

**Automated pollination monitoring: a method that provides
complementary information in community-level studies**



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INTRODUCTION

Automated video monitoring of pollination in the field

Studies of plant-pollinator interactions usually involve collecting data from observations, which presents several difficulties. These include problems in achieving a sufficient sampling effort because manual observations are time-consuming and logistically limited by labour force and environmental conditions. The observer must identify the flower visitors at the time of census or collect them for identification later in the laboratory, with the risk of impacting the pollinators' populations. Moreover, the presence of an observer may affect the pollinator's behaviour (Pegoraro et al. 2020). Using video recording systems to monitor animal activity is not a new field (Green & Anderson, 1961; Carthew & Slater, 1991), but it takes advantage of widespread video monitoring technologies to facilitate the collection of wildlife data. It can thus be an essential complementary tool to achieve a more realistic data set.

Camera traps are commonly used to monitor biodiversity. These cameras are a valuable tool to monitor, for instance, plant-frugivore interactions, as they were designed for hunting with optimal optics to focus on animals like birds, mammals and reptiles (Gogarten et al. 2020; Pegoraro et al. 2020; Ahumanda et al. 2013). Currently, there are no camera traps able to optimally record plant-pollinator interactions, as the flower visitors are primarily insects. The recent emerging low-cost automated recording devices, such as some single-board computers (*Raspberry Pi*), are perfect for attaching a considerable assortment of cameras and choosing the optimal camera to focus on little flowers and insects (Pegoraro et al. 2020). Providing portable energy and protecting it from the field, this gadget is perfect for recording plant-animal interactions. Camera traps can

provide huge amounts of videos, and their classification is time-consuming (Norouzzadeh et al. 2018). Furthermore, camera traps contain a motion sensor, and the camera starts recording when an animal appears and when the plant shakes because of the wind, amassing useless videos. Conversely, *Raspberry Pi* has the option to run a deep learning network to detect potential pollinators and start recording when they appear automatically (Borowiec et al. 2022). Thus, applying new technologies in the field can lead to more precise data from the ecosystems.

Applications of deep learning in ecology

Deep learning is already considered in ecology, with 589 studies published since 2019 (Borowiec et al. 2022). Ecology researchers and conservationists increasingly collect large amounts of data using emerging tools such as low-cost automated recording devices (Pegoraro et al. 2020). Deep learning is a promising computational approach that can deal with analyses of large datasets (Lamba et al. 2019). Moreover, deep learning is an optimal solution to reduce mechanical tasks like reviewing many camera trap videos (Norouzzadeh et al. 2018).

Acquiring data on ecological networks is currently very time demanding and expensive. Automating the data acquisition and analysis process increases ecological network studies' efficiency and improves the results' reliability. Deep learning-based neural networks can be an optimal solution for developing a methodology where computer-controlled cameras can instantly film and recognize a floral visitor and even create a list of which appears in each video without needing review. This way, automatic field data of plant-animal interactions, such as pollination, can be created. Signaroli et al. (2022) used cameras controlled by *Raspberry Pi* to record fish behaviours and then developed

a neural network based on deep learning, which identified such behaviours, achieving a 93% accuracy. There are already several studies that automatically identify species of different taxa via deep learning: bacteria (Satoto et al., 2020), protozoans (Hsiang et al., 2019), plants (Schuettpelez et al., 2017; Younis et al., 2018), insects (Marques et al., 2018; Boer and Vos, 2018; Valan et al., 2019; Hansen et al., 2020), and vertebrates (Villon et al., 2018; Norouzzadeh et al., 2018). This method, thus, can be used to recognize flower visitors automatically (Fig. 1).

The urgent need to study Mediterranean pollinator communities

Understanding the insect pollinator diversity patterns is the first step to protecting it (Tur et al. 2016; Lázaro et al. 2010). Pollinators are vital in terrestrial ecosystems because approximately 94% of wild plant species in the four tropical regions and 78% of temperate regions depend on pollinators to reproduce (Ollerton et al. 2011). Despite their importance, pollinating insects are among the species most vulnerable to human changes in recent years. More than half of the planet's insect species, and therefore their pollination supply, are rapidly declining, and a third are already on the verge of extinction due to anthropogenic causes such as habitat destruction, the introduction of invasive alien species or climate change (Sánchez-Bayo & Wyckhuys, 2019). The Iberian-Balearic region is one of the most diverse areas in the world, especially in bees, although it has been much less studied than the regions of central and northern Europe (but see Petanidou & Vokou 1993; Potts et al. 2006; Tur et al. 2013; Castro-Urgal & Traveset 2016; Beltrán & Traveset 2018; Azpiazu et al. 2020). Although insect pollination is preferentially associated with bees (Hymenoptera; Anthophila), other groups such as beetles, lepidopterans, dipterans, and hemipterans act as

effective pollinators (Proctor et al., 1996; Weiss 2001; Willmer 2011; Rader et al., 2016). In Mediterranean environments, these pollinators are quantitatively and qualitatively as crucial as bees and are generally affected by landscape changes, including agricultural intensification (Herrera, 1988; Gómez et al., 2007; Reverté et al., 2016). Therefore, the functions of all wild pollinators are of equal importance, as they contribute in an additive way to pollination and are necessary to optimize the global service of crop pollination and contribute to the maintenance of many plant species (Stefanescu et al., 2018). Studies on plant-pollinator interaction networks at the local community level are essential to developing proper conservation management and to favour the pollination services they all provide to natural terrestrial and agricultural ecosystems. Given the continuing decline of both pollinators and the plants on which they depend (Biesmeijer et al. 2006), it is crucial to implement effective methods that increase the efficiency of field sampling (Pornon et al. 2016).

In this study, we chose Cabrera island (Balearic Islands, Western Mediterranean), where the pollinators' communities are understudied, and where the endemic lizard, *Podarcis lilfordi*, plays an essential role as a pollinator (Fig. 2; Traveset & Sáez, 1997; Fuster & Traveset 2020). Cabrera is the largest island (1569 ha) of the Archipelago of Cabrera, being a National Park since 1992.

Manual and automatic censuses for a pollinator community study

For the first time, we applied automated cameras and deep learning in a study of the pollinators at a community level. We recorded plant-pollinator interactions with manual censuses and automated cameras in two habitats and four study sites on Cabrera. We also developed and evaluated the accuracy of a neural network based on deep learning for automatically detecting any possible insect

flower visitor. The insects are classified as either a “butterfly” or simply as ‘insect’ if it belongs to any of the other functional groups (bees, coleopterans, dipterans, hoverflies, hemipterans, ants, others).

Specifically, we want to answer the following questions:

(1) **Is it possible to develop a neural network based on deep learning that allow us to recognise insect pollinators?** If the neural network recognises the two categories properly, it will be the first step to avoiding video reviewing plant-pollinator interactions collected in the field.

(2) **Can we obtain complementary pollinator activity information with the censuses performed by the automated cameras?** Placing cameras in front of flowering plants might record more and new plant-animal interactions that we may miss by manual censuses, as human presence might alter the visits of some animal taxa (e.g. birds, lizards, insects).

(3) **How do the plant-pollinator networks differ when considering data from the automated cameras and only manual censuses?** Manual and automated censuses are applied to a pollinator community study for the first time. Data analysis will be performed twice, considering only manual data and adding the data obtained from the automated cameras.

(4) **How does plant-pollinator network structure differ among sites?** As the different study sites show a particular floral composition, differences in pollinator diversity and in the structure of the pollination networks are expected.

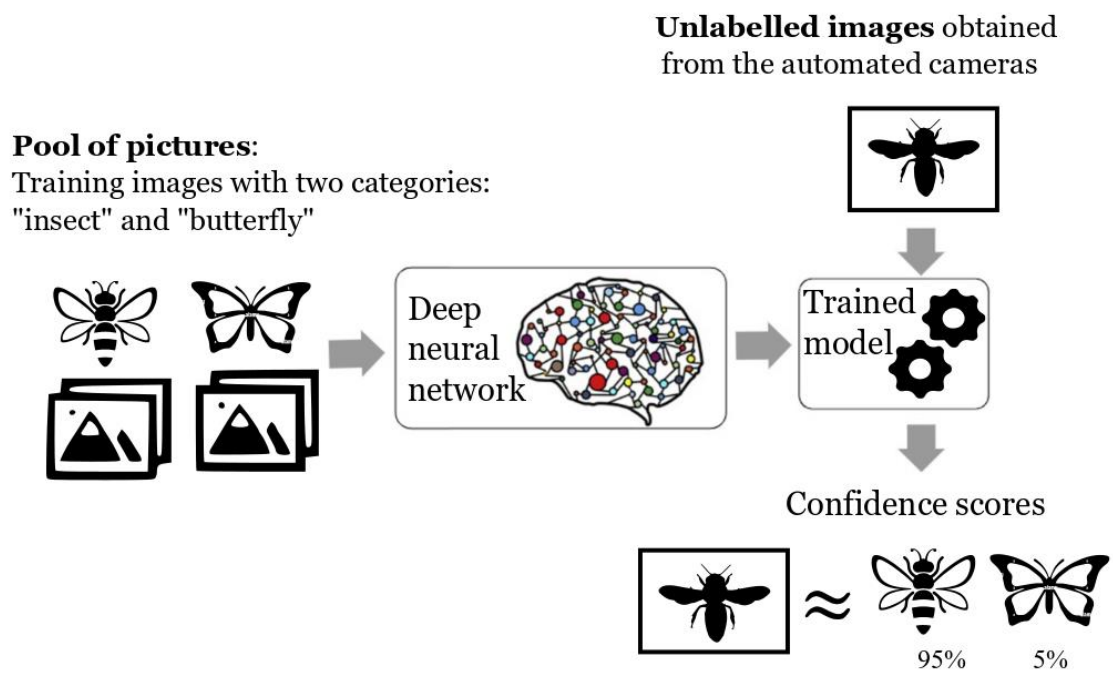


Figure 1. A workflow for the classification of images of pollinators using deep learning.



Figure 2. *Podarcis lilfordi* on an inflorescence of *Daucus carota* sub. *majoricus* in Cabrera Island.

METHODS

Development of the automated monitoring system

Prototype camera assembly

The assembly has a camera with an optimal optical resolution for small objects such as little insects and flowers. This camera is controlled by a single-board computer, which can program the cycles of video desired to perform in the field. A power bank was used to supply the energy for the single-board computer, and a plastic box protected the whole assembly in the field.

Considering our requirements and budget, the 5MP Module V2 camera controlled by a *Raspberry Pi 4* (single-board computer) was the optimal option. With this assembly, we obtained a 1080p/30-frame video (Figure 3). We used a portable battery with these features: 1000mAh Li-polymer battery; 5.0V-2.1A to obtain six hours of autonomy. The videos were saved into a 32 GB USB.

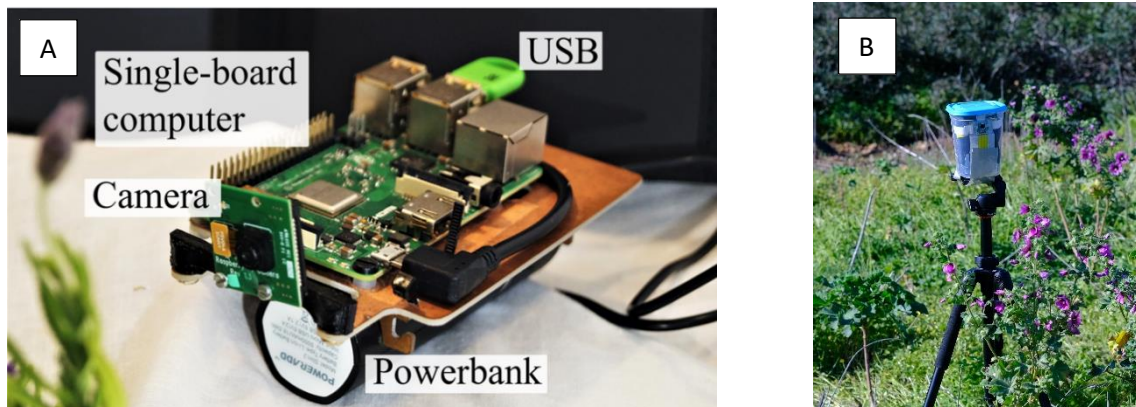


Figure 3. The prototype assembly: A) A single-board computer (*Raspberry Pi*) with a camera, power bank and a USB. B) The prototype within a plastic box and on a tripod, recording plant-pollinator interactions.

We used a *Raspberry Pi 4*, which has the following features: A high-performance 64-bit quad-core processor. Dual display support with resolutions up to 4K via a pair of micro-HDMI ports. Hardware video decoding up to 4Kp60. 4 GB of RAM.

A connection to the dual-band wireless local area network 2.4/5.0 GHz. Bluetooth 5.0 / Gigabit Ethernet / USB 3.0 / PoE features (via a separate HAT PoE add-on module). A camera Module V2 is attached; this features 5MP Camera Module V2 for *Raspberry Pi*, which is an alternative and fully compatible with the official ones. High-Definition video camera for *Raspberry Pi*. 5MPixel sensor with Omnivision OV5647 sensor in a fixed-focus lens. Software autofocus lens: B0176. Integral IR filter. Still picture resolution: 2592 x 1944. Max video resolution: 1080p. USB 3.0 quick development and evaluation board for sensors like OV5647.

Programming for automatic censuses

We have programmed the *crontab* to automate the *Raspberry Pi 4* with a ‘.ssh’ file. This way, when the *Raspberry Pi 4* is turned on automatically orders the camera to start recording cycles of 10 minutes-videos, one hour and a half straight. The camera performs autofocus which was programmed through Python 3.0 (<https://www.python.org/>).

Photo-library development and image tagging

To develop the neural network capable of extracting features from the objects appearing in an image and classifying the butterflies as: “butterfly” and other insects than butterflies as: “insect”, we created a reference image bank. We built a photographic library of 12,000 images containing insect pollinators, 6,000 containing only butterflies. Many of them were obtained from the pollinator webpage of the terrestrial ecology laboratory at IMEDEA (<http://polinib.info/?lang=en>). Also, single-board computer-controlled cameras provided us with videos of plant-pollinator interactions of past field campaigns (from Menorca, Mallorca and Tenerife islands). The objects from the frames were

tagged with the program *LabelImg* (<https://github.com/tzutalin/labelImg>) as “butterfly” or “insect” (all insects which were not a butterfly). The photo library was introduced to the deep learning neural network with the package *Tensorflow* (<https://www.tensorflow.org/>) managed using Python 3.0.

Neural network based on deep learning development

For the development of the neural network based on deep learning, called Faster R-CNN Inception-V2, we used a computer located at IMEDEA (UIB-CSIC) research centre, which has the following characteristics: Product name: MW51-HP0-00; Graphics processor: 65: 00.0; VGA compatible driver: NVIDIA Corporation GV100GL; Driver version: 430.64; CUDA (Unified Calculation Device Architecture) Version: 10.1. The Faster R-CNN proceeds in four steps managed through Python 3 (Fig. 4):

- 1) Base network: From the bank of 18,000 images of insects we provide, R-CNN creates features to extract them from the images that will be used in the following steps.

- 2) Select proposal square (Regional proposal network): using the functions R-CNN, find a defined number of regions and marks with a box "object", differentiating it from the background.

- 3) Region of interest pooling: The feature map created by CNN preformatted in the first step is used to extract relevant new features from the object inside the boxes created in step 2.

- 4) New R-CNN neural network object. In our study, the "objects" will be the pollinators, such as the categories: “butterfly” and “insect”. The trained deep learning neural network will classify the two categories according to pixel

similarity when appearing in the videos obtained from the cameras placed in the field.

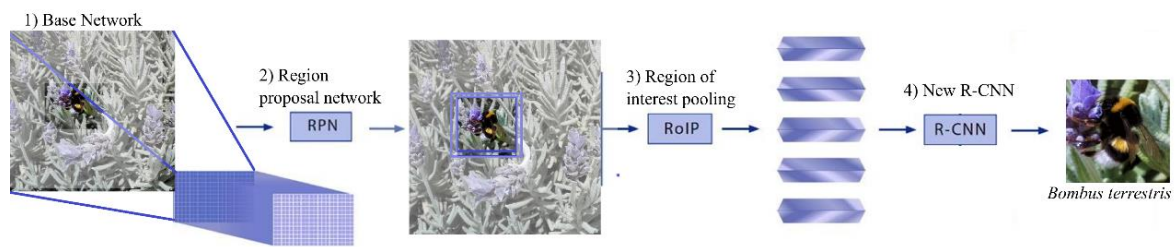


Figure 4. The four steps of a Faster R-CNN illustrated.

Validation of the neural network based on deep learning

For this step, we pooled pictures from the field campaigns in Cabrera island, where we know the objects. These pictures were new to the algorithm. This pool was introduced through *Tensorflow*, and the neural network classified the objects. Through Python 3.0, we obtained the metrics to evaluate the accuracy of the neural network. The accuracy takes into account the true positives (TP), false positives (FP), and false negatives (FN) to obtain the metrics of the neural network:

- *Threshold*: The validation creates nine different models, considering detections with an accuracy higher than 10%, 20% up to 90%.
- *Precision*: is the ratio of True Positives rightly classified to a total number of classified positive samples (either correctly or incorrectly).

$$Precision = \frac{TP}{TP + FP}$$

- *Recall*: is the ratio between the numbers of Positive samples accurately classified as Positive to the total number of Positive samples. The recall measures the capacity to detect positive samples.

$$Recall = \frac{TP}{TP + FN}$$

- *F1 score*: combines the precision and recall metrics into one metric.

$$F1\ score = 2 \cdot \frac{Precision \cdot Recall}{Precision + Recall}$$

- *Intersection over Union (IoU)*: is the area overlap/area union (Fig. 5)

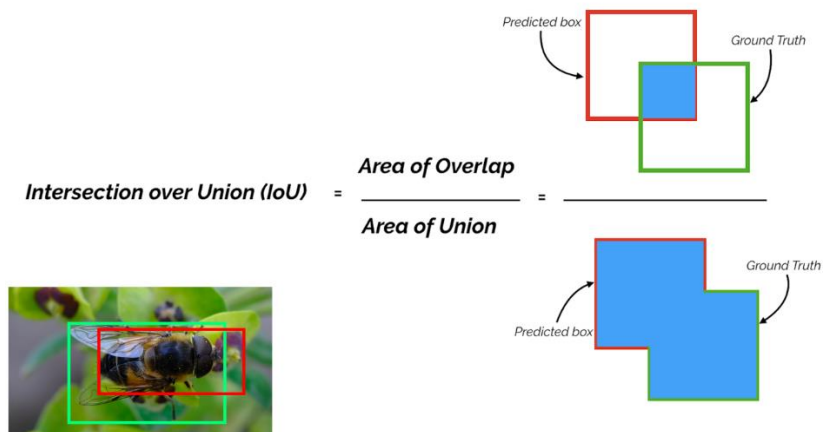


Figure 5. Diagram of the Intersection over Union (IoU), and a picture of our bank of images with the predicted box (red) and the ground truth (green).

Community diversity and structure of pollinator communities

Study areas

Data were obtained from four locations in Cabrera (Fig. 6): (1) a coastal dune system -*Espalmador*-, located at the north-eastern coast of the island (39.131161, 2.925352; Coastal dune 1, D1 hereafter); (2) a rocky coast at the eastern part of Cabrera, -*Ensiola*- (39.131161, 2.925352; Rocky coastal 1, R1 hereafter); (3) another coastal dune at the northwest of the island -*La Olla*- (39.151304, 2.965555; Coastal dune 2, D2 hereafter); (4) and another rocky coast at the north, -*Cala Gandulf*- (39.148246, 2.942302; Rocky coastal 2, R2 hereafter). The dune system vegetation presents herbaceous species such as *Cakile maritima* and

Teucrium maritimum, *Helichrysum stoechas*, *Limonium minutum* and *Daucus carota* subesp. *majoricus* predominate in the rocky coastal system.

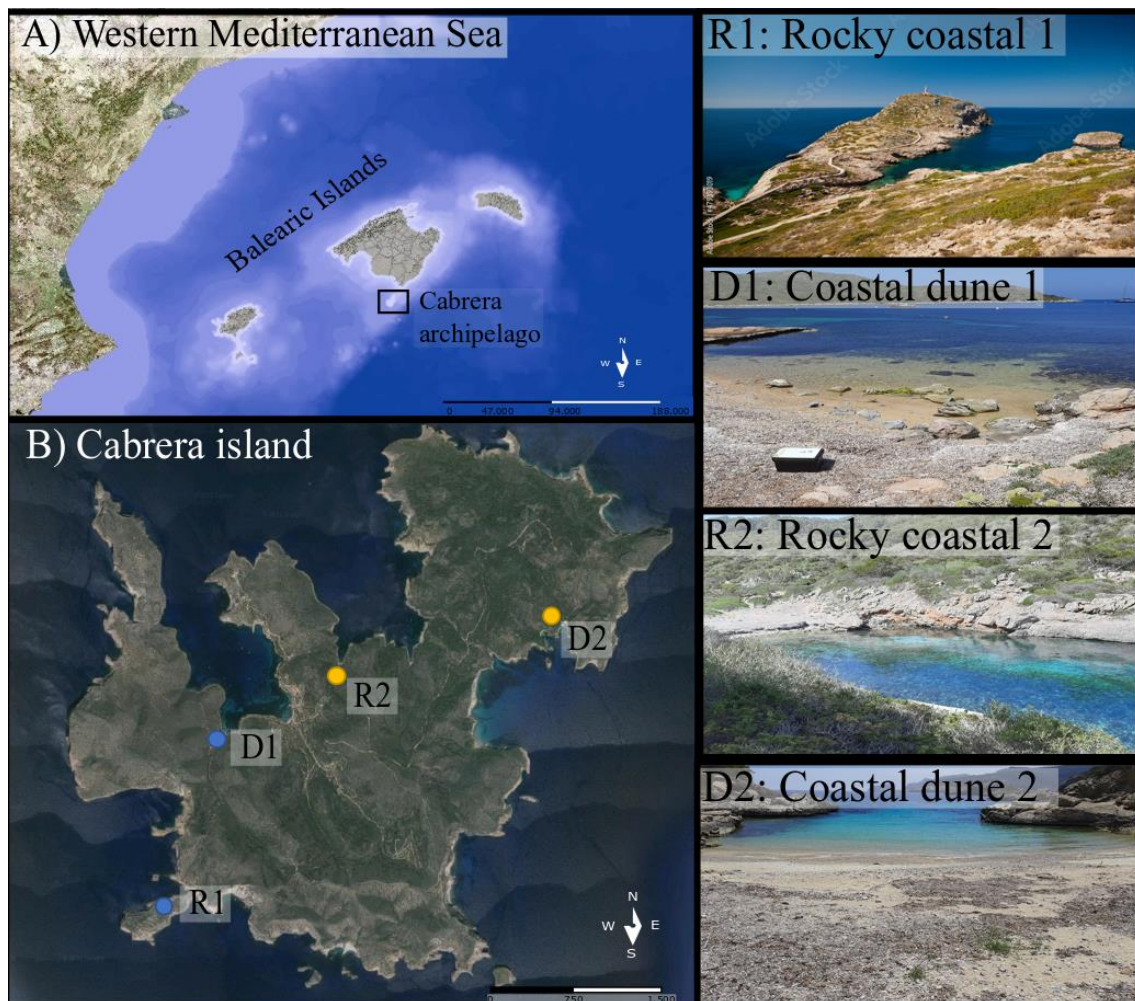


Figure 6. A) Western Mediterranean Sea where Cabrera Archipelago is indicated with a black square. B) The study sites' locations on Cabrera island picture, with a representative picture of each study site and habitat indicated.

Sampling procedures

Manual censuses of pollinator visits to flowers were performed in 50 x 2 m belt transects in each study site. In each census, the following variables were recorded: (1) taxonomic identity of the plant species observed, (2) taxonomic identity of the insect species visiting the flowers (unidentified species were captured and taken to the laboratory for later identification by expert taxonomists; only insects

contacting the flowers and, thus, potentially pollinating them were recorded), (3) number of visits of each pollinator species to the plant, and (4) number of flowers contacted by each pollinator. Total time spent censusing plant-pollinator interactions was 480 minutes in D1, 450 minutes in D2, 1200 minutes in the R1 and 850 minutes in the R2. We performed different sample efforts depending on the flower abundance of each community. We censused from April to the end of June, four days during the first half of the month and four days at the end of the month. All plant species in bloom were sampled between 10:00 am and 5:00 pm, on sunny and non-windy days. Automated censuses were performed by placing the cameras in front of flowering plants, in the same study areas, recording an hour and a half, 10-minute cycles and 1-minute pauses on the same days and time of day that manual censuses were performed.

Insect species were identified through pictures and utilising the collection from IMEDEA (Research Centre in Mallorca, Spain); the doubtful species were caught after the census and later identified by an entomologist.

Diversity and network parameters

We registered the number of flowers, number of plant-insect interactions, number of vertebrate interactions. With these data, we obtained: (1) *Species richness*: is the number of species appearing within a community. (2) *Shannon index diversity (H')*: is a widely used index to obtain the alpha diversity that considers the number of species and the abundance of individuals in the community. It ranges from 0 (low diversity) to 4.5~5 (high diversity). It was obtained with *vegan* package (v.2.5-6; Oksanen et al. 2013) through R software (<https://www.r-project.org/>).

We also constructed a bipartite network by pooling all plant-pollinator interactions for each study site (D1, D2, R1 and R2). We did this twice, with and without considering the data obtained from the automated monitoring. Each bipartite network consists of (a) nodes representing the observable pollinators and the flowering plant species they visited; (b) a set of links connecting those nodes, with different widths proportionally to the *weight* of each node. The *weight* was quantified as the frequency of occurrence of each pollinator:

$$\text{Frequency of occurrence} = \frac{\text{N}^{\circ} \text{ of plants where the flower visitor appears}}{\text{n}^{\circ} \text{ of censused plants}}$$

Frequency of occurrence was the best option as we obtained data from two different methods (manual and automated censuses). To build the plant-pollinators networks, we used the *bipartite* package (v.2.3; Dormann et al 2009) run in the R software, with which we obtained the following parameters:

- *Quantitative connectance* (C_q): is the ratio of interactions that occur out of all possible ones. It is a measure of the network generalisation level that informs how connected all species are in the community.
- *Weighted NODF* ($wNODF$; *Weighted Nestedness based on Overlap and Decreasing Fill*): measures the nestedness of networks. Nestedness estimates the trend of specialist species (with fewer interactions) to interact with a subset of the interaction partners of more generalist species (most connected ones). It ranges from zero (not nested network) to 100 (highly nested network).
- *Network specialisation* (H_2'): measures the selectiveness of a network. It meanders between zero (opportunistic, high niche overlapping) and unity (selective, high niche differentiation). Selectiveness is when a specie interacts with low abundant species.

- *Interaction evenness (IE)*: measures the uniformity of interactions between species based on *Shannon's evenness*. It ranges from zero (fully variable) to unity (entirely uniform).

RESULTS

Automated monitoring of the plant-animal interactions

We developed an automatic camera which provides proper quality pollinator interaction pictures in the field, as shown in figure 7.

The neural network based on deep learning programmed can automatically recognise insects in the pictures and classify the butterflies as “butterfly” and other insects as “insect” (Fig. 7). We performed the validation of the Faster R-CNN (Tab. 1) where the model with a threshold of 0.9 (considering detections with a reliability of 90%) obtained the highest *F1 score* (accuracy) of 78,7%, where the *precision* and *recall* are balanced (Tab.1). The FN increases as well as the *precision*. Lower values of FP and TP imply lower *recall* values. However, FP presents the most downward trend, while TP and FN hardly fluctuate. The *precision* increase from 0.51 to 0.77, and the *recall* remains with similar values in all models, increasing the *F1 score*.

Table 1. Metrics from the validation of the neural network based on deep learning Faster R-CNN. Where TP means true positive, FP false positive and FN false negative.

Threshold	N° detections	TP	FP	FN	Precision	Recall	F1 score
0.1	3089	1579	1510	255	0.511	0.861	0.641
0.2	2748	1569	1179	265	0.571	0.856	0.685
0.3	2584	1559	1025	275	0.603	0.850	0.706
0.4	2444	1555	889	279	0.636	0.848	0.727
0.5	2344	1551	793	283	0.662	0.846	0.742
0.6	2244	1542	702	292	0.687	0.841	0.756
0.7	2151	1527	624	307	0.710	0.833	0.766
0.8	2027	1506	521	328	0.743	0.821	0.780
0.9	1914	1475	439	359	0.771	0.804	0.787

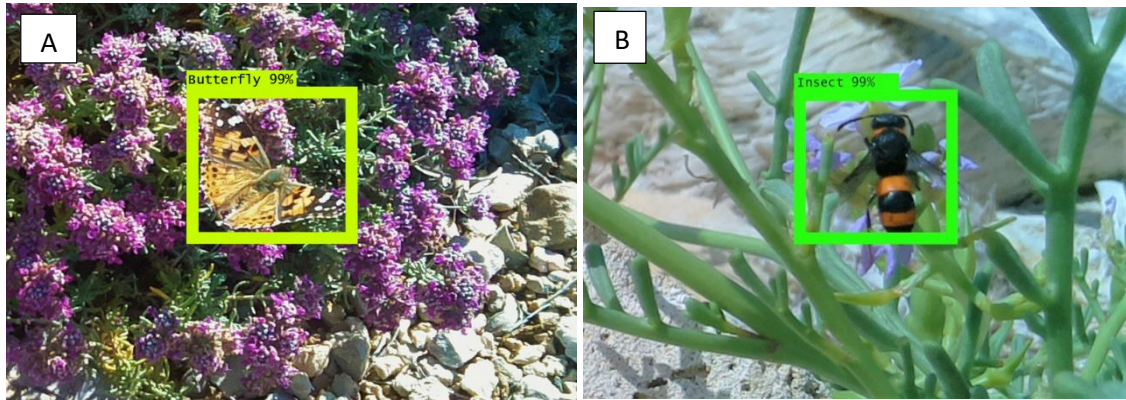


Figure 7. Pictures obtained with a camera controlled by a *Raspberry Pi 4*: A) *Vanessa cardui* on *Teucrium capitatum* recognised as a “butterfly” and B) the balearic endemic wasp B) *Ancistrocerus ebusitanus* as an “insect” by the Faster R-CNN we trained, both with a 99% accuracy.

Community diversity and structure of pollinator communities

We recorded a total of 2980 minutes (49,70 h) manually and 1534 interactions, while the cameras recorded 1335 minutes (22,25h) and 764 interactions (Tab. 2). We obtained a different rate of vertebrate interactions when comparing manual censuses and automated censuses. Both *species richness* and *Shannon diversity* (H') were higher in the rocky coastal communities than in the coastal dunes (Tab. 2). For both parameters, the automated camera provided complementary information (Tab. 2). Hoverflies and bees were the groups showing the highest *species richness* in all study sites (Fig. 8). *Syrphidae* was the most prevalent family and was more diverse than bees. *Lasioglossum* was the most predominant genus among the bees.

The plant-pollinator networks' metrics presented little variability (Tab. 2) and different structures (Fig. 9) when considering only manual and both censuses (manual plus automatic). When comparing communities, C_q was similar in each community network, although the D2 showed the highest values. From all

network parameters, the $wNODF$ in D1 had the largest difference when comparing both data sets (manual and manual plus automatic, Tab. 2), increasing from 18.27 to 31.29. However, all communities displayed $wNODF$ low values (< 50). When considering both datasets, R2 seems to be the most specialised community, i.e. showed the highest selectiveness ($H2'$ values) and the lowest generalisation (C_q values), while R1 had the lowest $H2'$ values. R2 showed the lowest values in *interaction evenness (IE)* when considering manual and both data, and all communities had values between 0.6 and 0.7.

Some pollinators were detected exclusively by the automated cameras, such as *Lasioglossum minutissimum* (interacting with *Cakile maritima* and *Limonium minutum*) in the D2; an unidentified species of wasp (interacting with *Helichrysum stoechas*) was filmed in the R1; unidentified coleopterans and dipterans (interacting with *Teucrium capitatum*) were recorded in the R2. At the same study site, the bird *Phoenicurus ochruros* was registered only with the cameras interacting with *C. maritima* (Fig. 10). Furthermore, the cameras provided new interactions among already registered species compared to the manual censuses. For instance, the automatic cameras recorded more lizard interactions than the manual censuses. (Tab. 2; Fig. 11). Moreover, the cameras provided more interactions for *D. carota* and *Sedum sediforme* in D1 (Fig. 9). Also, the orchid *Anacamptis pyramidalis* and *T. capitatum* showed a few interactions only registered with the cameras (Fig. 9). This pattern was consistent among communities.

Table 2. Time invested in total interactions, vertebrate interactions and species richness found in each study site. The left value belongs to the manual census, and the right value to the automated census, except in *Shannon diversity (H')* and *Species richness*, where the left value is obtained from both methods.

	Time (min)	n° flowers	n° interactions	n° vertebrate interactions	Species richness	H'
D1	480 / 360	263	171 / 180	13 / 18	26 / 29	3.034 / 3.234
D2	450 / 550	703	251 / 201	1 / 0	28 / 38	3.093 / 3.165
R1	1200 / 185	9466	624 / 259	23 / 16	61 / 63	3.840 / 3.883
R2	850 / 240	2741	488 / 124	12 / 3	51 / 54	3.381 / 3.426

Table 3. Network parameters for each community studied: *Quantitative connectance (C_q)*; *weighted NODF (wNODF)*; *Network selectiveness (H2')* and *interaction evenness (IE)*. The right value belongs to the manual census whereas the left value corresponds to the census performed by automatic cameras.

	C_q	wNODF	H2'	IE
D1	0.3 / 0.269	18.269 / 31.29	0.597 / 0.457	0.692 / 0.677
D2	0.365 / 0.385	29.114 / 31.309	0.568 / 0.547	0.691 / 0.693
R1	0.264 / 0.269	41.517 / 40.765	0.447 / 0.433	0.678 / 0.682
R2	0.28 / 0.249	19.844 / 19.499	0.583 / 0.579	0.655 / 0.654

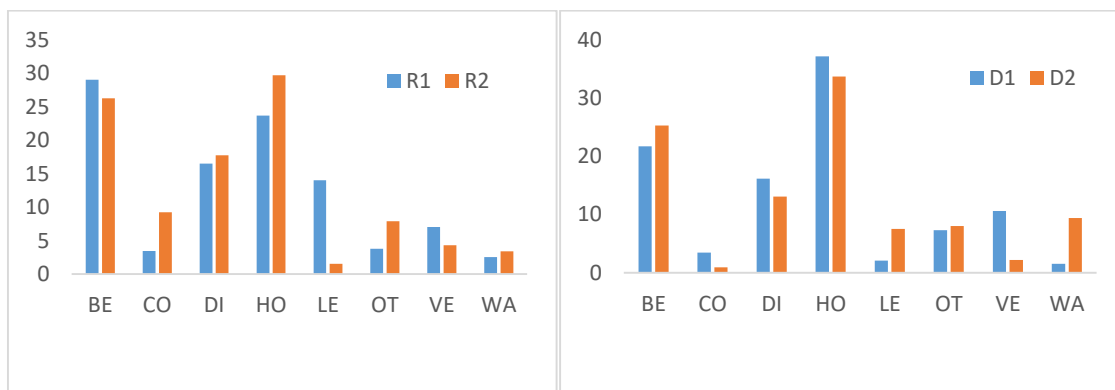


Figure 8. The percentage of the species richness of each functional group: bee (BE), coleoptera (CO), dipterans (DI), hoverflies (HO), lepidopterans (LE), others (OT), vertebrates (VE) and wasps (WA) in each community. The rocky coastal communities: are R1 and R2, and the dune systems: are D1 and D2 on the left side.

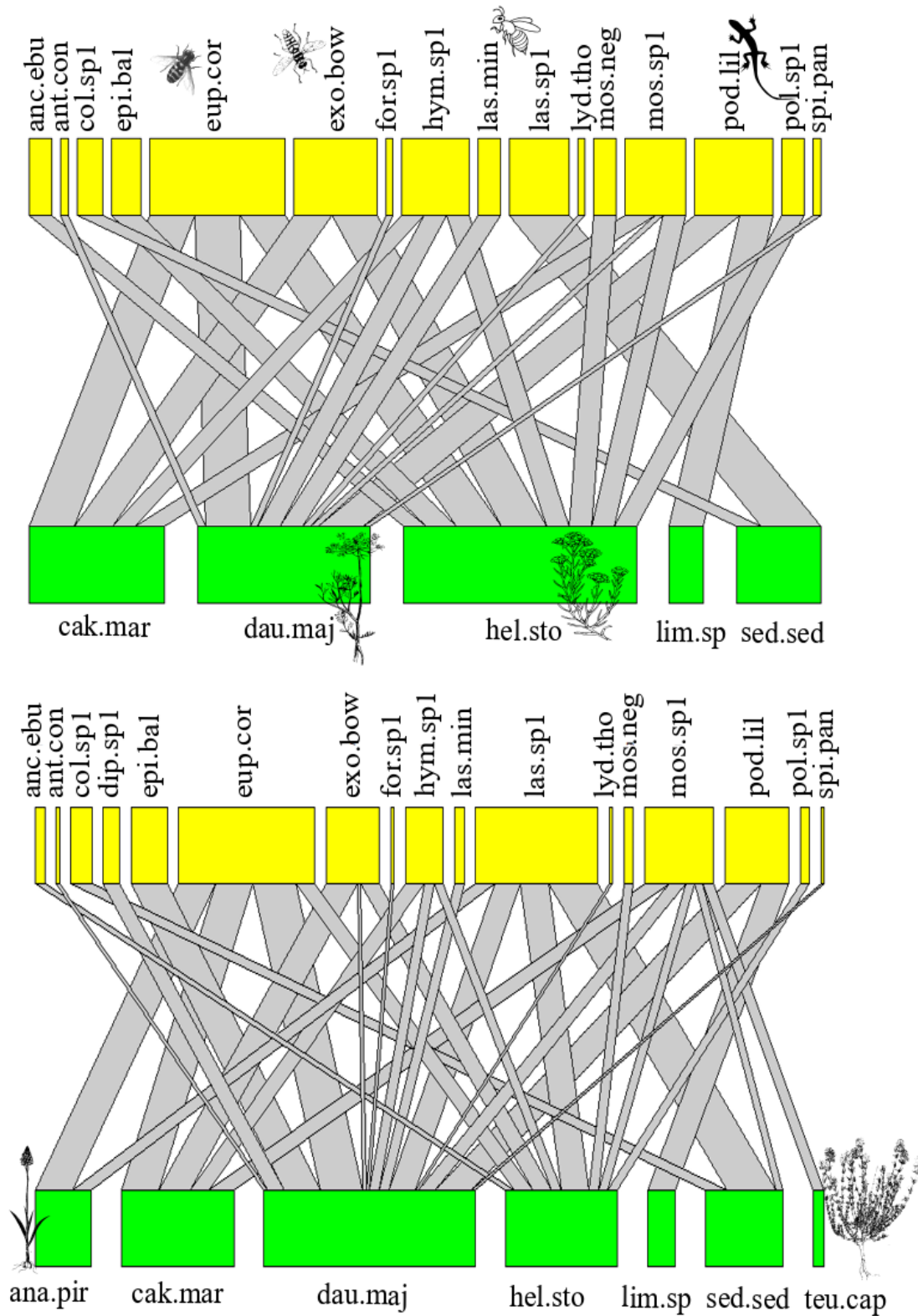


Figure 9. Two plant-pollinator networks of the coastal dune community 1, where plants in green and pollinators in yellow, species indicated with codes. The first network was obtained with the manual censuses and the second one pooling data using both methodologies (manual and automated censuses).



Figure 10. Two frames from videos of a *Phoenicurus ochruros* visiting a flower of *Cakile maritima* in Cabrera island were recorded by automated cameras controlled by a *Raspberry Pi 4*.

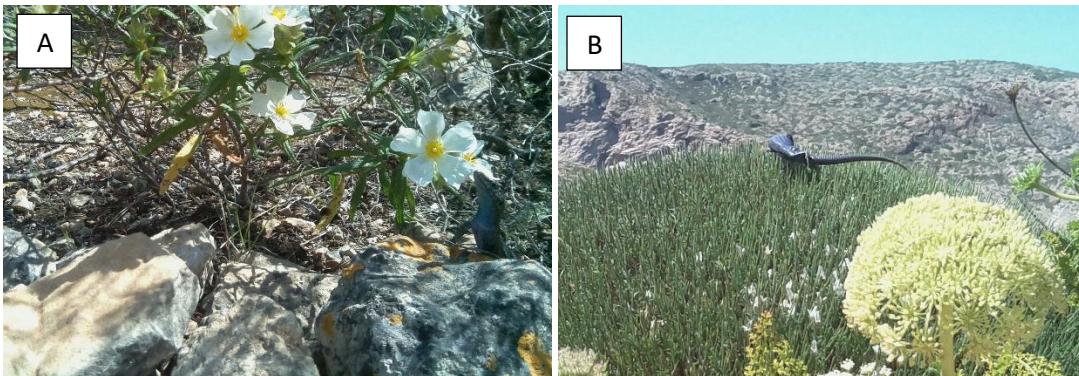


Figure 11. Plant-lizard interactions (*Podarcis lilfordi* sicking A: *Cistus monspeliensis* flower; B: feeding on a flower of *Astragalus balearicus*) in Cabrera island were recorded by automated cameras controlled by a *Raspberry Pi 4*.

DISCUSSION

Increasing the sampling efficiency of species interactions during fieldwork without investing more time or funds is much desired, especially in areas where sampling is difficult and biodiversity is low (and thus, the probability of detecting interactions by direct observations is low). This is, for instance, the case of island ecosystems, highly vulnerable in the context of global change. Island pollinator interactions, specifically, are not easy to document. In this study, we developed automated cameras and tested them in a plant-pollinator network study on Cabrera Island. We showed that such cameras allow an increase in the sampling

efficiency and permit to gather complementary data to that of direct manual censuses.

Automatic monitoring of plant-pollinator interactions

We trained a Faster R-CNN able to detect flower visitors as "insect" or directly as "butterfly" with proper accuracy ($F1\ score = 0,787$ with a threshold of 0.9). This $F1\ score$ is close to previous published studies (Signaroli et al. 2022; Norouzzadeh et al. 2018; Marques et al., 2018; Boer and Vos, 2018; Valan et al., 2019; Hansen et al., 2020), which is the first step to reduce video reviewing. Even though neural networks increase the accuracy as more pictures are tagged, obtaining a neural network able to recognise taxa at the species level is not yet affordable. For this, we would need a giant bank of labelled images for each species. Our study showed that it is possible to reduce, although not avoid, video reviewing. In other words, we had to review only the frames containing flower visitors, sorted as "insect" or "butterfly", but not all videos.

It is important to consider that, occasionally, the Faster R-CNN does not detect some insects in the pictures, considered as false negatives (FN), or others are detected when they are not there, i.e., false positives (FP). Depending on the study's aim, FP is more important than FN, and vice versa; in some cases, the goal may be to have both variables balanced. As identifying species was not affordable at the moment, we revised only the frames detected as positives (i.e. containing a flower visitor), sorted within a functional group. Reducing the FN is essential to avoid losing information. FN is information that will not be revised and contains flower visitors, and FP are pictures without flower visitors that will be revised; in that case, a model with a high *recall* ($FP > FN$) will be desired, so the first neural network model in Table 1 will be the most useful. The next step is to increase the

F1 score and reduce the FN when considering the model with a threshold of 0.1 (see Tab. 1).

Application of manual and automatic censusing in a study case

Automated cameras provided more plant-pollinator interactions than manual censuses per time invested (Tab. 2). Specifically, the number of visits by lizards, birds and lepidopterans was higher when cameras were used. This might be due to the effect of human presence, which can disturb in different ways plant-insect interactions and plant-vertebrate interactions, although not all insects and vertebrates respond equally to human presence. Furthermore, more data accumulated with the automated cameras provide more interactions and, thus, more realistic information on animals visiting the flowers of the different plant species.

Interestingly, we found that the plant-pollinator networks showed a different structure when comparing the datasets obtained with both methods. At the species level, for instance, *H. stoechas* presented more interactions than *D. carota* in the network obtained from manual censuses (Figure 9). When adding the data set from the automated cameras, *D. carota* seems to have a more central position in the network as the most generalist of the plant community. Hence, as more interactions are registered, more accurate information on the specific role of each species in the network will be found. At the network level, D2 was found to be the most generalised community as it presented higher values of *quantitative connectance* (C_q), consistently with both datasets. The highest C_q indicates that this community is probably the most resilient community, or in other words, it is less vulnerable to disturbances that affect species loss (due to the high level of species generalization). On the other hand, D1 showed higher

values of *interaction evenness (IE)* than the rocky coastal communities, i.e. the interactions in D1 were more homogeneous than in either of the two rocky coastal communities. This might be related to the smaller network size, due in turn to the fewer plant species present in the area. The plant-pollinator networks of each study site showed low values of *weighted NODF (wNODF <50)*, indicating a reduced nestedness and thus low resilience of the plant-pollinator networks to perturbations (Rohr et al. 2014). Island communities are, in general, vulnerable to disturbances due to the lower network complexity compared to mainland areas (Traveset et al. 2019). The R2 is the most vulnerable pollinator community, presenting low nestedness values (<20). D2 showed a huge difference for the *wNODF* when comparing results considering the manual dataset or the dataset obtained from both. The automated cameras could trigger that difference as providing new interactions implies complementary information for the communities.

The loss of one species has more impact on a network with a low number of species than on a network with many nodes and highly nested. In small islands such as Cabrera, the pollination is performed mainly by small insects, such as small bees in the genus *Lasioglossum*, small hoverflies and small flies in a narrow space of time, where plants usually adopt a generalised strategy, interacting with a wide array of pollinators (Olesen et al. 2008). For instance, *D. carota*, *H. stoechas*, *T. capitatum* or *C. maritima* are the most generalised plant species with a higher diversity of interactions and occupy central positions in the networks. The different total species richness (or network size) among communities can be explained by floral richness, as the rocky coastal communities have more plant species than the dune systems.

Conclusions

Although some video review has to be performed, it is worth placing automated cameras, as they increase efficiency and provide complementary information. However, we are not proposing to replace manual censuses with automated cameras but we suggest combining both methodologies.

The potential of automated cameras to provide complementary information in plant-pollinator networks should be confirmed with a more extensive dataset.

The pollinator communities from Cabrera Island, which are understudied, seem to be vulnerable to disturbances, with low resilience, as we found simple low number of species and interactions, especially in the dune communities.

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