Biological Conservation 309 (2025) 111323

Contents lists available at ScienceDirect

Biological Conservation

journal homepage: www.elsevier.com/locate/biocon

UAV-assisted deep learning to support results-based agri-environmental schemes: Facilitating Eco-Scheme 5 implementation in Germany☆

Deepak H. Basavegowda [a,b,*], Inga Schleip [c], Sonoko Dorothea Bellingrath-Kimura [d], Cornelia Weltzien [a,b]

[a] Leibniz Institute for Agricultural Engineering and Bioeconomy, Max-Eyth-Allee 100, 14469 Potsdam, Germany
[b] Technische Universität Berlin, Straße des 17. Juni 144, 10623 Berlin, Germany
[c] Eberswalde University for Sustainable Development, Schickerstraße 5, 16225 Eberswalde, Germany
[d] Leibniz Centre for Agricultural Landscape Research e.V., Eberswalder Straße 84, Müncheberg D-15374, Germany

ARTICLE INFO

Keywords:
Digitalization
Biodiversity monitoring
Deep learning
Cross-domain generalization
UAVs

ABSTRACT

Results-based agri-environmental schemes (AES) hold significant potential to promote biodiversity and ecosystem services within agricultural landscapes. However, a key obstacle to their widespread adoption is the practical challenge of verifying target species (result indicators) accurately and cost-effectively. This study presents a digital and automated approach to verify (result) indicators in grasslands to facilitate the implementation of Eco-Scheme 5, a results-based AES introduced in Germany. The presented approach employs a deep learning-based object detection framework to automatically detect indicator plant species in high-resolution RGB images acquired using unmanned aerial vehicles (UAVs). Additionally, the study explores whether incorporating ground-based imagery into the UAV training dataset could enhance model performance on UAV imagery, hypothesizing robust generalization across these image domains. The Baseline model, trained exclusively on UAV imagery, achieved an average precision (AP_{50}) of 74.0, with performance affected primarily by insufficient training data and class imbalance, particularly affecting species with fewer instances. In contrast, the Enhanced model, trained on UAV imagery enriched with ground-based data, achieved a significantly higher AP_{50} of 94.2 on the UAV test dataset, demonstrating improved detection accuracy and robust cross-domain generalization. These findings validate the benefits of cross-domain training in improving model performance and emphasize the potential of UAV-integrated artificial intelligence for efficient biodiversity monitoring and supporting the implementation of results-based AES.

1. Introduction

Intensified land and sea use, largely driven by food production, significantly contributes to biodiversity decline and the degradation of associated ecosystem services (IPBES, 2019). Agriculture continues to be the primary driver of this intensification, and with over half of the world's inhabited land under agricultural use, high-intensity farming practices have contributed significantly to the current biodiversity crisis (EEA, 2015; Tscharntke et al., 2024). Conversely, biodiversity is fundamental to achieving more productive, sustainable, and profitable agriculture. It provides essential ecosystem services for agricultural production, including nutrient recycling, climate and water regulation, pollination, and pest control (Altieri, 1999; Bengtsson et al., 2019; O'Mara, 2012). As these services are inherently biological, their loss due to biological simplification can result in significant ecological and economic repercussions (Altieri, 1999). For instance, the absence of such services necessitates increased reliance on external inputs such as chemical fertilizers, pesticides, and artificial pollination. Consequently, conserving and promoting biodiversity within agricultural landscapes is an essential societal task to ensure food security, human well-being, and healthy agroecosystems.

Agri-environment schemes (AES) serve as a key policy instrument used by governments or conservation bodies, particularly in Europe, to promote biodiversity and other environmental objectives within

☆ This article is part of a special issue entitled: 'Technologies for new AES' published in Biological Conservation.

* Corresponding author at: Leibniz Institute for Agricultural Engineering and Bioeconomy.
E-mail addresses: dbasavegowda@atb-potsdam.de (D. H. Basavegowda), Inga.Schleip@hnee.de (I. Schleip), Sonoko.Bellingrath-Kimura@zalf.de (S. Dorothea Bellingrath-Kimura), CWeltzien@atb-potsdam.de (C. Weltzien).

https://doi.org/10.1016/j.biocon.2025.111323
Received 24 September 2024; Received in revised form 5 June 2025; Accepted 16 June 2025
Available online 28 June 2025

agricultural landscapes, predominantly by incentivizing land managers to implement specific farming practices through payments (Allen et al., 2014; Batáry et al., 2015; Baylis et al., 2008; Melzer et al., 2025; Simoncini et al., 2019; Wätzold et al., 2024). In conventional management-based payment schemes, land managers receive a flat-rate compensation for implementing predefined land management practices, rather than being rewarded for delivering measurable environmental results (Burton and Schwarz, 2013). However, there are a number of serious concerns about these schemes, including their often limited effectiveness in protecting target species and promoting overall biodiversity, as well as their lack of flexibility, which restricts land managers' ability to innovate and adapt practices to local conditions (Allen et al., 2014; Bartkowski et al., 2021; Burton and Schwarz, 2013).

In light of these concerns, results-based payment (RBP) schemes have emerged as a promising alternative to management-based payment schemes, as they have a high potential to deliver targeted and verifiable biodiversity objectives in a cost-effective manner (Allen et al., 2014; Elmiger et al., 2023; v. Haaren and Bathke, 2008). Under RBP schemes, land managers are rewarded solely on the basis of delivering environmental results, such as demonstrating the presence of target species (Burton and Schwarz, 2013; Kaiser et al., 2019). These schemes not only increase farmers' intrinsic interest in achieving environmental objectives but also allow them, at least in principle, to innovate based on their experience and local knowledge to achieve more beneficial environmental outcomes (Bartkowski et al., 2021; Birge et al., 2017; Burton and Schwarz, 2013). To date, the majority of RBP schemes have primarily targeted biodiversity conservation in permanent grasslands (Krieger et al., 2022).

Eco-Scheme 5 is one such RBP scheme implemented in Germany under the European Union's Common Agricultural Policy (CAP) to promote extensive management of permanent grasslands (EC., 2022; Pe'er et al., 2022). The objective of Eco-Scheme 5, *results-based extensive management of permanent grassland areas with evidence of at least four regional indicator plant species* (hereafter referred to as *indicators*), is to promote biodiversity in permanent grasslands. To receive payments, land managers are required to demonstrate the presence of at least four regionally typical indicators on their grasslands. Only areas of permanent grasslands are eligible under this scheme, and the indicators used for the assessment come from a list of species or species groups of semi-natural grasslands, as determined by the respective federal state. It is irrelevant how the eligible grassland is managed; the only decisive factor is the presence of indicators (BMEL, 2023).

Despite the generally positive reception of RBP schemes, including Eco-Scheme 5, which provide flexibility in implementing conservation measures to achieve predetermined environmental results (target species), the uncertainty and verification of environmental results are the major obstacles to the widespread implementation of these schemes (Matzdorf and Lorenz, 2010). In Eco-Scheme 5 and other analogous RBP schemes that use plants or plant organs as outcomes of the implemented conservation measures, field surveys (or expert monitoring) are periodically conducted to verify the results. However, these field-based surveys are laborious, costly, and can potentially damage the vegetation. This underscores the need for a reliable, cost-effective, and scalable monitoring and evaluation system that, where possible, readily provides evidence of the presence of target or indicator species. The use of unmanned aerial vehicles (UAVs) combined with cutting-edge artificial intelligence (AI), such as deep learning (DL), is a promising approach to this problem. Furthermore, automated and digitalized plant species recognition systems are useful in other use cases beyond biodiversity monitoring in grasslands, such as estimating the distribution of nutritious forage and identifying toxic plants.

Recent advancements in UAV-based remote sensing and DL have opened up a wide range of applications in agriculture and conservation, including crop and weed identification (Liu et al., n.d.; Lottes et al., 2017), classification of habitat types and land-cover classes (Buchelt et al., 2024), and wildlife monitoring (Kellenberger et al., 2018; Reddy, 2021). For grassland ecosystems, satellite- and UAV-based remote sensing applications have been applied to identify and monitor natural vegetation areas at different spatial levels, ranging from the landscape level to the community level (Lu and He, 2017; Stenzel et al., 2017). Nevertheless, the limited spatial resolution of satellite imagery makes it unsuitable for mapping species at the individual level. While UAV-assisted DL applications have shown great potential for crop and weed monitoring in arable landscapes (Osco et al., 2021; Shamshiri et al., 2024), the number of studies applied to grassland landscapes is very sparse (Basavegowda et al., 2024b; Valente et al., 2019). The intricate spatio-temporal dynamics of grasslands, coupled with their lower economic returns compared to high-value crops, make them a less attractive focus for technological investment (Lowenberg-DeBoer et al., 2020; Schellberg and Verbruggen, 2013).

Furthermore, there is limited research specifically addressing the integration of UAVs and DL approaches to assist RBP schemes (Schöttker et al., 2023), particularly in grassland ecosystems (Basavegowda et al., 2024a). At present, the costs associated with automated monitoring remain relatively high compared to traditional expert monitoring methods (Schöttker et al., 2023), primarily due to the high costs of UAV and sensing technology, as well as the initial investment and complexity involved in developing AI-based autonomous monitoring systems for grassland plant species. Nevertheless, ongoing technological advancements in image sensing, artificial intelligence (AI), and UAV technology—coupled with the increasing availability of high-quality open data (GBIF.Org, 2025)—are expected to significantly reduce these costs over time. Consequently, it remains largely uncertain whether UAV-assisted DL can reliably detect plant species at the individual level in grasslands and thereby support the implementation of biodiversity-focused RBP schemes, such as Eco-Scheme 5.

Accordingly, this study aims to address this research gap by exploring how recent advancements in remote sensing and artificial intelligence, particularly deep learning (DL), can be leveraged for reliably detecting indicators characterized by distinctive morphological traits in grassland ecosystems. Using Eco-Scheme 5 as a practical case study, the study focuses on developing and evaluating an automated DL-based detection framework using high-resolution UAV imagery. Specifically, this study has three main objectives: i) to develop a DL-based detection model to assess the reliability of DL in identifying indicator plants in grasslands using UAV imagery, ii) to assess and discuss the practical relevance and potential usefulness of this automated approach in supporting the implementation of RBP schemes, with a specific focus on Eco-Scheme 5, and iii) to investigate the feasibility and impact of integrating UAV-acquired imagery with ground-based imagery (close-up images) to mitigate common challenges in UAV datasets, such as data scarcity and class imbalance. For this, we hypothesize that a trained model would remain robust in generalizing across ground-based and high-resolution UAV imagery.

2. Materials and methods

2.1. Indicator species

Each indicator used to evaluate Eco-Scheme 5 is either a single plant species or a group of plant species within a genus (BfN, 2020). In most cases, a group of plant species within a genus is counted as one indicator, but this categorization is not applied consistently across all regions. For instance, in most regions, all species of the *Campanula* genus are counted as one indicator, except in the MW region, where *Campanula glomerata* is counted as an additional indicator alongside other *Campanula* species, resulting in two indicators from the same genus (BfN, 2020). Fig. 1(a) illustrates the number of indicators used in each region, while Fig. 1(b) categorizes plant species based on their exclusivity to a single region or their recognition as indicators in multiple regions. This categorization information offers valuable insights for developing automated species recognition systems. By identifying indicators recognized across

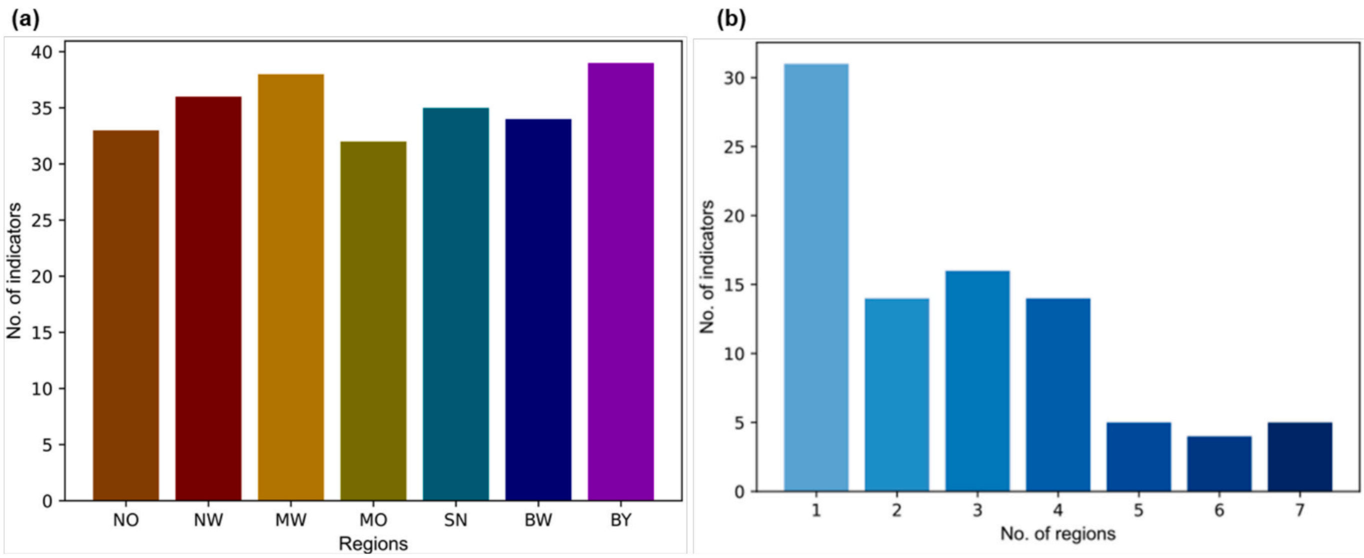

Fig. 1. (a). Number of indicators used to assess grasslands in various regions of Germany (status in 2020). The regions are grouped as follows: NO - Mecklenburg-Vorpommern and Brandenburg, NW - Schleswig-Holstein and Lower Saxony, MW - Hesse, Rhineland-Palatinate and Saarland, MO - Saxony-Anhalt and Thuringia, SN - Saxony, BW - Baden-Wuerttemberg and BY - Bavaria. Fig. 1 (b). Distribution of indicators based on their commonality across the regions. For example, 31 plant species and/or genera (left-end) are region-specific indicators, recognized only in any one of the seven regions, whereas five species and/or genera (right-end) are common indicators recognized in all seven regions.

multiple regions, redundant efforts can be minimized at the national level.

For this study, six indicator species were selected: *Armeria maritima*, *Centaurea jacea*, *Cirsium oleraceum, Daucus carota*, *Knautia arvensis*, and *Lychnis flos-cuculi* (see Fig. 2). Among these, *Centaurea jacea*, *Cirsium oleraceum*, *Knautia arvensis*, and *Lychnis flos-cuculi* are common indicators across all regions, whereas *Armeria maritima* and *Daucus carota* are specific to the NO region. The selected species exhibit distinct and diverse morphological traits, resulting in varying levels of detection difficulty. For instance, in grasslands, *Armeria maritima* is very challenging to identify because of its narrow, needle-shaped (grass-like) leaves, whereas *Cirsium oleraceum* is relatively easier to identify because of its broad leaves. Furthermore, identifying plants in grasslands is an extremely challenging task due to the intricate spatio-temporal dynamics of vegetation cover (Lopatin et al., 2017; Schmidt et al., 2018), particularly in the context of semi-natural and natural grasslands. The selected indicators also differ in their ecological requirements. *Armeria maritima* and *Knautia arvensis* thrive in dry grasslands, *Centaurea jacea*

Fig. 2. Sample images of the selected indicators from the UAV and ground-based image (GBI) datasets, illustrating variations in perspective, resolution, and development stages. GBIs I refers to ground-based images from our previous work, whereas GBIs II includes images sourced from the Global Biodiversity Information Facility database (GBIF).

and *Daucus carota* are typical of semi-dry grassland, and *Cirsium oleraceum* and *Lychnis flos-cuculi* are moist grassland species. Consequently, it is very unlikely that all these species would naturally occur in one location.

2.2. Data enrichment

A significant challenge in developing a reliable and robust UAV-assisted plant recognition system for grasslands is developing a detection model that can be generalized to multiple grasslands. In DL, model generalization is generally enhanced by training on high-quality datasets. For plant species identification, a dataset is considered to be of high quality if it contains a substantial number of images exhibiting sufficient variations, such as images from multiple fields representing different growth stages, significant inter- and intraspecific variations, and diverse image acquisition conditions representing multiple spatial resolutions and lighting conditions (Wäldchen et al., 2018). The generalization problem is further exacerbated by the higher complexity gradient of grasslands compared to other agricultural landscapes, driven by their complex spatio-temporal dynamics.

In general, data preparation is a costly and labor-intensive process (Paton, 2019), and preparing high-quality UAV datasets for grassland species is even more resource- and effort-intensive work. This is primarily due to: i) grasslands are home to a considerable part of Europe's flora and fauna (Eurostat, 2020), requiring the identification of a vast array of plant taxa, and ii) the high plot-level diversity of grasslands (Brunbjerg et al., 2018), which poses challenges for both ground-truthing and image annotation tasks. In the context of indicator species, these challenges are further amplified, as indicators serve as proxies for high biodiversity in grasslands, which is rapidly declining nowadays, making some species extremely difficult to find. Additionally, categorizing multiple species within a genus as a single indicator necessitates the development of a recognition system capable of identifying numerous species within that genus. For instance, selected species under the genus *Centaurea*, which has a diversity of more than 700 species (Mabberley, 1997), is counted as a single indicator across all regions (BfN, 2020).

Therefore, designing a cost-effective data pipeline is of great interest when developing automated species recognition systems using UAVs. In this context, we propose a practical and scalable approach that involves collecting a limited amount of time-series UAV data for the target species from a fixed number of representative grassland sites and enriching it with publicly available ground-based image datasets—such as those provided by GBIF (GBIF.Org, 2025)—to pretrain or adapt deep learning models to the UAV image domain. As illustrated in Fig. 3, the study investigates the potential of this approach by evaluating the effectiveness of ground-based imagery in enhancing model performance in the UAV image domain. For this, we hypothesize that a trained model would remain robust in generalizing between ground-based and high-resolution UAV imagery, based on the assumption that DL techniques can be applied to learn universal representations (Bilen and Vedaldi, 2017)—specifically, in our case, domain-invariant features that are transferable across the image domains. Furthermore, this data enhancement approach aims to address the common issue of class imbalance in UAV datasets (Alirezazadeh et al., 2024; Johnson and Khoshgoftaar, 2019) by enriching the representation of under-sampled species classes, thereby improving model performance and reliability on tail classes.

2.3. Data

2.3.1. UAV data

For the UAV data collection, the indicators were planted on a 20 m × 30 m experimental grassland plot at the Field Lab for Digital Agriculture, Leibniz Institute for Agricultural Engineering and Bioeconomy (ATB), Potsdam-Marquardt, Germany. Planting activities took place between the third week of April and the second week of May 2022, and again in the first week of May 2023. For this study, 50 to 100 plants per species were planted in total. This approach minimized logistical hurdles associated with data collection activities, given the inherent difficulty of identifying all these indicators in a single, naturally occurring location. UAV flights were carried out between May and August of both 2022 and 2023 using a DJI Matrice 300 RTK (SZ DJI Technology, Shenzhen, China). The UAV was equipped with one of two RGB image sensors: a Zenmuse P1 (SZ DJI Technology, Shenzhen, China) with a 45-megapixel (MP) resolution or a Sony α-6000 (Sony Group Corporation, Tokyo, Japan) with a 24.7 MP resolution. Images were captured from a nadir perspective, with a ground sampling distance (GSD) ranging from 0.5 mm to 1 mm.

The study used images from 10 UAV field campaigns, each of which was conducted approximately once per month between April and August of both years. The raw images had dimensions of 8192 × 5460 pixels (Zenmuse P1) and 6000 × 4000 pixels (Sony α-6000). To reduce redundancy and streamline the annotation process, the UAV flights were conducted with minimal image overlap settings. Approximately 20 % of the grassland plot was reserved for preparing the test dataset. The raw images were tiled to preserve the resolution and facilitate the annotation and training. Zenmuse P1 images were split into 2048 × 1820-pixel tiles, yielding 12 tiles per image, while Sony α-6000 images were divided into 2000 × 2000-pixel tiles, resulting 6 tiles per image. These tiles were manually annotated with bounding boxes to prepare the training and validation datasets. Tiles without indicators were programmatically

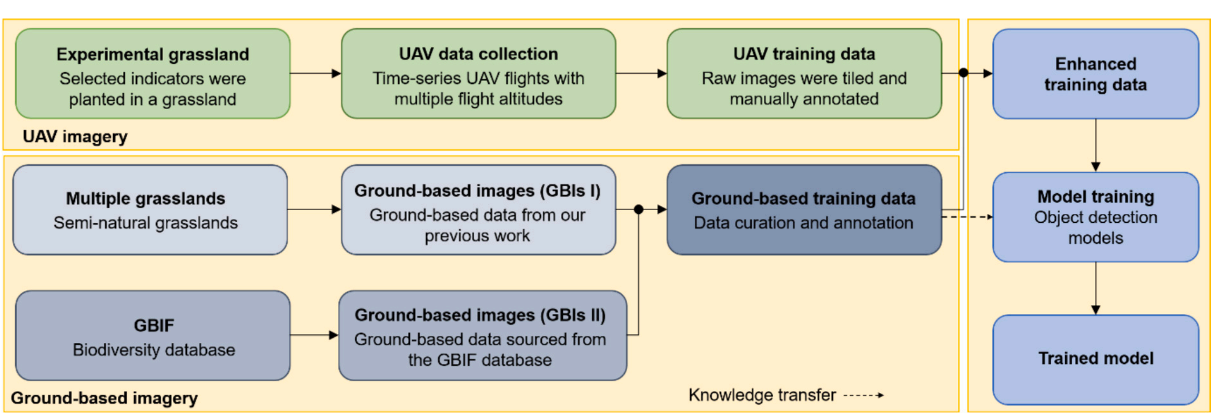

Fig. 3. Schematic overview of the proposed data enhancement approach for cross-domain knowledge transfer between UAV and ground-based image domains. The high-resolution UAV training dataset was enriched with ground-based imagery to enhance model generalization and improve species detection in UAV images. The data enhancement approach was based on the assumption that deep learning models can be applied to learn universal representation across these two image domains.

filtered out to optimize dataset quality and reduce computational overhead. Prior to training, all retained tiles were resized to 768 × 768 pixels to standardize input dimensions across datasets. The number of image instances per indicator species across different datasets is summarized in Table 1, while Fig. 2 shows representative samples from different datasets used in the study.

2.3.2. Ground-based data

To enrich the UAV training dataset and thus to improve the model generalization, we incorporated ground-based images (GBIs) from two sources: curated image data from our previous work on indicator species identification (Basavegowda et al., 2024b) and open-sourced images retrieved from the Global Biodiversity Information Facility database (GBIF.Org, 2025). By integrating these heterogeneous datasets, we aimed to provide the model with diverse visual perspectives and morphological variations, thereby enhancing its robustness across different imaging conditions and viewpoints. For each indicator species, the combined dataset—including UAV imagery and ground-based images—was balanced to include approximately 3000 annotated instances. Detailed information on the number of image instances per species across the multiple datasets is presented in Table 1.

2.3.2.1. Ground-based images (GBIs I). This dataset comprises images collected from the experimental grassland plot and several grassland sites around Eberswalde and Potsdam, Germany (see Table 1). Images acquisition was carried out during multiple field campaigns under varying field conditions and growth stages, using either a smartphone or a Sony α-6000 camera. For further details on the data collection work, please refer to Basavegowda et al., 2024a, 2024b. In preparing the training dataset, priority was given to images from our own fieldwork over those retrieved from the GBIF, as these images were captured from a nadir perspective—closely resembling UAV-acquired imagery—and were more consistently centered on the target plant species. To prevent potential spatial and temporal data leakage and ensure a clear separation between training and validations sets, ground-based images collected from the experimental plot during UAV flight periods were excluded from the training dataset.

2.3.2.2. Ground-based images (GBIs II). To achieve a target of approximately 3000 annotated image instances per species for model training, additional images were sourced from the GBIF database (Basavegowda, 2025) for those species where our own data collection (GBIs I) efforts provided insufficient samples. However, it was observed that GBIF-sourced images exhibited several limitations, including a strong bias toward specific phenological stages—particularly flowering—as well as issues such as variable image quality, non-nadir viewing angles, and occlusion by surrounding vegetation. To address these inconsistencies and improve the dataset quality, a systematic data curation process was applied. This process aimed to minimize reduce overrepresentation of flowering-stage images, without entirely removing such images, while also removing distorted or low-quality images to improve overall quality and consistency.

Table 1
Number of image instances of each indicator species across different datasets used for training and evaluation. Ground-based images (GBIs) were exclusively used for model training together with the UAV training data, while model evaluation was conducted solely on the UAV test dataset. GBIs I refers to ground-based images from our previous work, whereas GBIs II includes images sourced from the Global Biodiversity Information Facility database (GBIF).

Species name	Train data			Test data
	UAV	GBIs I	GBIs II	UAV
Armeria maritima	771	1831	455	55
Centaurea jacea	436	1057	1488	73
Cirsium oleraceum	630	2500	150	68
Daucus carota	1042	1986	–	196
Knautia arvensis	518	1143	1480	93
Lychnis flos-cuculi	488	805	1700	58

2.4. Object detection

In this study, we used a single-stage object detection model based on the EfficientDet architecture to develop a real-time detection model with higher accuracy (Tan et al., 2020). The standard outputs of the object detection models include the predicted classes and the spatial locations of the detected objects, represented by bounding box coordinates. Average precision (AP) is a widely used metric for evaluating object detection model performance. To compute AP, a threshold for Intersection over Union (IoU) is first set to distinguish between true positive (TP), false positive (FP), and false negative (FN) detections. IoU is the ratio of the area of overlap to the area of union, $\frac{b \cap b_g}{b \cup b_g}$, where b is the area of the predicted bounding box, and b_g is the area of the ground-truth bounding box. A detection is classified as a TP if the predicted class c matches the ground-truth class c_g and the IoU value exceeds the predefined threshold. Otherwise, the prediction is considered FP. FN is counted when a ground-truth object is not detected. Precision (P) indicates what proportion of the positive identification was actually correct $P = \frac{TP}{TP+FP}$. Recall (R) indicates what proportion of actual positives was correctly identified $R = \frac{TP}{TP+FN}$. Finally, average precision (AP) is computed by averaging precision values over recall values ranging from 0 to 1.

$$\mathrm{AP} = \int_{R=0}^{1} P(R)dR \tag{1}$$

AP was computed according to the COCO (Common Objects in Context) object-detection evaluation standards (Lin et al., 2014). It is calculated by averaging precision values across ten IoU thresholds, ranging from 0.5 and 0.95 in increments of 0.05 (AP at IoU = 0.50: 0.05: 0.95), considering all classes. A higher AP indicates that a model achieves both high precision and recall, meaning it can accurately identify objects while minimizing false positives and false negatives. For AP calculation at a specific IoU value, the area under the precision-recall curve for that specific IoU value is used. The choice of IoU threshold determines how strictly detections are considered correct or incorrect. For example, $\mathrm{AP}^{\mathrm{IoU}=0.50}$ (AP_{50}) counts detections at IoU values of 0.5 and above as correct, and $\mathrm{AP}^{\mathrm{IoU}=0.75}$ counts detections at IoU values of 0.75 and above as correct, with a perfect match occurring at IoU = 1.

2.5. Implementation details

The images were annotated using LabelImg, an open-source image annotation tool, and were resized to 768 × 768 pixels prior to training. Model training was performed using Stochastic Gradient Descent (SGD) optimizer with a momentum of 0.9 and weight decay of 4×10^{-5}. Learning rate was linearly increased from 0 to 0.05 in the first training epoch and then annealed down using the cosine decay rule. Focal loss function was applied with a focusing parameter ($\gamma = 1.5$) and weighting factor ($\alpha = 0.25$). Training was conducted for 300 epochs with a total batch size of 12, utilizing four NVIDIA GeForce RTX 2080Ti GPUs, each with 11 GB of memory. TensorFlow 2 and Python 3 were used for the implementation.

3. Results

3.1. Model generalization across UAV and ground-based imagery

Our findings strongly support the hypothesis that a trained DL model remains robust in generalizing across ground-based and high-resolution UAV imagery. As shown in Table 2 and Table 3, the enhanced models

Table 2
Model evaluation results on the UAV test dataset across different experimental setups. Performance is reported using standard Average Precision (AP) and AP at an IoU threshold of 0.5 (AP_{50}), which are widely used metrics for object detection performance. The table provides a comparative analysis illustrating how enriching UAV training data with ground-based imagery and applying pretraining strategies improved model generalization and detection performance.

Experimental setup				UAV test data	
No.	Models	Trained on	Training settings	AP	AP_{50}
(i)	Baseline	UAV data	Training from scratch	40.4	74.0
	Baseline-PreTr		Fine-tuning with pre-trained weights	54.4	89.3
(ii)	Enhanced	Enriched data (UAV and ground-based)	Training from scratch	**59.2**	**94.2**
	Enhanced-PreTr		Fine-tuning with pre-trained weights	57.8	90.8

(Enhanced and Enhanced-PreTr), which were trained on the UAV data enriched with ground-based images, demonstrated superior performance in comparison to the baseline models (Baseline and Baseline-PreTr) that were trained exclusively on UAV imagery. The baseline models were trained using a total of 3885 indicator image instances, with sample sizes of species ranging from 436 to 1042 instances. On the other hand, the enhanced models were trained on 18,480 image instances, ensuring a minimum of 3000 instances per species. (see Table 1). In terms of performance on the UAV test dataset, the Baseline and Baseline-PreTr models achieved an average precision (AP) of 40.4 and 54.4, respectively, whereas the Enhanced and Enhanced-PreTr models attained AP scores of **59.2** and **57.8**, respectively (see Table 2). The Enhanced model demonstrated a substantial performance improvement of approximately **19** average precision (AP) points over the Baseline model, underscoring the value of integrating ground-based imagery to enrich UAV training datasets.

When evaluated individually, the baseline models detected all indicators, though their performance varied significantly across the indicators. For instance, the Baseline model achieved an AP of 22.2 for *Daucus carota* and 64.3 for *Armeria maritima* (see Table 3). The relatively higher AP scores for *Armeria maritima*, *Cirsium oleraceum*, and *Knautia arvensis* contributed to an overall higher AP of the baseline models. In contrast, the enhanced models demonstrated improved performance across all the indicators compared to the baseline models. This suggests that enriching the training data with ground-based imagery enhanced the models' ability to generalize to the UAV dataset while also helping to address the class imbalance problem in the UAV dataset. For instance, *Centaurea jacea* and *Knautia arvensis* were underrepresented in the UAV training dataset, with only 436 and 518 image instances, respectively. The Baseline model achieved AP scores of 35.7 for *Centaurea jacea* and 43.0 for *Knautia arvensis*. In comparison, the Enhanced-PreTr model demonstrated significantly improved performance, achieving **60.5** AP and **59.8** AP, respectively, for these species (see Table 3).

3.2. Fine-tuning vs. or training from scratch

Fine-tuning enables the transfer of learned representations from large-scale datasets to more specialized tasks (Zhuang et al., 2021), offering a significant advantage in computer vision tasks where datasets are often insufficient for training from scratch. To examine the benefits of fine-tuning a pre-trained model on the UAV training data, characterized by limited and imbalanced data, we fine-tuned the model (Baseline-PreTr) by unfreezing all layers and compared its performance with the Baseline model, which was trained from scratch with randomly initialized weights. The pre-trained model used in this study was trained on the COCO dataset (Lin et al., 2014). The Baseline-PreTr model attained 54.4 AP and 89.3 AP_{50} on the UAV test dataset, outperforming the Baseline model by approximately **14** AP points. Notable improvements were observed across all indicator species. For instance, *Centaurea jacea* showed a performance gain of nearly **19** AP points, with the Baseline-PreTr model achieving significantly higher AP than the Baseline model (see Table 3). These results demonstrate that fine-tuning a model pre-trained on a large-scale, diverse dataset can substantially improve detection performance, particularly for specific species. However, it is important to note that both enhanced models, which incorporated ground-based imagery into training, surpassed the Baseline-PreTr model in overall detection performance, highlighting the added value of data enrichment beyond pretraining alone.

To assess the effect of fine-tuning in scenarios where a substantial amount of training data is available, we further fine-tuned the model (Enhanced-PreTr) using the UAV dataset enriched with ground-based images and compared its performance to the Enhanced model, which was trained from scratch. The Enhanced-PreTr model achieved 57.8 AP and 90.8 AP_{50} on the UAV test dataset (see Table 2). However, the comparative results between the Enhanced and Enhanced-PreTr models were ambiguous. While the Enhanced model slightly outperformed the Enhanced-PreTr model in overall performance—by **1.4** AP and **3.4** AP_{50} points—the Enhanced-PreTr model showed superior detection performance for certain indicator species, particularly broad-leaved species. In contrast, performance declined for others (see Table *3*). For instance, the Enhanced-PreTr model outperformed the Enhanced model by 3.2 AP points for *Cirsium oleraceum*, but underperformed by 4.1 AP points for *Daucus carota.*

3.3. Species-specific detection accuracy

All indicators, except *Armeria maritima* and *Lychnis flos-cuculi*, were detected during both the vegetative and flowering phases. Detection scores for broad-leaved indicators were higher than other indicators, especially for *Cirsium oleraceum.* Interestingly, *Daucus carota* had the lowest detection score among all indicators, despite being one of the most represented species in the UAV training dataset. *Armeria maritima*

Table 3
Evaluation results for individual indicator species across different experimental setups. The table presents species-specific AP values, illustrating variation in detection performance due to species-specific characteristics as well as the effects of data availability and fine-tuning strategies. The results highlight how model performance is affected by morphological traits, class imbalance, and the availability of diverse training data.

Models	*Armeria maritima*	*Centaurea jacea*	*Cirsium oleraceum*	*Daucus carota*	*Knautia arvensis*	*Lychnis flos-cuculi*
	Flowering					*Flowering*
Baseline	64.3	35.7	43.5	22.2	43.0	35.7
Baseline-PreTr	64.7	54.4	65.3	41.0	55.2	46.9
Enhanced	69.4	60.5	67.2	46.2	58.8	53.0
Enhanced-PreTr	67.3	60.5	70.4	42.1	59.8	48.2

and *Lychnis flos-cuculi* were only detected during the flowering phase, as the UAV dataset lacked images of these species from the vegetative growth phase. *Armeria maritima* was annotated based on the presence of flowers in UAV images, as it is extremely challenging to distinguish it from grass during the vegetative phase. In the case of *Lychnis flos-cuculi,* the plants were visible in UAV images, but as the vegetation density increased, identifying them without flowers became increasingly difficult. For this reason, there were insufficient images of *Lychnis flos-cuculi* from the vegetative phase.

4. Discussion

Verifying environmental outcomes in agricultural landscapes remains a significant challenge for the widespread implementation of results-based payment (RBP) schemes, as it necessitates the periodic identification of (result) indicators across the enrolled areas (Matzdorf and Lorenz, 2010). This study demonstrates the feasibility and reliability of an automated approach using UAVs and deep learning (DL) to identify indicator plant species in grasslands, thus facilitating biodiversity-focused RBP schemes. Despite the distinctive morphological traits of the selected indicators—including size variations and diverse leaf characteristics—all species were successfully detected using UAV imagery. Furthermore, we explored the potential of enriching UAV data with ground-based imagery to enhance model learning and improve detection accuracy, hypothesizing that a trained DL model would remain robust in generalizing across ground-based and high-resolution UAV imagery. The superior performances of the enhanced models (Enhanced and Enhanced-PreTr) compared to the baseline models (Baseline and Baseline-PreTr) support this hypothesis.

4.1. Indicator species detection and potential of ground-based imagery

The enhanced models achieved significantly higher detection performance than the baseline models (see Table 2 and Table 3), confirming that the inclusion of ground-based imagery improved model generalization, resulting in more accurate detections on UAV data. Although UAVs and ground-based vehicles, including agricultural robots, are the two most commonly used platforms for data collection and computer vision applications in agriculture (Patrício and Rieder, 2018), the cross-platform applicability of deep learning models remains largely unexplored. This gap is largely due to substantial domain differences between UAV and ground-based imagery, particularly regarding resolution, scale, and perspective (Gao et al., 2024). To address these challenges and improve cross-domain generalization, we used high-resolution UAV imagery. Additionally, nadir-perspective ground-based images (GBIs I) were incorporated as an intermediate domain to bridge the gap between UAV data and crowd-sourced data (GBIs II). The performance gain observed in the enhanced models demonstrates successful transfer of learned features from the ground-based image domain to the UAV image domain. Furthermore, EfficientDet's architectural design (Tan et al., 2020) likely enhanced this domain-invariant feature extraction.

Nevertheless, this study relied on high-resolution UAV imagery for this cross-domain feature transfer, and further research is needed to identify the threshold at which increasing the GSD—implying coarser spatial resolutions—would significantly degrade model performance. Enriching the UAV training dataset with ground-based images collected from multiple grasslands, along with crowd-sourced images from the GBIF data infrastructure, effectively addressed the data scarcity problem and helped mitigate class imbalance, challenges that commonly hinder UAV-assisted AI applications in biodiversity monitoring (Alirezazadeh et al., 2024). The comparative analysis highlighted the critical role of dataset size, as demonstrated by the lower performance of the Baseline model trained from scratch. Meanwhile, the improved performance of the Baseline-PreTr model highlighted the importance of transfer learning (Zhuang et al., 2021) for smaller, less diverse datasets. The higher performance of the enhanced models underscores the importance of training on large, high-quality datasets to improve model generalization and detection performance. Although the Enhanced model achieved slightly higher overall performance than the Enhanced-PreTr model, species-specific performances varied between these models, highlighting that the benefits of transfer learning depend on the similarity between the source and target datasets.

The Enhanced–PreTr model achieved higher detection performance for broad-leaved plant species, particularly for *Cirsium oleraceum* (see Table 3). This improvement is likely due to the pre-trained model used in the study, which was trained on the COCO dataset (Lin et al., 2014), a dataset containing numerous images of broad-leaved plants. This finding aligns with the principle that feature transferability improves as the similarity between the base and target tasks increases (Yosinski et al., 2014). Species with visually distinctive morphological characteristics, both from the background and from one another, such as *Centaurea jacea*, *Cirsium oleraceum*, and *Knautia arvensis*, resulted in higher detection scores, due to their easily distinguishable features like leaf shape (Wäldchen et al., 2018) and flower color (Gröschler and Oppelt, 2022). The detection scores for *Daucus carota* are relatively lower than other indicators, despite its substantial representation in the UAV training dataset. This discrepancy can be attributed to its morphological complexity, particularly its intricate leaf structure and spatial clustering of individuals. In dense stands, smaller plants were frequently overshadowed by larger ones, complicating both annotation and detection tasks and reducing the model's ability to reliably distinguish individuals.

Although detection accuracy for *Armeria maritima* was high, its results are not directly comparable to other indicators, as it was exclusively trained and evaluated using images from the flowering period. The visually distinctive (floral) features (LeCun et al., 2015) from the background likely contributed to the consistently high detection scores across all experiments, even when the baseline models were trained on limited data. However, *Armeria maritima* is among the most difficult species to detect during its vegetative period, as its foliage closely resembles the surrounding grass, making it visually indistinct in images (Basavegowda et al., 2024b). Identifying it in the vegetative period requires close inspection, making annotation and detection particularly difficult in UAV images. Similarly, *Lychnis flos-cuculi*, which has narrow, lanceolate leaves, is also difficult to identify in grasslands during the vegetative period without close inspection, especially when partially obscured by other vegetation. For these reasons, we relied on images from the flowering period to train and evaluate these two species. However, unlike *Armeria maritima*, the leaves of *Lychnis flos-cuculi* were distinguishable from grass and were visible in UAV images, enabling models to learn more contextual features beyond just floral features. This may explain why detection rates for *Lychnis flos-cuculi* were lower than *Armeria maritima*.

4.2. Opportunities and challenges of UAV-assisted deep learning for grassland monitoring

Our results (see Table 2 and Table 3) demonstrate that DL models can effectively identify indicators in grasslands, provided that at least part of the plant remains visible in UAV images. To assess the effectiveness of DL models in detecting plant species with distinct morphological characteristics, we selected and evaluated species of varying sizes and leaf shapes. UAV images were initially collected at high spatial resolutions, with ground sampling distances (GSDs) ranging from 0.5 mm to 1 mm. However, prior to model training, the tiled images (e.g., 2000×2000 pixels) were resized to 768×768 pixels, effectively increasing the GSDs to an estimated range of approximately 1.3 to 2.5 mm per pixel. While we did not directly evaluate model performance using the original, finer-resolution images, the results from the resized images suggest that reliable species detection remains feasible within this reduced spatial resolution range. Nonetheless, the optimal GSD value for a species detection depends on its morphological characteristics, often imposing constraints on UAV flight altitude. For example, the exclusion of *Armeria maritima* from the detection list would have allowed UAVs to operate at higher altitudes, as the remaining indicators could be detected at relatively coarser GSDs. This finding aligns with Gallmann et al. (2022), who reported greater difficulty in identifying smaller *Lotus Corniculatus* flowers compared to relatively larger *Knautia arvensis* flowers at coarser GSDs.

Additionally, the spatio-temporal dynamics of grasslands significantly influence detection accuracy. As vegetation density increases, individual plants become increasingly obscured by surrounding biomass, making accurate identification and annotation more challenging and resulting in a noticeable decline in species detection performance over time. This observation highlights the impact of phenological changes and increasing canopy cover on the appearance and visibility of plants, which in turn constrains a model's ability to learn and generalize robust visual features for species detection. These challenges become more pronounced in species-rich grasslands, where overlapping foliage and structural complexity further obscure target plants. Given these challenges, we do not anticipate significant improvements in detection accuracy for understorey species, even with the development of more advanced detection models in future studies (Lopatin et al., 2017). Computer vision models fundamentally rely on visual features, meaning species that are not visible in RGB imagery will remain undetectable, regardless of model advancements. Therefore, despite the use of high-resolution UAV imagery, several factors continue to hinder the reliable detection of plant species in grasslands through spatial-based remote sensing. These include: i) species whose spatial features blend homogeneously with the background, as seen with *Armeria maritima* during the vegetation phase, making it indistinguishable from the surrounding vegetation, ii) (understorey) species that are obscured by overstorey vegetation, as observed with *Lychnis flos-cuculi*, reducing their visibility, and iii) species with high morphological similarity, leading to frequent misclassification, such as *Anthriscus sylvestris*, *Conium maculatum*, and *Daucus carota*.

Addressing these challenges will require both methodological innovations and strategic integration of domain-specific knowledge about plant morphology, phenology, and spatial context into detection workflows. Leveraging distinct morphological and phenological traits—such as unique leaf shapes, flowering times, or growth habits—can provide more robust cues for models. Utilizing multi-temporal data and fusing data from multiple sensors can significantly enhance the robustness of automated monitoring systems, shifting the emphasis from purely visual features toward a deeper ecological understanding. Integrating such contextual information into the model training and verification process, while carefully accounting for the capabilities and limitations of UAV remote sensing with RGB image sensors, can substantially improve species detection and system reliability. For instance, enhancing UAV survey planning and species identification hinges on answering pivotal questions, including: What is the optimal time window for species detection? Which species can be monitored together? How can UAV flight parameters, such as altitude, be optimized? Species that can only be identified when in bloom should be monitored during their flowering periods, while species that remain identifiable throughout the season can be surveyed alongside them to maximize efficiency. Selecting an appropriate time window for identifying understorey species is crucial, as their visibility decreases with increasing vegetation density and is further influenced by factors such as grazing and mowing. Nonetheless, some of these challenges could potentially be mitigated with hyperspectral imaging (Li et al., 2021), which provides finer spectral information, allowing for better differentiation of plant species in grasslands. Furthermore, exploring advanced architectures like transformer-based object detection models (Carion et al., 2020) could further enhance detection accuracy by leveraging their ability to capture complex spatial relationships.

4.3. Transferability of the approach to support RBP schemes

Our findings suggest that a UAV-assisted DL-based monitoring system holds significant potential to facilitate the result verification process in results-based AES schemes such as Eco-Scheme 5. This study demonstrated the capability of such a system in identifying (result) indicator plants in grasslands, supporting the implementation of biodiversity-focused RBP schemes. However, progressing toward an operational approach necessitates further research, specifically to: i) validate the approach with coarser GSDs, ii) determine the optimal time window for indicators detection, and iii) integrate contextual information, such as flowering period, co-occurrence patterns, habitat type, and geographic location, to further improve species detection. Additionally, we explored how data from open-access and public biodiversity databases, such as GBIF, can be leveraged to enhance model generalization, thereby improving species detection in the UAV image domain. The potential of this integrated approach is immense: as UAV and AI technologies advance, coupling high-resolution remote sensing with large-scale biodiversity databases could revolutionize biodiversity assessment, making conservation monitoring more cost-effective, scalable, and automated worldwide.

Ongoing technological advances, particularly in remote sensing and artificial intelligence (AI), coupled with the increasing availability of high-quality annotated datasets, are significantly improving monitoring capabilities and reducing associated costs. These developments offer opportunities to rethink the way AES are designed and implemented, particularly in the context of RBP schemes (Zavalloni et al., 2025) and collective agri-environmental action (Reichenspurner and Matzdorf, 2025). Potential improvements include selecting more ecologically meaningful indicators, targeting biodiversity conservation and ecosystem service provision at the landscape scale through collective action, and fostering societal appreciation for farming. Traditionally, indicator species are largely selected based on distinct morphological traits that are visually recognizable by human experts, along with their alignment with intended environmental objectives (Ruas et al., 2021). The technology advancements enable the capture and analysis of subtle information beyond human visual capabilities, allowing for the inclusion of previously overlooked species as indicators. This shift could lead to the development of more ecologically meaningful indicator sets, where species are selected based on their ecological significance rather than purely morphological traits, potentially enabling earlier detection of ecological changes and ultimately improving the overall effectiveness and adaptability of biodiversity conservation schemes.

The effective use of digital technologies in conservation depends not only on their technical capabilities but also on the willingness of farmers to engage with them, as the implementation measures, adoption of related technologies, and resulting conservation outcomes rely on their voluntary participation (Prager and Nagel, 2008). To foster meaningful adoption, it is therefore essential to understand farmers' perspectives on digital tools. While farmers acknowledge the potential benefits of these technologies, they often express significant reservations. These reservations are shaped by a range of factors, including the usability and technological complexity of the tools, associated costs, access to reliable digital infrastructure, and the compatibility of different solutions (Kernecker et al., 2020; Schulze Schwering et al., 2022). Trust also plays a pivotal role in shaping adoption decisions. Uncertainties regarding the transparency of digital platforms and the credibility of the institutions behind them can further undermine farmers' willingness to engage. Moreover, as highlighted by Reichenspurner and Matzdorf (2025), farmers' attitudes toward the use of digital applications often reflect their different attitude toward AES, which are closely linked to their identity as a food-producer and good farmer, with digitalization sometimes challenging traditional notions of what it means to be a farmer.

Therefore, the successful adoption of digital technologies to support the transition toward digitally enabled implementation of AES requires clear communication of practical purposes and demonstrable benefits, such as reduced workload and simplified compliance processes (Reichenspurner and Matzdorf, 2025). Building institutional trust through the provision of reliable, mature technological solutions and transparent institutional frameworks is essential for sustained farmer engagement (Sander et al., 2024). For example, AI-based monitoring systems can enhance efficiency and reduce monitoring costs, but their credibility and acceptance improve significantly when human expertise is integrated at a higher verification level. Land managers and other stakeholders are more likely to trust and adopt AI-based monitoring systems if they are actively involved in the verification process, which aligns with the Human-in-the-Loop (HITL) approach. HITL systems are grounded in the belief that human-machine collaboration yields superior results, fostering trust by inserting human oversight into the AI life cycle (Middleton et al., 2022).

Addressing technological complexity through tailored training and participatory development processes that include direct farmer input can bridge gaps between technology providers and end users, enhancing the relevance and acceptance of digital tools (Geppert et al., 2023; Mouratiadou et al., 2023). Early adopters, those farmers who already see clear benefits from digital applications, should be strategically targeted to promote broader acceptance among more skeptical groups. Furthermore, demonstrating ecological benefits through scientifically validated monitoring results can strengthen the perceived value and trust in digital solutions (Dessart et al., 2019; Finger and Möhring, 2022; Wilson et al., 2009). Social dynamics also play a crucial role; farmer networks and peer interactions significantly influence technology uptake. As such, digital tools should complement—not replace—personal exchanges, facilitating communication, networking, and peer learning within farming communities (Finger, 2023; Massfeller and Storm, 2024; Schiller et al., 2021). It is equally important to highlight practical, successful examples, such as a decision support system (DSS) like DAKIS (Mouratiadou et al., 2023), through accessible media. Finally, while digital technologies hold considerable potential to improve the efficiency and effectiveness of agri-environmental action, they cannot fix the structural deficits of the (AES) system; rather, the system itself must be improved, with digital tools serving as supportive instruments to facilitate and strengthen these necessary reforms (Reichenspurner and Matzdorf, 2025).

5. Conclusion

This study successfully demonstrates the significant potential of integrating UAVs and deep learning (DL) for scalable biodiversity monitoring in grasslands, effectively addressing a major barrier to the broader implementation of results-based payment (RBP) schemes: the reliable verification of environmental outcomes. Our research provides a viable approach to support the implementation of biodiversity-focused agri-environmental schemes (AES) like Eco-Scheme 5. A key finding was that enriching UAV training data with ground-based imagery effectively addressed data scarcity and class imbalance issues commonly observed in UAV datasets, particularly for grassland plant species, leading to improved model generalization and species detection accuracy. This data enhancement approach has immense potential to significantly advance biodiversity monitoring, making it more cost-effective and scalable.

The integration of UAVs and DL for biodiversity monitoring is an area of active research, attracting increasing attention from the scientific community. However, developing such monitoring tools exclusively for RBP schemes may be economically unviable. To enhance feasibility and economic appeal, it is crucial to explore broader applications of automated plant species recognition in grasslands beyond RBP schemes. For instance, integrating indicator species identification with applications such as biomass estimation, forage quality assessment, invasive and toxic plant detection, and pest and disease management could increase the economic viability of these technologies. Additionally, the precise species-level information provided by UAV and AI technologies can positively impact biodiversity conservation by enabling precision agriculture practices that reduce reliance on synthetic fertilizers and pesticides, promoting more sustainable land management.

CRediT authorship contribution statement

Deepak H. Basavegowda: Writing – original draft, Visualization, Validation, Software, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Inga Schleip:** Writing – review & editing, Supervision, Methodology, Funding acquisition, Conceptualization. **Sonoko Dorothea Bellingrath-Kimura:** Writing – review & editing, Supervision, Methodology, Funding acquisition, Conceptualization. **Cornelia Weltzien:** Writing – review & editing, Validation, Supervision, Resources, Project administration, Methodology, Funding acquisition, Conceptualization.

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.

Acknowledgments

This work was part of the project *Digital Agriculture Knowledge and Information System* (DAKIS, grant ID: FKZ 031B0729H), financed by the German Federal Ministry of Education and Research (BMBF). We thank Andre Hamdorf, Franziska Gleiniger, and Marc Zimne for UAV data collection activities, Antje Giebel and Benjamin Trost for help in developing the experimental grassland plot.

Data availability

Data will be made available on request.

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