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Machine learning for biodiversity: UAV-based flower detection as an indirect proxy for bee abundance

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ABSTRACT

Pollination plays a crucial role in supporting agriculture and ecosystem functioning, making it an essential ecosystem service provided by bees and other insects. However, bee populations are increasingly threatened by habitat fragmentation, intensive agriculture, and climate change, among other threats. Improved monitoring of critical habitat factors, such as flower cover, is crucial to restore pollinator populations. Traditional approaches, such as field analyses, are often time-consuming and expensive, prompting the adoption of alternative methods to achieve greater efficiency and cost-effectiveness. Here, we introduce a novel approach that incorporates machine learning algorithms and optical images obtained from an unoccupied aerial vehicle (UAV). Using machine learning methods on RGB UAV imagery enabled us to estimate flower cover in UAV-monitored areas and make numerical inferences of wild bee pollinator abundance from those estimates.

Unlike our previous study, which relied on separate machine learning models for each study area, our new method develops a single model that can automatically and efficiently recognize flower cover in various grassland ecosystems to successively estimate bee abundance and diversity. In addiction to this main objective, we also sought to determine which machine learning model would perform this important task best. The machine learning models used, particularly the Gradient Boost Machine (GBM), highlighted the capability of UAV RGB images combined with artificial intelligence to predict flower cover over time, which was highly correlated with bee abundance and diversity.

This development represents an additional starting point for the use of machine learning and deep learning techniques in biodiversity studies within AES systems.

1. Introduction

Over the decades, global biodiversity has steadily decreased. This undermines a crucial resource that supports ecosystem processes, maintains ecological balance, and underpins a wide range of essential goods and services for human survival (David et al., 2015; Bradley et al., 2012).

The most widespread threats to biodiversity are habitat fragmentation and intensive agriculture (Denis et al., 1991). Natural habitats have been turned into large monocultures with high fertilizer and pesticide use, drastically reducing the biological diversity of agricultural areas (David et al., 2002, 2009). Industrialization, increased use of pesticides in industry, and the inadequacy of current EU regulations are all contributing to these issues. Additionally, these anthropogenic pressures may exacerbate one another, further threatening bee populations at multiple spatial and temporal scales (Claire et al., 2002).

Among the insects most vulnerable to such changes, wild bee pollinators are among the most studied (Rachael et al., 2009). Research highlights the catastrophic losses in both the abundance and diversity of bee populations, both nationally and locally (Stephen et al., 2012;

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Jaboury, 2005; Ingolf et al., 2005; Jacobus et al., 2006; Paul and Osborne, 2009). Habitat loss, intensive agriculture, climate change, and host plant reduction are among the identified major causes (Jeroen et al., 2014). Pollinators contribute to the pollination and production of approximately 76% of the world's leading food crops (Alexandra-Maria et al., 2007) and contribute to seed set in an additional 87% of wild plants globally (Jeff et al., 2011). Bees are the most economically and ecologically significant group. Overall, one-third of human food production relies directly on this ecosystem service, valued at over 150 billion euros annually worldwide (Gallmann et al., 2022; Nicola et al., 2009).

Despite an increased understanding of the causes of declines and of potential solutions, knowledge about the magnitude of the decline attributed to habitat quality remains limited (Torresani et al., 2023).

Unlike butterflies, for which citizen science monitoring networks have been established in Europe (Swaay et al., 2008), bees are notoriously difficult to monitor for species identification. Therefore, most studies of bee abundance occur at the local scale, and larger-scale analyses often rely on distribution data, which tends to be a poor proxy of population trends (Jacobus et al., 2006).

Recent European initiatives (EU Pollinators Initiative, EU Pollinator Monitoring Scheme, Strategy for Biodiversity 2030) (Potts et al., 2021) seek to address this problem through standardized monitoring programs. The high cost of field monitoring, largely due to the labor-intensive nature of data collection, the need for taxonomic expertise, and the logistical difficulties of accessing remote or heterogeneous landscapes, will inevitably restrict geographical coverage. Additional cost factors include the need for repeated site visits within a narrow time window to ensure temporal consistency across multiple areas, acquisition and maintenance of specialized sampling equipment, and time and coordination required to train observers and implement standardized protocols at scale.

Floral cover and diversity are indirect methods for estimating bee abundance and richness. This correlation has been confirmed in various studies because bees exclusively feed on nectar and pollen from flowers, and their life cycle depends on these resources (Simon et al., 2003; Louis et al., 2017; Segre et al., 2023). This method is substantially faster than counting and identifying individual bees and can be automated, allowing the development of fast and efficient protocols for studying floral cover.

In parallel to indirect floral-based approaches, recent advances in artificial intelligence have enabled direct monitoring of bee populations through both acoustic and visual methods. For instance, Ballesteros et al. (2024) demonstrated that analyzing bee wingbeat sounds can provide valuable insights into species identification and stress levels. Similarly, Sledevič et al. (2025) developed a computer vision system based on YOLOv8 to automatically detect and classify the behaviors of honeybees at the hive entrance. Although these approaches offer promising avenues for direct bee monitoring, they often require specialized equipment and limited spatial coverage.

AI gained prominence in 2012 when the deep convolutional neural network AlexNet won the ImageNet competition (ILSVRC), outperforming other methods with improved accuracy (Krizhevsky et al., 2012b). Machine learning or deep learning applications have been applied in several fields, including big and complex datasets (Sylvain et al., 2019). With ecological data becoming increasingly large and complex, AI and ML can address current and future challenges, such as large-scale monitoring.

Remote sensing has undergone significant development in standardized biodiversity studies across large spatial scales (Bradley et al., 2003; Torresani et al., 2020; Daniel et al., 2021; Duccio et al., 2021; Torresani et al., 2018; Duccio et al., 2022). While satellite remote sensing can cover vast areas and provide essential biodiversity parameters (Rúna et al., 2021; Duccio et al., 2022; Torresani et al., 2022), it is insufficient in offering precise measurements for finer details, such as floral cover estimation (Mitchell et al., 2016). Remote sensing by unoccupied aerial vehicles (UAVs) plays a crucial role in this regard.

UAVs can carry high-resolution cameras that fly at low altitudes, thus providing detailed imagery with accuracy as high as a few millimeters (Gallmann et al., 2022; Teja et al., 2020; Michele et al., 2024). UAV imagery can be used to assess some vegetation characteristics, including diversity (Qinghua et al., 2016), species and community distributions (Korehisa and Nohara, 2014), plant functional traits (Alessandra et al., 2015), and invasive species mapping and monitoring (Flor et al., 2017).

More recently, UAV imagery has also proven effective for detecting flowering vegetation and supporting pollinator ecology. For example, Atanas et al. (2024) developed a UAV-RGB-based algorithm for identifying white-flowering honey trees in mixed forest ecosystems, demonstrating its utility in apiculture and forest mapping. Perrone et al. (2024) investigated the effect of flowering on spectral diversity metrics derived from UAV multispectral imagery, reinforcing the connection between flowering phenology and plant diversity assessment. These recent studies reflect the increasing potential of UAVs in ecological monitoring. Building on this foundation, our study focuses on open-field, species-rich grasslands, applying machine learning models to UAV RGB imagery to scalable and standardized floral cover estimation. This method is particularly suited to support large-scale pollinator monitoring programs.

Although our current study focuses exclusively on quantifying floral cover rather than identifying individual plant species, species-level identification could offer further ecological insights. However, such identification typically requires higher spatial resolution and the integration of derived image features, such as CLAHE, Sobel, texture layers, and entropy filters (Liang et al., 2018; Chen et al., 2020), which can enhance model performance by capturing structural and textural floral traits. Although technically feasible, this step was intentionally omitted because it would exceed our project's scope and primary aim.

This study proposes an indirect yet scalable and efficient approach for estimating pollinator abundance based on floral cover mapping through UAV imagery and automatic flower classification using machine learning models. In this study, remote sensing methods using drones were applied to capture high-resolution images, while various machine learning algorithms were tested for flower classification. With a well-structured protocol, reliable results can be obtained from new data within a short timeframe. Therefore, we believe it is crucial to better understand and continue exploring the application of ML models in ecological contexts, with the broader aim of supporting pollinator conservation and contributing to the development of standardized indicators of ecosystem health in agricultural landscapes.

The most crucial aspect of this study was the selection of testing models. We tested the performance of Random Forest(RF), Support Vector Machine(SVM), Neural Network(NNET), and Gradient Boost Machine(GBM). Despite conflicting reports in the literature (Torresani et al., 2023) on the use of SVM, we decided to test it with the addition of numerous optimization parameters to develop a more thorough understanding of how well it would perform for our specific application. Merging these four models with high-quality high-resolution images has great potential to advance ecological monitoring because it would allow for faster processing in areas of study and an efficient vegetation characterization (Randelović, 2020).

2. Materials and methods

2.1. Study area

The study area is located in the southern part of the Netherlands (Fig. 1), specifically near the town of Gulpen, and spans approximately 7 × 10 km. A diverse array of land uses, ranging from intensive agriculture and low-intensity farming to natural reserves, can be observed within our study area. We considered 30 grasslands within a land

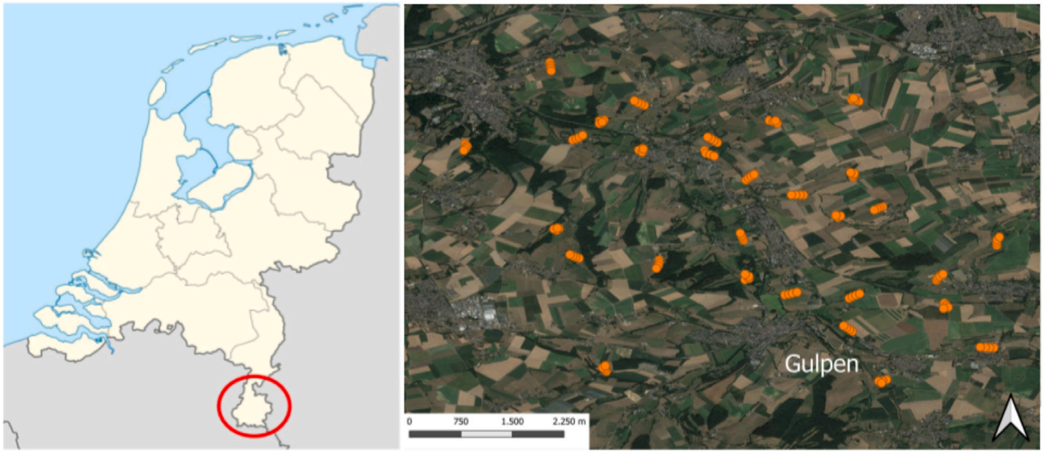

Fig. 1. Study area in the southern region of the Netherlands, specifically in the Gulpen area.

use intensity gradient ranging from nutrient-poor, biodiversity-rich semi-natural grasslands to intensively fertilized grasslands for fodder production. Our areas are part of the experimental biodiversity area network of the “SHOWCASE” project and are situated on loess soils (soils formed by the accumulation of wind-blown silt), colluvial clay deposits, and locally on lime-rich soils, with an elevation range from 70 to 171 m above sea level.

2.2. Field data collection

A 150-m-long transect with a 1-m-wide buffer was defined in each of the 30 grasslands. Each transect was then divided into three sections of 50 m. The transect was created by placing markers in the field, clearly visible from the drone imagery. The transects were positioned from the edge to the center of the grassland and crossed elevational differences within the grassland, if present, to represent heterogeneity. The transects were spaced at a minimum distance of 435 m apart but, on average, more than 500 m apart to avoid repeat sampling of the same bee populations. Although some studies have indicated that some species, such as bumblebees, can forage over distances of several kilometers, the average foraging distance ranges between 250-550 m, while smaller bees forage over even shorter distances (John et al., 2016). Within the 30 transects, both bees and flowers were monitored to collect the necessary data for our project. Wild bees and the honeybee *Apis mellifera* were counted by walking along the transects, which is a standard method for studying plant–pollinator associations (Catrin et al., 2008). Only wild bees were included in the field analysis, whereas other bees were sampled and excluded from the analyses.

To mitigate potential issues related to human error by different operators, all transects were monitored by the same two trained and experienced observers. They counted all the bees using a butterfly net. The observers walked along the outlined transect for 15 min each for study standardization, excluding the time dedicated to handling and species identification. The samples were identified using the identification keys for Dutch Apidae (Falk and Lewington, 2017; nie, 2016, 2020). A significant portion of the samples could be analyzed in the field, while others required more detailed analysis.

Identification in the laboratory using stereomicroscopes and with a pollinator expert’s assistance in some isolated cases. After observation, the bees were handled and collected in jars when necessary before proceeding with the survey. The time of day and weather can indeed influence observations; therefore, sampling was conducted under appropriate conditions and timings. Specifically, the fieldwork was conducted between April 19, 2022, and April 30, 2022, from 10:00 a.m. to 5:00 p.m., under favorable weather conditions (dry, > 50% sunshine, and at least 15 °C with wind speeds < 2 Beaufort) to ensure optimal sampling. Flower and bee surveys were conducted consistently within a two-day period. The abundance of bees (the total number of bees observed), bee species richness (number of unique species), and the Shannon diversity index (Chrystalla, 1966) were derived at the plot level.

$$H' = -\sum_{i=1}^{S} p_i \ln(p_i) \tag{1}$$

Shannon Index: *H' is the Shannon Index, S is the total number of species, p_i is the proportion of individuals belonging to species i, and $\ln$ is the natural logarithm.*

In ecological applications, Shannon’s index captures both species richness and evenness. The index increases when individuals are more evenly distributed across species, reflecting a more balanced and diverse community. For example, a transect with two equally represented species will yield a higher H' value than a transect where one species dominates, even if both contain the same number of species. This reflects the idea that ecological diversity involves not only the presence of multiple species, but also the uniformity of their relative abundance.

Flowers were sampled in each transect on the same day as the bees were monitored and sampled following the Scheper et al.’s methodology (Jeroen et al., 2015). The number of open flowers in a given species was determined.

2.3. UAV data acquisition and processing

Two certified pilots affiliated with Wageningen University conducted the UAV flights. The flights of UAVs were simultaneously carried out using “DJI Matrice 210 RTK” to carry the RGB Zenmuse X5 camera (16.0 MP, 17.3 × 13.0 mm sensor) with an integrated RTK GPS. The images taken during the flight mission reached a ground sampling overlap of approximately 85%, which enabled the production of all the orthomosaics necessary for the successive phases of analysis. Flights were executed with the UAV flying at an altitude of 30 m above ground level.

For data preprocessing, the protocol outlined by Torresani et al. (2023) was followed (Torresani et al., 2023). UAV images were processed using Agisoft Metashape Professional Edition (Agisoft, 2023),a photogrammetric software that applies structure-from-motion and stereo-matching algorithms for image alignment and 3D reconstruction. This workflow allowed us to generate high-resolution orthomosaics—geometrically corrected aerial images with uniform scale obtained by stitching together multiple overlapping photos and corrected for camera tilt and terrain distortion. Its intuitive workflow combines

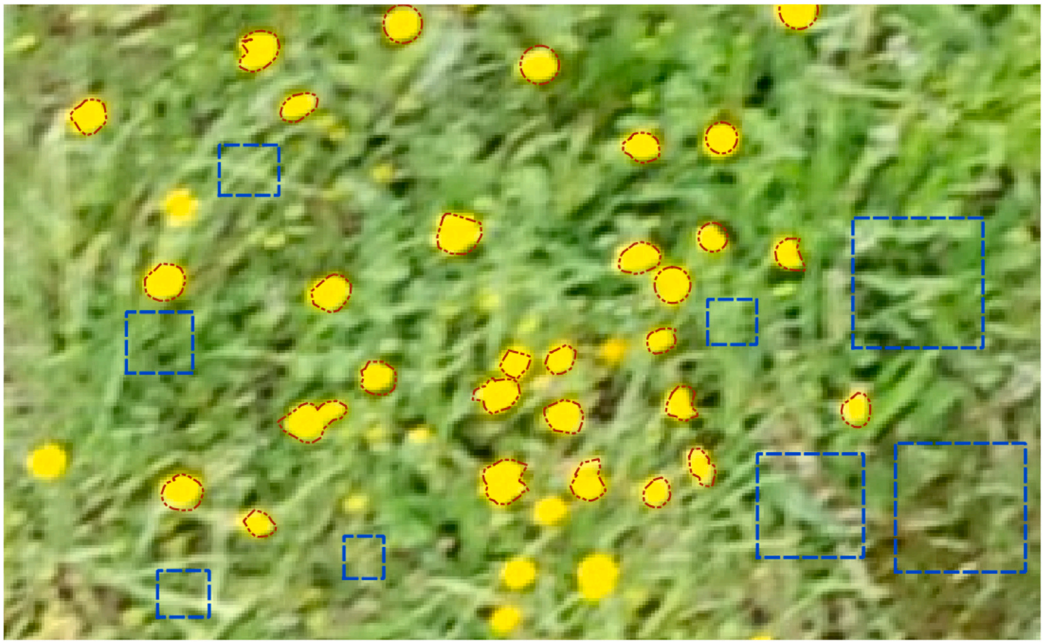

Fig. 2. Zoomed-in section of a UAV image from one of the transects, showing manual annotations of vegetation elements. Polygons with red borders represent flowers, while polygons with blue dashed borders represent grass. The annotations were created using QGIS based on visual interpretation of the UAV imagery.

structure-from-motion and stereo-matching algorithms for image alignment and 3D image reconstruction (Moe et al., 2020). The overall steps in the workflow included image alignment, dense point cloud creation and assessment, digital elevation model (DEM) development, and orthomosaic generation. In the first step with the "high" precision setting, the program analyzes and compares features within the images, creating a sparse 3D point cloud representation. During the same process, it automatically detects the details of the "Ground Control Points", downloading their GPS coordinates. It was also at this "high" level of detail that the denser point cloud was generated. The default settings of Metashape for DEM generation and final orthomosaic have been accepted. The latter were exported in GeoTIFF format, selecting the highest available spatial resolution, which is approximately 0.5 cm on average for the 30 examined areas. Once the orthomosaics were generated, they were imported into the QGIS software for further spatial processing and labeling. To ensure spatial consistency across all study sites, the orthomosaics were georeferenced using the WGS 84/UTM Zone 32 *N* coordinate system (EPSG: 32632). The labeling phase involved the manual creation of 150 flower and 150 grass polygons per transect (Fig. 2). The number of polygons was arbitrarily chosen to maximize the amount of available training data for model development.

2.4. Machine learning methods

The choice of AI models in machine learning necessitated a conscious consideration of our initial data and objectives. The binary nature of our data aimed at discriminating between "flowers" and "non-flowers", and high dimensionality motivated us to go for a machine learning model that could reasonably serve our purpose. When selecting an appropriate ML model, several factors, such as the size and nature of the dataset, the complexity of the problem, the need for model interpretability, and the time available for training and prediction, are considered (Kuhn and Johnson, 2013; Cutler et al., 2012). All models were created, trained, and tested using the R programming language.

The spectral bands used in our models were derived from RGB images acquired by the same UAV sensor under homogeneous environmental conditions. The bands are naturally correlated, a well-documented phenomenon in remote sensing applications. To ensure that this correlation did not negatively impact our models, we computed a correlation matrix and the Variance Inflation Factor (VIF). The results confirmed high correlation values among the RGB bands, ranging from 0.77 to 0.91, but a low Variance Inflation Factor (VIF) of 2.47. This indicates that multicollinearity is not a critical issue. All the RGB bands in the models were retained. This decision was further supported by the fact that models such as GBM and RF are inherently robust to correlated features, and SVM and NNET can tolerate moderate collinearity.

While previous studies (Torresani et al., 2023) developed machine learning models for each individual transect of the study area, this study used a more holistic approach where all transects from our study areas were integrated into the model design. This added a significant level of complexity to the project because the areas were highly heterogeneous and had differing characteristics. An exhaustive assessment of the most appropriate parameters and hyperparameters was performed to establish a more reliable, generalized, and flexible method for discriminating flower cover, which can then be correlated with bee abundance.

2.4.1. Random Forest (RF)

RF (Breiman, 1996, 2001)because it is one of the most robust methods in high-dimensional and noisy data, which is quite normal in many UAV-based ecological studies. The ensemble approach of averaging multiple decision trees helps reduce overfitting, making it suitable for the complex task of distinguishing flower and non-flower areas in high-resolution drone imagery. This structure provides greater robustness and generalization capability than many other models (Breiman, 2001). RF works by creating a collection of decision trees at the time of training: each tree is grown using a random sample of the training data, selected by replacement, a process known as bootstrapping (Andy and Wiener, 2002). Moreover, at each split of a tree node, only candidates for splitting are chosen at random from a subset of available variables. This randomization helps decorrelate the trees, reducing model variance with only a slight increase in bias. Once the trees have been built, the predicted class is determined by a majority vote across all trees (Nasiri et al., 2022; Kuhn and Johnson, 2013; Cutler et al., 2012).

A RF algorithm was implemented to train the classification model using the ranger package. The model was then optimized via a grid search over key tuning parameters. The first important tune parameter is `mtry`: it regulates the number of variables that are randomly selected at each split. The value of `mtry` varied from 2 to the maximum, computed as the square root of the available variables minus one. Then, the `splitrule` tested with `Gini` impurity measure, which favors purer class separation, and the method of `extratrees` with robustness was improved by combining several split strategies. Finally, we explored the balance between model complexity and overfitting by tuning `min.node.size` from 1, 5, 10, and 15 as the minimum number of observations in each node.

Model performance was assessed by 10-fold cross-validation: the training set was divided into 10 sub-samples, one of which was chosen for validation and the rest for training in each iteration. The main metric of evaluation is represented by AUC-ROC, its most accurate measure of the model's ability to discriminate between the positive and negative classes. In doing so, this approach allowed for the testing of various combinations of parameters to find the best configuration that maximizes the predictive capability of the model, thereby enhancing classification performance between flowers and grass with effective handling of sensitivity and specificity trade-offs.

2.4.2. Gradient Boosting Machines (GBM)

GBM falls within the realm of ensemble learning techniques in machine learning, similar to RF, yet they belong to a distinct category of methods (Dietterich, 2000). While RF is categorized under Bagging (Bootstrap Aggregating) models, GBMs are situated within the Boosting methods, where each model aims to correct the errors made by preceding models. Meanwhile, in the case of training each model on random subsets of data, Boosting increases the weight of poorly classified instances, allowing the subsequent models focus more on those instances (Natekin and Knoll, 2013). This was a sequential approach to enable GBM to iteratively refine the predictions, thus being particularly effective in capturing the variability of floral cover in such heterogeneous ecosystems of grasslands.

These techniques take their cue from the so-called "wisdom of crowds" (Surowiecki, 2005), an important sociological factor in which the aggregation of independent, varied, and sometimes simplistic predictions leads to a globally superior result. The key for the GBM technique is to iteratively join many weak models, usually decision trees, each new model learning from previous ones where they went wrong (Natekin and Knoll, 2013). The power of this approach lies in its ability to capture data complexities that could not be narrated through simpler models. Moreover, it is quite flexible and can be easily employed for both classification and regression tasks, thereby handling numerous data types (Friedman, 2002).

GBM was chosen because it manages complex nonlinear interactions within high-dimensional ecological data. Its sequential learning approach captures the tiny variations in UAV imagery that distinguish the presence of flowers from background noise, whereby each corrects the previous models' errors. One of the key challenges of using GBMs is their natural tendency to overfit the first set of data they are presented with Friedman (2002).

To avoid this problem, a lot of attention had to be paid to proper data management, namely, careful adjustment of training and test datasets. Cross-validation and regularization techniques were used to balance the risk of overfitting and `shrinkage`, which slows down the learning process while generalizing the model to unseen data. A GBM algorithm is applied to the `caret` R library to train this classification model. The final model was optimized through a grid search on several key parameters: the `interaction.depth` parameter, which prescribes the maximum depth of the trees in the model and thus determines the complexity of interactions among variables, was explored with values of 1, 3, and 5; the number of trees, expressed by the argument `n.trees`, representing the number of boosting iterations, was tested with 50, 100, and 150 trees; the shrinkage parameter, which accounts for the reduction of each tree's impact to prevent overfitting by tuning the learning rate, was varied from 0.01 to 0.1; and `n.minobsinnode`, which specifies the minimum number of observations required in a terminal node, was tested with 10 and 20 to balance model complexity and generalization, respectively. These parameters are selected based on their ability to balance model flexibility with the need to avoid overfitting in data with high feature variability, including UAV-derived imagery across diverse grasslands.

Performance was tested by 10-fold cross-validation: a robust approach in which the training set is divided into 10 subsets. Each subset is used for validation, and the other subsets are used for training. This technique reduces the model variance and ensures an intensive performance check.

2.4.3. Support Vector Machines (SVMs)

SVMs represent a powerful class of supervised ML classifiers that effectively operate on binary classification tasks (Vapnik, 1995). SVMs stand out for their ability to effectively create a hyperplane or margin within high-dimensional space that effectively separates the two classes. This feature makes SVMs very applicable in various classification problems and on highly complicated and high-dimensional datasets, including those related to image recognition (Cervantes et al., 2020). The implementation of kernel functions further enhances the versatility and strength of SVMs. These functions allow SVMs to work in a transformed feature space without explicitly computing the data coordinates within that space (Cristianini and Shawe-Taylor, 2013). The use of the "kernel trick" enables SVMs to work upon an original space dataset that is not linearly separable because they map it into a higher-dimensional space in which the linear separation becomes possible. This approach enables SVMs to effectively handle complex nonlinear relationships between features (Schölkopf and Smola, 2018). Moreover, SVMs are designed based on the principle of margin maximization. The algorithm maximizes the distance between the separating hyperplane and each class's nearest data points, which are referred to as support vectors. The greater the margin, the greater the model's generalization capability, reducing the risk of overfitting and yielding better prediction power against new data (Schölkopf and Smola, 2018). The kernel function selection and tuning of SVM parameters, such as the regularization and kernel parameters, are crucial to the success of this model. The commonly used kernels include linear, polynomial, radial basis function (RBF), and sigmoid (Cristianini and Shawe-Taylor, 2013). Each kernel offers advantages and is suited to different types of data and relationships.

A linear kernel was selected for the proposed SVM. The training included 10-fold cross-validation with class probability estimates and the ROC metrics as evaluation criteria. Hyperparameter tuning was performed using a grid search over a range of regularization parameters, C, from 10^{-2} to 10^{2}. To ensure process integrity, the missing values were cleaned from both the training and test data before model training.

2.4.4. Neural Network (NNETs)

Among the most powerful models, NNETs are well-known in classification and regression problems, capturing intricate patterns in data (Goodfellow et al., 2016). A neural network is constructed from interconnected layers of nodes or neurons through which a multilayer architecture is used to process input data (LeCun et al., 2015).

Weight adjustment trains NNETs using the backpropagation technique to minimize gradient descent prediction errors (Rumelhart et al., 1986). They are composed of input, hidden, and output layers; nonlinear activation functions like ReLU or sigmoid make the network learn abstract features (Nair and Hinton, 2010).

Regularization techniques, such as dropout and L2 regularization, prevent overfitting (Srivastava et al., 2014). During training, dropout randomly turns off neurons, whereas large weights are punished by L2 regularization. The early termination stops the training if the performance on a validation set starts stabilizing, thereby preventing overfitting (Prechelt, 1998).

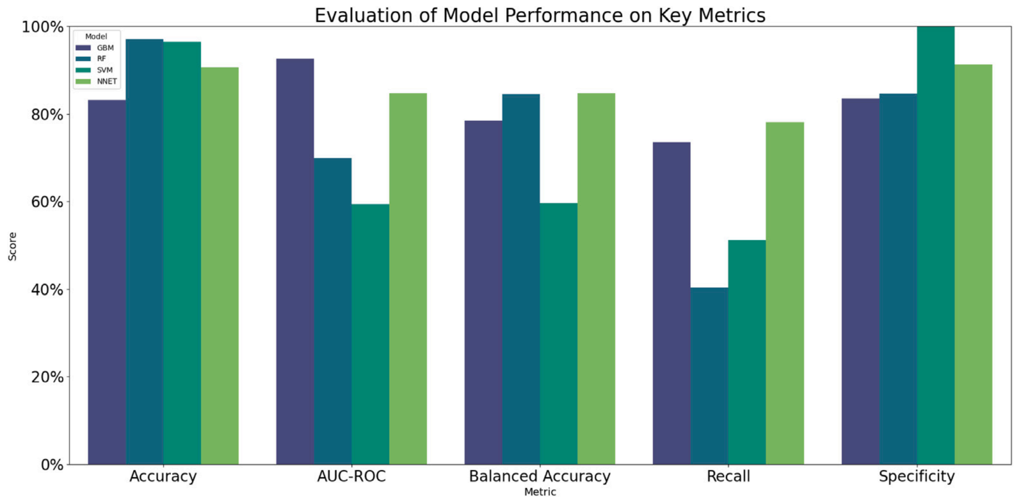

Fig. 3. Performance metrics for each model: the histograms display evaluation metrics - such as accuracy, specificity, recall and AUC-ROC - used to assess the effectiveness of the classification models in estimating floral cover. The models presented are, in order: Gradient Boosting Machine (GBM), Random Forest (RF), Support Vector Machine (SVM), and Neural Network (NNET), with GBM demonstrating the highest overall robustness. All metrics were derived from the confusion matrices generated during model validation. Colors were selected to be readable by individuals with color vision deficiencies (Rocchini et al., 2024).

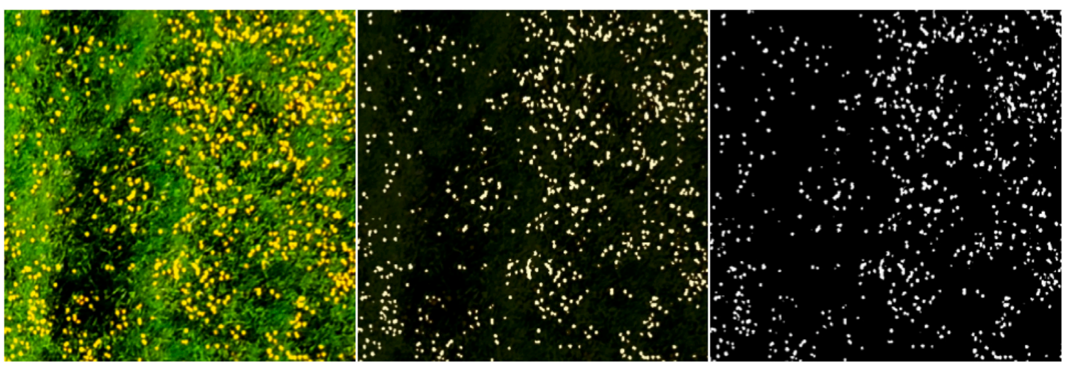

Fig. 4. Example of automatic flower classification in RGB images.
(a) Original drone-acquired image showing herbaceous vegetation with yellow flowers.
(b) Overlay of the predicted mask on the original image, with pixels classified as "flowers" highlighted in white.
(c) Final binary mask resulting from the classification, where white pixels represent areas identified as flowers.
This process enables the automatic and spatially explicit estimation of floral cover, which is subsequently used as an indirect proxy to infer the potential presence of pollinators.

NNETs have applications in image recognition, binary data recognition, and many other areas due to their flexibility and scalability (Krizhevsky et al., 2012a). Thus, neural networks can be characterized as a robust, flexible model with high-accuracy applications that can adapt to complex data-related challenges (Goodfellow et al., 2016).

Then, the Neural Network algorithm using the `nnet` method in the caret package was applied. The model was optimized by a grid search over critical hyperparameters: the `decay` parameter, which applies a regularization penalty to prevent overfitting by controlling weight size, was tested with values of 0.5, 0.01, and 0.0001; the `size` parameter, which defines the number of neurons in the hidden layer, was varied to 2, 4, and 8 to explore the model's different levels of complexity. The model's architecture was selected to balance flexibility and generalization capacity, considering the trade-offs between model accuracy and computational efficiency.

We employed 10-fold cross-validation to guide the training process. This means that the training set will be divided into 10 subsets, with one subset used for validation and the remaining subsets used in every training iteration. This gives a very robust performance estimate from the model and prevents overfitting.

Class weighting was performed in case of an imbalance between classes; the network used a weight of 10 for "flower" and 1 for "grass" to give proper importance to the minority classes. Then, the code takes advantage of parallel processing, speeding up the training process without sacrificing the accuracy of the results.

3. Results

The machine learning models employed for estimating floral cover demonstrated a high level of robustness. For instance, Fig. 3 shows the models' evaluation, not only in terms of the accuracy, which has always been greater than 80%, but also regarding different performance metrics: precision, recall, F1 score, and AUC-ROC to provide a comprehensive overview.

The GBM model achieved the highest AUC-ROC value of 0.926, demonstrating its ability to balance the presence and background of flowers. This is reflected in its accuracy of 0.831, combined with a balanced accuracy of 0.785, which collectively indicate a reliable overall performance across various conditions. Furthermore, the high specificity of the model (0.835) suggests that it is effective in minimizing false positives, a crucial aspect in achieving precise flower counting.

The RF model was quite accurate at 0.97, and its precision was relatively good at 0.778, proving its effectiveness in accurately identifying the presence of flowers. However, the recall of the model is a relatively low at 0.403, indicating some difficulties in finding all flower instances. Nevertheless, this interaction between high accuracy and precision shows that it may be useful for cases where false positives are much more important than missed detections.

The SVM model achieved near-perfect specificity (0.999) and strong accuracy (0.965), with lower AUC-ROC and balanced accuracy scores (both 0.594), which may limit its reliability in diverse or complex backgrounds. This suggests that SVM, while highly selective, may struggle to effectively generalize across all test conditions, possibly missing some true flower instances.

The NNETs model was quite balanced, with high specificity (0.913) and strong performance on most metrics, such as an accuracy rate of 0.907 and an AUC-ROC score of 0.847. This shows its reliability and suggests that it can handle fluctuations in flower detection without the specific precision or specialization that might be obtained using the GBM or RF. We computed 95% confidence intervals for the AUC-ROC values using DeLong's method, a nonparametric approach specifically designed for estimating AUC, to provide additional support for evaluating model performance. Additionally, we applied a bootstrapping procedure with 2000 resamples to assess the variability of the AUC estimates. The confidence intervals for each model are as follows: GBM (0.9241–0.9298), NNET (0.8465–0.8574), RF (0.6975–0.7098), and SVM (0.5891–0.6052). Using these criteria, we conclude that the models, in particular GBM and RF, fulfilled the technical reliability standards, and their strengths fit the specific demands in floral cover estimation. The models achieved high accuracy and robustness, indicating their effectiveness in automated flower counting.

The Fig. 4 shows an example of the classification workflow and how the GBM accurately and efficiently identified the flowers.

The floral cover estimates obtained from RGB UAV images from our models were generally positively correlated with those made by expert field observers 5. We displayed a subset of 20 sites in each figure to ensure visual clarity and avoid overlapping points that would reduce interpretability. The selection was made to ensure representativeness, and all models were applied to the full dataset. The site exclusion in the figures was solely for graphical purposes and does not affect the consistency of model comparison. The GBM model was the most performant among the four, achieving an R^2 correlation exceeding 70%. All models involved in this phase demonstrated a p-value < 0.05. Specifically, GBM provided accurate floral cover estimates, whereas RF and NNET tended to overestimate, whereas SVM significantly underestimated the results.

Only the GBM and RF produced acceptable results regarding the correlation between bee abundance and flower area in graphs, with an R^2 correlation of 42% and 54%, respectively, and a p-value < 0.05 (see Fig. 6).

For bee species richness, the highest results were obtained with GBM and RF, both presenting an R^2 close to 40% and 50% and a p-value < 0.05 (Graph 7).

This indicates that, in our case, decision tree models are the most effective for binary image classification tasks, specifically distinguishing between flower and non-flower.

A correlation was ultimately found between the floral area in cm^2 estimated by our models and the Shannon index (Graph 8). The RF and GBM models were the most effective at achieving an average value correlation.

4. Discussion

Our project initially focused on identifying suitable ML models to achieve our objective. Models were trained using a consistent protocol across all study areas. This uniform protocol allows for quicker and more efficient analyses in the succeeding years and even for the expansion of study areas. In this study, we present a new, alternative, and complementary approach for estimating floral coverage correlated with field analyses. Using RGB aerial images from UAVs can accelerate the analysis process, providing key parameters for future studies. Additionally, UAV-based surveys in our study were conducted with minimal environmental disturbance. To avoid direct interaction with vegetation and pollinators, UAVs were launched from roads or non-sensitive areas. Furthermore, they operated at an altitude of 30 m, which has negligible effects on pollinator activity. This methodological choice allows for large-scale biodiversity monitoring while minimizing ecosystem disruption. Despite the large initial dataset and its heterogeneity, our analyses revealed highly significant and positive correlations between floral coverage estimates obtained through UAV RGB images, our ML methods, and traditional in situ estimates by expert botanists. In a previous study (Torresani et al., 2023), correlations were higher than in our current results due to the high specificity for each area, achieved by analyzing each area individually. However, we managed to maintain a higher level of model reliability by integrating all study areas within our dataset, allowing them to be generalized.

These results highlight the capability of this approach in ecological monitoring and biodiversity management, providing a fast and scalable approach for assessing floral coverage in large-scale conservation efforts. Positive correlations were identified between bee abundance, Shannon index, bee species richness, and floral area (in cm^2) estimated by our models. However, not all models showed optimal results with these parameters. This could be mainly due to the nature of our data. Despite its simplicity, the data's binary nature (flower/non-flower) presents limitations, such as the inability to integrate useful parameters to support the recognition of more complex patterns. Decision tree models, particularly GBM, demonstrated excellent performance in this context. We attribute this result to several factors: decision trees can leverage the simplicity of binary data due to their iterative nature on the most relevant features. Moreover, unlike SVM and NNET (Kavzoglu et al., 2020), which often requires advanced tuning with various data preprocessing steps, decision trees can account for nonlinear relationships in the data without complex transformation (Zhang et al., 2019). Furthermore, decision trees are less sensitive to noise in the data than SVM and NNET. If the dataset contains noise or anomalies, as in our case, decision trees can better manage them, offering more stable performance (Zhang et al., 2019).

Although models such as SVM and NNET demonstrate excellent performance on certain metrics — with SVM achieving almost 100% specificity — the GBM and RF models' actual capability in predicting floral cover proved superior. This difference can be attributed to the resilience and adaptability of tree-based algorithms in handling the variability present in the dataset, including factors such as lighting conditions and background characteristics. GBM performs better in generalizing complex scenarios because of its ability to effectively select relevant features and handle noise, as demonstrated by the balance between accuracy and recall metrics. This stability allowed for a more reliable flower count, reducing errors from false positives/negatives, and enabling high precision even in more challenging conditions. Moreover, the hierarchical structure of trees makes GBM particularly effective in handling high-resolution image datasets, where the capability to capture fine details is fundamental for accurately estimating floral cover. Owing to their ability to balance high accuracy with operational flexibility, these models not only offer solid performance in quantitative tests but also prove more suitable for fulfilling the specific needs of our application. Therefore, although other models may show high values on isolated metrics, GBM represents the best balance for our study. This fact, in addition to justifying its use in the current research, suggests that it may be the optimal choice for future applications in floral cover estimation and other complex ecological contexts, where reliability and scalability are essential.

There are several considerations regarding flower classification using our models. In our study, the average weighted size of the flowers was 1.66 cm^2. With the pixel size likely up to 3.2 cm^2, this would suggest that a pixel would have been correctly classified if it contained one whole flower, and larger pixels could easily have caused misclassification. In our study, the issue of mixed pixels likely affected the

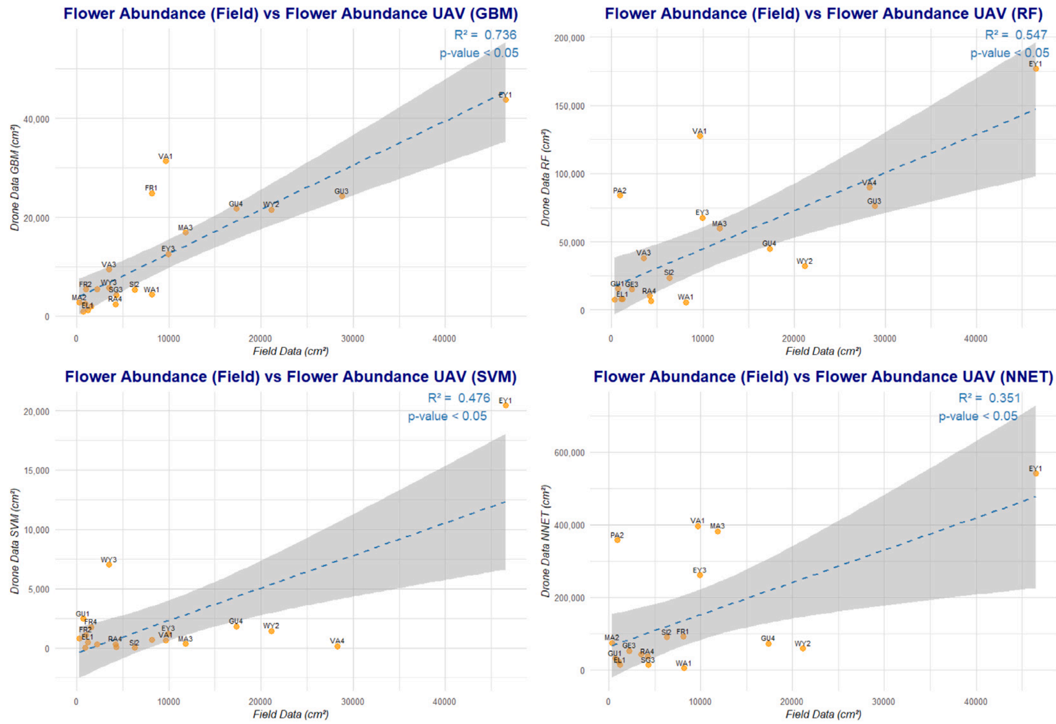

Fig. 5. Graphs of correlations between flower cover estimated in situ by botanical experts and flower cover estimated through machine learning models, using RGB images captured by UAV drones.

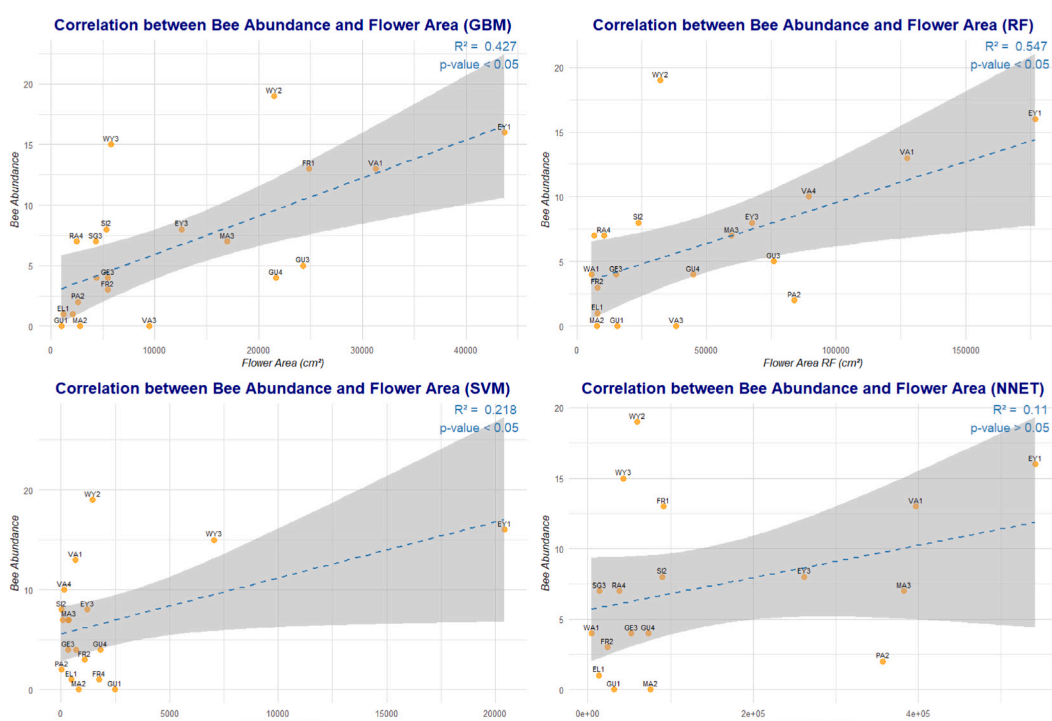

Fig. 6. Graphs of correlations between bee abundance estimated in situ by experts and flower area in cm^2 estimated through machine learning models trained on RGB images captured by UAV drones.

underestimation or overestimation of UAV RGB-estimated floral coverage. This may have occurred because pixels with less than 50% floral coverage were classified as having 0% coverage, whereas those with more than 50% coverage were classified as having 100%. However, this problem can be easily addressed by capturing more detailed resolution images. Flights at 30 m resulted in negligible flowers occupying only one pixel of the image in some cases, making classification difficult. Using images obtained from flights at lower altitudes, such as 15 m, we can incorporate more complex features, such as shape and floral formula, into our datasets. Our orthomosaics encompassed a significant unused area outside the analysis transects. We suggest decreasing the flight altitude, focusing more on the transect area to maintain the same

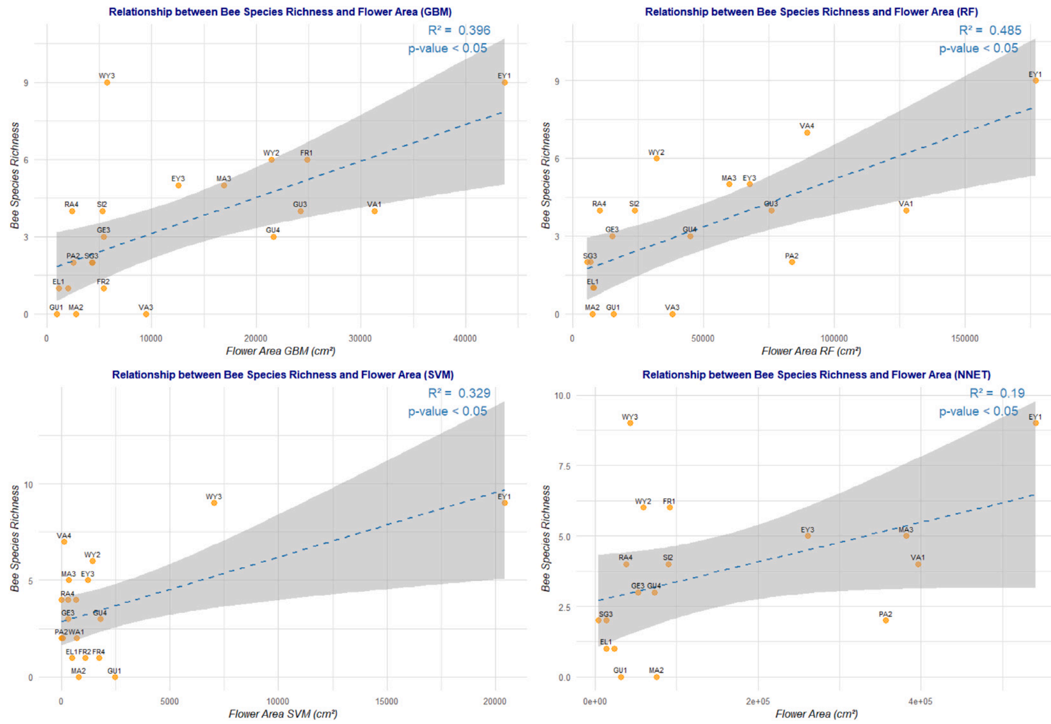

Fig. 7. Graphs of correlations between bee species richness and flower area in cm^2 estimated through machine learning models trained on RGB images captured by UAV drones.

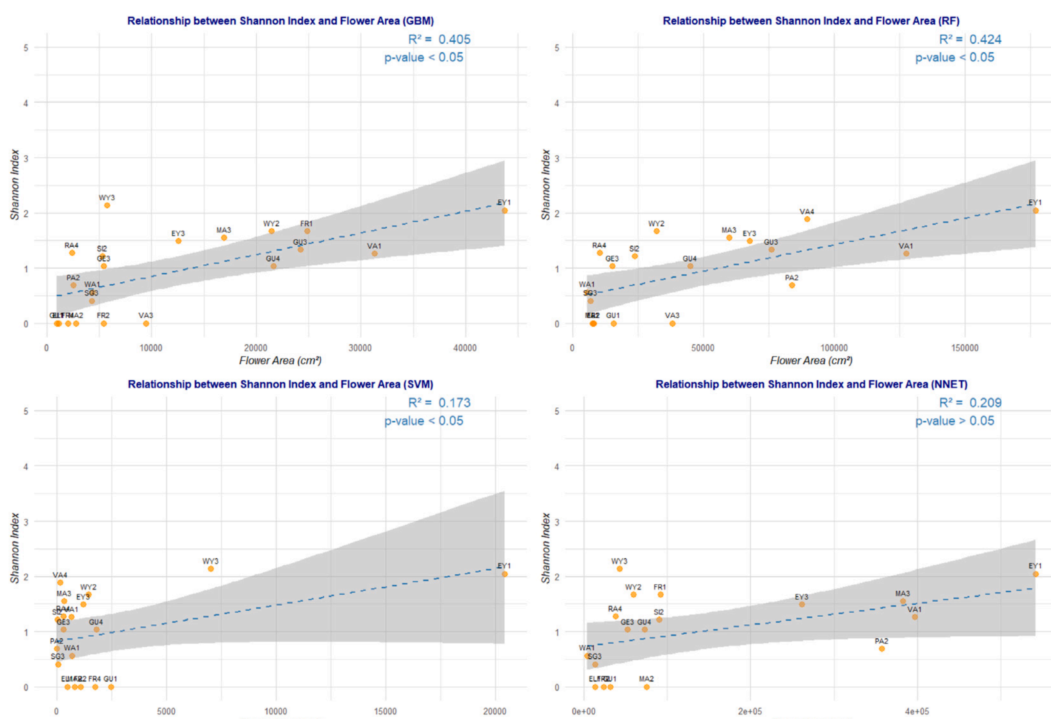

Fig. 8. Graphs of correlations between Shannon index and flower area in cm^2 estimated through machine learning models trained on RGB images captured by UAV drones.

flight time while obtaining more precise images. This allows for a much more accurate assessment and provides the opportunity to study not only floral cover but also diversity, enabling exploration of additional ecological and biological topics.

In our previous research (Torresani et al., 2023), we evaluated the effectiveness of using RGB aerial images from UAVs combined with appropriate ML methods by creating individual models for each analyzed area. This study confirms the effectiveness of this method and proposes a new protocol that focuses on creating unified models that encompass all considered areas. Working in this manner may result in a slight decrease in accuracy due to the increased number of variables. However, it ensures faster and more generalized analysis, which better manages overfitting compared to creating individual models for each area. Furthermore, the best model by Torresani et al. (2023) (RF) overestimated the floral coverage by approximately a factor of two compared to in situ analyses. In our study, however, the correlation between field analyses and those based on the combination of RGB UAV imagery and GBM was close to 1:1, despite the model being trained using all data simultaneously.

The accuracy of the correlation between our estimated floral coverage and the in situ floral coverage was higher than that of the correlation with in situ bee abundance. This was expected because the algorithms were trained to discriminate between the flower and non-flower variables. Bees are currently too small and difficult to detect in UAV RGB images, and their abundance and species diversity can only be indirectly inferred, as they generally show a strong relationship with flower availability (Louis et al., 2017; Simon et al., 2003). Previous studies have shown that bee abundance and species diversity are strongly correlated with floral coverage and species diversity. Bee species diversity is generally better predicted by floral species diversity (Simon et al., 2003; Jochen et al., 2010; Neumüller et al., 2021), whereas bee abundance is more closely linked to floral coverage (Brett and Isaacs, 2014; Scheper et al., 2021). However, floral coverage and species diversity are often correlated, and floral species diversity is linked to bee abundance (Steffan-Dewenter and Tscharntke, 2001; Theodorou et al., 2020), whereas floral coverage is associated with bee species diversity (Anne et al., 2008).

This study contributes to the growing body of research aimed at developing scalable, cost-effective methods for monitoring pollinators to support EUPoMS. Although our approach is indirect, it offers the potential for rapid assessments over large areas, particularly in agricultural landscapes where spatial coverage is limited by the logistical burden of fieldwork. Floral cover, as detected via UAV and automated classification, may serve as a proxy to identify changes in pollinator resource availability and help prioritize areas for more detailed species-level investigations. This method can complement rather than replace taxonomic sampling and contribute to reversing pollinator decline across Europe.

The method used in this study aims to explore the vast applications of ML models in the ecological and biological fields, areas that are still relatively new with infinite possibilities for exploration. Similar to other research that has employed machine learning to enhance and expedite ecological analyses (Thessen, 2016; Zelin et al., 2018), our study has identified current limitations during the image acquisition phase using four machine learning models, leading to the optimal planning of future UAV flight missions and the subsequent development of optimized multi-parameter models. We have recognized the enormous potential of these models, particularly GBM, which can be further developed by incorporating increasingly complex parameters, with the ultimate goal of creating a model capable of operating efficiently and semi-autonomously.

5. Conclusion

This study demonstrates the potential of combining UAV-acquired imagery with machine learning methods for large-scale floral coverage, a key factor in pollinator habitat quality. We offer a highly efficient and scalable approach that improves traditional biodiversity monitoring methods through automation and reproducibility using unmanned aerial vehicle (UAV) RGB imagery and sophisticated classification models.

Our findings indicate that decision tree-based models, particularly GBM, offer the most reliable performance for estimating floral cover from UAV imagery, exhibiting strong correlations with field observations. Although alternative models, such as SVM and NNET, yielded promising results in specific cases, they lacked the overall robustness required for generalized ecological applications. These findings underscore the importance of model selection when applying AI techniques to environmental studies.

This study has broader implications for pollinator conservation and ecological monitoring beyond its methodological contribution. Our approach can support conservation strategies, inform land management practices, and mitigate pollinator decline by enabling rapid and cost-effective floral resource assessments. Future research should focus on improving UAV imagery's spatial resolution, integrating multispectral and hyperspectral data, and exploring deep learning techniques to enhance model generalization across diverse ecosystems. This study aims to bridge the gap between remote sensing, AI, and ecological research to pave the way for more efficient, scalable, and data-driven biodiversity monitoring approaches. Continued advancements in these technologies are crucial for addressing the challenges of global biodiversity loss and supporting sustainable conservation initiatives.

5.1. Future work and project directions

Further steps of our study include assessing the optimal flight parameters for capturing images with the best level of detail and continuing to develop our models in order to estimate floral cover and floral diversity in the study areas. Such models would, in fact, set the base for quite a few further studies and ecological applications.

Moreover, full exploitation of UAV capabilities will be ensured through the employment of simultaneous acquisitions from different spectral sensors. Beyond RGB sensors, images from UV and multispectral sensors will be integrated in order to explore and optimize their full potential.

We will explore new models of machine learning and deep learning with the intention of studying their performance to find out which model best fits our needs.

CRediT authorship contribution statement

Ludovico Chieffallo: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Michele Torresani:** Writing – review & editing, Visualization, Validation, Supervision, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Piero Zannini:** Writing – review & editing, Visualization, Validation, Methodology, Formal analysis. **Jan Peter Reinier de Vries:** Writing – review & editing, Methodology, Data curation. **Marharyta Blaha:** Writing – review & editing, Software. **Alessio Monacchia:** Formal analysis, Data curation, Conceptualization. **David Kleijn:** Visualization, Validation, Supervision, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Duccio Rocchini:** Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization.

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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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Data availability

We acknowledge the importance of immediate accessibility. However, the dataset used in this article is too large to be shared in its entirety (several terabytes). To ensure the replicability of our study while maintaining practical feasibility, we have provided a representative subset on Zenodo at https://zenodo.org/records/14793347. This repository also includes an ISO 19115 metadata file in XML format to ensure dataset reproducibility and traceability. For specific requests regarding access to the full dataset, we offer direct data transfer support. You can find all code about our machine learning models at this link https://github.com/Ludovico-Chieffallo/Machine_Learning_for_biodiversity.git.

References

Nieuwenhuijsen, Hans, Peeters, Theo (Eds.), 2016. Nederlandse bijen op naam brengen: deel 1. Stichting Jeugdbondsuitgeverij.

Nieuwenhuijsen, Hans, e Dominic Dijkshoorn, Theo Peeters (Eds.), 2020. Nederlandse bijen op naam brengen: deel 2. Stichting Jeugdbondsuitgeverij.

Agisoft, LLC, 2023. Agisoft metashape (versione 1.7.1) [software]. https://www.agisoft.com.

Alessandra, Capolupo, et al., 2015. Estimating plant traits of grasslands from UAV-acquired hyperspectral images: a comparison of statistical approaches. ISPRS Int. J. Geo- Inf. 4 (4), 2792–2820.

Alexandra-Maria, Klein, et al., 2007. Importance of pollinators in changing landscapes for world crops. Proc. R. Soc. B: Biological Sci. 274 (1608), 303–313.

Andy, Liaw, Wiener, Matthew, 2002. Classification and regression by randomforest. R News 2 (3), 18–22.

Anne, Ebeling, et al., 2008. How does plant richness affect pollinator richness and temporal stability of flower visits? Oikos 117 (12), 1808–1815.

Atanas, Z. Atanasov, et al., 2024. A novel algorithm to detect white flowering honey trees in mixed forest ecosystems using UAV-based RGB imaging. AgriEngineering 6 (1), 95–112.

Ballesteros, Rodrí.guez, Alberto, et al., 2024. Towards acoustic monitoring of bees: wingbeat sounds are related to species and individual traits. Philos. Trans. R. Soc. B 379 (1904), 20230111.

Bradley, C. Reed, White, Michael, Brown, Jesslyn F., 2003. Remote sensing phenology. Phenol.: An Integr. Environ. Sci. 365–381.

Bradley, J. Cardinale, et al., 2012. Biodiversity loss and its impact on humanity. Nature 486 (7401), 59–67.

Breiman, L., 1996. Bagging predictors. Mach Learn. 24, 123–140. http://dx.doi.org/10.1007/BF00058655.

Breiman, L., 2001. Random forests. Mach. Learn. 45, 5–32. http://dx.doi.org/10.1023/A:1010933404324.

Brett, R. Blaauw, Isaacs, Rufus, 2014. Flower plantings increase wild bee abundance and the pollination services provided to a pollination-dependent crop. J. Appl. Ecol. 51 (4), 890–898.

Catrin, Westphal, et al., 2008. Measuring bee diversity in different European habitats and biogeographical regions. Ecol. Monograph. 78 (4), 653–671.

Cervantes, Jair, et al., 2020. A comprehensive survey on support vector machine classification: Applications, challenges and trends. Neurocomputing 408, 189–215.

Chen, Guobin, Jiang, Zhiyong, Kamruzzaman, M.M., 2020. Radar remote sensing image retrieval algorithm based on improved sobel operator. J. Vis. Commun. Image Represent. 71, 102720.

Chrystalla, Pielou Evelyn, 1966. Shannon's formula as a measure of specific diversity: its use and misuse. Amer. Nat. 100 (914), 463–465.

Claire, Kremen, Williams, Neal M., Thorp, Robbin W., 2002. Crop pollination from native bees at risk from agricultural intensification. Proc. Natl. Acad. Sci. 99 (26), 16812–16816.

Cristianini, N., Shawe-Taylor, J., 2013. Kernel-induced feature spaces. In: An Introduction To Support Vector Machines and Other Kernel-Based Learning Methods, vol. 2000, Cambridge University Press, pp. 26–51.

Cutler, A., Cutler, D.R., Stevens, J.R., 2012. Random forests. In: Zhang, C., Ma, Y. (Eds.), Ensemble Machine Learning. Springer, New York, NY, http://dx.doi.org/10.1007/978-1-4419-9326-7_5.

Daniel, Tamburlin, et al., 2021. Testing the height variation hypothesis with the R rasterdiv package for tree species diversity estimation. Remote. Sens. 13 (18), 3569.

David, Tilman, et al., 2002. Agricultural sustainability and intensive production practices. Nature 418 (6898), 671–677.

David, Kleijn, et al., 2009. On the relationship between farmland biodiversity and land-use intensity in europe. Proc. R. Soc. B: Biological Sci. 276 (1658), 903–909.

David, Kleijn, et al., 2015. Delivery of crop pollination services is an insufficient argument for wild pollinator conservation. Nat. Commun. 6 (1), 7414.

Denis, A. Saunders, Hobbs, Richard J., Margules, Chris R., 1991. Biological consequences of ecosystem fragmentation: a review. Conserv. Biol. 5 (1), 18–32.

Dietterich, T.G., 2000. Ensemble methods in machine learning. In: Multiple Classifier Systems. MCS 2000. In: Lecture Notes in Computer Science, vol. 1857, Springer, Berlin, Heidelberg, http://dx.doi.org/10.1007/3-540-45014-9_1.

Duccio, Rocchini, et al., 2021. Rasterdiv—An information theory tailored r package for measuring ecosystem heterogeneity from space: To the origin and back. Methods Ecol. Evol. 12 (6), 1093–1102.

Duccio, Rocchini, et al., 2022. Double down on remote sensing for biodiversity estimation: a biological mindset. Community Ecol. 23 (3), 267–276.

Falk, Steven, Lewington, R., 2017. Veldgids bijen voor nederland en vlaanderen.

Flor, Alvarez-Taboada, Paredes, Claudio, Julián-Pelaz, Julia, 2017. Mapping of the invasive species hakea sericea using unmanned aerial vehicle (UAV) and WorldView-2 imagery and an object-oriented approach. Remote. Sens. 9 (9), 913.

Friedman, Jerome H., 2002. Stochastic gradient boosting. Comput. Statist. Data Anal. 38 (4), 367–378.

Gallmann, Johannes, et al., 2022. Flower mapping in grasslands with drones and deep learning. Front. Plant Sci. 12, 774965.

Goodfellow, Ian, Bengio, Yoshua, Courville, Aaron, 2016. Deep Learning. MIT Press.

Ingolf, Steffan-Dewenter, Potts, Simon G., Packer, Laurence, 2005. Pollinator diversity and crop pollination services are at risk. Trends Ecol. Evolut. 20 (12), 651–652.

Jaboury, Ghazoul, 2005. Buzziness as usual? Questioning the global pollination crisis. Trends Ecol. Evolut. 20 (7), 367–373.

Jacobus, C. Biesmeijer, et al., 2006. Parallel declines in pollinators and insect-pollinated plants in britain and the netherlands. Science 313 (5785), 351–354.

Jeff, Ollerton, Winfree, Rachael, Tarrant, Sam, 2011. How many flowering plants are pollinated by animals? Oikos 120 (3), 321–326.

Jeroen, Scheper, et al., 2014. Museum specimens reveal loss of pollen host plants as key factor driving wild bee decline in The Netherlands. Proc. Natl. Acad. Sci. 111 (49), 17552–17557.

Jeroen, Scheper, et al., 2015. Local and landscape-level floral resources explain effects of wildflower strips on wild bees across four European countries. J. Appl. Ecol. 52 (5), 1165–1175.

Jochen, Fründ, Linsenmair, Kar. Eduard, Blüthgen, Nico, 2010. Pollinator diversity and specialization in relation to flower diversity. Oikos 119 (10), 1581–1590.

John, W. Redhead, et al., 2016. Effects of habitat composition and landscape structure on worker foraging distances of five bumble bee species. Ecol. Appl. 26 (3), 726–739.

Kavzoglu, Taskin, Bilucan, Furkan, Teke, Alihan, 2020. Comparison of support vector machines, random forest and decision tree methods for classification of sentinel-2A image using different band combinations. ACRS 2020, In: 41st Asian Conference on Remote Sensing, vol. 41.

Korehisa, Kaneko, Nohara, Seiich, 2014. Review of effective vegetation mapping using the UAV (unmanned aerial vehicle) method. J. Geogr. Inf. Syst. 6 (06), 733.

Krizhevsky, A., Sutskever, I., Hinton, G.E., 2012a. ImageNet classification with deep convolutional neural networks. In: Advances in Neural Information Processing Systems, vol. 25, pp. 1097–1105.

Krizhevsky, Alex, Sutskever, Ilya, Hinton, Geoffrey E., 2012b. Imagenet classification with deep convolutional neural networks. In: Advances in Neural Information Processing Systems, vol. 25.

Kuhn, M., Johnson, K., 2013. Applied Predictive Modeling. Springer New York, NY, http://dx.doi.org/10.1007/978-1-4614-6849-3.

LeCun, Yann, Bengio, Yoshua, Hinton, Geoffrey, 2015. Deep learning. Nature 521 (7553), 436–444.

Liang, Xining, et al., 2018. A real-time infrared image enhancement algorithm based on improved CLAHE. In: 2018 International Conference on Image and Video Processing, and Artificial Intelligence. 10836. SPIE.
Louis, Sutter, et al., 2017. Enhancing plant diversity in agricultural landscapes promotes both rare bees and dominant crop-pollinating bees through complementary increase in key floral resources. J. Appl. Ecol. 54 (6), 1856–1864.
Michele, Torresani, et al., 2024. Grassland vertical height heterogeneity predicts flower and bee diversity: an UAV photogrammetric approach. Sci. Rep. 14 (1), 809.
Mitchell, B. Cruzan, et al., 2016. Small unmanned aerial vehicles (micro-UAVs, drones) in plant ecology. Appl. Plant Sci. 4 (9), 1600041.
Moe, Thu Kyaw, et al., 2020. Comparing individual tree height information derived from field surveys, LiDAR and UAV-DAP for high-value timber species in northern Japan. Forests 11 (2), 223.
Nair, V., Hinton, G.E., 2010. Rectified linear units improve restricted Boltzmann machines. In: Proceedings of the 27th International Conference on Machine Learning. ICML-10.
Nasiri, Vahid, et al., 2022. Modeling forest canopy cover: a synergistic use of sentinel-2, aerial photogrammetry data, and machine learning. Remote. Sens. 14 (6), 1453.
Natekin, Alexey, Knoll, Alois, 2013. Gradient boosting machines, a tutorial. Front. Neurorobotics 7, 21.
Neumüller, Ulrich, et al., 2021. Prolonged blooming season of flower plantings increases wild bee abundance and richness in agricultural landscapes. Biodivers. Conserv. 30, 3003–3021.
Nicola, Gallai, et al., 2009. Economic valuation of the vulnerability of world agriculture confronted with pollinator decline. Ecol. Econom. 68 (3), 810–821.
Paul, H. Williams, Osborne, Juliet L., 2009. Bumblebee vulnerability and conservation world-wide. Apidologie 40 (3), 367–387.
Perrone, Michela, et al., 2024. Flower power: How flowering affects spectral diversity metrics and their relationship with plant diversity. Ecol. Inform 81, 102589.
Potts, Simon, et al., 2021. Proposal for an EU pollinator monitoring scheme.
Prechelt, L., 1998. Early stopping - but when? Neural Netw.: Tricks the Trade 5, 5–69.
Qinghua, Guo, et al., 2016. Perspectives and prospects of unmanned aerial vehicle in remote sensing monitoring of biodiversity. Biodivers. Sci. 24 (11), 1267.
Rachael, Winfree, et al., 2009. A meta-analysis of bees' responses to anthropogenic disturbance. Ecology 90 (8), 2068–2076.
Randelović, Predrag., 2020. Prediction of soybean plant density using a machine learning model and vegetation indices extracted from RGB images taken with a UAV. Agron. EspaÑa 10 (8), 1108.
Rocchini, Duccio, et al., 2024. Under the mantra:'make use of colorblind friendly graphs'. Environmetrics e2877.
Rumelhart, D.E., Hinton, G.E., Williams, R.J., 1986. Learning representations by back-propagating errors. Nature 323 (6088), 533–536.
Rúna, Í. Magnússon, et al., 2021. Shrub decline and expansion of wetland vegetation revealed by very high resolution land cover change detection in the siberian lowland tundra. Sci. Total Environ. 782, 146877.
Scheper, Jeroen, et al., 2021. Attractiveness of sown wildflower strips to flower-visiting insects depends on seed mixture and establishment success. Basic Appl. Ecol. 56, 401–415.
Schölkopf, B., Smola, A.J., 2018. Learning with Kernels: Support Vector Machines, Regularization, Optimization, and beyond. The MIT Press, http://dx.doi.org/10.7551/mitpress/4175.001.0001.
Segre, Hila, et al., 2023. Butterflies are not a robust bioindicator for assessing pollinator communities, but floral resources offer a promising way forward. Ecol. Indic. 154, 110842.
Simon, G. Potts, et al., 2003. Linking bees and flowers: how do floral communities structure pollinator communities? Ecology 84 (10), 2628–2642.
Sledevič, Tomyslav, et al., 2025. Visual recognition of honeybee behavior patterns at the hive entrance. PloS One 20 (2), e0318401.
Srivastava, N., Hinton, G., Krizhevsky, A., Sutskever, I., Salakhutdinov, R., 2014. Dropout: A simple way to prevent neural networks from overfitting. J. Mach. Learn. Res. 15 (1), 1929–1958.
Steffan-Dewenter, I., Tscharntke, T., 2001. Succession of bee communities on fallows. Ecography (Cop.) 24, 83–93.
Stephen, D. Wratten, et al., 2012. Pollinator habitat enhancement: benefits to other ecosystem services. Agric. Ecosyst. Environ. 159, 112–122.
Surowiecki, James, 2005. The Wisdom of Crowds/James Surowiecki. Anchor, NY..
Swaay, van, Chris, A.M., et al., 2008. Butterfly monitoring in Europe: methods, applications and perspectives. Biodivers. Conserv. 17, 3455–3469.
Sylvain, Christin, Hervet, Éric, Lecomte, Nicolas, 2019. Applications for deep learning in ecology. Methods Ecol. Evol. 10 (10), 1632–1644.
Teja, Kattenborn, et al., 2020. Convolutional neural networks accurately predict cover fractions of plant species and communities in unmanned aerial vehicle imagery. Remote. Sens. Ecol. Conserv. 6 (4), 472–486.
Theodorou, Panagiotis, et al., 2020. Urban fragmentation leads to lower floral diversity, with knock-on impacts on bee biodiversity. Sci. Rep. 10 (1), 21756.
Thessen, Anne, 2016. Adoption of machine learning techniques in ecology and earth science. One Ecosyst. 1, e8621.
Torresani, et al., 2018. Testing the spectral variation hypothesis by using the RAO-q index to estimate forest biodiversity: Effect of spatial resolution. In: IGARSS 2018-2018 IEEE International Geoscience and Remote Sensing Symposium. IEEE.
Torresani, Michele, et al., 2020. Height variation hypothesis: A new approach for estimating forest species diversity with CHM LiDAR data. Ecol. Indic. 117, 106520.
Torresani, Michele, et al., 2022. Correlation analysis of evapotranspiration, emissivity contrast and water deficit indices: A case study in four eddy covariance sites in italy with different environmental habitats. Land 11 (11), 1903.
Torresani, Michele, et al., 2023. A novel approach for surveying flowers as a proxy for bee pollinators using drone images. Ecol. Indic. 149, 110123.
Vapnik, V. N, 1995. The Nature of Statistical Learning Theory. Springer New York, NY, http://dx.doi.org/10.1007/978-1-4757-2440-0.
Zelin, Liu, et al., 2018. Application of machine-learning methods in forest ecology: recent progress and future challenges. Environ. Rev. 26 (4), 339–350.
Zhang, Yatao, et al., 2019. Comparing the performance of random forest, SVM and their variants for ECG quality assessment combined with nonlinear features. J. Med. Biol Eng. 39, 381–392.