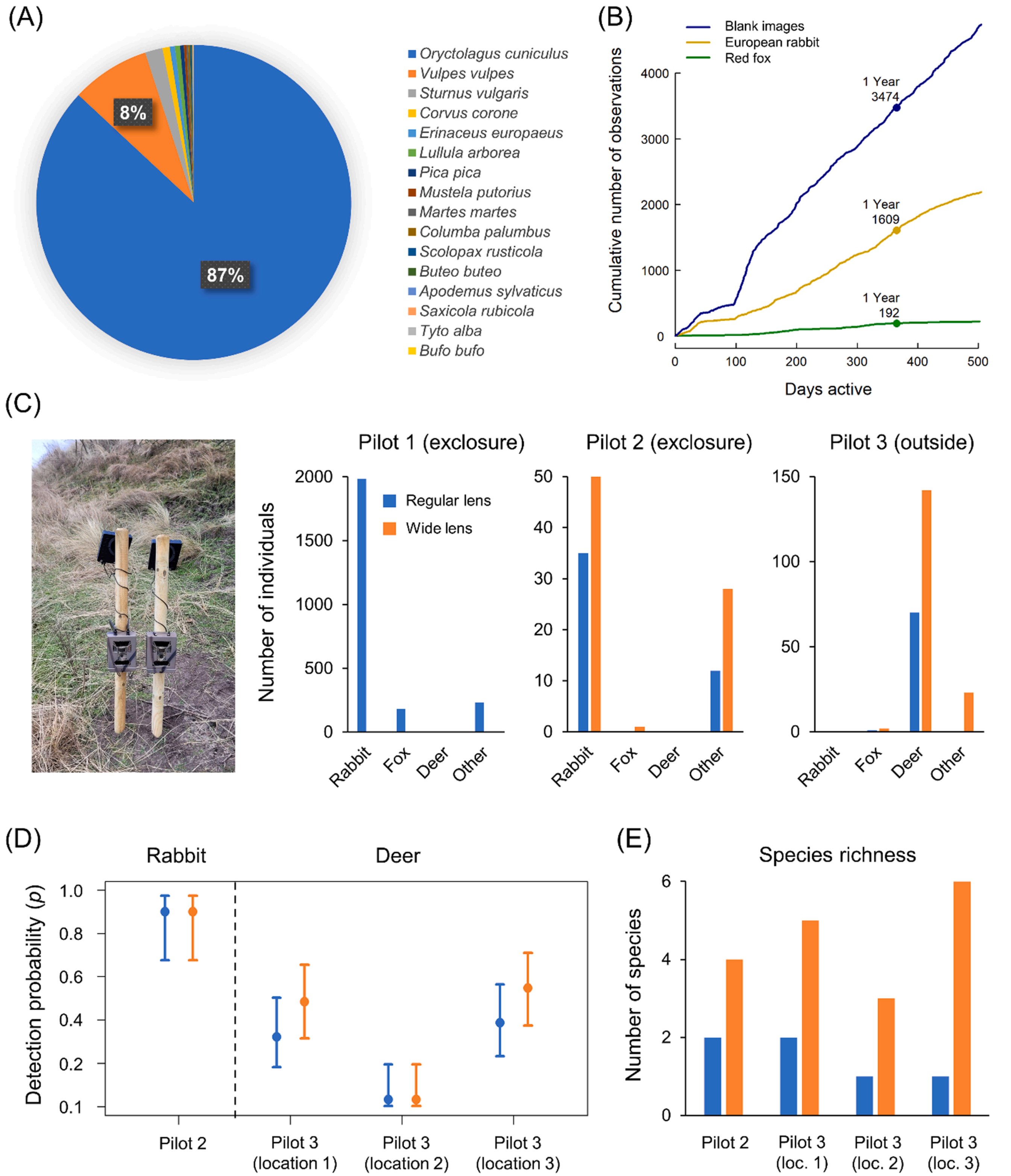


Fig. 2. Results of pilot studies. (A) Number of wildlife species detected in images from pilot 1 (three cameras in exclosures over >1 year). Species are ordered by decreasing numbers (see Appendix C: Table C.2). (B) Examples of data accumulation over time (pilot 1). (C) Total number of detected individuals of focal species (pilots 1, 2 and 3). Photo shows pilot installation with paired cameras, one with a regular lens (52°, left) and one with a wide lens (100°, right). (D) Differences between regular angle (blue) and wide angle (orange) in detection probabilities of rabbit (pilot 2) and fallow deer (pilot 3). (E) Differences in species richness caused by lens angles.

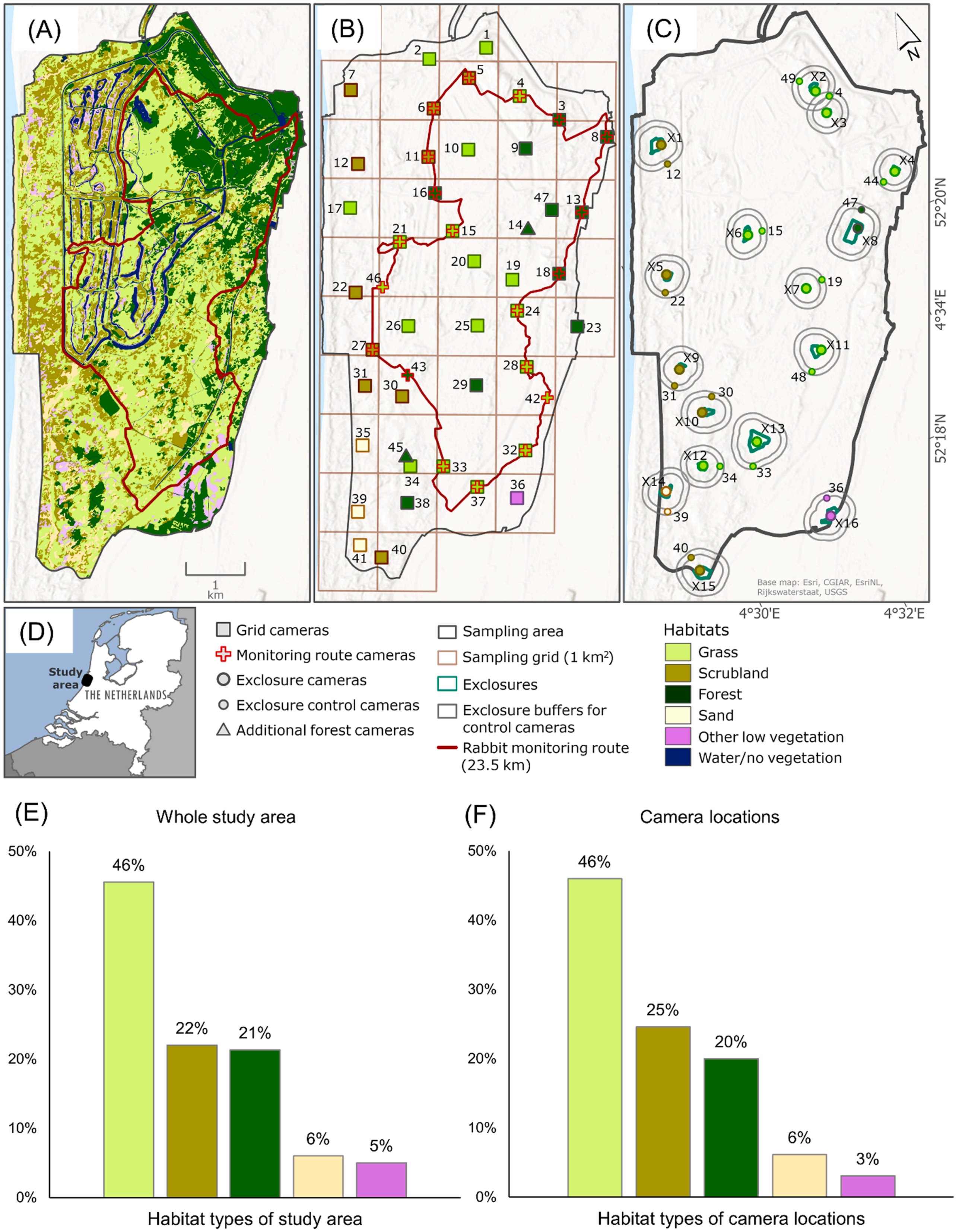


Fig. 3. Habitats and sampling design. (A) Major habitat types of the study area. (B) Locations of wildlife cameras for grid-based sampling design (one camera per 1 km^2 grid cell) and along an existing rabbit monitoring route (red line). (C) Exclosure design with one camera inside and one outside sixteen exclosures. (D) Location of the study area in the Netherlands. (E) Percentage of habitat types in the whole study area (~32 km^2 of vegetated area). (F) Percentage of habitat types of camera locations (n = 65). See Appendix A: Table A.2 for details on the stratification of camera placement. A story map is available online (https://arcg.is/1OPb1X).

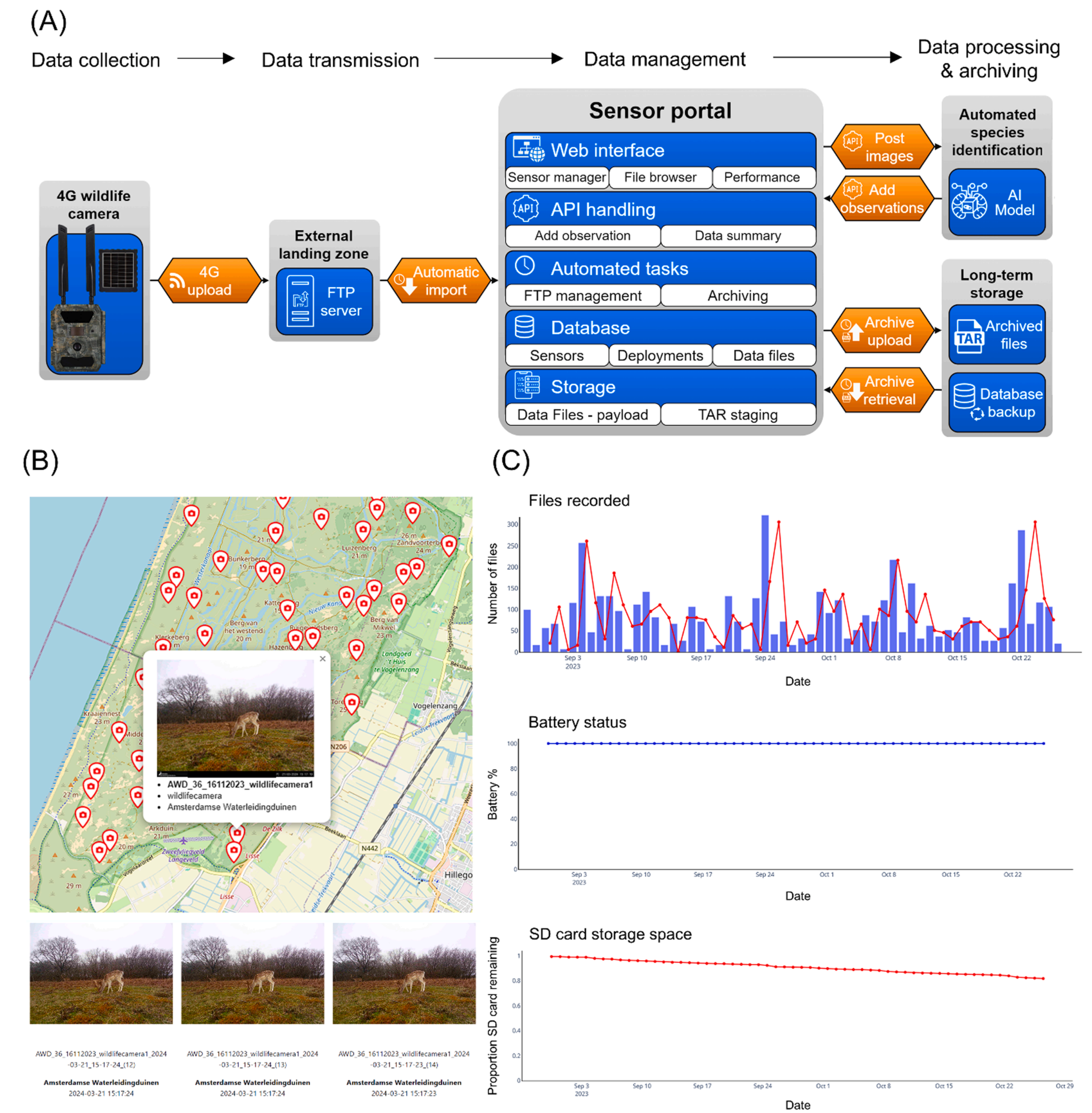


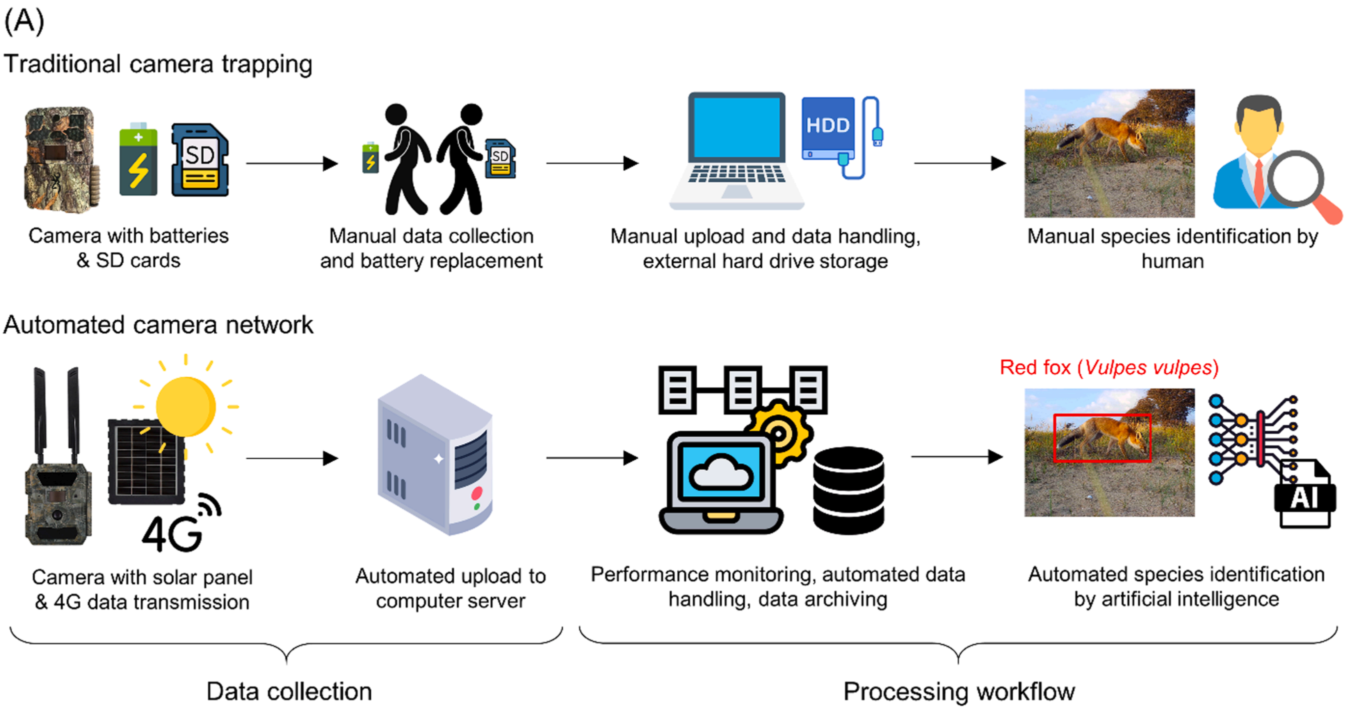
Fig. 4. Data management and performance monitoring of wildlife cameras. (A) End-to-end data pipeline (sensor -> sensor portal -> data processing and archiving services). (B) Map viewer and file browser of the sensor portal. (C) Monitoring of sensor performance. See Appendix E for sensor portal details.

Automated species identification

The accuracy assessment showed that the deep learning model performed reasonably well for automatically identifying the focal species (Appendix F: Table F.2). The fox showed the highest balanced accuracy (0.88) and recall (0.78) of the three focal species, followed by the rabbit (0.75, 0.50) and the fallow deer (0.69, 0.42). The fallow deer had the highest prevalence whereas the rabbit and the fox showed a low prevalence in the validation dataset (Appendix F: Table F.2). The model performed particularly well in detecting humans (balanced accuracy = 0.90; recall = 0.85). Blank images had a low balanced accuracy (0.60) and low recall (0.51).

Cost estimation

Comparing the data collection and processing workflows of a traditional vs. an automated system (Fig. 5A) showed that establishment costs of the automated camera network are 62,918 € (+131 %) higher than traditional camera trapping, especially due to the higher material costs for data collection and the staff time needed for workflow set-up (Fig. 5B). However, the automated system strongly reduces the staff costs for annual data collection, workflow maintenance and species identification, leading to a saving of 57,156 € per year (−51 %) for the annual operating costs compared to the traditional camera trapping (Fig. 5B). Overall, the total costs (incl. establishment and annual



(B)

Cost categories and cost items		Automated camera network	Traditional camera trapping	Difference
Establishment costs				
Data collection	Materials for data collection	77,134 €	40,695 €	36,480 € (+90%)
	Staff for camera set-up	7,664 €	6,706 €	958 € (+14%)
Processing workflow	Materials for workflow	325 €	690 €	-365 € (-53%)
	Staff for workflow set-up	25,845 €	0 €	25,845 € (+100%)
Total establishment costs		**111,009 €**	**48,091 €**	**62,918 € (+131%)**
Annual operating costs				
Data collection	Fuel for maintenance of data collection	80 €	1,087 €	-1,006 € (-93%)
	Material losses of data collection	1,427 €	761 €	665 € (+87%)
	Staff for annual data collection	2,228 €	20,695 €	-18,467 € (-89%)
Processing workflow	Workflow costs of data transmission	29 €	0 €	29 € (+100%)
	Workflow costs for data storage	86 €	25 €	62 € (+251%)
	Staff for workflow maintenance	307 €	15,153 €	-14,846 € (-98%)
	Staff for species identification	10,104 €	33,674 €	-23,569 € (-70%)
Administration	Administration	40,831 €	40,831 €	0 €
Total annual operating costs		**55,069 €**	**112,225 €**	**-57,156 € (-51%)**
Total costs				
Overall (10 years)		**661,696 €**	**1,170,341 €**	**-508,645 € (-43%)**

Fig. 5. Comparing traditional and automated camera trapping. (A) Conceptual illustration of data collection and processing workflows for traditional camera trapping and automated camera networks. Icons from https://www.flaticon.com/. (B) Costs over a 10-year period for establishment and annual operation of camera trapping and automated camera networks. The difference shows the% cost increase or decrease of the automated system relative to the traditional one. See Appendix G: Table G.2 for a 5-year calculation.

operation) of the automated system over a 10-year period are 43 % lower, with a cost saving of >500,000 € (Fig. 5B). Over a 5-year period, overall costs of both the traditional and automated system are ~50 % lower than over a 10-year period (Appendix G: Table G.2), but the cost-efficiency of the automated camera network remains nearly the same (−40 % vs. −43 %).

Discussion

Our results demonstrate that wildlife monitoring in a central European coastal dune ecosystem can be operationalized with autonomous wildlife cameras, automated data pipelines and AI species identification using deep learning. The pilot studies suggest that the installation of wildlife cameras with a wide lens has advantages compared to a regular lens because it increases the detection of rare and infrequently visiting species and thereby improves estimation of community-level parameters such as species richness. The cost analysis demonstrated that an automated system can be >40 % more cost-efficient than data collection and processing with traditional camera traps. Near-real-time data streams additionally provide several advantages. Camera performance can be remotely monitored, including battery status, SD card usage, file uploads, potential damage from wildlife, water ingress, blank images caused by misfires, or vegetation grown in front of cameras. This reduces the need for regular site visits and thus makes the automated system more efficient. Moreover, the rapid sharing of rare and unusual observations with site managers also allows timely information about biodiversity for visitors in the nature reserve. In addition to cost-efficiency and public outreach, camera traps are also more effective than traditional survey methods in detecting a wide range of wildlife species and for recording a large number of detections of focal species (Wearn & Glover-Kapfer, 2019).

Expanding the extent and resolution of biodiversity monitoring with camera traps in our study area provides several opportunities for research and management. Rabbits are currently surveyed only twice per year from a car along a monitoring route which is limited to path and road sides. The automated wildlife camera network therefore expands the rabbit monitoring not only with a higher temporal frequency, but also to the whole study area (i.e. beyond the transect route). Rabbit populations in the mainland coastal dunes of the Netherlands have strongly collapsed in recent years (Dijkstra et al., 2023) and wildlife cameras are now used in our study area to assess reintroduction efforts and changes in occupancy. Other mammals such as red fox (*V. vulpes*), European hare (*Lepus europaeus*) and roe deer (*Capreolus capreolus*) are currently not sufficiently monitored and wildlife cameras will thus provide new insights into their distribution, habitat use, activity and phenology. For fallow deer, wildlife cameras can provide additional information on population structure such as sex ratios and age classes which are relevant for assessing the effectiveness of culling management. The continuous monitoring with wildlife cameras can also provide novel insights into the role of species interactions such as competition between rabbit and hare or between fallow deer and roe deer, and for the detection of rare, cryptic or inconspicuous species such as the night-active European polecat (*Mustela putorius*), which are difficult to monitor with traditional survey methods. The wildlife cameras will also enable estimation of community-level parameters such as species richness and β-diversity of ground-dwelling wildlife, and enable the detection of rapid changes in wildlife distributions that require interventions (such as the population collapses of rabbits). The new wildlife camera network therefore provides a single sampling tool for a broad range of research and management purposes which is more effective than combining a range of other survey methods such as line transects, live traps, track plots and scat surveys (Wearn & Glover-Kapfer, 2019).

Operationalizing a wildlife camera network in an area where large herbivores and humans are present requires to take several practical aspects into account. Installing camera traps in areas where large ungulates are present (e.g. through rewilding projects) can attract animals such as horses, cows, bison and red deer to scratch on poles or to chew the antennae. Such damages would require additional protection (e.g. with small wooden exclosures). This was not an issue in our study area where only ungulates such as European fallow deer and roe deer are present. However, humans are clearly a factor in a recreational area with >1 million visitors a year, creating the risk of theft and vandalism. We therefore installed metal security cages with locks around the cameras and an additional custom-designed security cage for the solar panels. Cameras and solar panels were mounted on wooden poles and hammered up to 1 m into the ground to minimize theft and vandalism (Meek et al., 2019). In addition, access to settings and image viewing in each camera is password protected. Stickers were added on the security cages of the cameras with a personal and polite message and a QR code to inform about the project, which can reduce potential negative interactions with people (Clarin et al., 2014). The visitor centre of the nature reserve also has information about the camera network, e.g. about the ongoing research with the wildlife cameras.

AI algorithms are becoming crucial tools for the efficient handling of wildlife camera images (Tuia et al., 2022). For automated species identification, we tested a convolutional neural network with the ResNet101 as a base model (Chalmers et al., 2023; Fergus et al., 2023). This deep learning algorithm already showed good performance for detecting humans and red fox (balanced accuracy of 0.90 and 0.88, respectively). For fallow deer and rabbit, the recall was low (0.42 and 0.50, respectively), suggesting that there were many images in which the species remained undetected. However, fallow deer showed a high precision (0.88), demonstrating that once it was detected in an image, the species identification was mostly correct. For rabbits, precision was low (0.27), probably due to confusion with the European hare. Overall, automated species identification needs to be further improved. This could be efficiently addressed by an active learning cycle in which AI algorithms minimize labelling by optimally selecting the most informative samples for model improvement (Bodesheim et al., 2022; Norouzzadeh et al., 2021; van Ommen Kloeke et al., in press). This would reduce staff costs for image labelling and (re-)training and extending the AI model beyond the focal species. The wildlife monitoring network in the Dutch dunes has enough cameras to study species richness and community composition of ground-dwelling wildlife species (Kays et al., 2020), but the AI model needs to be extended to identify all wildlife species of the study area. The key challenge here is to have sufficient images with high-quality labels (i.e. bounding boxes) for the rare species. While there are several projects and initiatives already working on a (western) European wildlife AI model, there is currently no model that shows satisfactory performance to automatically identify all wildlife species in our study area.

Biodiversity monitoring in Europe is characterized by short-term budgets and a lack of financial resources (Moersberger et al., 2024). It is thus important to test whether long-term biodiversity monitoring can be cost-effective (Breeze et al., 2021). We provide the first detailed cost calculation of an automated wildlife camera network and its cost efficiency relative to traditional camera traps. We show that the initial establishment costs of an automated system might be >130 % higher, but that a significant reduction (>50 %) in annual operating costs can be achieved with automation, resulting in an overall cost saving of >40 % over a 5- or 10-year period. These cost estimations depend on various assumptions. For instance, our calculation assumes that traditional camera traps require 18 field visits per year (every three weeks) whereas automated cameras require only four visits per year (due to solar panels and the remote monitoring of camera performance). Reducing the number of field visits for traditional camera traps to four visits per year would lower the annual operating costs by up to 75 % (Appendix G: Fig. G.2A). However, a low visitation rate introduces a high risk of data loss due to human, environmental or wildlife damages, empty batteries, overwriting of images on SD cards, grown-up vegetation etc. We therefore assumed (and recommend) 3–4 weekly visits to traditional camera traps to minimize data loss. The cost differences between traditional and automated monitoring can also be sensitive to the annual operating costs for the processing workflow, especially salary costs for manual species identification ('tagging') in the traditional system, and for manual validation of AI image classification (i.e. correcting species names and bounding boxes) and labeling of images (with bounding boxes) in the automated system. For traditional camera trapping workflows, one of the most-needed technological developments are algorithms for automated filtering of blank images (Glover-Kapfer et al., 2019). This would strongly reduce the staff costs for manual species identification. The recent development of open-source object detection models such as the Microsoft AI for Earth MegaDetector already provides exciting opportunities for filtering out human and blank images (Mitterwallner et al., 2023; Tuia et al., 2022). For automated wildlife detection, annual operating costs will strongly depend on the costs for manual validation of the AI image classification and additional labelling (e.g. to improve current models and to expand them to other species). We assumed that each year 10 % of the images from the AI model classification (~95,000 images across all 65 cameras) would be either manually validated (90 %, i.e. correcting species names and bounding boxes) or newly labelled (10 %, i.e. creating bounding boxes for improving the AI model for focal or new species). Increasing this to 20 % would double the respective annual staff costs to €20,206, but reducing it to 5 % (assuming improved AI model performance) would lower it to €5053 per year. We expect that costs are likely to further decrease with the rapid development of suitable AI algorithms for automated wildlife detection. We also emphasize that our staff cost calculations are relatively high because the Netherlands has one of the highest wages in Europe.

Conclusions

The development of a wireless 4G wildlife camera network in a coastal nature reserve of the Netherlands with an associated end-to-end data pipeline represents an innovative example of how advanced technology can automate biodiversity monitoring. While the initial establishment costs of automated monitoring systems can be high, this can pay off because these systems can be more cost-efficient in their annual operation than manual data collection and data processing. We suggest that monitoring systems similar to the one presented here can be implemented in many other temperate nature reserves where sufficient 4G coverage and sunlight is available. Costs will be lower in countries with low wages and with the availability of open-source wildlife and object detection models. Interdisciplinary collaborations with computer vision researchers, software developers, data scientists and stakeholders will clearly advance sensor portals and deep learning algorithms for automated species identification (Ahumada et al., 2020; ENETWILD Consortium et al., 2022; Tuia et al., 2022; van Ommen Kloeke et al., in press). This will innovate biodiversity monitoring and conservation efforts while simultaneously providing new opportunities for extended biodiversity monitoring and improved nature management.

Data availability

The data (images, observations, metadata) from this paper are described in a data paper (Evans, Zilber, & Kissling, 2024) and made available on the Zenodo repository (https://zenodo.org/doi/10.5281/zenodo.10671147). The datasets are also accessible on GBIF where the images and occurrence records can be directly viewed for pilot 1 (https://www.gbif.org/dataset/74196cd9-7ebc-4b20-bc27-3c2d22e31ed7), pilot 2 (https://www.gbif.org/dataset/f9ba3c2e-0636-4f66-a4b5-b8c138046e9e) and pilot 3 (https://www.gbif.org/dataset/bc0acb9a-131f-4085-93ae-a46e08564ac5).

CRediT authorship contribution statement

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Supplementary materials

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