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# 1 **Buzzy bees, quantifying bee activity within** 2 **sunflower fields using acoustic monitoring** 3 **and deep learning**

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26

27 **ABSTRACT**

28 Since 70% of the world's crops depend on pollinators for production and concerns are  
29 growing regarding insect decline, it is essential to implement robust and efficient  
30 monitoring of pollinator activity. However, traditional methods of pollinator monitoring are  
31 generally time-consuming and destructive. With the rise of technology, passive methods  
32 are being developed using computer vision or acoustic recording coupled with machine  
33 learning, and are offering the possibility to increase the temporal and spatial coverage of  
34 biodiversity and ecosystem functions monitoring. Passive acoustic monitoring is a  
35 promising method for tracking pollinators. However, it has rarely been implemented, and  
36 has mostly used relatively old machine learning methods. Deep learning methods,  
37 originally, developed for image analysis are beginning to be used for acoustic monitoring  
38 of various taxa, including flying insects. Here we proposed a method for quantifying  
39 pollinator activity in sunflower fields, based on the automatic identification of sounds  
40 produced by their beating wings. We tested a random forest and a deep learning algorithm  
41 on acoustic recordings using a new open access software dedicated to acoustic biodiversity  
42 monitoring, named TadariDeep. We found a higher performance of deep learning  
43 compared to random forest algorithms for the classification of pollinator flight sounds. The  
44 comparison of the acoustic monitoring of insects with pollinator activity estimated from a  
45 common protocol based on visual observations validates this method. We found that  
46 acoustic monitoring coupled with deep learning sound recognition provides a more  
47 realistic view of pollinator activity than visual observations, thanks to continuous  
48 monitoring. Acoustic monitoring of pollinators using deep learning, therefore, appears as a  
49 reliable method to quantify pollinator activity and might be used to monitor insect  
50 pollination over large spatial and temporal scales. Further improvements are however still  
51 needed for the species identification of pollinators.

52 **Keywords:** *Convolutional neural networks, Data augmentation, Passive acoustic monitoring,*  
53 *Pollination services*

## Introduction

55 Animal pollination is an essential ecological function involved in the reproduction of 90% of  
56 flowering plants, often through insects (Ollerton et al., 2011). In agricultural landscapes, 70% of  
57 major global food crops benefit from insect pollination, representing approximately 35% of the  
58 annual global food production (Klein et al., 2007). This makes insect pollination a major  
59 ecosystem service that is, however, being threatened by pollinator decline (Biesmeijer et al.,  
60 2006; Potts et al., 2010; Zattara and Aizen, 2021). Because pollinator communities exhibit  
61 significant spatial and temporal variability (Gay et al., 2024; Reverté et al., 2019), pollinator  
62 monitoring is important to quantify pollinator activity over space and time and indirectly assess  
63 pollination services.

64 Several methods are used to monitor insect pollinators. The most common involve  
65 capturing insects using pan traps or sweep nets along transects (O'Connor et al., 2019; Westphal  
66 et al., 2008). These are often used to make spatial comparisons of the pollinator diversity  
67 according to the landscape features and/or agricultural practices, to identify the interactions  
68 they establish with flowering plants (e.g. Crochard et al., 2022) and to study the contribution of  
69 insect-pollination to crop yield (e.g. Perrot et al., 2019). These methods usually involve the  
70 killing of captured individuals and are highly labor-intensive and time-consuming since they  
71 require a significant amount of time in the field to catch pollinators and in the laboratory to  
72 identify them (Montgomery et al., 2021). This high time cost tends to limit the spatial and  
73 temporal coverage of pollination studies.

74 Thanks to technological developments, passive and non-destructive methods of  
75 biodiversity monitoring are being developed (van Klink et al., 2022). In particular, bio-acoustic  
76 methods based on automatic sound classification with machine learning algorithms (Gibb et  
77 al., 2019), are already used to study birds (e.g., Kahl et al., 2021; Metcalf et al., 2022), bats (e.g.,  
78 Kerbiriou et al., 2019; Roemer et al., 2021), and marine mammals (e.g., Shiu et al., 2020; Van  
79 Uffelen et al., 2017). Regarding insects, acoustic monitoring has already been developed to  
80 study the impact of anthropogenic pressures on Orthopteran communities (Jeliakov et al.,  
81 2016; Penone et al., 2013) but also for aquatic insects (Desjonquères et al., 2020; Gottesman et  
82 al., 2020). In the case of flying insects such as pollinators, they can be detected through the  
83 sound they make beating their wings in flight (Kawakita and Ichikawa, 2019). Early studies on  
84 pollinator acoustics focused mainly on bumblebees. They studied colony dynamics (Heise et  
85 al., 2020), the link between their characteristic sound frequencies and morphological traits  
86 known to play a role in pollination efficiency (Miller-Struttman et al., 2017) or the specific  
87 identification of a limited number of bumblebee species (Gradišek et al. 2017) or bee and hornet  
88 species (Kawakita and Ichikawa 2019). Nevertheless, these studies rely on rather potentially  
89 outdated machine learning methods, such as support-vector machine or random forest, to  
90 identify and classify the sounds emitted by pollinators. Since 2016, a machine learning method  
91 relying on convolutional neural networks has become increasingly popular in bioacoustics  
92 (Stowell, 2022). This class of methods achieved breakthroughs in automatic image  
93 classification (Hicks et al., 2021; Mohanty et al., 2016; Weinstein, 2018) and can analyze the  
94 spectrograms of recorded sounds analogously. This method has been widely used because it is  
95 more efficient than classical machine learning methods, making fewer errors in sound  
96 classification, and it can be used for the monitoring of various taxa, such as birds, marine  
97 mammals, bats, fish (Stowell, 2022) and most recently flying insects (Folliot et al., 2022).

98 In this context, we aimed to develop a convolutional neural network for automatically  
99 recognizing and classifying sounds emitted by pollinators during their flight to quantify  
100 pollinator activity in agricultural fields. Sunflower is the most important oil crop in terms of  
101 cultivated area in Europe (FAOSTAT, 2020), and the yield increase due to insect pollination is  
102 estimated to be between 18% and 100% (i.e. doubling the yield) (Carvalho et al., 2011;  
103 Garibaldi et al., 2016; Greenleaf and Kremen, 2006; Perrot et al., 2019). Sunflower is mostly  
104 visited and pollinated by honeybees, which account for between 72 and 97.8% of pollinator  
105 visits (Bartual et al., 2018; Carvalho et al., 2011; Greenleaf and Kremen, 2006). This makes it  
106 a good candidate for monitoring the dynamics of pollinator activity, without necessarily  
107 knowing their species identity (Rader et al., 2016). Here, we first compared the performance of  
108 a deep learning method based on convolutional neural networks trained on spectrograms  
109 using the newly developed TadariDeep software (<https://github.com/YvesBas/TadariDeep>)  
110 with a random forest based method trained on sound events features using the Tadarida  
111 software. Then, to test the reliability of acoustic monitoring, we investigated whether the  
112 estimate of pollinator activity from continuous acoustic monitoring reflects those estimated by  
113 a classical method, i.e. replicated sweep net sampling along transects. We studied the  
114 relationship between the number of buzzes detected and the number of honeybees sampled  
115 along the transects both on the days of transect sampling and throughout the flowering period  
116 of the sunflower fields.

117

118

## Material & Methods

### 119 A) Site description

120 In 2020, we selected 30 sunflower fields from the Long-Term Social-Ecological Research site  
121 “Zone Atelier Plaine & Val de Sèvre” in South-West France. This research site is 435 km<sup>2</sup> and  
122 composed of 87% of cultivated areas (Bretagnolle et al., 2018 a,b), dominated by cereals and  
123 sunflowers, representing roughly 55% and 13% of the cultivated area, respectively. To promote  
124 heterogeneity in pollinator activity among sunflower fields, fields were selected to cover the  
125 landscape gradients of semi-natural habitats, sunflowers, and organic fields. Selected  
126 sunflower fields had an average area of 6 ha ( $\pm 4.6$  SD). The flowering of these fields ranged from  
127 early July to mid-August, and lasted between 2 and 3 weeks per field.

### 128 B) Acoustic records

#### 129 *Recording device and records pretreatment*

130 We used AudioMoth recorders, which are low-cost, small, and low-energy (Hill et al.,  
131 2018) to perform audio recording (see SI.A for the description and parameters). In each field,  
132 approximately 20m from the field edge, we placed an Audiomoth 10 to 20 cm from a randomly  
133 selected sunflower head. A windscreen covered the Audiomoth to reduce the wind sound. We  
134 made continuous audio recordings between 6 am and 10 pm, at 16 kHz sampling rate, to cover  
135 the period between sunrise and sunset at our study site during July and August.

136 We aimed to compare the performance of random forest and convolutional neural networks  
137 for pollinator buzz detection. This requires a training dataset, but to our knowledge there is no  
138 a database of annotated pollinator buzzes. To build our training dataset we proceeded in two

139 steps. First, we manually annotated a restricted number of audio records for which we knew  
140 that pollinators were present (see “Step 1: Building the training datasets”). By annotating 60  
141 minutes of records, we obtained 225 pollinator sounds and 1627 other sounds. Second, to  
142 increase the size of our training dataset without spending too much time listening to recordings  
143 to manually annotate pollinator buzzes, we trained a random forest classifier on this initial  
144 training dataset and used it to identify pollinator buzzes in more than 400,000 audio recordings.  
145 Thanks to a stratified sampling of the results that were listened to and manually annotated, we  
146 obtained 12 644 extra pollinator sounds and 9 565 extra other sounds.

147 These steps were achieved using the Tadarida toolbox (Bas et al., 2017) designed to analyze  
148 the recordings and build classifiers of sound events. To optimize the use of this toolbox, it was  
149 necessary to pre-process our recordings. We cut them into sub-records of 10 seconds thanks to  
150 Kaleidoscope (<https://www.wildlifeacoustics.com/products/kaleidoscope-pro>) software and  
151 thus obtained 4 014 996 10-second records. Then, Tadarida-L, a component of Tadarida  
152 toolbox, was used to detect sound events on spectrograms of all of these records (Table S1).  
153 Fast Fourier Transformation window was set to a size of 1024 and an overlap of 75 % so that  
154 the time resolution is 16 ms, and the frequency resolution is 7.8 Hz. To train Tadarida-C  
155 classifiers to recognize flying pollinators from other sound events, we built several training  
156 datasets. For this, we proceeded in several steps.

#### 157 *Step 1: Building the training datasets*

##### 158 - *Training dataset A*

159 Machine learning classification methods need a training dataset from which the algorithm  
160 learns to classify sound events into predefined categories. Such training datasets are made of  
161 labeled sound events, the labels corresponding to the classes into which sounds should be  
162 classified *a posteriori*. To ensure that our training dataset included pollinator sound events, we  
163 randomly selected the recordings from 12 out of 291 5-minute long observation sessions,  
164 representing 375 10-second long recordings, for which we knew that pollinators were present  
165 (see Supporting Information B). Sound events that Tadarida-L detected within these 375  
166 records were listened to and labeled using eight classes still using Tadarida-L. Three of the  
167 classes corresponded to pollinators "*Apis mellifera*", "*Bombus sp.*", and "Unidentified  
168 pollinator", which we could differentiate thanks to the visual observations made. Table S2  
169 presents the full list of classes and the number of sound events labeled correspondingly that  
170 constitute the training dataset A, comprising a total of 225 pollinator sound events. Then from  
171 this training dataset, we used Tadarida-C to build the first classifier based on a random forest  
172 algorithm, hereafter named “RF-0” (Fig. 1 and see the "Step 2: Classifier training" section for  
173 details).

##### 174 - *Training dataset B*

175 To ensure that all possible sound conditions were represented in our training dataset, 10%  
176 of all records not coupled to the visual observations were randomly selected. Based on their  
177 acoustic features, we classified all sound events detected in these with our classifier “random  
178 forest-0” and obtained for each recording a confidence score for the "pollinator" class, which  
179 corresponds to the sum of the confidence scores of “*Apis mellifera*”, “*Bombus sp.*” and  
180 “Unidentified pollinator” classes. The higher the score, the more likely it is that the record  
181 contains a pollinator sound. We defined six pollinator score groups based on the confidence

182 score of the “pollinator” class (i.e. 1: 0-0.5; 2: >0.5-0.6; 3: >0.6-0.7; 4: >0.7-0.8; 5: >0.8-0.9; 6: >0.9).  
183 To improve the training dataset, we wanted to increase the number of sound events in the  
184 “pollinator” class and correct the main errors made by the classifier “random forest-0” (not a  
185 pollinator but a high confidence score of the "pollinator" class). For this, we conducted a  
186 sampling of the recordings stratified by sunflower field and “pollinator” confidence score  
187 group, with the number of recordings sampled increasing with confidence score groups. All of  
188 these recordings were listened to and all sound events were labelled with Tadarida-L. We  
189 obtained a training dataset B with 17 classes of sounds and a total of 12 869 sound events  
190 corresponding to pollinators (Fig. 1 and Table S3 to see the list of classes and the number of  
191 sound events we had labeled per class).

#### 192 - *Training datasets C & D*

193 Data augmentation consists of artificially increasing the size of the training dataset by  
194 sampling data to which a small modification is applied (Stowell, 2022). Our preliminary tests  
195 showed that the human voice could be the source of many classification errors. To improve the  
196 performance of our classifier in differentiating between pollinator sounds and human voice, we  
197 increased the class of sounds corresponding to the human voice. To do so, we collected human  
198 voice events from the Common Voice Corpus 9.0 database  
199 (<https://commonvoice.mozilla.org/fr/datasets>) and mixed these events with the events from  
200 the training dataset B, with an amplitude ratio randomly selected between 1% and 99%. A  
201 training dataset C was then created by adding to the training dataset B, 1700 of these events  
202 mixing human voice and sound events from our recordings in sunflower fields (Fig. 1c). In the  
203 same way, we created training dataset D by adding 3300 sound events mixing human voice  
204 mixing events and sound events from our recordings to the training dataset C (Fig. 1d). In the  
205 following, we only use the training datasets B, C, and D.

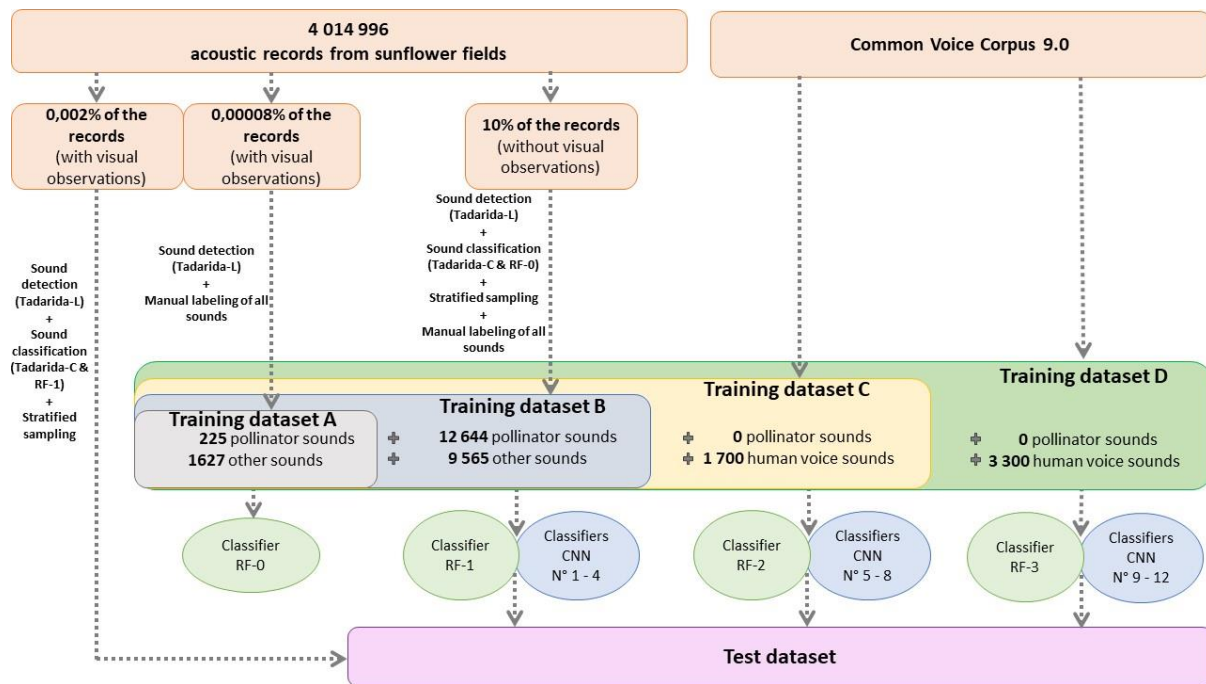
#### 206 *Step 2: Classifier training*

207 We compared two different machine learning methods, i.e., random forest and  
208 convolutional neural networks, to classify sound events as pollinator flight sounds versus other  
209 sounds emitted in the same frequency band. To do so we used two softwares: Tadarida-C, a  
210 component of Tadarida toolbox (Bas et al., 2017) and TadariDeep  
211 (<https://github.com/YvesBas/TadariDeep>). The first allowed us to extract 269 acoustic features  
212 for each labelled sound event and train a classifier using a random forest classification. The  
213 second, based on computer vision, using Tensorflow 2.0.0 framework and transfer learning  
214 (MobileNet architecture), allowed to train a classifier based on convolutional neural networks.  
215 For this last method, we optimized the batch size and the number of iterations (nbepochs). For  
216 both methods, we used the training datasets B, C, and D, previously described, leading to a total  
217 of 15 classifiers (see Fig.1, and Table S4 for the characteristics of each classifier).

218 It is also important to note that the detection process is the same for both machine learning  
219 methods. Nevertheless, with TadariDeep used for the convolutional neural networks, a filter  
220 was applied to limit short sound events with a small amount of information. Thus, only sound  
221 events with a duration of 90 ms or more were taken into account for this method.

222  
223





224

225 Figure 1: Overview of the building of training datasets and classifiers. The orange boxes  
 226 represent the original datasets used to build the different training and test datasets. The  
 227 arrows indicate the different operations performed during the building of the datasets.  
 228 The green circles represent the random forest classifiers built with Taradida-C. The blue  
 229 circles represent the convolutional neural networks classifiers built with TadariDeep.  
 230

231 *Step 3: Classifiers testing*

232 We tested the effectiveness of the random forest and convolutional neural network  
 233 classifiers using a test dataset of 100 recordings per pollinator score group (as defined in the  
 234 part “Training dataset B”). These recordings were randomly selected from the set of 8709  
 235 unlabelled 10-second recordings for which we also had visual observation of the pollinator run  
 236 (see section C of Materials and Methods below) after all sound events in these recordings had  
 237 been classified with the classifier RF-1 (see Table S4).

238 Thanks to the test dataset, we assessed the efficiency of our 15 classifiers to identify  
 239 pollinators against other sounds with receiver operator characteristics (ROC) curves. These  
 240 curves are generated based on the probability (confidence score) that the classifier classifies a  
 241 pollinator sound event as a “pollinator” accounting for the specificity (inverse of false positive  
 242 rate) and sensitivity (inverse of false negative rate). We made a ROC curve for each classifier we  
 243 created. We calculated the area under the curve (AUC) which provides a summary of the  
 244 classifier's performance.  
 245

246 **C) Reliability tests of continuous acoustic monitoring compared with a**  
 247 **traditional monitoring method to estimate pollinator activity**

248 **Comparing acoustic monitoring with counts of pollinators in field transects**

249



250 We compared acoustic monitoring with pollinator counts along transects within  
251 sunflower fields. To do so, in each field, we counted the number of visits of honeybees to  
252 sunflowers along transects. The transects were 5-meter wide and 20-meter long, starting 10  
253 meters from the edge of the field and ending 30 meters away, and they were not timed. The  
254 position of the transects was chosen so that they were within a few meters of the sunflower  
255 plant being acoustically monitored. For each field, transects were repeated 4 to 6 times during  
256 a period that encompasses the sunflower bloom, with some counts conducted before, during,  
257 and after the flowering (Supplementary Figure S1).

258 For this analysis, only fields with little or no failure of the recording equipment during the  
259 flowering period were used, i.e. 20 fields (Fig.S1). Only days with at least 14 hours of recording  
260 out of the theoretical 16 hours were retained. We considered all sounds with a pollinator  
261 confidence score, obtained with convolutional neural networks greater than or equal to 78.1 to  
262 be pollinator sounds. This confidence score maximizes both sensitivity and specificity (see the  
263 red dot in Fig. 2). With this confidence threshold, the average number of pollinator buzzes per  
264 field throughout the season was 4880 ( $\pm$  2588 SD) and the average number of pollinator buzzes  
265 per day was 197 ( $\pm$  259 SD).

266 We first tested for a relationship between the number of honeybees counted per  
267 transect, and the number of flying insects detected on acoustic recordings on the same day. To  
268 do so, we modeled the number of buzzes detected during the days of transect sampling, with  
269 the number of honeybees counted per transect as explanatory variable. Second, to explore the  
270 same relationship but over the entire flowering period of the sunflower fields, we tested for a  
271 relationship between the average number of flying insects detected per day of acoustic  
272 monitoring and the average number of honeybees counted per transect performed in the same  
273 fields. For both tests, we used generalized mixed linear models with negative binomial  
274 distribution and field identity as a random effect on the intercept.

275 All statistical analyses were performed using R (R Core Team, 2022). The residuals of all  
276 models were visually inspected with the R package DHarma (Hartig and Lohse, 2022).

277

278

## Results

### 279 Comparison of convolutional neural networks and random forest classifiers for pollinator 280 acoustic monitoring

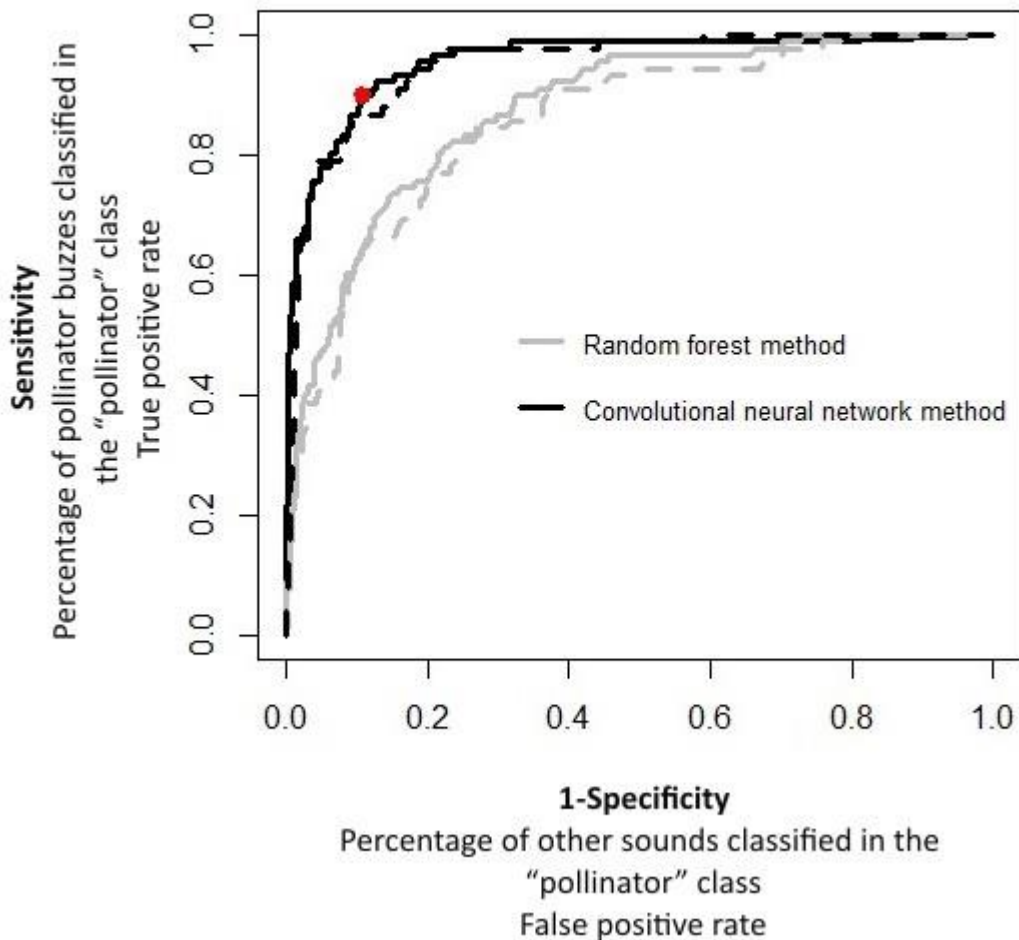
281 Random forest and Convolutional Neural Network methods involved different sound  
282 detection algorithms. Tadarida-L detected sound events in 99.3% of the records of the test  
283 dataset (596 out of 600 records) while TadariDeep detected them in 95% of the records (570 out  
284 of 600 records). This difference between the two software was explained by the filter applied to  
285 the sound events in TadariDeep (minimum duration 90). In the 600 records, composing the test  
286 dataset, we counted 94 records that contained at least one pollinator sound. Tadarida-L  
287 detected sound events for all of them but for the same reasons as above, TadarariDeep  
288 detected sound events corresponding to pollinator sound for only 91 of these recordings.

289 As comparison of classifier performance is only possible when considering the same  
290 detection lists, to compare the classification accuracy of the two methods, we considered only

291 the recordings for which both methods detected sound events, i.e. 95% of the recordings in the  
292 test dataset.

293 ROC curves and their AUC showed that, for both the random forest and the convolutional  
294 neural networks method, the best performance was obtained using the training dataset D, the  
295 one composed of the labeled sound events from sunflower fields, augmented with 3300 mixed  
296 human voice sound events. The Area Under the Curve was equal to 0.878 for Random Forests,  
297 and 0.957 for convolutional neural networks, with a batchsize of 16 and 160 iterations (Fig. 2).  
298 Without data augmentation, the area under the curve of the best classifiers was equal to 0.856  
299 for Random Forests and 0.953 for convolutional neural networks (Fig. 2). While both methods  
300 performed better with data augmentation, the benefit was greater for Random Forest method  
301 with an AUC increase of 2.6% while convolutional neural networks only increased by 0.4% (Fig.  
302 2). Whatever the training dataset used, the convolutional neural networks outperformed the  
303 random forest. By calculating the average error rate according to the different selection  
304 thresholds (1-AUC), we were able to determine that the error rate of the convolutional neural  
305 networks method was three times lower than that of the random forest method for the  
306 classification of pollinator flight sounds.

307



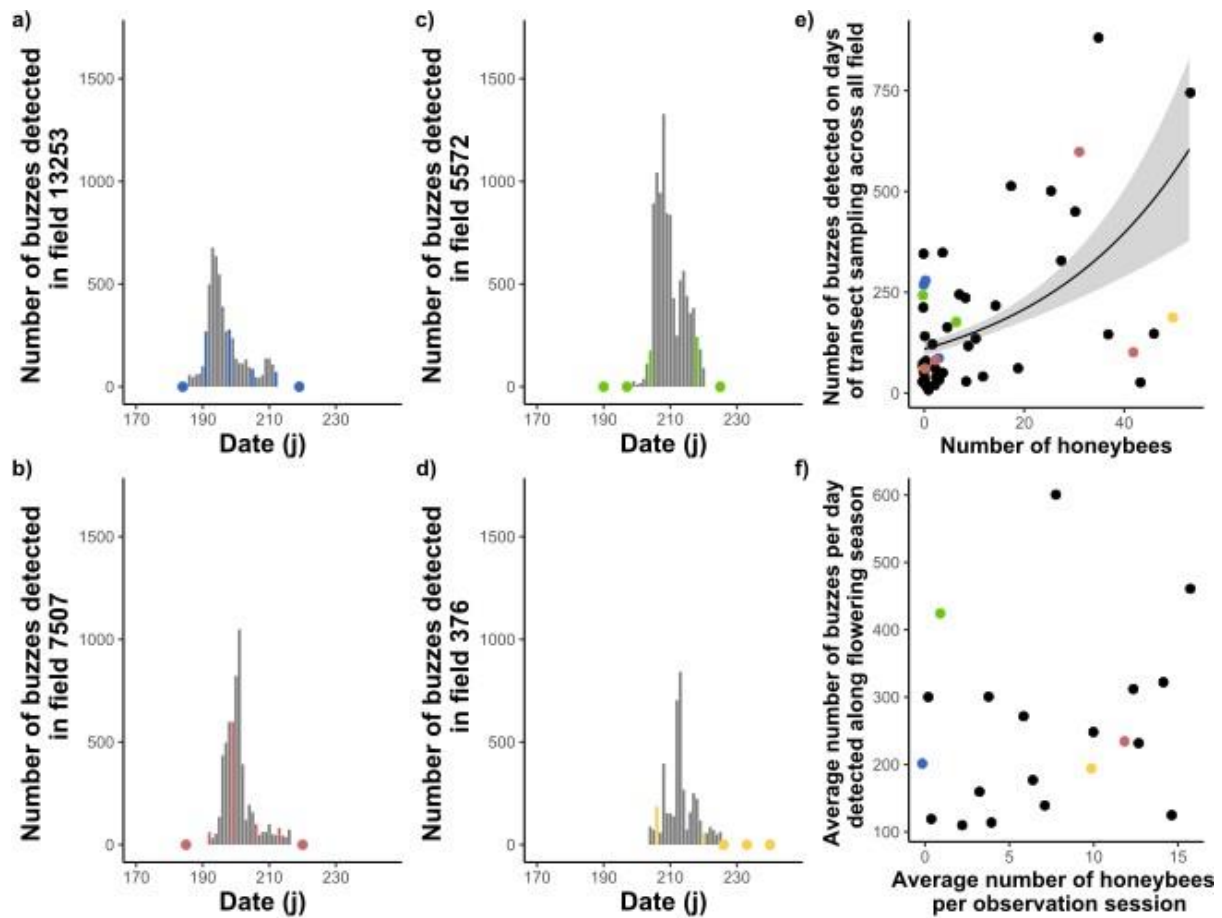
308

309 Figure.2: Receiver operating characteristic (ROC) curves between the confidence score of  
 310 the false-positive rate (FPR) and the true-positive rate (TPR) for the best classifiers of the  
 311 random forest method (grey curves) and the best classifiers of the convolutional neural  
 312 network method (black curves). Each point on the ROC curve corresponds to a  
 313 confidence score for the "pollinator" class. For each of them, the sensitivity,  
 314 corresponding to the frequency that a sound emitted by a pollinator is correctly classified  
 315 in the "pollinator" class by the classifier, and 1-Specificity (the false positive rate),  
 316 corresponding to the frequency that a sound not emitted by a pollinator is classified in  
 317 the "pollinator" class, are calculated. Continuous lines correspond to the best classifiers  
 318 trained with data augmentation, based on training dataset D, and dashed lines without  
 319 data augmentation, based on training dataset B. The red point corresponds to the  
 320 threshold (78.1) selected for the other parts of the study concerning the "pollinator"  
 321 confidence.

322

323 **Comparing acoustic monitoring with counts of pollinators in field transects**

324 When acoustic monitoring was restricted to the days of visual counts along transects, we  
325 found a significant positive relationship between the number of buzzes recorded during the day  
326 of an observation session, obtained with the convolutional neural networks method, and the  
327 number of honeybees counted along this transect ( $\text{Chisq}=14.485$ ,  $p\text{-value} < 0.001$ , Fig.3e). When  
328 acoustic detections and transect counts were averaged per day over the entire flowering  
329 season, we found no relationship between the average number of buzzes detected per day and  
330 the number of honeybees counted per transect averaged over the season ( $\chi^2=1.1577$ ,  $p\text{-}$   
331  $\text{value}=0.2819$ , Fig. 3f).



332

333 Figure 3 – Relationships between the number of buzzes detected by acoustic monitoring  
334 and the number of pollinators counted along transects. a, b, c, d: Number of buzzes  
335 detected per day along the flowering season for four examples from four monitored  
336 fields. The days on which transects were performed in each field are represented by  
337 colored dots and bars. e: Relationship between the number of honeybees counted per  
338 transect and the number of buzzes detected by acoustic monitoring on the same day.  
339 The black line corresponds to the prediction from the generalized linear model with the  
340 associated standard error symbolized as a grey ribbon. f: Relationship between the  
341 number of honeybees per transect averaged per field and the average number of buzzes  
342 per day detected by acoustic monitoring during the entire flowering season. The colored  
343 points in e match the colored bars and points used in a-d. Colored points in f match with  
344 fields presented in a-d. To prevent overlapping points on panel e and f, the coordinates  
345 of points were jitted.  
346

347

## Discussion

### 348 **Convolutional neural networks outperform random forest classifiers for acoustic monitoring** 349 **of pollinator activity**

350 Our study shows that monitoring pollinator activity in sunflower fields using acoustic  
351 recordings is feasible and promising. We further demonstrate that convolutional neural  
352 networks are more powerful than random forests for such a task, being three times more  
353 reliable than the random forest method to classify the sounds emitted by flying pollinators from  
354 other sounds in agricultural landscapes. Such better performance of convolutional neural  
355 networks over other machine learning algorithms is not always the rule (Garcia et al., 2020), but  
356 has also been found in singing birds (Knight et al., 2017; Marchal et al., 2022).

357 During the training of our different classifiers, we noticed that the human voice was often  
358 misclassified as bee buzz, reaching high confidence scores for pollinator sound classes, and this  
359 was despite the data augmentation we carried out (see Fig. 2 and SI. B). This kind of problem  
360 with the human voice has already been noted in bird detection (Stowell et al., 2019). Here, the  
361 human voices recordings are due to the voices of the experimenters who were close to the  
362 sound recorders during the observation sessions in the sunflower fields. The human voice data  
363 that we used for data augmentation came from recordings of people speaking in front of their  
364 computers without background noise. Although we mixed it with field recordings to add some  
365 background noises, we could not get rid of all the false positives and the performance of the  
366 classifiers was only slightly better than that of classifiers without data augmentation. This  
367 suggests that the human voice recordings used for data augmentation were quite different  
368 from the human voice recorded in the sunflower fields, or that the Signal-to-Noise Ratio was  
369 too low. This highlights the importance of using recordings from the study sites for training and  
370 testing machine learning algorithms as well as the need to create large, diversified, and open  
371 annotated reference datasets.

372 Comparing the number of buzzes detected by acoustic monitoring coupled with  
373 convolutional neural networks with the number of honeybees counted along sunflower field  
374 transects, we found contrasting results depending on the temporal window used. When  
375 restricting acoustic data to the days of transect sampling, we found that these two methods  
376 provided concordant information on pollinator activity. However, when considering acoustic  
377 data from all days during the flowering season, the relationship between the two proxies of  
378 pollinator activity vanished. This stems from the fact that, although replicated 5 or 6 times per  
379 field throughout the flowering season, the transects remain punctual observations that may  
380 not be representative of the entire flowering season, because fieldwork organization  
381 constraints make it very difficult to sample different fields or locations evenly during the peak  
382 of pollinator activity. Indeed, matching days of transect sampling with peaks of pollinator  
383 activity is difficult (Figure 3 and S1) as activity depends on weather, notably the temperature  
384 (Blažytė-Čereškienė et al., 2010; Woyke et al., 2003), and on the phenology of floral resources  
385 available in the landscape (Polatto et al., 2014; Guezen & Forrest, 2021) with pollinators  
386 optimizing their energy consumption (Stabentheiner & Kovac 2014). Albeit issues related the  
387 functioning of the recording device, acoustic monitoring allows monitoring several sampling  
388 sites simultaneously and continuously making the estimation of pollinator activity for the  
389 entire flowering season more representative than the more commonly used transects. Yet, we

390 might expect that proxies for pollinator activity at these broad temporal scales should best  
391 reflect pollination services (i.e. fruit production from successive visits throughout the flowering  
392 season), unlike the punctual monitoring traditionally used.

### 393 **Perspectives and limits to overcome**

394 Passive acoustic monitoring of pollinators method is thus a promising method to estimate  
395 pollination services (van Klink et al., 2022). For crops such as sunflower, where the effect of  
396 pollinators on yield appears to depend mainly on honeybee abundance (Altayeb and Nagi,  
397 2015; Aslan and Yavuksuz, 2010; Perrot et al., 2019), a simple quantification of flying insect  
398 sounds, as we did, could give a good estimate of insect-pollination benefit to yield. However,  
399 some methodological developments for species identification are needed for other crops  
400 visited by a larger diversity of pollinators, such as oilseed rape (Garibaldi et al., 2011; Jauker et  
401 al., 2012; Kremen et al., 2002; Rader et al., 2016), for which the effect of pollinator diversity on  
402 yield has been demonstrated (Bartomeus et al., 2014; Perrot et al., 2018; Zou et al., 2017). Such  
403 pollinator identification from buzz sounds has already been achieved for a limited number of  
404 species: three bee and one hornet species (Kawakita and Ichikawa 2019), and 12 bumblebee  
405 species (Gradišek et al. 2017). We can expect improvements in identifying pollinator species  
406 from the sound of their wings beats as more and more annotated pollinator sounds become  
407 available. Nevertheless, detecting small pollinators that emit lower sound levels than larger  
408 ones, such as honeybees or bumblebees, remains challenging.

409 Better knowledge of the detection range of the pollinators around the sound recorder is also  
410 needed to assess pollination services within an agricultural field. Compared to other methods  
411 such as transects, which are conducted over a large area, our method measures pollinator  
412 activity at a fixed point in the field and close to a plant. Several recorders per field might be  
413 needed to accurately account for hedge effects, where the activity of pollinators decrease  
414 towards the center of the agricultural fields (Hevia et al., 2016).

415 Our results suggest that passive acoustic monitoring is at least as effective as traditional  
416 methods for monitoring pollinator activity, as long as the diversity of pollinators is not of  
417 interest. Continuous monitoring further avoids the biases related to the choice of sampling  
418 dates that occur with most other methods. Assessing methods for species identification from  
419 acoustic pollinator flight sounds as well as relating acoustic activity to pollination success  
420 appear to be the next step to propose pollination services indicators based on passive acoustic  
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427

## Conflict of interest disclosure

428 The authors declare that they comply with the PCI rule of having no financial conflicts of  
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430

## Data, scripts, code, and supplementary information availability

431 Data, script, and supplementary materials to this article can be found online at:  
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433

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