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Deep-learning based population monitoring of the endangered plant species *Gladiolus illyricus:* lessons learned for implementation of a technology-based biodiversity monitoring approach

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ABSTRACT

New technologies offer promising possibilities in biodiversity monitoring to increase standardization of sampling methods and improve cost efficiency. Among the former, uncrewed aerial systems (UAS) are widely used today to produce orthomosaics of a particular area. At the same time, computer-intensive methods for automated object detection within images have increased accordingly. While they are widely used in science, applied nature conservation makes little use of these methods. The current study aimed to test the applicability of UAS in combination with a deep-learning based object detection workflow in Schütt-Graschelitzen, a small-scale Natura 2000 protected area near Villach, Austria. For this purpose, we trained a YOLO_v8 algorithm with flowers of *Gladiolus illyricus* from an orthomosaic. The orthomosaic was split into about 1000 equally sized tiles with 80 tiles used for training and 20 tiles used for validation. For ground truthing, the individual inflorescences were counted manually. Our main findings indicated moderate model performance with the training and validation dataset and also with new data. Moderate – rather than strong – performance is likely a result of too little training data. While object detection worked considerably well, background revealed too high variability, making reliable classifications challenging. Comparing the different work steps (without UAS mission) suggests that creating a representative training dataset is the most time-intensive part of the workflow. For small areas and a single survey, this is likely not efficient compared to traditional field sampling methods. However, its efficiency increases with each resurvey event, as pretrained deep-learning models developed during prior monitoring cycles can be reused. This can reduce the amount of training data required in a subsequent survey. Additionally, UAS- and deep-learning based monitoring can help at sites with high sensitivity to trampling and favors large study areas, as its efficiency increases with the sample size area.

KEYWORDS

- Deep-learning
- biodiversity-monitoring
- *Gladiolus illyricus*
- flower detection
- UAS

Deep-learning basiertes Populationsmonitoring der gefährdeten Sumpfgladiole Gladiolus illyricus: Erkenntnisse zur Implementierung eines technologiebasierten Biodiversitätsmonitoring

ZUSAMMENFASSUNG

Neue Technologien bieten vielversprechende Möglichkeiten für Biodiversitätsmonitoring, um die Standardisierung von Erhebungen zu erhöhen und die Kosteneffizienz zu verbessern. Zu diesen Technologien gehören unbemannte Luftfahrtsysteme (UAS), die heute weit verbreitet sind, um Orthomosaike eines bestimmten Gebiets zu erstellen. Gleichzeitig haben rechenintensive Methoden zur automatisierten Objekterkennung in Bildern entsprechend zugenommen. Während diese Methoden in der Wissenschaft mittlerweile weit verbreitet sind, werden sie im angewandten Naturschutz wenig genutzt. Die aktuelle Studie hatte zum Ziel, die Anwendbarkeit von UAS in Kombination mit einem Deep-Learning-basierten Objekterkennungs-Workflow im Gebiet Schütt-Graschelitzen, einem kleinräumigen Natura 2000-Schutzgebiet in der Nähe von Villach, Österreich, zu testen. Zu diesem Zweck haben wir einen YOLO_v8-Algorithmus mit Blütenfotos von Gladiolus illyricus aus einem Orthomosaik trainiert. Das Orthomosaik wurde in etwa 1.000 gleich große Kacheln aufgeteilt, wobei 80 Kacheln für das Training und 20 Kacheln für die Validierung verwendet wurden. Um die Treffsicherheit des Modells zu bestimmen wurden die am Orthomosaik sichtbaren Infloreszenzen manuell gezählt. Unser Hauptergebnis zeigt eine mittelmäßige Modellleistung mit dem Trainings- und Validierungsdatensatz, sowie mit Objektdetektierungen in neuen Daten. Dies ist wahrscheinlich auf zu wenig Trainingsdaten zurückzuführen. Die Objektdetektierung lieferte dabei zufriedenstellende Ergebnisse, aber vor allem bei der Klassifikation von Hintergrund (Bilder ohne ein Vorkommen des Zielobjekts) hatte das Modell Probleme. Der Vergleich der verschiedenen Arbeitsschritte (ohne UAS-Mission) legt nahe, dass die Erstellung eines repräsentativen Trainingsdatensatzes der zeitintensivste Teil des Workflows ist. Für kleine Gebiete und eine einzelne Erhebung ist dies wahrscheinlich nicht effizient im Vergleich zu traditionellen Feldprobennahmemethoden. Allerdings steigt die Effizienz mit jeder erneuten Erhebung, da vortrainierte Deep-Learning-Modelle, die während vorheriger Überwachungszyklen entwickelt wurden, wiederverwendet werden können. Dies kann die Menge der benötigten Trainingsdaten bei einer nachfolgenden Erhebung reduzieren. Von Vorteil kann der Einsatz von UAS und automatisierter Bilderkennung insbesondere sein, wenn ein Untersuchungsgebiet empfindlich auf Betritt ist.

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INTRODUCTION

Halting global biodiversity loss is among the greatest challenges of our time. Taking directed management actions, therefore, is of utmost importance for the global nature conservation movement [1]. Evidence-based decisions are required to improve the current state of biodiversity [2]. This evidence is chiefly derived by determining the status and trends of biodiversity indicators, allowing future projections [3]. Knowledge on long-term trends is particularly important for taking directed actions [4, 5]. A lack of experts and limited financial resources are still among the main reasons for the scarcity of biodiversity time series [6]. New technologies offer promising opportunities to increase the frequency and consistency of biodiversity monitoring programs. Notably, technological approaches can help make expert knowledge more broadly available and allow its application over large spatial areas. However, application of expert knowledge in nature conservation is often a limitation because of potentially high costs, communication challenges with stakeholders, and data processing limitations [7].

In the present work, we tested two technologies in combination – aerial images by uncrewed aerial systems (UAS) and a deep-learning image detection algorithm – that offer promising opportunities to improve biodiversity monitoring programs. UAS are used today in nature conservation to assist with habitat classification [8] and to monitor mammals in open landscapes [9], among other applications. Combined with AI-based image detection algorithms, a high degree of automatization is possible. The hardware and software requirements can be accommodated today on a standard personal computer [10]. However, the use of these technologies in applied conservation by environmental agencies, regional governments, NGOs, and environmental consultancy firms remains limited. This is partly because certain official reporting requirements (e.g., Habitats Directive Article 17) do not currently consider new technological advancements. Lack of awareness about these technological opportunities, as well as uncertainty regarding the required personal and financial resources to implement them, are relevant factors [7, 11].

The primary goal of this study was to assess a workflow for applying a deep-learning algorithm on imagery of a rare plant species gathered from a UAS mission. Specifically, we aimed to determine whether reliable detection of an easily recognizable target is possible without requiring advanced technological expertise. We determined which aspects of the workflow are the most time-intensive. To address these questions, we evaluated the ability of the algorithm to automatically detect and count flowers of *Gladiolus illyricus*, wild gladiolus, in a protected area southwest of Villach, Austria, using UAS imagery.

METHODS & WORKFLOW

The study area was located in the Alpine biogeographical region, southwest of Villach, Austria in a Natura 2000 area called Schütt-Graschelitzen (site code AT2120000, https://biodiversity.europa.eu/sites/natura2000/AT2120000; Figure 1). The study object was an easily recognizable plant species, *G. illyricus*, that is known in Austria only within the wet meadows of the “Gladiolenwiese” of Dobratsch Nature Park, Carinthia. The Gladiolenwiese is owned by a conservation NGO and is specifically managed to support the habitat of *G. illyricus*. Management practices include controlled mowing to prevent the encroachment of reed (*Phragmites australis*), tall herbaceous plants, and woody species.

We developed a UAS-generated RGB orthomosaic from images taken at flight altitude 30 m and horizontal speed of 5 m s^{-1} by an aerial vehicle (drone: DJI Matrice 600 RTK; camera: Sony Alpha 7R II with 50mm objective). The drone flight was performed during peak flowering of *G. illyricus* on June 8th, 2022 at noon. Weather conditions consisted of scattered clouds resulting in mixed light conditions (mix of direct and diffuse sunlight).

The forward/side overlap of images was 80/80. Post-processing of the orthomosaic was conducted using Metashape Version 1.7.4 build 13028 (Agisoft LLC, St. Petersburg, Russia) software and resulted in a ground sampling distance of 0.85 cm pixel^{-1}.

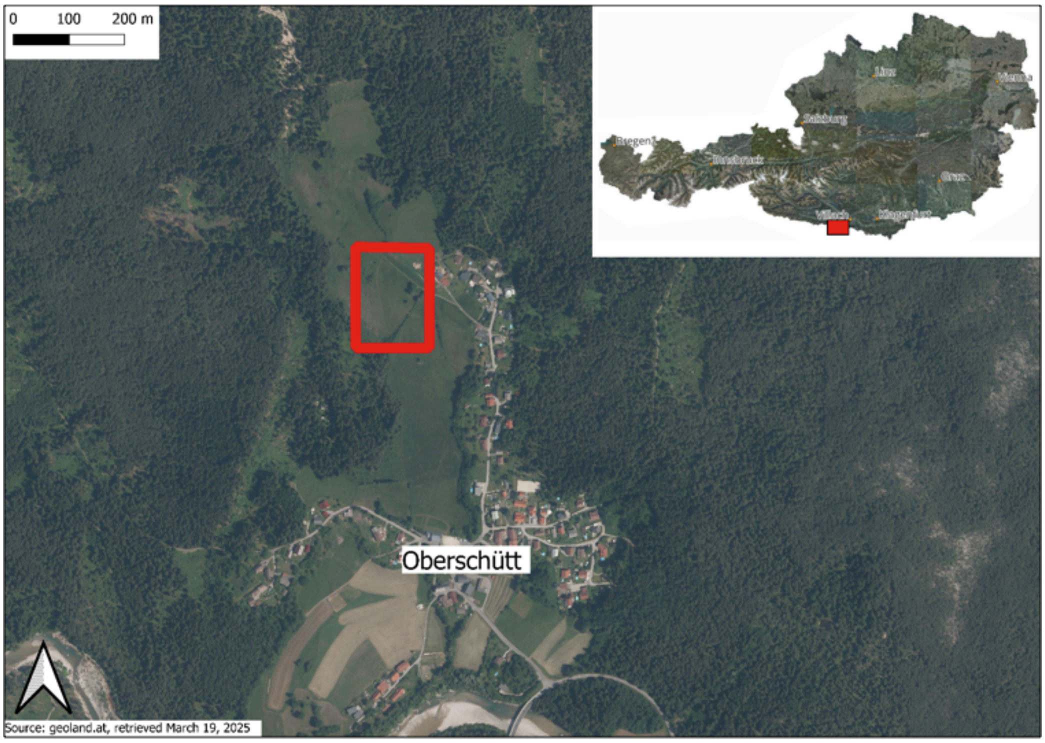

Fig. 1

Figure 1: Overview of the study area. The area of the actual UAS mission is indicated in red.

Abbildung 1: *Überblick des Untersuchungsgebiet. Der Bereich indem die UAS-Mission durchgeführt wurde ist in roter Farbe dargestellt.*

For ground truthing, flowers of *G. illyricus* were counted manually on the orthomosaic. The manual identification of *G. illyricus* from the orthomosaic was conducted using QGIS 3.30 [12]. For automated detection of inflorescences of *G. illyricus* we used a YOLO_v8 [13, 14] algorithm in a Python environment. Model performance was assessed on the object (label) level. We used the three key metrics: normalized confusion matrix, F1 score, and mean average Precision (mAP) [15]. In the normalized confusion matrix each row represents the distribution of predicted classes for a given true class. The normalized confusion matrix is further used to calculate precision (ratio of true positives to total number of predicted positives) and recall (ratio of true positives to total number of actual positives). Precision and recall are further used to calculate the F1 score at different confidence levels. The F1 score helps understand how well a model handles false positives or false negatives at different confidence levels [15]. Plotting precision against recall allows quantification of the area under the resulting precision-recall curve. This area reflects the average precision (AP). The metric mAP50 suggests that a detection is considered correct when the Intersection over Union (IoU) exceeds 0.5. IoU is calculated as the ratio of the area of overlap between the ground truth bounding box and the predicted bounding box to the area of their union [16]. For mAP50, a detection is considered correct if 50% of the predicted and true bounding boxes are overlapping. mAP50–95 reflects a more comprehensive assessment by calculating the average precision across multiple IoU thresholds, typically from 0.5 to 0.95 in steps of 0.05.

Our basic workflow is represented in Figure 2 and consisted of the following steps:

1. Generating an orthomosaic of the entire study area using orthophotos from the UAS mission (Figure 2a).

2. Cropping the orthomosaic into equally sized tiles of 448 × 448 pixels per tile (Figure 2b). This step was conducted using R [14], with the packages raster [17], terra [18], sf [19, 20], and stars [21]. As the orthomosaic was not perfectly rectangular, white parts containing no information were included in the tiles.

3. Selecting training images: A subset of 100 tiles was selected (representing around 10% of the overall tiles) reflecting a medium to high presence of *G. illyricus* flowers (different light conditions, different background), which were marked accordingly with bounding boxes (Figure 2c). This task was performed using the online software tool CVAT (Computer Vision Annotation tool, https://app.cvat.ai). This tool allows uploading of training images, marking the target objects and saving the output in the format required for YOLO algorithms (i.e., one folder containing the training image and a second folder with a .txt file including labels and coordinates of the target objects).

4. Randomly split the 100 tiles into training (80 tiles) and validation data (20 tiles).

5. Setting up the YOLO model with the training data in Python.

6. Using the trained YOLO model for detection of target objects in new images (Figure 2d).

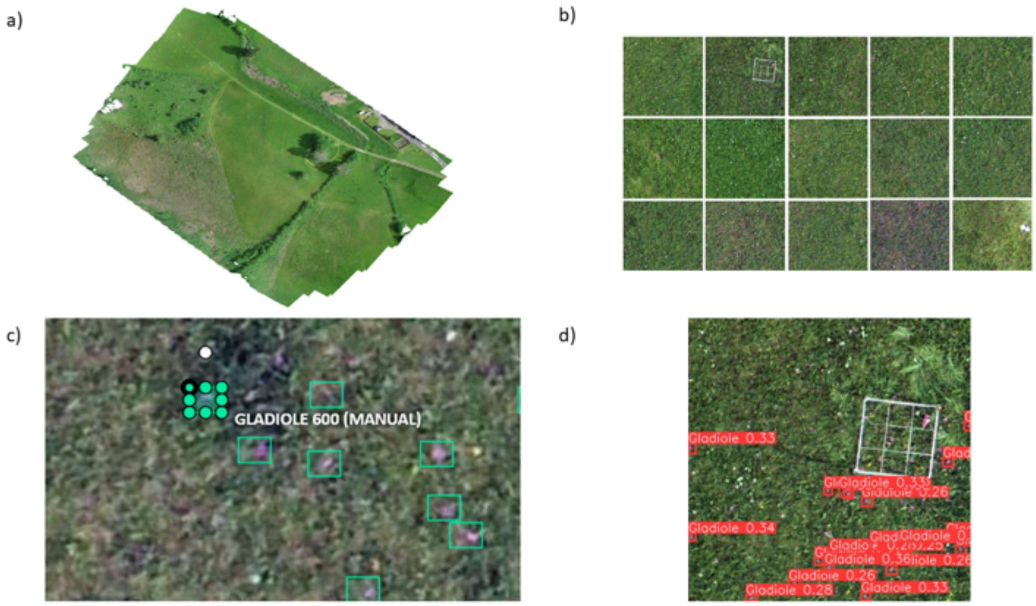

Fig. 2

Figure 2:
Basic steps for deep-learning based monitoring of *Gladiolus illyricus*. Letters a-d denote work steps. a) UAS orthomosaic of the study area; b) the UAS orthomosaic cropped into equally sized tiles (e.g., 448 × 448 pixels); c) 100 tiles were used for creation of a training dataset; and d) after training, the model was used for detection of new target objects. The numbers in step d denote confidence scores of the trained model.

Abbildung 2:
Grundlegende Schritte für das Deep-learning basierte Monitoring von Gladiolus illyricus. Die Beschriftung von a-d spiegelt einzelne Arbeitsschritte wider. a) UAS-Orthofoto des Untersuchungsgebiets; b) UAS-Orthomosaik wurde in gleich große Kacheln (z. B. 448 × 448 Pixel) unterteilt; c) 100 Kacheln wurden zur Erstellung eines Trainingsdatensatzes verwendet; d) nach dem Training wurde das Modell zur Erkennung neuer Zielobjekte eingesetzt. Die Zahlen in Schritt d geben den Confidence Score des Modells wieder.

RESULTS & DISCUSSION

In the current study, comparison between automatically detected flowers and manual counting indicated a difference of 12% more automatic detections (5,444 flowers) compared to manual verification (4,866 flowers). The normalized confusion matrix, however, showed a high ratio of correct detections for the validation data (0.84) and no false detections of *G. illyricus* flowers (Figure 3). The final model showed satisfactory prediction values

(Table 1). The model had high precision (0.88; very few false detections), moderate recall (0.80; most of the objects are detected), and good performance (mAP50 = 0.89). Model performance dropped at stricter IoU thresholds (mAP50-95 = 0.50). Although a majority of model parameters were within an acceptable range, the fact that 12% more flowers were detected by the model compared to manual counting indicated problems with overfitting and a small training dataset. In addition, the confidence scores of detections tended to be rather low (< 0.40; Figure 2.d, Figure 4). Moreover, the model lacks the ability to detect background at its current stage. Even an increase of background training data by 120 tiles couldn't solve this problem. This indicates that the background shows high variability, a factor that needs to be addressed in future work. Poor background differentiation explains the low confidence scores for the detected flowers.

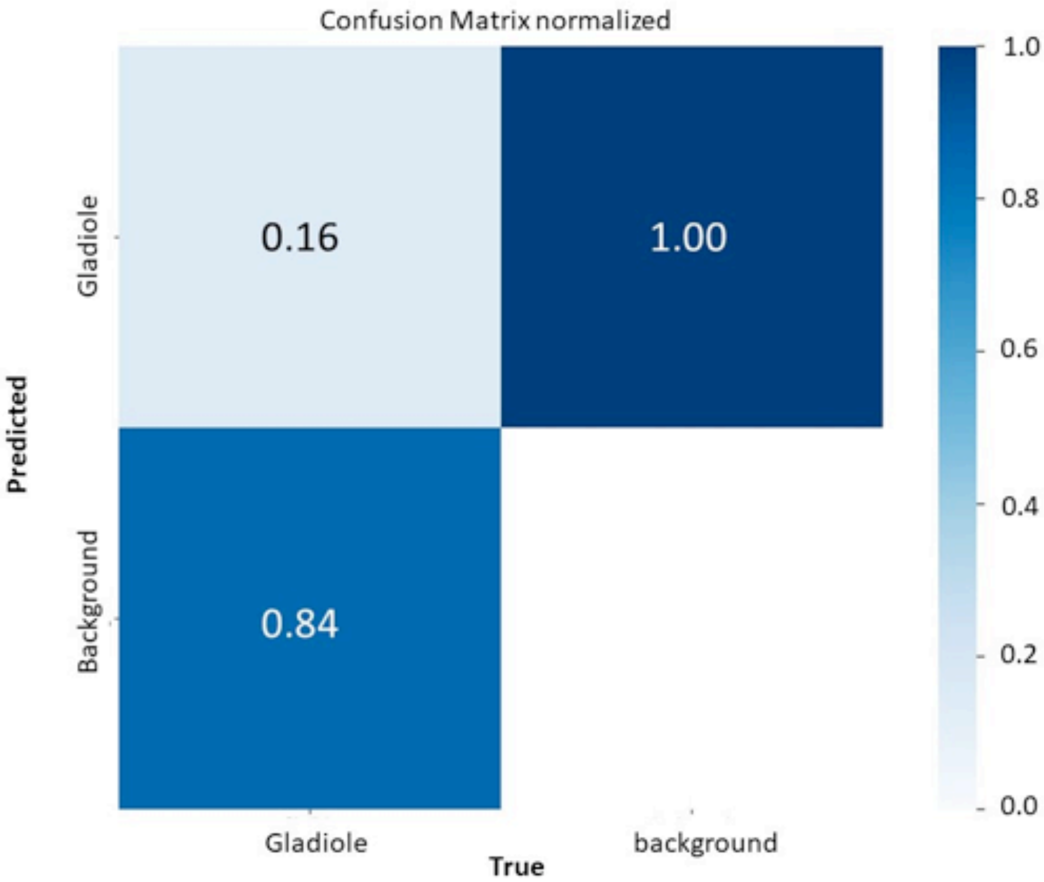

Fig. 2

Figure 3:
Normalized confusion matrix of the YOLO_v8 model for 20 tiles of the validation dataset.

Abbildung 3:
Normalisierte Konfusion Matrix des YOLO_v8 Modells für die 20 Kacheln der Validierungsdaten.

Tab. 1

Performance parameter	Model performance
mAP50	0.89
mAP50-95	0.50
Precision	0.88
Recall	0.80
Fitness	0.54

Table 1:
Model performance parameters of the final used YOLO_v8 model.

Tabelle 1:
Modell performance Parameter des finalen YOLO_v8 Modells

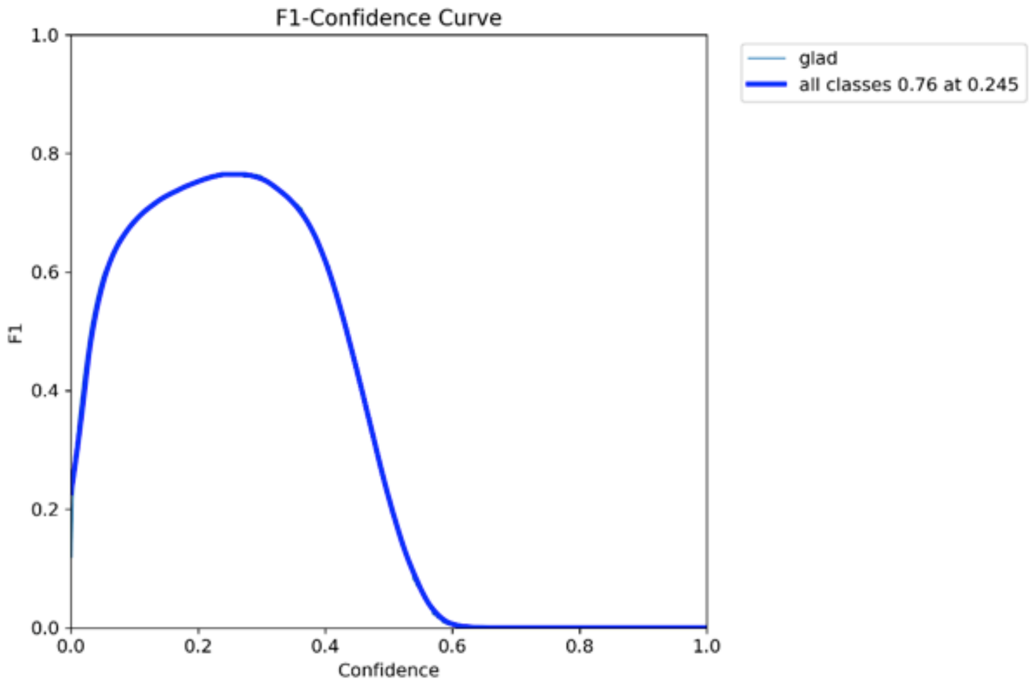

Fig. 4

Figure 4:
F1 Confidence Curve of the YOLO_v8 model.

Abbildung 4:
Konfidenz-Kurve des YOLO_v8 Modells

The selected tile size of 448 × 448 pixels produced a total of about 1,000 tiles from the area of interest. In terms of time, preparation of the training data demanded the greatest amount of resources. The process of marking and labeling the 100 training tiles took about 24 hours, or three full working days. The amount of time needed for creating training datasets is the most critical point for deep-learning-based monitoring techniques and must be evaluated carefully. Noteworthy, for monitoring a single site one time only, the time effort might be too high. On the other hand, if long-term monitoring is planned with several resurveys over an area of interest of several hectares, the approach will be more cost-effective.

One criterion that was not formally assessed in this study was conducting the UAS mission itself, including material costs and time requirements. For mission planning, a wide range of models and software is available, as well as software for post-processing of aerial images. UAS missions are a widely used earth observation approach that is often subcontracted to private companies at competitive prices. Terrain characteristics (e.g., steep or rugged terrain) and the size of the area of interest may affect the ease at which a flight campaign can be accomplished; thus, flight campaigns represent a cost factor that must be taken into account. A notable advantage of a UAS mission is its airborne nature. Traditional methods of accurately surveying plant populations in natural habitats often require physically entering the area, which can be hazardous to the field worker and potentially disruptive to the environment. These problems can be avoided by using UAS technology. However, UAS may disturb non-target species through the generation of noise or because the equipment resembles predatory species. Local flight regulations and restrictions must be carefully followed.

Using only 100 training images can be considered too few for training data (cf. [22]). Given the complexity and variation of biological data, this low volume of training data is insufficient to cover the variation expected under natural conditions. High variation in biological datasets can be considered the rule, not the exception, and should be accounted for when planning a biodiversity monitoring program. Sources of variability include changing light and weather conditions during UAS missions, variable background, potentially different sensors used in different missions, and variability in the study object itself. Given natural variability, a considerably higher volume of training data (500-1,000 training images) is recommended [23]. This implies further that for a new monitoring cycle a smaller set of supplemental training images should be considered. The amount of new training images needed for a resurvey wasn't tested in detail and will be addressed in future research. However, methods like transfer learning can help reduce the number of new required training images [24, 25]. In the current study, where only one UAS mission was conducted over a small area of interest, weather-related sources of variability were mitigated and all equipment was used according to internal standard protocols.

Marking the object of interest prior to the UAS flight is important in situations when similar species or objects of similar appearance and/or color are present at the study site. This is needed for the preparation of the training dataset to ensure that only the target object is used for training. In our case, *G. illyricus* was the only pink-colored flower present in the meadow from a bird's-eye view. Therefore, we were able to confidently mark our object of interest on the tiles of the orthomosaic. Accurate marking of flowering plants could be realized through the use of a differential GPS, but for small clustered objects such as the flowers in this study, marking could be imprecise. Labeling target objects in the field could be a major time-consuming part of the overall workflow, requiring labeling of some 500-1,000 individual points. The spatial arrangement of target objects in the field (scattered vs. clustered) affecting walking distances, and the terrain itself are additional factors that should be considered.

To address our research question, we trained the deep-learning algorithm to detect *G. illyricus* inflorescences. This allowed quantification of phenological trends but provided no direct estimation of the population, since the number of flowers varies by individual plants. This is an important consideration when preparing training data. To estimate population size, one approach could be to calculate the mean number of flowers per individual and use this value to estimate the number of plants present based on number of inflorescences detected [26]. While population size is ecologically relevant, for the purposes of producing a model, individual flower clusters can be used to train the algorithm.

Overall, we conclude that the YOLO_v8 model is a promising tool for reliable detection of inflorescences of *G. illyricus* from orthomosaics. At the current stage, however, the model shows several limitations that have to be resolved before further use in UAS-based monitoring. The most critical point is the collection of sufficient training data and testing the model on novel data sets [27]. Insufficient training hinders reliable estimation of the model performance. Nevertheless, given that a majority of *G. illyricus* inflorescences were detected while false detections were lacking, the basic utility of the model was confirmed.

Additional challenges relate to the necessary practical aspects of performing UAS missions, post-processing of the data, and training a deep-learning algorithm. From our perspective, the obstacles have decreased considerably in the past decade but still require considerable technological understanding and programming skills. Though the current challenges are undeniable, we see the growing potential for developing the workflow for future biodiversity monitoring. One major advantage arises from the reusability of pre-trained deep-learning models, decreasing the amount of training data required in a follow-up survey. Embedded in a smart biodiversity monitoring program, adequately addressing the challenges stemming from this technology can help to improve standardization and increase the spatial coverage and temporal frequency of surveys.

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BACK TO CONTENT