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Master's degree in
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Flower cover and bee diversity estimate by drone RGB images

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Abstract

Worldwide, biodiversity is decreasing due to climate change, habitat fragmentation and agricultural intensification. Bees are essential crops pollinator, but their abundance and species richness are decreasing as well. For their conservation, it is necessary to assess the status of bee population. Field data collection methods are expensive and time consuming, thus, recently, new methods based on remote sensing are used.

In this study we tested the possibility of using flower cover diversity estimated by UAV images to assess bee diversity and abundance in 10 agricultural meadows in the Southeast of the Netherlands. In order to do so, field data of flower and bee diversity and abundance were collected during a campaign in May 2021. Furthermore, RGB images of the areas have been collected using Unmanned Aerial Vehicle (UAV) and then, post-processed into orthomosaics. Lastly, Random Forest machine learning algorithm was applied to estimate flower cover diversity of the species detected in each field. Flower cover diversity estimated by UAV was expressed with Shannon and Simpson diversity indices, which were successively correlated to bee Shannon and Simpson diversity indices, abundance and species richness.

The results showed a positive relationship between flower cover diversity estimated by UAV images and in-situ collected data about bee diversity, evaluated with Shannon index, bee abundance and species richness. The strongest relationship was found between flower cover diversity expressed by Shannon Index and bee abundance with R^2 value of 0.52. Following, good correlations were found between flower cover diversity and bee species richness (R^2=0.39) and bee diversity expressed by Shannon Index (R^2=0.37). R^2 values of the relationship between flower cover diversity expressed by Simpson Index and bee abundance, species richness and diversity were slightly inferior (0.45, 0.37 and 0.35, respectively).

Our results suggest that the proposed method based on the coupling of UAV imagery and machine learning for the assessment of flower species diversity could be developed into valuable tools for large-scale, standardized and cost-effective monitoring of flower cover and of the habitat quality for bees.

Contents

1 Introduction

1.1 Biodiversity and bee importance

Biodiversity provides manifold benefits to human well-being. Ecosystem services include clean drinking water, food provision, maintenance of soil fertility and regulation of diseases. However, the climate change is causing decline in the distribution and abundance of species, the composition of communities and the ecosystem's ecological functions [Whitehorn et al. (2019)]. Consequently, the loss of biodiversity threatens the ability of the ecosystems to provide the services on which humanity relies on [Cardinale et al. (2012)]. Agricultural intensification and habitat fragmentation are two of the main drivers of loss of biodiversity in agricultural areas [Lanz et al. (2018); Saunders et al. (1991)].

Pollinator species visit both crops and wild plants, ensuring seed and fruit set, thus sustaining biodiversity. It is estimated that 78% of flowering plants in temperate-zone are animal pollinated, and bees are considered the most important group of pollinators due to their large numbers and specialization of floral resources [Senapathi et al. (2015); Ollerton et al. (2011); Ollerton (2017)]. Around only 2% of pollinators species carried out approximately 80% of global pollination services [Kleijn et al. (2015)]. Wild bee species, along with honey bees (*Apis mellifera*) and managed bumble bees (*Bombus* spp.) are some of the essential crop pollinators [Cariveau and Winfree (2015)]. Pollinators are important for the functioning and health of many ecosystems and their importance can also be interpreted in term of economics contribution to agricultural production: the ecosystem service of food production provided by pollinators is valued being 153€ billion annually worldwide [Iwasaki and Hogendoorn (2021); Gallai et al. (2009)]. Pesticides, pathogens, land-use change and climate change are some of the drivers of the pollinators' decline, along with loss of host plants, habitat fragmentation and loss and intensification of farming [Cariveau and Winfree (2015); Scheper et al. (2014)]. Abundance and richness of populations are declining at local scale, whereas the distribution is declining at national scales [Williams and Osborne (2009); Ghazoul (2005)].

1.2 Importance of flowers diversity to estimate bee diversity

Plant-pollinator relationships is a very important ecological interaction because, without pollinators, many plants could not set seed and reproduce, with a knock-on effects for other species, including human ones [Kearns et al. (1998)]. This is one of the reasons for which evidence of pollinators abundance and diversity decline has generated widespread concern [Ollerton et al. (2011)].

To make a valid assessment of the status of bee population is necessary a reliable and robust methodology. Some available in-situ sampling methods are sweep net, pan and vane traps, baits, trap-nest, observation plots and transect walks [Prendergast et al. (2020); Westphal et al. (2008)]. However, capture probability is different across bee species and it may yield incorrect relative abundance of the species in a community [Briggs et al. (2022)]. Moreover, the above-mentioned methods require surveyors with certain collection skills, they are labor-intensive and catch rates vary with environmental conditions, such as temperature, wind and time of the day [Prendergast et al. (2020)].

It has been identified that the availability of floral resources is a key driver of bee diversity and abundance both in agricultural and natural ecosystems [Isbell et al. (2017)]. Diverse plantings could sustain and attract a more richer bee community, because many bee species are specialized on a particular plant taxon. Moreover, diverse plant communities can provide floral and pollen resources during the season, which can support a potentially richer-species bee community. As a matter of fact, bees rely on pollen throughout all their life cycle [Gerner and Sargent (2022)]. Other studies, for instance Potts et al. (2003) and Sutter et al. (2017), link bee abundance and diversity to flower cover diversity. Hence, flower cover diversity can be a good indicator of bee habitat quality and the diversity of the local geographic species pool. In addition, an advantage of this mentioned association is that assessing flower cover diversity require less time and skills than evaluating bee diversity, abundance and species richness through more classical methods. Especially now that we can count on automatic device, e.g. drones equip with cameras.

1.3 Importance of remote sensing data

Remote sensing has been applied in many ecological fields, for example land use classification and change [Ma et al. (2019)] and to detect plant biodiversity in various ecosystems [Torresani et al. (2019); Wang and Gamon (2019)]. RS is convenient because it can provide data at large spatial scale in an objective and consistent fashion [Wang and Gamon (2019)]. Lately, the Unmanned Aerial Vehicles (UAVs) has been used for remote sensing application thanks to the development of sensors to be installed onboard [Pajares (2015)]. The advantages of UAV data are the ultra-high spatial resolution (up to some millimeters), flexibility in acquisition, obtaining of coherent geometric and spectral data and the possibility of using multi-sensor data at the same time [Yao et al. (2019)]. UAVs technology and images have already been used in many ecological contexts, which include plant biodiversity estimation [Getzin et al. (2012)], prediction of cover fraction of plants [Kattenborn et al. (2020)] and collection of information about flower abundance and species diversity in grassland by using a deep-learning object detection method [Gallmann et al. (2021)].

1.4 Aim of the study

The aim of this study is to assess whether the flower cover diversity estimated by UAV images can be utilized to estimate bee diversity and abundance. A positive correlation between such two biodiversity property could enhance the ability of monitoring bee population in a less costly manner. In order to do so, high-spatial resolution (some centimeters) RGB UAV images of 10 grasslands with different land usage have been taken. To estimate flower cover diversity of the present flower species in each grassland it is necessary to distinguish flower pixels from grass and soil ones. Eventually, flower Shannon and Simpson diversity index were calculated.

2 Materials and Methods

2.1 Study area

The study area is located in the Southeast of The Netherlands, close to Maastricht, and its width is 7 x 10 km (Figure 1). This area is part of the experimental biodiversity area network of the European SHOWCASE project and it is characterized by a mosaic of different land use types. The 10 selected grasslands have a land use intensity gradient, therefore are included natural reserves, low-intensity farming and intensively fertilized grasslands. The soils are loess, colluvial clay deposits and locally lime-rich and the elevation range is 70 - 171 m asl.

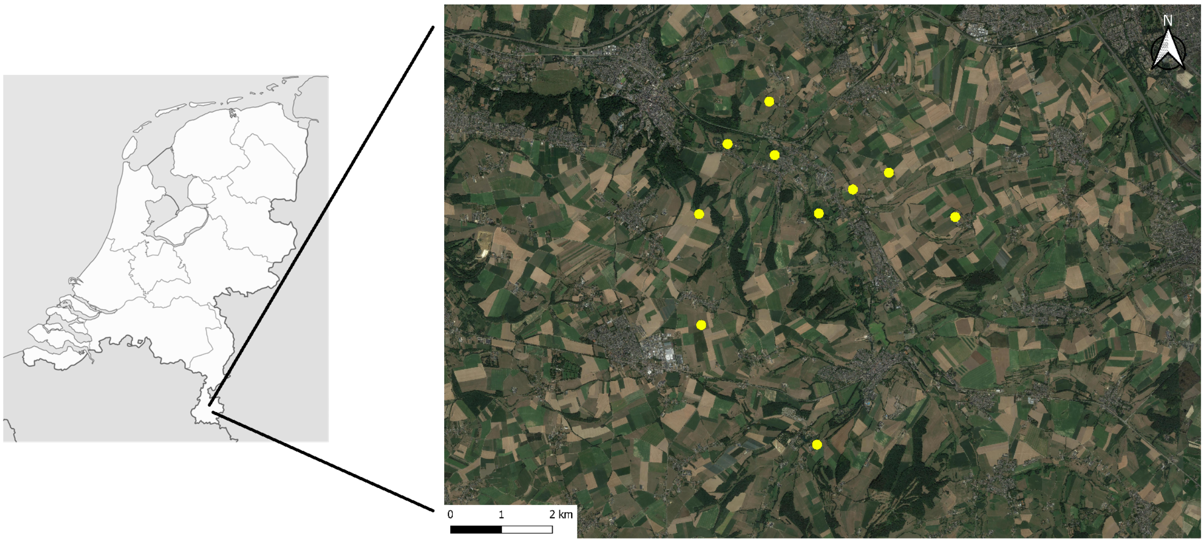

Figure 1: The study area and the 10 selected grasslands

2.2 Field data collection

In every selected grassland was defined a 150 x 1 m transect split up in three sections of 50 m each. If the field displays some elevation difference, the transect followed such gradient to highlight the heterogeneity. The grassland were at least 250 m apart to avoid sampling the same bee population. Flowers and bee data were collected in May 2021, 12th-31st, between 10 a.m. and 5 p.m., on days with a temperature range of 12-22°C, a mean percentage of 83% of sun and a maximum of 3 Beaufort wind speed. Usually, flowers and bee information were assessed the same day, with some exception due to logistical reasons.

Flowers species and abundance were evaluated following Scheper et al. method [Scheper et al. (2015)]. It means walking through the transect, record and identify every flowering species at the time of the survey.

Bee species and abundance were evaluated following the transect walks method [Westphal et al. (2008)]. Two observers walked slowly through the transect for 15 minutes counting every bee they see up to a metre in front of them. Moreover, they caught bees individual in order to identified them at species level. If the identification was not successful the bee were brought to the lab.

2.3 UAV Data Acquisition and Data Processing

The UAV model "DJI Matrice 210 RTK" was used to collect RGB images of the grasslands. The drone was equipped with a RGB Zenmuse X5 camera (16.0 MP, 17.3 x 13.0 mm sensor) and an integrated RTK gps. RGB images are true colored images with Red, Green and Blue wavelength bands. Images acquisition was carried out the same day of field data collection and the flight height was around 20 m above the ground altitude.

The images were taken with an overlapping rate of 80% to facilitate the orthomosaics creation for the following analysis. In order to produce the orthomosaics we used the Agisoft Metashape Professional software. This application processes RGB or multispectral images into dense point clouds, textured polygonal models, georeferenced orthomosaics based on SfM (Structure from Motion) technology and DSMs/DTMs [Han and Hong (2019), https://www.agisoft.com/pdf/metashape_presentation.pdf]. The orthomosaics creation required 4 procedural steps:

1. Image alignment: accuracy was set as "high" and the software extracts feature within the images and produces a sparse 3D point cloud;
2. Dense point cloud assessment: accuracy was set as "high";
3. Development of the Digital Elevation Model: default setting were used;
4. Building of the orthomosaic: default setting were used. At last, the orthomosaic was exported as GeoTIFF with the higher spatial resolution.

2.4 Modelling of flower cover

First of all, a manual interpretation of the orthomosaics was necessary. Based on grassland specific flowers species data, for every orthomosaic were created about 20 polygons for each present class, namely grass (always present), yellow flowers, white flowers, blue flowers and purple flowers. It means that in some grassland there was, e.g. grass and yellow flowers polygons and in others, e.g. grass, white and purple flowers. This step was realized on QGIS. Due to the different polygons size, the number of pixels for each class was also different. For this reason, prior to the construction of the training and testing sets, a number of pixels for each class (30-300) were randomly chosen on R environment. Thus, the strategy for classification is more statistically robust and reliable. Within the selected pixels, 70% were used to built a training set and 30% were used as testing set.

Later on, the Random Forest machine learning algorithm was used in order to assess the species flower cover. RF is a collection of tree-structured classifiers [Breiman (2001)]. Every tree is planted on the basis of a training sample set and a random variable. The combination of the unit vote for the most popular class by each tree get the final sort result. RF is characterized by an high classification accuracy and never got overfitting [Liu et al. (2012)].

At last, model accuracy was estimated building a confusion matrix. Overall accuracy and Kappa were took into account.
The overall accuracy is the total number of correctly classified samples for each class divided by the total number of samples. So it measures the accuracy of the entire grassland model without any indication of the accuracy of individual class. The Kappa coefficient of agreement is a measure of true positive (the diagonal elements of the matrix) minus change agreement (product of row and column marginals values). Kappa measures how the classification model performs as compared to the reference data [Fung and LeDrew (1988)]. Kappa may have value between -1 and +1. A value of +1 implies a perfect agreement between the raters; whereas a value of 0 implies that there is no relationship [Kılıç (2015)].

2.5 Assessment of the association between flower cover diversity estimated by RGB UAV images and bee diversity, abundance and richness

Flower Shannon's Index H and flower Simpson's Index were calculated, along with bee Shannon and Simpson's indices. Later, flower Shannon's H and bee diversity (H and Simpson), abundance and species richness association were assessed. Same possible correlation was evaluated using flower Simpson's Index.

3 Results

The figure 2 explains how the Random Forest machine learning algorithm works and what the output is. The model is the estimate pixels classification to grass and different species of flowers (the classes). As an example, in the below image there is a portion of a grassland area used in this study. The mean accuracy and Kappa of the 10 prediction models of the analysed areas are, respectively, 0.9787 and 0.9677 (Table 1).

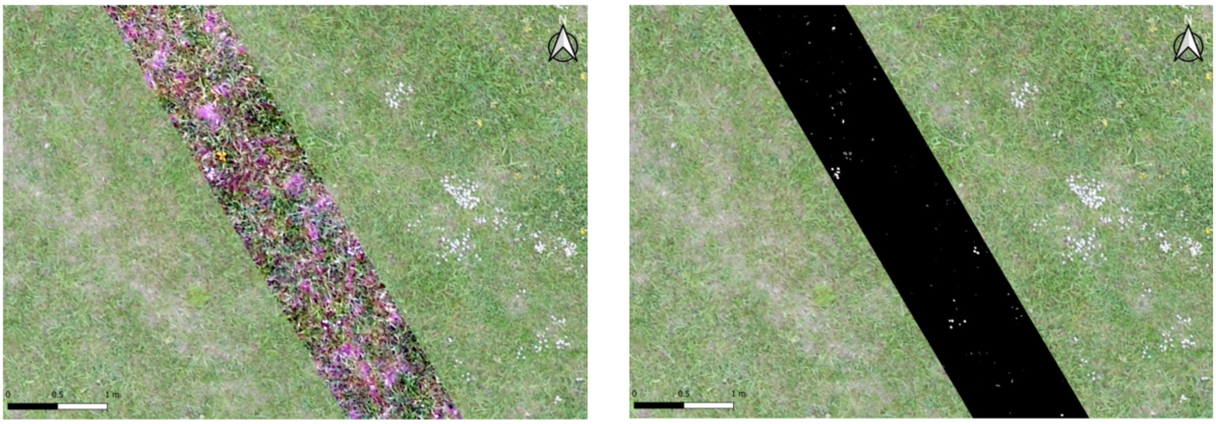

Figure 2: Output from the RF machine learning algorithm. On the left there is the buffer zone used to select the training polygons of the classes. On the right we can see the prediction model which classified pixels to their class.

Mean Accuracy	Mean Kappa
0.9787	0.9677

Table 1: Mean accuracy and kappa of the 10 prediction models

Figure 3 represents the correlation between flower cover diversity estimated by UAV images and expressed by the Shannon's index H and bee diversity (stated through both the Shannon's index H and Simpson's index), species richness and abundance. Bee species diversity Shannon's H R^2 is 0.37, bee species diversity Simpson R^2 is <0.01, bee species richness R^2 is 0.39 and bee abundance R^2 is 0.52.

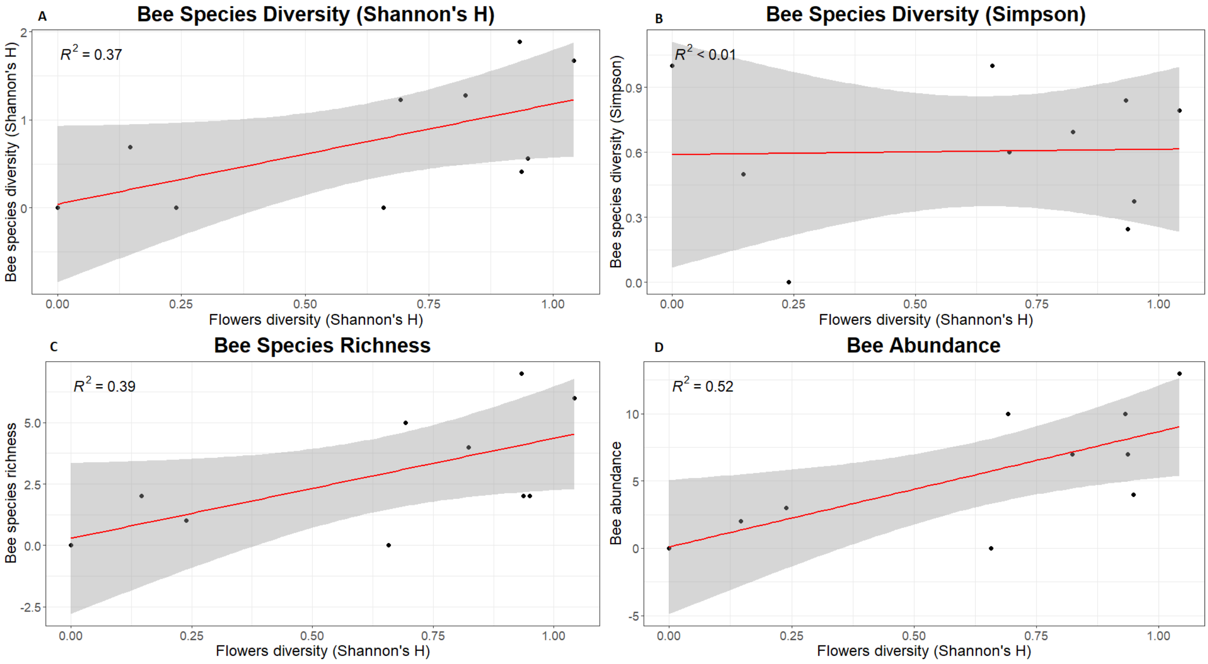

Figure 3: The graphs shows the relationships between flower cover diversity (Shannon's H) and (A) Bee species diversity using Shannon's H; (B) Bee species diversity using Simpson; (C) Bee species richness; (D) Bee abundance.

Figure 4 represents the correlation between flower cover diversity estimated by UAV images and expressed by the Simpson's index and bee diversity (stated through both the Shannon's index H and Simpson's index), species richness and abundance. Bee species diversity Shannon's H R^2 is 0.35, bee species diversity Simpson R^2 is 0.01, bee species richness R^2 is 0.37 and bee abundance R^2 is 0.45.

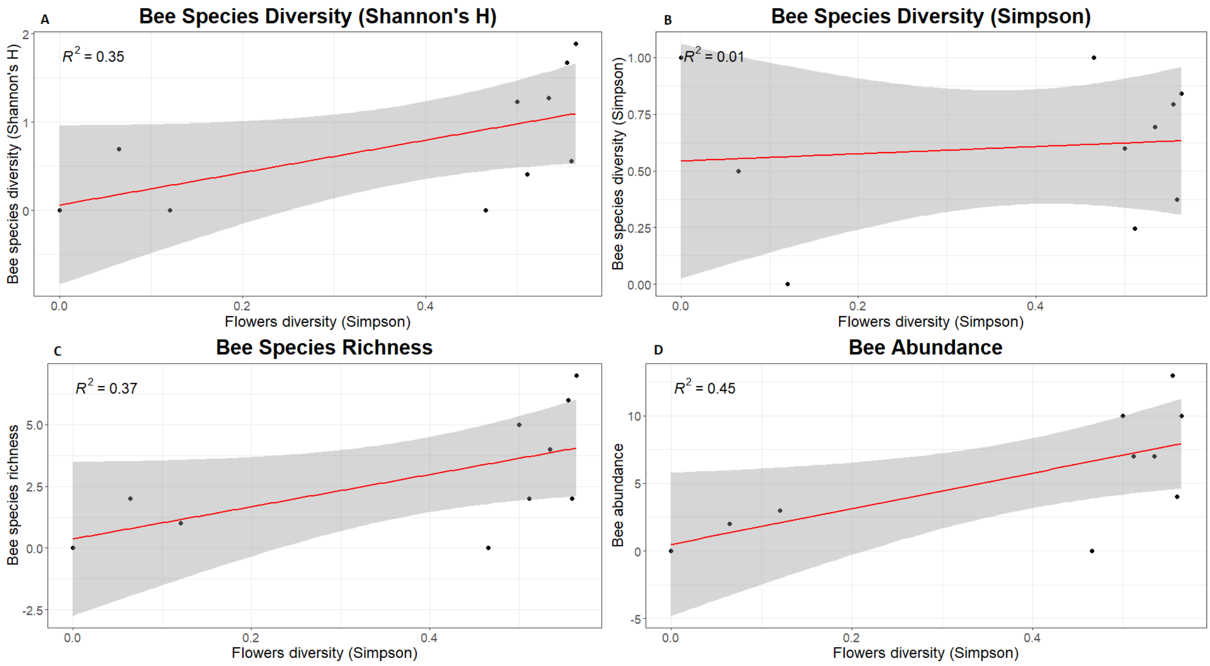

Figure 4: The graphs shows the relationships between flower cover diversity (Simpson) and (A) Bee species diversity using Shannon's H; (B) Bee species diversity using Simpson; (C) bee species richness; (D) Bee abundance.

4 Discussion

In this study we tested a novel method to assess bee diversity and abundance using flower cover diversity estimated by RGB UAV images and Random Forest machine learning algorithm. The results showed a positive relationship between flower cover diversity estimated by UAV images (explained with Shannon index) and in-situ collected data about bee abundance, bee species richness and bee diversity (explained with Shannon index). The same correlation was tested using Simpson diversity index applied to flower cover diversity estimated by UAV images, resulting in a positive, but slightly inferior, relationship with bee communities properties. In each case, the strongest relationship is between flower cover diversity estimated by UAV images and bee abundance (Fig. 3.D and 4.D) with R^2 value of, respectively, 0.52 and 0.45. Following, good correlations with very little discrepancy, are between bee species richness and bee diversity expressed by Shannon Index (Fig. 3.C, 3.D and 4.C, 4.D).

We decided to use Random Forest machine learning algorithm because it is one of the most efficient classification methods and it has already been used for land cover analysis [Akar and Güngör (2012); Kulkarni and Lowe (2016)]. Furthermore, it is not sensitive to noise, it is robust against overfitting and it is fast [Akar and Güngör (2012)]. In our case, RF algorithm created a model of the grassland, identifying a maximum of five classes: grass and four different flower colors (yellow, white, blue and purple). We estimated flower diversity based on flower colors because, due to RGB images, that is visible spectrum, it was impossible to select each flower species classified during a field campaign. Another issue about UAV images is the effect of "mixed pixels" related to the spatial resolution, which could impact the model accuracy [Hu et al. (2021)]. Spectrally mixed pixels occur when more than one type of land cover [Small (2004)] or vegetative organisms, such as grass, flowers, shrubs, are integrated. Therefore, it became difficult to clearly identify boundaries between grass, flowers, leafs and other objects on the ground, because there could be more noise than information [Rocchini et al. (2010)]. However, mean overall accuracy and kappa of the ten created models are very high, as shown in Tab. 1. Range of overall accuracy values is 0.8942-1, whereas kappa values range is 0.8237-1. The good accuracy of flower cover estimation of our grassland areas might be due to the simultaneous collection of RGB UAV images and field observations. Furthermore, even though the chosen areas are all agricultural land, vegetation difference between them are not many and the ground was basically free of other elements (e.g. stones). On the contrary, other studies using RGB drone images to compare flower classification or abundance estimation to field data showed less accurate relationship. Smigaj and Gaulton flower abundance estimation through RGB images relationship with ground measurements of hedgerow was poor due to confusion with woody material [Smigaj and Gaulton (2021)]. De Sa et al. found a weak correlation between the number of flowers counted in field and the flower cover area in the UAV imagery. This could be explained by the high variability of morphology and phenology of the researched invasive plant and the differences in the habitats where the specie lives [De Sa et al. (2018)]. To improve the relationship between flower classification and ground measurements, a strategy might be to employ a multispectral imagery with near-infrared channel included [Smigaj and Gaulton (2021)].

A linear correlation between flower diversity and bee diversity is demonstrated in various studies. Fründ at al. recorded flower and pollinators species in meadows with varying flower diversity and found a positive correlation among flower diversity and flower-visiting insects diversity, confirming the importance of flower diversity for bee communities [Fründ et al. (2010)]. Furthermore, bee diversity seems to benefit from a high diversity of flowering plants, whereas bee abundance is often correlated with flower cover [Steffan-Dewenter and Tscharntke (2001)]. Bee diversity is also linked to landscape heterogeneity, because a heterogeneous habitat can support a higher diversity of flowering plants [Holzschuh et al. (2007)].

Flower cover diversity estimated through RGB UAV images is positively correlated with bee abundance, species richness and diversity assessed in the field. Therefore, this method could be used to monitor bee population in a less time-consuming approach. We decided to use RGB images because they are more economically affordable and require less post-processing analysis. However, RGB images characterized the different vegetation spectral signature with less strength in comparison with multispectral or hyperspectral images.

The use of UAVs provides near-earth aerial imaging with high spatial resolution, without cloud disturbance and at a lower cost than sampling methods [Sagan et al. (2019)]. Moreover, nowadays, there are not only RGB low-cost and highly engineered sensors, but also multispectral, hyperspectral, short/mid-wave range cameras and light-weight LiDAR. So, there can be many applications of UAVs, for example land cover/use mapping, vegetation detection and analysis, crop monitoring, vegetation indices estimation, estimation of forest carbon absorption and so on [Yao et al. (2019)]. Disadvantages of UAV usage may be the need of multiple flight campaigns within a single year if flowering times of flower species do not overlap, flying area restriction or lack of landowner's permission and privacy issues [Smigaj and Gaulton (2021); Shadiev and Yi (2022)].

5 Conclusion

The aim of this study was to assess whether the flower cover diversity estimated by UAV images can be utilized to estimate bee diversity and abundance. As first approach, RGB images were used because of their lower cost and less need of post-processing analysis.

The results showed a positive relationship between flower cover diversity estimated by RGB UAV images and bee diversity and abundance. We are aware that this method might work on fields with low number of flower species (3 or 4), due to the impossibility of classifying different species of the same color using RGB images.

The use of multispectral and hyperspectral data will probably increase the final accuracy, due to the higher ability to characterize different flower species. In this way, it became possible to test the relationship between flower cover diversity estimated by UAV images and bee diversity and abundance in a greater number of grasslands. A further analysis could focus on testing the proposed approach using images at different spatial resolution, in order to understand how the approach is influenced by the pixel size.

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