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Original Articles

A novel approach for surveying flowers as a proxy for bee pollinators using drone images

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ABSTRACT

The abundance and diversity of plants and insects are important indicators of biodiversity, overall ecosystem health and agricultural production. Bees in particular are interesting indicators as they provide a key ecosystem service in many agricultural crops. Worldwide, habitat loss and fragmentation, agricultural intensification and climate change are important drivers of plant and bee decline. Monitoring of plants and bees is a crucial first step to safeguard their diversity and the services they provide but traditional *in situ* methods are time consuming and expensive. Remote sensing and Earth observation have the advantages that they can cover large areas and provides repeated, spatially continuous and standardized information. However, to date it has proven challenging to use these methods to assess small-scaled species-level biodiversity components with this approach. Here we surveyed bees and flowering plants using conventional field methods in 30 grasslands along a land-use intensity gradient in the Southeast of the Netherlands. We took RGB (true colored Red-Green–Blue) images using an Unmanned Aerial Vehicle (UAV) from the same fields and tested whether remote sensing can provide accurate assessments of flower cover and diversity and, by association, bee abundance and diversity. We explored the performance of different machine learning methods: Random Forest (RF), Neural Networks (NNET) and Support-Vector Machine (SVM). To evaluate the effect of the spatial resolution on the accuracy of the estimates, we tested all approaches using images at the original spatial resolution ($\sim$ 0.5 cm) and re-sampled at 1 cm, 2 cm and 5 cm. We generally found significant relationships between UAV RGB derived estimates of flower cover and *in situ* estimates of flower cover and bee abundance and diversity. The highest resolution images generally resulted in the strongest relationships, with RF and NNET methods producing considerably better results than SVM methods (flower cover RF $R^2 = 0.8$, NNET $R^2 = 0.79$; bee abundance RF $R^2 = 0.65$, NNET $R^2 = 0.54$, bee species richness RF $R^2 = 0.62$, NNET $R^2 = 0.52$; bee species diversity RF $R^2 = 0.54$, NNET $R^2 = 0.46$). Our results suggest that methods based on the coupling of UAV imagery and machine learning methods can be developed into valuable tools for large-scale, standardized and cost-effective monitoring of flower cover and therefore of an important aspect of habitat quality for bees.

1. Introduction

Worldwide, biodiversity is declining at unprecedented rates, threatening the persistence of many species and the benefits that humans derive from ecosystems (Kleijn et al., 2015). Since the second half of the 20th century, biodiversity in agricultural areas in particular has been decreasing drastically due to habitat fragmentation and intensification of farming practices (Saunders et al., 1991; Robinson and Sutherland, 2002; Kleijn et al., 2009) with negative consequences on ecosystem functioning (Kremen et al., 2002). Bees are one of the best

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studied species groups in this respect. Studies show a marked decline in the distribution of populations at national scales and in abundance and richness of populations at the local scale (Wratten et al., 2012; Ghazoul, 2005; Steffan-Dewenter et al., 2005; Biesmeijer et al., 2006; Williams and Osborne, 2009). These have mainly been attributed to habitat loss and fragmentation, intensification of farming, climate change and loss of host plants (Scheper et al., 2014). Bees provide essential pollination services that support maximum productivity of different 76% of the leading global food crops (Klein et al., 2007), and promote seed set of about 87% of wild plants globally (Ollerton et al., 2011). In fact, one-third of the worldwide food production take advantage directly or indirectly from this ecosystem service which is valued more than 150 billion euros a year worldwide (Gallmann et al., 2021; Gallai et al., 2009).

We now have a relatively good understanding of drivers of bee population decline and the effectiveness of mitigation measures. However, we still have a poor understanding of the actual extent of population decline itself, especially at large spatial scales, and how this is linked to the quality of their habitat. Unlike butterflies, that are being monitored in a standardized way by citizen scientists in more than 10 European countries (van Swaay et al., 2008), large-scale surveying of bees by laypersons is challenging because bee species are difficult to identify. Studies examining trends in bee abundance are therefore invariably small-scaled while large scale trends are based on bee distribution data (Biesmeijer et al., 2006), which generally underestimates population trends. There are now advanced proposals for standardized monitoring of pollinators in EU member states (Potts et al., 2021). Although this will vastly improve our grasp on pollinator trends, because *in situ* monitoring is costly, a standardized monitoring program can inevitably cover only a small proportion of the relevant surface area. A complementary approach could be to infer trends in bee pollinators from trends in flower cover and species richness. Bees forage for nectar and pollen from flowers and rely exclusively on these resources for sustenance throughout their lifecycles. Flower cover and diversity have been linked to bee abundance and diversity in several studies (Potts et al., 2003; Sutter et al., 2017) and can therefore be considered an indicator of an important aspect of bee habitat quality. Assessing flower cover and diversity is less time-consuming than assessing bee abundance and species richness especially when this can be done in an automated fashion.

Recently, remote sensing and Earth observation has made significant progress with estimating various aspects of biodiversity in a standardized way at large spatial scales (Torresani et al., 2020; Tamburlin et al., 2021; Rocchini et al., 2021; Michele et al., 2018; Rocchini et al., 2022). Satellite remote sensing (hereafter SRS) has the advantage that it covers vast spatial scales, it can provide information on a variety of ecological characteristics such as vegetation distribution (e.g. vegetation dynamics (Magnússon et al., 2021; Torresani et al., 2022), plant phenology (Reed et al., 2009), habitat and environmental diversity (Torresani et al., 2021; Rocchini et al., 2022; Thouverai et al., 2023), and plant size distributions (Sheeren et al., 2016; van Lier et al., 2009) over large areas. However, it has not yet been proven possible to accurately describe with SRS vegetation aspects that can only be measured at detailed scales of up to a few mm, such as the estimation of flower cover (Cruzan et al., 2016). The technology that has recently evolved around Unmanned Aerial Vehicles (UAVs), in particular photogrammetry based on structure-from-motion algorithms, has led to the development of highly detailed orthomosaics and 3D information over large areas at a relatively low cost with the accuracy of some mm's to cm's (Gallmann et al., 2021; Kattenborn et al., 2020). So far, studies have shown that it is possible to use UAV images to estimate vegetation properties such as vegetation diversity (Guo et al., 2016), species and plant community distribution (Kaneko et al., 2014), plant trait distribution (Capolupo et al., 2015) and the mapping and monitoring of invasive species (Alvarez-Taboada et al., 2017).

In this paper we aim to assess flower cover as a proxy for bee abundance using images from a UAV. The fundamental step in estimating flower cover is distinguishing flower pixels from grass or soil pixels by means of differences in the spectral signatures (Hu et al., 2021). Different types of images can be used for this purpose. In our study, we decided to rely on RGB (Red-Green–Blue, true colored) images. These images, in comparison with multispectral/hyperspectral images (i.e. the collection of image layers that have been acquired each at a different wavelength band), have less power in characterizing the different spectral signatures of vegetation but they have a number of strengths that make them highly competitive in ecological classification analysis. RGB cameras are relatively cheap, readily available on the market and often come mounted as an integral part of commercial drones. Furthermore, RGB images require less pre-post processing analyses. This makes RGB cameras more user-friendly and allow for a more easy reproduction of analyses done by different operators or stakeholders (e.g., ecologists, farmers, researchers).

The spatial resolution of the images also plays an important role in the assessment of flower cover. Generally, fine spatial resolution offers more detailed information and reduces the mixed pixel issue (Hu et al., 2021). On the other hand, fine spatial resolution requires lower flight heights which limits the geographical area covered by the UAV in a single flight (Jin et al., 2017). In addition to spectral and spatial resolution issues, the choice of an adequate classification method is also significant for the generation of reliable classification results. Since more than two decades, different machine learning methods such Random Forest (RF), Neural Networks (NNET) and Support-vector machine (SVM) have been used extensively for classification with remote sensing data with good results (Kwak and Park, 2019). With the information obtained from UAV data, these models can be a powerful and efficient tool for the detailed characterization of the vegetation (Randelović et al., 2020). For example, Guo et al. (Guo et al., 2020) estimated the chlorophyll content of maize with UAV RGB images using three different ML methods (RF, SVM and NNET) finding that RF performed the best for their purpose. Sandino et al. (Sandino et al., 2018) made use of UAV images and an Extreme Gradient Boosting ML algorithm for monitoring of invasive grasses and vegetation in remote arid lands reaching a detection rates of around 96 %. A similar level of accuracy was found by combining convolutional neural network ML algorithms and RGB UAV images for the estimation of *Convallaria keiskei* patches (Shirai et al., 2020).

The aim of this study is to test whether we can estimate flower cover using UAV RGB images and to assess whether flower cover can be used as a proxy for bee abundance and diversity. Additionally we explored to what extent the observed relationships were affected by using different machine learning algorithms (RF, NNET, SVM) and by using image data with different spatial resolution (0.5 cm, 1 cm, 2 cm and 5 cm). Our study system consists of grasslands situated in the Southeast of the Netherlands that vary strongly in management intensity and therefore represent a gradient in flower cover. From each grassland, *in situ* data was collected within two days of obtaining the UAV images.

2. Materials and methods

2.1. Study area

The study area (7 × 10 km) is located in the Southeast of the Netherlands (Fig. 1) and consists of a mosaic of different land use types including intensive agriculture, low-intensity farming and nature reserves. We selected 30 grasslands that covered a land use intensity gradient ranging from nutrient-poor, biodiversity-rich semi-natural grasslands to intensively fertilized grasslands for fodder production. The study sites are part of the experimental biodiversity area network of the EU Showcase project https://showcase-project.eu/. The study sites are situated on loess soils, colluvial clay deposits and locally lime-rich soils, and range in elevation from 70 to 171 m asl. We minimized spatial clustering of specific grassland types by selecting semi-natural,

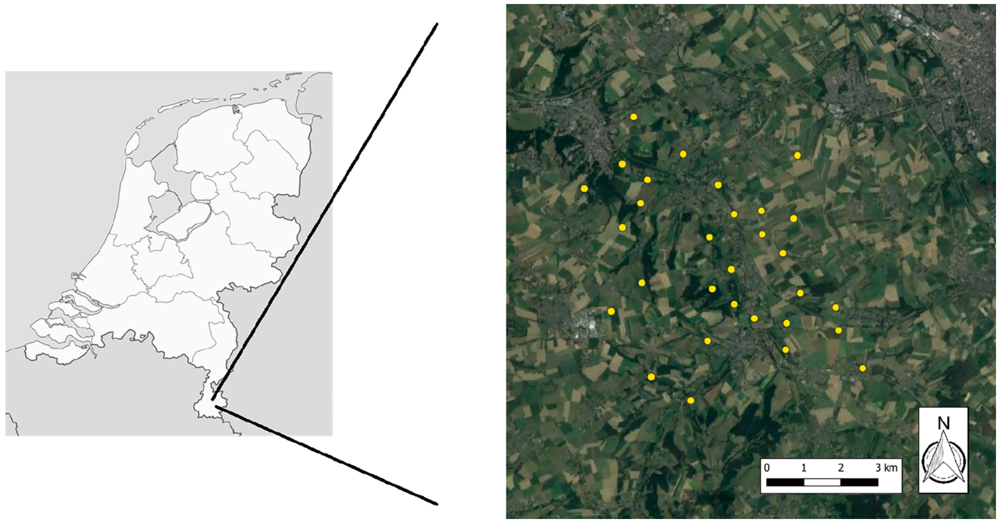

Fig. 1. The study area located in the Southeast of the Netherlands. The 30 plots are indicated by yellow dots (Basemap: Google Earth map at August 2022).

extensively used and intensively used grasslands from different parts of the study area.

2.2. Field data collection

A transect of 150 by 1 m, subdivided in three parts of 50 m, was set up in each grassland and was marked by plates clearly visible from drone imagery. The transects were placed from the edge to the center of the grassland, and led across elevational differences within the grassland if present, in order to represent heterogeneity within the grassland. To avoid sampling the same bee populations, adjacent transects were mostly separated by distances of >500 m (minimum 435 m). Studies have shown that although large-bodied bees such as bumblebees can forage at distances of a few kilometer, they mainly forage at short distances (mean distance about 250–550 m), while smaller wild bees forage at yet shorter distances (Redhead et al., 2016). Both bees and flowers were surveyed along each transect. Wild bees as well as the honeybee *Apis mellifera* were counted by transect walks which is a standard method for studying plant-pollinator associations (Westphal et al., 2008). All transects were surveyed by the same two observers who counted all bees up to a meter in front of them while slowly walking along the transect for 15 min, excluding handling time of caught specimens. Specimens were identified using keys to the Dutch Apidae (Falk and Lewington, 2017; Nieuwenhuijsen and Peeters, 2015; Nieuwenhuijsen et al., 2020). Distinct species could be identified in the field, while other specimens were collected and identified in the lab using stereo-microscopes and, in some cases, expert consultation. The counts were performed during May 12th-31st 2021, between 10 a.m. and 17 p.m., and under favourable weather conditions (dry, >50% sunny and at least 15 degrees Celsius with a wind speed < 2 Beaufort). Bee data collected in the field were used to derive at plot level, bee abundance (the total number of observed bees), bee species richness (the number of unique species) and the Shannon's H index (Pielou, 1966) as an indicator of bee diversity. In each transect, flowers were surveyed generally on the same day as the bee surveys following the method of Scheper et al.(Scheper et al., 2015). For logistical reasons some grasslands were surveyed one or two days before or after the bee survey. The number of open flowers of a given species was counted. Which was then used to calculate flower cover per transect by multiplying counts with species-specific estimates of flower size and summing over all observed flowering plant species (Scheper et al., 2015).

2.3. UAV data acquisition and data processing

The UAV data collection was carried out in parallel with the collection of the field data. The UAV model "DJI Matrice 210 RTK" was used to carry the RGB Zenmuse X5 camera (16.0 MP, 17.3 × 13.0 mm sensor) with an integrated RTK gps. The images were acquired with an overlapping rate of 80% in order to facilitate the creation of the final orthomosaic. All flights were performed at a height of approximately 20 m above ground altitude.

We used the Agisoft Metashape Professional Edition software for UAV photogrammetric processing. The software offers a user-friendly workflow that combines algorithms based on structure-for-motion and stereo-matching for image alignment and reconstruction of the 3D image (Moe et al., 2020). In order to create the orthomosaic of the collected RGB images, 4 procedural stages have been followed: image alignment, dense point cloud assessment, development of the digital elevation model (DEM) and finally the building of the orthomosaic. In the first step, set with "high" accuracy, the software extract features within the images and match them in order to produce a sparse 3D point cloud. In this stage the software automatically detects the precise features of the "Ground Control Points" - extracting the GPS coordinates to each of them. We kept the "high" accuracy also in the building of the dense cloud stage. We used the Metashape default setting for building the DEM and the final orthomosaic that was successively exported as GeoTIFF with the higher spatial resolution (the mean spatial resolution of the 30 considered areas is about 0.5 cm) to assess the role of spatial resolution in the estimation of the flower cover, we exported the orthomosaic also with a spatial resolution of 1 cm, 2 cm and 5 cm.

2.4. Modelling of UAV image estimates of flower cover

Three common machine learning algorithms included in the caret R package (Team, 2014; Kuhn, 2015) were used to assess the flower cover over the study areas: RF, SVM, NNET.

RF is an effective machine learning method based on a series of decision trees. Its algorithm uses bootstrapping to build a large number of different training subsets based on a randomly selected sample of the training samples and after constructing multiple decision trees voting is used to obtain the final prediction. Each decision tree returns a classification result for the samples not chosen as training samples. The final class prediction is determined by the largest number of votes given by the decision tree for that class (Nasiri et al., 2022; Immitzer et al., 2012). SVM is a supervised learning model that uses learning algorithms to examine data for classification and a support vector regression. It is based on a kernel function (that helps to reflect similarity between data points and the cost loss function) in order to convert initial feature space into an N-dimensional space, searching later for a hyperplane to split classes (Nasiri et al., 2022). Recently, NNET models have become very popular due to the increase of computational capacity of computers and the higher availability of big data with which these models can be "trained". NNET are based on several layers of processors that are connected to each other attempting to recognize hidden relationships though a process that simulates the human brain (Kreig et al., 2021).

The training and testing data were collected based on the manual interpretation of the orthomosaic images creating 70 polygons for each class (e.g. flowers vs grass/soil). Due to the different polygon sizes, the number of pixels for each class also differed. For this reason, in order to build a more statistically robust and more reliable strategy for classification a total of 750 points were randomly chosen within the polygons per class. Out of them, 70% were used as training sets, and 30% were used as testing sets. The performance accuracy is calculated based on the testing data-set to avoid the problem of overfitting.

We used a 10-fold cross-validation method to estimate the model accuracy (Yu et al., 2021). After building the confusion matrix, validity and reliability of the selected models was evaluated using the following metrics: Accuracy, Kappa, Precision, Sensitivity, Specificity, Negative Predictive Value, Positive Predictive Value, Balanced Accuracy, F1. Accuracy indicates the percentage of correct predictions. The sum of false negatives and true positives is divided by the total number of predictions. Kappa is a metric that compares an Observed Accuracy with an Expected Accuracy (random chance). It is used not only to evaluate a single classifier, but also to evaluate classifiers amongst themselves. In addition, it takes into account random chance (agreement with a random classifier), which generally means it is less misleading than simply using accuracy as a metric (an Observed Accuracy of 80% is a lot less impressive with an Expected Accuracy of 75% versus an Expected Accuracy of 50%). Precision identifies the accuracy with which the model predicted positive classes (number of true positive divided by the number of all positive results). Sensitivity is defined as the proportion of positive results out of the number of samples which were actually positive while Specificity is measured as the number of correct negative results divided by the total number of negatives. The positive predictive value is defined as the percent of predicted positives that are actually positive while the negative predictive value is defined as the percent of negative positives that are actually negative. The F1 is used to compare the performance of two classifiers, combining the precision and recall of a classifier into a single measure, considering their harmonic mean. Balanced accuracy is the arithmetic mean of sensitivity and specificity, and it is used when one of the target classes appears a lot more than the other (e.g. areas with a lot of grass and less flowers).

2.5. *Assessment of the relationship between UAV image flower cover estimates and estimates based on in situ data*

We examined whether the estimated flower cover using UAV images was significantly correlated with *in situ* estimated flower cover, bee abundance, species richness and diversity (Shannon's H) using simple linear regression analysis. Next, we compared the fit of these relationships when using different machine learning algorithms and different spatial resolutions of the UAV images.

3. Results

The *in situ* surveys of flowering plants showed that the species with the largest flower cover across all transects were three Ranunculus species (*R. repens*, *R. acris* and *R. bulbosus*) and *Leucanthemum vulgare*, followed by *Trifolium pratense*, *Bellis perennis* and *Taraxacum officinale* (see in Appendix 1 a table with details on the in situ flower survey). These seven species represent 84% of the total flower cover recorded and are generally the most widespread flowering forbs in the studied grasslands. Examples of grasslands with contrasting flower cover can be found in Appendix 2.

Flower cover estimated by RGB UAV images was generally significantly positively related to flower cover estimates made in the field by trained observers (Fig. 2a and Appendix 3 for the linear regressions). The goodness of fit of the relationship varied considerably with the algorithm and spatial resolution used, however the accuracy of the relationships generally declined with a decrease in the spatial resolution of the image data. The only exception was the SVM algorithm that had a higher R^2 at 1 cm resolution than at 0.5 cm resolution. The flower cover estimates produced by RF and NNET algorithms both performed similar with generally high R^2 values, while the SVM algorithms performed much worse although it still produced significant relations with field estimated flower cover data. The accuracy, ranged from a robust high 0.8 for RF algorithm using images with a 0.5 cm spatial resolution (linear regression shown in Fig. 5)) to 0.31 for the SVM algorithm using images with a 5 cm spatial resolution.

Bee abundance, species richness and diversity were also significantly and positively related to flower cover estimated by the RGB UAV images (Fig. 2b-c-d). The goodness of fit for the bee variables followed patterns that were very similar to those for flower cover with the R^2 generally declining with decreasing spatial resolution and RF and NNET algorithm performing considerably better than SVM algorithms. Interestingly, goodness of fit of the best models that used RGB UAV estimates (RF with images at 0.5 cm spatial resolution) were considerably higher than those of the models that used flower cover estimates by field observers (Fig. 4). The best relationships with flower cover estimated from UAV RGB had R^2's of 0.65, 0.62 and 0.54 for bee abundance, bee species richness and diversity respectively.

Fig. 3 shows as an example the visual flower cover estimation by the RF machine learning method at the different spatial resolutions (0.5 cm, 1 cm, 2 cm, 5 cm) in one of the 30 study areas (the background image for the four sub-plots is at 0.5 cm resolution). It illustrates why the accuracy in the flower cover estimation is generally higher in images having the higher spatial resolution (0.5–1 cm). With lower spatial resolution of the images (e.g. from 0.5 to 2–5 cm) more pixels classified as flowers actually contain a mixture of flowers and green vegetation which leads to an overestimation of the flower cover.

The RGB UAV flower cover estimates of the best model was strongly positively related to flower cover as estimated by the observer in the field (Fig. 5). Interestingly, the goodness of fit of some models (RF in particular) that used RGB UAV (at 0.5 cm) estimates to predict bee abundance, richness and diversity were higher than those of the models that used flower cover estimates by field observers (Fig. 4).

Fig. 5 shows the relationship between the flower cover estimated by the *in situ* observations and the flower cover derived from the best machine learning UAV model (RF 0.5 cm). The relationship is positive and significant, with a R^2 value of 0.8.

Fig. 6 shows the performance of each machine learning model in the estimation of the flower cover using the images at different spatial resolution. The performance of the models (with the exception of the SVM model used with RGB images at 5 cm of spatial resolution) at the different spatial resolution is high, ranging for all the parameters between 0.8 and 1.

4. Discussion

In this paper we presented a novel approach for estimating flower cover, as an indicator of bee abundance and diversity in grassland ecosystems by using UAV RGB images and different machine learning methods. We find highly significant positive relationships between flower cover estimates obtained through UAV RGB images and machine learning algorithms and flower cover estimates obtained the traditional way, *in situ* by local observers. We also find reliable relationships between UAV RGB image obtained flower estimates and *in situ* bee

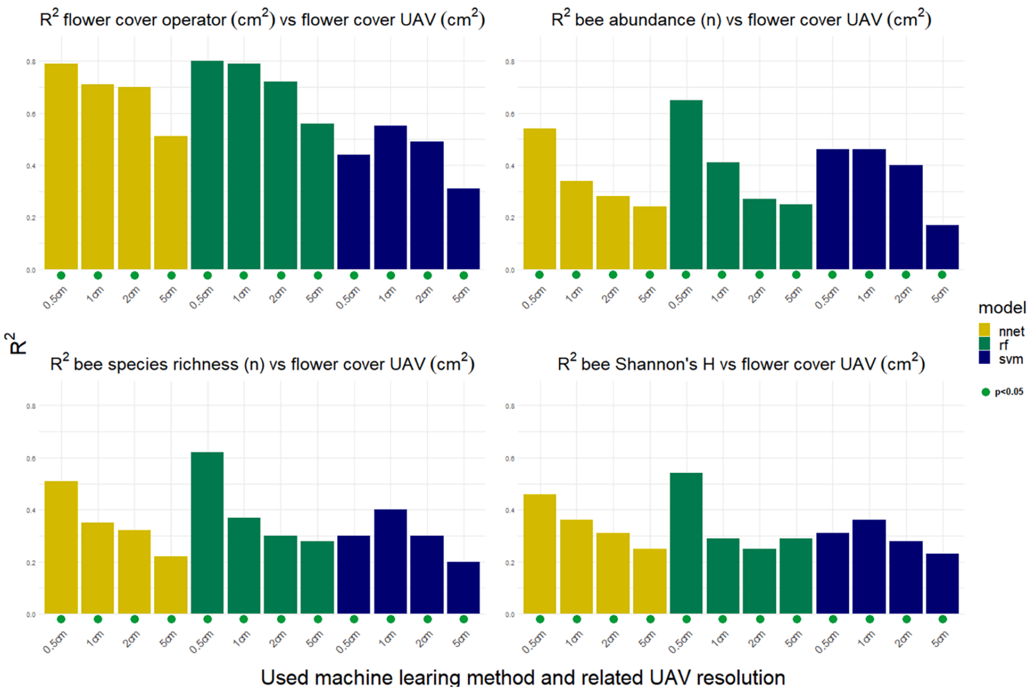

Fig. 2. R^2 values derived from the linear regression between the field data (flower cover, bee abundance, bee species richness and bee Shannon's H diversity) and the flower cover estimated by RGB UAV images at different spatial resolution (0.5 cm, 1 cm, 2 cm, 5 cm) using different machine learning methods. Green dots show statistically significant ($p < 0.05$) correlations.

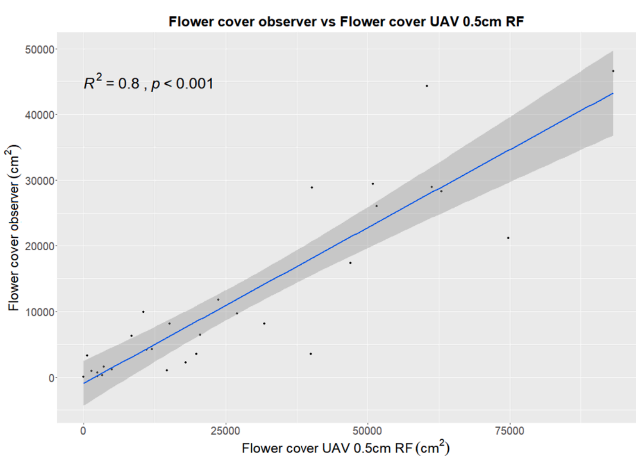

Fig. 5. The relationship between the *in situ* flower cover (Flower cover observer cm^2) and the flower cover estimated by the best machine learning UAV model (RF 0.5 cm).

abundance and diversity. This represents a proof of concept that imagery from UAVs can be used to reliably assess an important aspect of grassland quality for bees.

Overall, RF and NNET models trained with high-resolution images (<1 cm) showed the highest R^2 between the predicted flower cover estimated and the *in situ* observed flower cover, bee abundance, richness and Shannon's H. Goodness of fit metrics showed also a similar behaviour, with the highest scores observed for RF and NNET models trained with high-resolution images (<1 cm). SVM showed generally lower scores of R^2 and goodness of fit metrics compared to the other two approaches. Notwithstanding the good performances of the RF and NNET models, we argue that finding the absolute best machine-learning methods could be a challenging quest, as their results are heavily influenced by the quality of the training datasets (see for instance the class overlap and class imbalance issues), their task (classification *vs* regression) and the tuning of the models' hyperparameters ((Lovelace et al., 2019), Chapt. 11.5.2), which we decided to keep as default. Instead, one of the main outcomes of this study is the influence of the spatial resolution of the optical RGB UAV images on the flower cover estimates. Our results showed that, the higher the spatial resolution of the RGB UAV images for the assessment of flower cover, the higher the accuracy (through the goodness of fit) with the *in situ* flower cover and with the bee abundance, diversity and richness. This is probably largely the result of the fact that images with higher spatial resolution are better able to differentiate between flowers, grass or soil, offering higher information details and reducing the mixed pixel issue (Hu et al., 2021). Images with coarse spatial resolution result in mixed signal at pixel scale, integrating the spectral signature of various vegetative organisms (e.g. trees, shrubs, flowers), homogenizing the signal and causing difficulties to clearly identify boundaries between spatial entities (individuals, vegetation types, ecosystem types) (Rocchini et al., 2010; Šímová et al., 2019; Feilhauer et al., 2021). In our study, the weighted average flower size was 1.66 cm^2. Pixel sizes of up to 3.2 cm^2 (i.e. our two most detailed spatial resolution classes) would classify a pixel correctly if a full single flower would be in it, with larger pixels misclassifying. In our study, the mixed pixel issue most likely also led to an overestimation of the range in UAV RGB estimated flower cover because pixels with less than 50% flower cover are classified as 0% flower cover while pixels with more than 50% flower cover are classified as 100% flower cover. In flower-poor fields there will be disproportionately more pixels with less than 50% flower cover while in flower-rich fields there will be disproportionately more pixels with more than 50% flower cover. This probably explains why, in the case of the results shown in Fig. 5, the range in RGB UAV estimated flower cover is twice as wide as the range in the *in situ* collected flower cover data. A consequence of this is that care should be taken to use the relations from UAV RGB estimates of flower cover to predict effects of changing flower cover on bees. Because the slope of the relationship with bees is twice as low for RGB UAV flower cover compared to *in situ* flower cover (2.3 times for bee abundance, and 2.1 times for bee species richness and diversity), the predicted effects on bees of improving flower cover will be twice as low

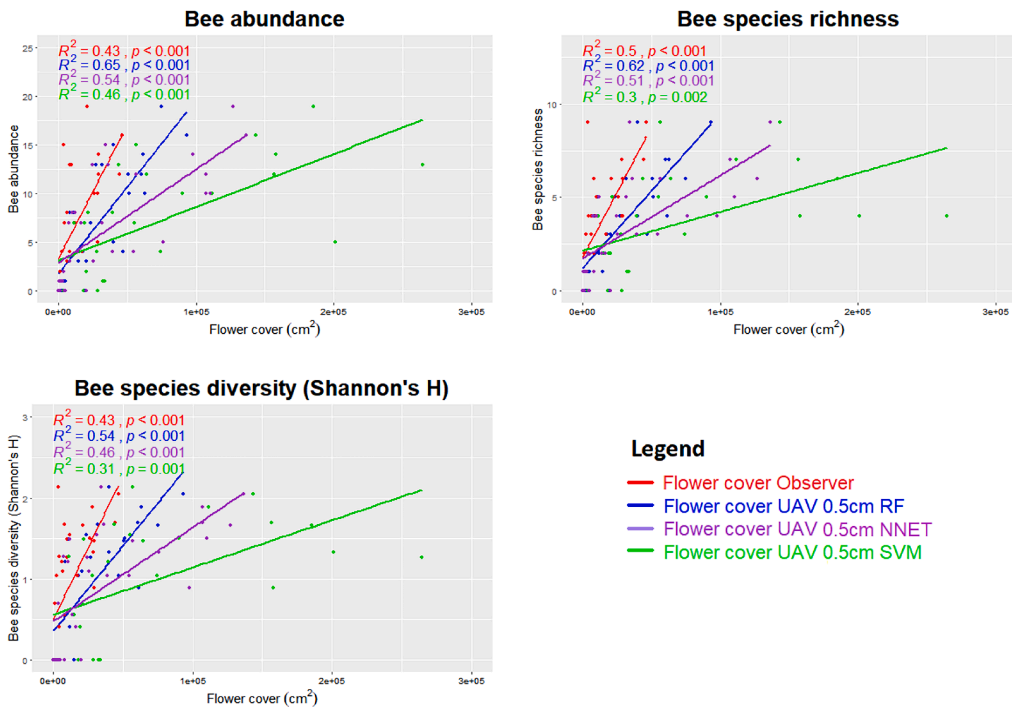

Fig. 4. The comparison of the relationships between bee abundance, species richness and diversity (Shannon's H) and the flower cover estimated by the *in situ* observations (Flower cover observer cm^2) and by the different machine learning models using RGB UAV images at the higher spatial resolution (0.5 cm).

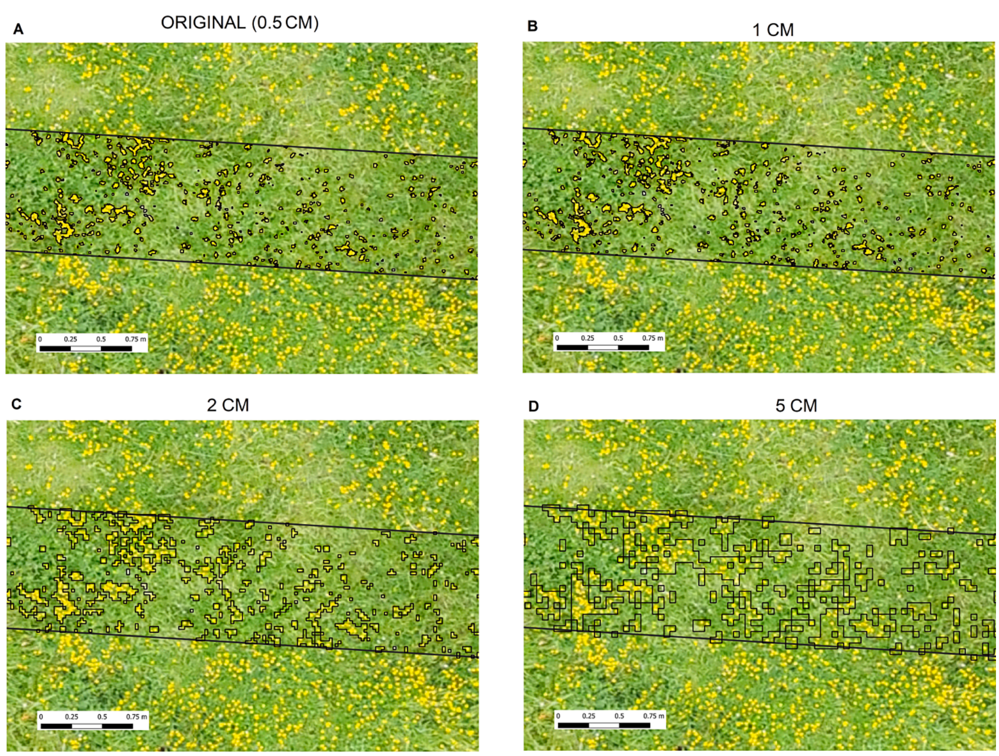

Fig. 3. A visualisation of the results of the flower cover estimation by the RF machine learning methods at the different spatial resolution in one of the 30 study sites. The background image for the four sub-plots is at 0.5 cm resolution.

as well.

With very few exceptions the accuracy of the relationships with *in situ* flower estimates were higher than those with *in situ* bee estimates. This is to be expected because the algorithms we used were trained to classify flower presence (Fig. 2, sub-plot A). Bees are too small and inconspicuous to be detected by UAV RGB imagery and their abundance and species richness can only be inferred using such images because they generally show a very strong relationship with flower availability (Sutter et al., 2017; Potts et al., 2003). Previous research shows that abundance and species richness of bees are often strongly related to the cover and species richness of flowers. Bee species richness is generally best predicted by the floral species richness (Potts et al., 2003; Fründ

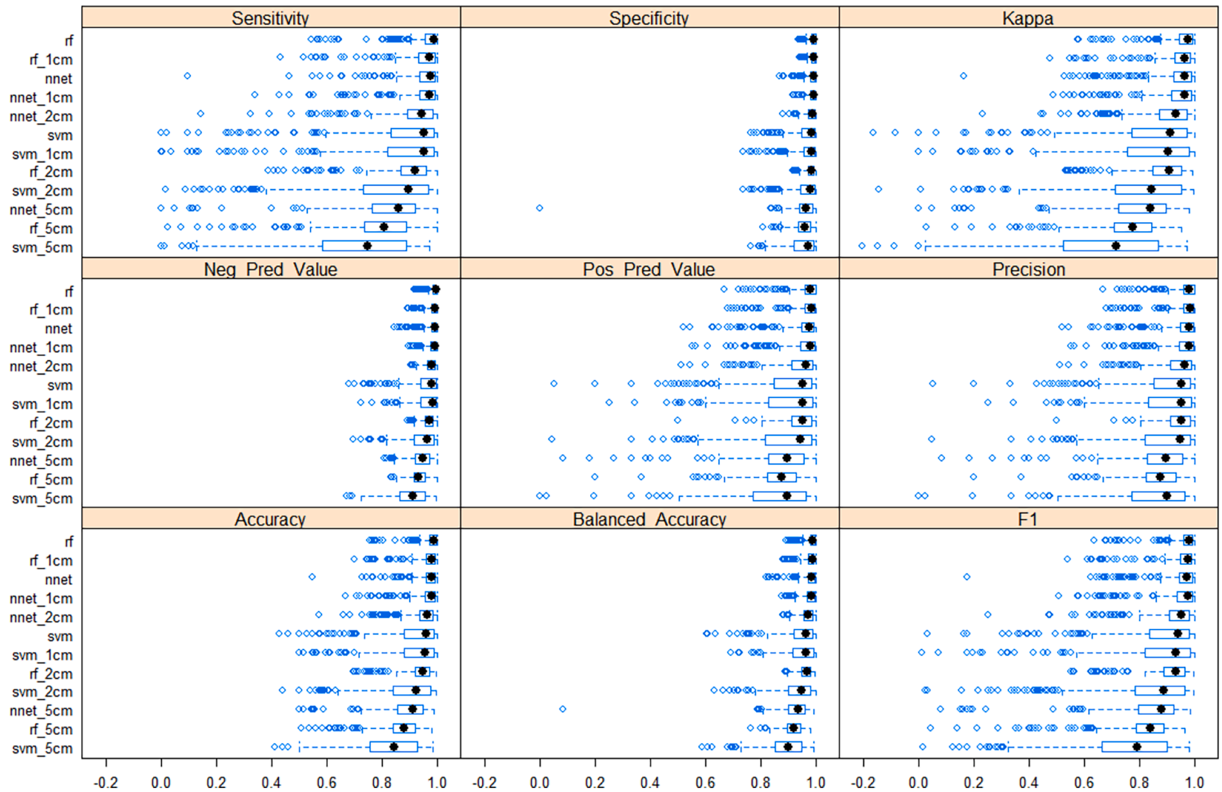

Fig. 6. Performance of the machine learning models (Sensitivity, Specificity, Neg.Pred.Value, Pos Pred Value, Precision, Recall, Accuracy, Balanced Accuracy, F1, Kappa) at the different spatial resolution.

et al., 2010; Neumüller et al., 2021) while bee abundance by flower cover (Blaauw and Isaacs, 2014; Scheper et al., 2021). However, flower species richness and cover are mostly correlated and flower species richness has also been found to be related to bee abundance (Steffan-Dewenter and Tscharntke, 2001; Theodorou et al., 2020) while flower cover has been shown to be related to bee species richness (Ebeling et al., 2008; Scheper et al., 2015). Which relationship predominates at a particular place and time is probably largely determined by the composition of both the local bee and the flowering plant community. Additional factors such as the quantity and quality of the reward offered by different flowers, the availability of nesting sites and landscape composition may additionally affect local bee abundance which probably explains the weaker correlation with UAV RGB imagery. It is perhaps surprising that the accuracies of the best models explaining bee variables that used RGB UAV estimates (RF with images at 0.5 cm spatial resolution) were considerably higher than those of the models that used flower cover estimates by field observers (Fig. 4). The goodness of fit of the observed relationships between our *in situ* collected flower and bee data varied between 0.43 and 0.5. This is not particularly low and in line with results from other empirical studies (e.g. 0.12–0.52 in Potts et al. (Potts et al., 2003)). Whether the UAV RGB image based estimates or observer based estimates better reflect reality is impossible to say, but the higher goodness-of-fit suggests that UAV RGB images capture some variation in flower cover that is relevant to bees and that was missed by our observers.

Our results contrast a bit with findings from other studies that attempted to relate flower estimates based on UAV RGB imagery to flower estimates from field observations and that show more mixed results (De Sa et al., 2018). Smigaj and Gaulton (Smigaj and Gaulton, 2021) made use of RGB and multispectral images for the flower abundance estimation in a farmland ecosystem in northeast England. The authors found RGB imagery to be poorly related to *in situ* estimates while multispectral images performed markedly better. This was explained by the fact that the multispectral images included the near infrared band that helped with the differentiation between flowers and woody parts of hedgerows (Smigaj and Gaulton, 2021). Also De Sá et al. (De Sa et al., 2018) found a poor correlation between the estimation of the number of flowers of an invasive shrub using RGB UAV images and field observations explaining this with the variability of the structure and phenology of the examined invasive plants and the variation of the different habitats where the species grows. An explanation for the good performance of the RGB images in our case might therefore be due to the relatively uniform herbaceous vegetation that we surveyed that lack components that have a reflectance similar to the flowers (identifiable with the red, green, and blue bands). Additional explanations could be that we collected our field data mostly on the same day as the UAV RGB images were made, which minimizes errors caused by the phenology of the flowering plants and the fact that the most dominant flowering plant species (e.g. *Ranunculus spp.*,*Taraxacum officinale*, *Leucanthemum vulgare*, *Bellis perennis*) had horizontal inflorescences that can be observed relatively accurately from aerial imagery.

The method presented in this paper opens up a wide range of uses beyond complementing the manual area estimation of flowers in grassland. Remote sensing approaches can increase the temporal and spatial efficiency of sampling methods, allowing large portions of land to be surveyed in less time, creating standardized and reproducible data. Optical UAV data could represent a potential answer to the lack of baseline ecological data for plant-pollinator interactions, as pointed out by the International Pollinator Initiative (Williams, 2003). UAV based methods could represent promising tools for monitoring habitat quality for bee pollinator communities because they are now affordable (Gonzales et al., 2022) and allow different operators (e.g., researchers, farmers, ecologists) to obtain high spatial resolution data from different sensors that can be carried simultaneously, covering large areas in a limited time. In time, they can be used with an ”on-demand” approach that allows to capture specific stages of vegetation phenology (flowering time) in particular in areas characterized by high cloud cover (Müllerová et al., 2017; De Sa et al., 2018). However, a number of challenges need to be addressed before any UAV based methods can be deployed routinely and at large spatial scales. As stressed in this study, the spatial and spectral resolution of the UAV images together with the choice of the appropriate ML algorithm, play a fundamental role in the characterization of the vegetation. Further limitations include the high amount of time needed to collect and to process the data, especially when using imagery and dense point clouds at the millimeter level (Vanbrabant et al., 2020). Topography, meteorological condition and the right time-window can also influence negatively the image acquisition and the successively correlation analysis. When applying the methodology explained in our study, it must be clear whether relationships determined in one area or year can be generalized to other areas and/or years (Blasi et al., 2021). If UAV based images indicate high flower cover, does that mean that a site is suitable for bees throughout the growing season or just during a few days or weeks before or after the day the image was obtained. Furthermore, we need to know whether UAV based images can also be used to survey flower cover and bee habitat quality in structurally more complex vegetation types and other colors of flowering plant species.

5. Conclusions

This paper shows proof-of-concept that flower cover, an important aspect of habitat quality for bees, in grasslands can be monitored using UAV RGB imagery which opens the way for large-scale, standardized and cost-effective monitoring strategies in one of the most wide-spread vegetation types globally. The results suggests that the higher the spatial resolution of the optical images, the higher the accuracy of the approach. Furthermore, the RF machine learning algorithms generally produced the most accurate relationships. The next steps will need to focus on operationalizing the approach, testing and validating with an independent data-set the proposed approach examining its reproducibility. Further analysis will focus on assessing the trade-off between UAV flight height and precision in order to understand how high the drone can fly in order to increase the flight area without losing accuracy in the assessment of flower cover. Through structure-from-motion technology UAV images could be used to characterize the 3D structure of different habitats in order assess how the habitat structure influences the bee diversity and abundance. Finally, an attempt could be made to standardize the method in order to obtain imagery from large areas and translate them automatically in 'flower cover data' and successively in bee information.

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CRediT authorship contribution statement

Michele Torresani: Conceptualization, Methodology, Validation, Formal analysis, Data curation, Writing – original draft. **David Kleijn:** Conceptualization, Methodology, Validation, Formal analysis, Writing – original draft, Supervision, Project administration, Funding acquisition. **Jan Peter Reinier de Vries:** Conceptualization, Methodology, Validation, Formal analysis, Writing – review & editing. **Harm Bartholomeus:** Conceptualization, Methodology, Validation, Data curation, Formal analysis, Writing – review & editing. **Ludovico Chieffallo:** Investigation, Formal analysis, Writing – review & editing. **Roberto Cazzolla Gatti:** Investigation, Formal analysis, Writing – review & editing. **Vítězslav Moudrý:** Investigation, Data curation, Formal analysis, Writing – review & editing. **Daniele Da Re:** Formal analysis, Writing – review & editing. **Enrico Tomelleri:** Investigation, Formal analysis, Writing – review & editing. **Duccio Rocchini:** Conceptualization, Methodology, Validation, Writing – review & editing.

Declaration of Competing Interest

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Data availability

Data will be made available on request.

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Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at https://doi.org/10.1016/j.ecolind.2023.110123.

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