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Using automated passive acoustic monitoring to measure changes in bird and bat vocal activity around hedgerows of different ages

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ABSTRACT

Hedgerows are a semi-natural habitat that supports farmland biodiversity by providing food, shelter, and habitat connectivity. Hedgerow planting goals have been set across many countries in Europe and agri-environment schemes (AES) play a key role in reaching these targets. Passive acoustic monitoring using automated vocalisation identification (automated PAM), offers a valuable opportunity to assess biodiversity changes following AES implementation using simple, community-level metrics, such as vocal activity of birds and bats. To evaluate whether vocal activity could be used to indicate the effectiveness of AES following hedgerow planting in future result-based or hybrid schemes, we surveyed twenty-four hedgerows in England classified into a chrono-sequence of three age categories (New, Young, Old). We recorded 4466 h over the course of 30 days and measured bird and bat vocal activity using BirdNET for birds and Kaleidoscope for bats. Vocal activity of all birds, farmland birds, and bats were modelled with age and predictors of hedgerow, habitat, and weather conditions to assess changes occurring from hedgerow planting to maturity. We show an increase of vocal activity in Young and Old hedgerows compared to New ones and highlight elements of the surrounding landscape that should be considered when evaluating AES implementation on bird and bat communities. We found high BirdNET precision in community-level vocal activity and low precision of species-level observations, and we argue that vocal activity may be used in novel AES to link a result-based payment component to automated PAM results, incentivising biodiversity effective hedgerow planting and management by farmers and landowners.

1. Introduction

Hedgerows –lines of managed shrubs and trees delineating agricultural fields (Montgomery et al., 2020)– can provide multiple benefits to farmed landscapes, such as supporting faunal and floral biodiversity (Froidevaux et al., 2019; Litza et al., 2022; Staley et al., 2023), sequestering carbon in woody biomass and in the soil, flood risk alleviation, nutrient cycling, and biological control of crop pests (Garratt et al., 2017; Holden et al., 2019; Drexler et al., 2021; Biffi et al., 2022, 2023).

Hedgerows are key linear features for habitat connectivity in agricultural landscapes, and, together with the wider landscape context in which they are found (e.g. presence of trees, woodland cover, and water bodies), they are important drivers of farmland biodiversity (Sullivan et al., 2017; Heath et al., 2017; Lacoeuilhe et al., 2018). Hedgerow structure, for example, is key in determining how different taxa use them (Graham et al., 2018; Melin et al., 2018; Froidevaux et al., 2019). Birds use hedges for foraging, breeding, and as refuge from predators; and, without hedges, access to resources would be restricted for many species that are otherwise unlikely to venture far from woodland cover (Hinsley and Bellamy, 2000; Dunn et al., 2016; Bravo et al., 2023). Bats also rely on hedgerows for food resource provision and they use these linear features to navigate the landscape when commuting to their foraging areas (Boughey et al., 2011; Froidevaux et al., 2017).

Agri-environment schemes (AES) are key incentives to increasing hedgerow length across Europe and improving habitat connectivity and

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Abbreviations: AES, agri-environment schemes; ARU, autonomous recording unit; FBI, farmland bird index; PAM, passive acoustic monitoring.

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resource provision for many farmland and woodland species. In Europe, agricultural expansion and intensification during the late 20th century were associated with hedgerow destruction and a strong decline in hedgerow length (Staley et al., 2012). This loss of semi-natural linear habitats is associated with the severe population declines of many bird and bat species across farmed landscapes (Fuller, 2000; Cornulier et al., 2011; Froidevaux et al., 2017). In an effort to halt and revert this loss, today hedgerows are part of Environmental Focus Areas in the EU Common Agricultural Policy and are listed as a Priority Habitat in the UK, and planting new hedgerows is widely encouraged within AES. Moreover, many European countries have recently set ambitious planting goals within their climate programmes (Levin et al., 2020; Drexler et al., 2021; Biffi et al., 2023). Establishing and managing hedgerows has time and cost implications, and farmers and landowners often seek compensation from AES. For example, AES are the primary contributor of new hedge length in the UK (Biffi et al., 2023). Thus, meeting national hedgerow planting and biodiversity goals largely depends on developing AES that can attract farmers. As policymakers are moving away from exclusively action-based AES, in which farmers are compensated for implementing the AES, these new designs will encompass biodiversity-oriented AES in which payment levels are determined by implementation evaluation (Cullen et al., 2018; Wuepper and Huber, 2022). Such AES could be result-based schemes, where payment is tied to a proven positive outcome of the action, or hybrid schemes that comprise a mix of guaranteed payments for action and bonus payments for positive results (Herzon et al., 2018).

Combining passive acoustic monitoring (PAM) and automated bird and bat vocalisation identification (ID) can provide a cost-efficient biodiversity survey method for birds and bats that allows for extensive sampling efforts in time and space (Sugai et al., 2019). PAM has become an increasingly popular method for non-invasive monitoring of bird (Darras et al., 2019; Pérez-Granados and Traba, 2021) and bat communities (MacSwiney et al., 2008; Froidevaux et al., 2014) thanks to the recent development of low-cost autonomous recording units (ARUs). However, the ID of vocalisations within the recordings, particularly for bird species, has been frequently processed manually or semi-automatically (e.g. Frommolt, 2017), relying on labour intensive expert evaluation. Fully automated vocalisation ID is a more recent technique, largely resulting from the increasingly widespread application of novel machine learning algorithms to mass-process large amounts of audio data, bypassing the need for expert evaluation of the recordings (Gibb et al., 2019; Wood et al., 2022; Nieto-Mora et al., 2023). While this is an already somewhat established practice for monitoring bats (e.g. Staton and Poulton, 2012), its application in bird field studies is new. However, algorithms for automated vocalisation ID can have high false positive rates of species ID (Findlay and Barclay, 2020; Ware et al., 2023). With their increase in popularity, there is an urgent demand for further research into the capabilities and drawbacks of these novel monitoring methods when applied to real-life, farm-scale context (Gibb et al., 2019; Pérez-Granados, 2023), such as their potential use for monitoring the biodiversity benefits of planting hedgerows within AES to support future AES design and promote the uptake of hedgerow planting and management options.

The aim of this study was to explore the potential of automated PAM to assess changes in the simple metric of bird and bat vocal activity (i.e. the number of vocalisations per hour) around hedgerows with time elapsed since planting. Vocal activity appears to be a good indicator of abundance (Digby et al., 2013; Borker et al., 2014; Pérez-Granados et al., 2019) and could be used as a community-level metric to assess relative biodiversity activity changes following AES implementation when individual species-level results are not required. It should be noted that vocal activity in birds and bats does not define the same behaviour, as usually it denotes territorial behaviour in birds and foraging behaviour in bats (Nowicki and Searcy, 2004; Thomas et al., 2004). We assessed bird and bats vocal activity around hedgerows of known ages using a space-for-time substitution approach to represent time after hedgerow planting. Vocal activity was monitored with automated PAM, using existing software packages (BirdNET and Kaleidoscope Pro) that identify matches (i.e., positive vocalisation IDs in the recordings) and attribute them to species. We defined bird and bat vocal activity as the total number of matches per hour and considered the vocal activity of all bird and bat species, as well as a subset of farmland bird specialists.

Our research questions were: (i) What is the precision of BirdNET, a fast-growing and not yet fully established software for bird species identification, in terms of both vocal activity and species-level ID? (ii) Does bird and bat vocal activity change with hedgerow age, when considering hedgerow characteristics and their spatial configuration, habitat context, and weather conditions? As managed hedges become more structurally and compositionally complex as they mature (Forman and Baudry, 1984; Litza and Diekmann, 2019), we hypothesised that older hedges would be associated with greater bird and bat activity than newer ones. Finally, we discuss what are the possible applications of automated PAM in aiding the design of AES to promote hedgerow planting in agricultural landscapes.

2. Materials & methods

2.1. Study sites

The study area comprised of five dairy farms within Cumbria, in the Northwest of England (Fig. 1). They were located in the Eden Valley, a wide south-north oriented valley separating the Cumbrian Mountains of the Lake District from the Northern Pennines. The Agricultural Land Class of the area is grade 3 (‘good to moderate quality agricultural land’, Natural England, 2010) and its primary land use is pasture for dairy and beef farming, interspersed with fragmented and declining small areas of semi-natural habitat (Natural England, 2013). The Koppen climate classification of the region is temperate oceanic (Beck et al., 2018). The farms' land cover was dominated by intensively managed grassland classified as ‘*Lolium perenne* L. reseeded grassland’ (MG7, Rodwell, 1998), cut annually for silage, usually multiple times a year.

2.2. Hedgerow characteristics

Across the study area, 24 hedgerows of three different ages were selected and categorised in a chrono-sequence of three age groups as follows: (1) ‘New’ if they were planted after 2017 (3–5 year old), (2) ‘Young’ if they were planted between 2010 and 2016 (~10 year old), and (3) ‘Old’ if they were planted before 2010 (this age category included a wide range of ages from decades to potentially hundreds of years old). Eight hedgerows were sampled from each age group, with New and Old hedges distributed across five farms, and Young hedges across four farms (Fig. 1). The age of hedgerows in this study is not a predictor of activity per se, but rather a surrogate for the range of structural changes that can affect biodiversity as the woody vegetation grows and is managed regularly with time after hedgerow planting. This space-for-time substitution is a common approach when studying changes in biodiversity in managed woodland (Wegiel et al., 2019; Harris and Betts, 2021). Hedgerow age was determined by consulting the farmers, as well as with time series from aerial photography and historic mapping (EDINA, 2010, 2018). Most hedgerows were fenced. Old hedgerows were regularly managed every one to two years by trimming using a tractor mounted flail mower and had been laid in the past.

2.3. Audio recordings

Audio recordings from each hedgerow were collected between June 15th and July 14th 2022 (30 days in total, of which 16 were in June). Each hedgerow was equipped with two automated recording units (ARUs, AudioMoth v1.2.0, Firmware 1.8.0 Hill et al., 2018) set ~2 m apart facing the same field, each enclosed in an AudioMoth IPX7

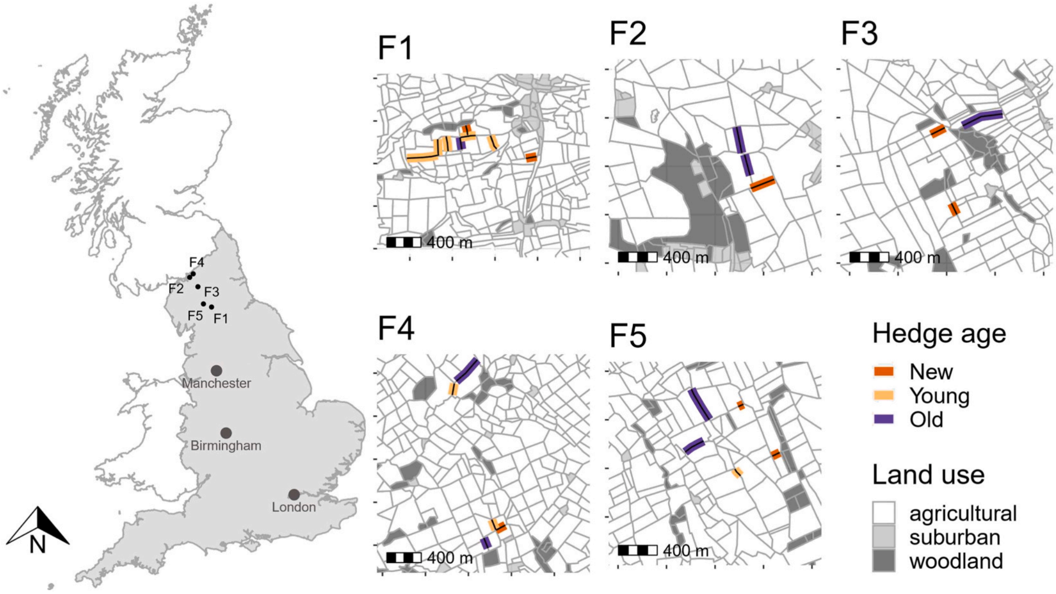

Fig. 1. Configuration of the 24 hedgerows of three age categories sampled across five farms in the Eden Valley, Northwest of England.

Waterproof Case and configured using AudioMoth Configuration App 1.7.0. ARUs were placed >10 m away from hedgerow trees. One ARU was programmed to turn on every day to capture dawn choruses of bird song (04:00–08:00 UTC + 1), recording in intervals of 55 s every minute. The sampling rate was 48 kHz and recordings were filtered to frequencies <12.6 kHz. The other ARU was programmed to start recording approximately 30 min after sunset for three consecutive hours (22:15–00:15 UTC1 + 1) to record bat activity. The sampling rate was 192 kHz, with recordings filtered to frequencies above 25 kHz, and an amplitude threshold of 416 to reduce file size (Open Acoustic Devices, 2020). Recordings were saved in WAV format.

ARUs on different hedgerows were placed >50 m apart and the average distance between ARUs on the same farm was 259 (95 % C.I. 180–380) m, ranging from 52 to 2000 m. Where possible, ARUs on hedgerows boundaries around the same field were placed facing different fields. The recording radius of AudioMoths varies depending on the surrounding landscape (Darras et al., 2016; Yip et al., 2017) and there is no definite minimum distance between ARU to avoid picking up the same vocal activity. Thus, the location of deployment can affect the accuracy of automated PAM (Knight and Bayne, 2019), as this also depends on the species considered. For example, Somervuo et al. (2023) found that goldfinch (*Carduelis carduelis*) IDs dropped as a function of distance in forest, but not in agricultural fields. Thus, we conducted a supplementary analysis to check if the similarity in species ID changed with total number of IDs and with increasing distance between recorders by considering all paired combinations of ARUs within each of the farms, which showed no strong trend in the data (see Appendix A).

2.4. Bird vocalisation ID using BirdNET

All dawn chorus recordings were processed using BirdNET V2.3. BirdNET is a free, deep convolutional neural network designed to handle large amounts of field recordings that uses sound spectrographs to identify bird vocalisations in small segments (3 s) of longer audio recordings (Kahl, 2020; Kahl et al., 2021). It has been trained for over five hundred European avian species and has generalization ability which allows, to some degree, to account for background noise.

The sensitivity parameter was set to 1, with no prediction segments overlap and no minimum confidence threshold set for the raw output. Farm coordinates and week number of the recording were input as spatial and temporal filters. As a post-processing step, the raw confidence scores output by BirdNET of each ARU by day were smoothed and pooled with a moving exponential average. This was done to reduce the false negative matches that can result from cutting the recordings in short intervals, as well as smoothing (reducing) any potential isolated high-confidence species observation (Wood et al., 2021). To do this, the BirdNET outputs of each species were joined to the complete list of 3 s intervals within the entire recording period of that day. The smoothing was performed using Dataframe.emw in Python v.3.9.0, using a width of 3 chunks (9 s). The processed data was then joined back to the original output. Appendix B shows the species confidence scores before and after smoothing.

Bird species richness was measured as the number of species identified during each hour of recording, conservatively selecting only observations that were attributed a (smoothed) confidence score above 0.5 to minimise the inclusion of false matches following Wood et al. (2021) and as supported by the results of our analysis on species precision (Section 2.4.1). Hourly bird vocal activity of all bird species was obtained as the total number of vocalisations per hour, after correcting the difference in time between an hour (3600 s) and actual recording time (55 s × 60 = 3300 s), as we recorded 55 s every minute. Additionally, we measured hourly farmland bird activity by only selecting matches with ≥ 0.5 confidence of a subset of the 19 species belonging to the UK Farmland Bird Index (FBI), a list of species that rely on farmland landscapes and are indicators of the quality of the farmed environment.

2.4.1. BirdNET match precision and species precision

We estimated BirdNET precision during a pilot study conducted in 2020 by manually comparing BirdNET matches to that of an expert ornithologist. We estimated the rate of false positive matches (i.e. match precision) to assess the reliability of raw vocal activity measures. Moreover, although our study does not present species-specific results, we assessed the species ID false positive match rate (i.e. species precision), to explore the reliability of BirdNET species ID for monitoring purposes. 408–3 s recordings were randomly selected from a total of 185,210 3 s recordings (03:00–07:00 UTC + 1) across the ARUs. First, each recording was blindly sent to the expert for ID. Secondly, the BirdNET ID was revealed and, if the IDs contrasted, the expert listened to the recording again to verify it. Precision was expressed as percentage and was calculated as the number of true positives divided by the sum of true and false positives. Background noise in the recording was also classified and recorded.

2.5. Bat vocalisation ID using Kaleidoscope Pro

All nocturnal audio recordings were processed using the cluster analysis and classifier software Kaleidoscope Pro v5.4.6 (Wildlife Acoustics, Maynard, MA, USA) to identify positive matches. Audio files from each ARU per site per night were batch processed and species IDs were made using the Bats of Europe Auto ID Species Classifier, version 5.4.0. The sensitivity of this classifier was set to the most conservative (accurate) level. Bat species richness was measured as the number of bat species identified during each hour of recording, thus excluding matches that were not identified to species ('NoID'). As automated PAM is a much more established practice in bat studies than bird studies (MacSwiney et al., 2008; Darras et al., 2019), we did not examine the match precision and species precision of Kaleidoscope. Instead, we measured the rate of matches of the same species that occurred during a one-minute window to assess the rate of potential passes of the same individual over the ARUs.

2.6. Hedgerow characteristics, habitat characteristics, and weather conditions

Hedge woody species diversity was quantified using the Simpson diversity index of all species recorded along a 30 m segment, following standard hedgerow survey recommendations (DEFRA, 2007). The species composition of hedgerows was typical of England and of Western Europe (Barr and Gillespie, 2000; Carey et al., 2007; Cumbria Biodiversity Data Centre, 2010), with a strong predominance of hawthorn (*Crataegus monogyna* Jacq. 70 %) and blackthorn (*Prunus spinosa* L., 15 %), and presence of hazel (*Corylus avellana* L., 2 %), elder (*Sambucus nigra* L., 1 %), holly (*Ilex aquifolium* L., <1 %), and dog-rose (*Rosa canina* L., <1 %). The length of hedgerows was measured from 25 cm resolution aerial imagery (EDINA, 2018). Hedge height and width were obtained as the average of ten measurements taken in the field per hedge. Hedgerow connectivity was measured following DEFRA (2007) guidelines by counting the number of other hedges connected to each end-point, counting two connections if a hedge was connected to woodland, and ignoring gateways or opening <20 m wide. For each hedgerow, a measure of herbaceous species diversity was obtained from a 2 × 2 m plot placed along the edge of the hedge. Ground flora species coverage within the plot was recorded using a Domin scale and transformed to percentage cover scale using the midpoint of each Domin category (DEFRA, 2007). Herbaceous species diversity was quantified using the Simpson diversity index of the percentage cover of all species recorded within a plot.

The proportion of (broadleaf) woodland land-cover in a buffer of 250 m radius around the ARUs was calculated using the Great Britain 25 m land-cover map (CEH, 2020). The number of isolated trees in a 100 m radius buffer was obtained by manually counting the number of isolated trees in the landscape from aerial photos with 25 cm resolution (EDINA, 2018). The distance from each hedgerow to the nearest watercourse was obtained from the Open Rivers database (EDINA, 2022). Table 1 summarises the average hedgerow and habitat characteristics for each of the three hedge age groups, indicating significant differences according to ANOVAs or non-parametric Kruskal-Wallis rank tests and post-hoc comparisons with Benjamini-Hochberg false discovery rate corrected *p*-values. Old hedgerows did not significantly differ to Young hedgerows for any of the characteristics considered in the study.

We collected hourly weather data of rainfall (mm), temperature (°C), and wind speed (mph) conditions using the closest available weather station (Met Office, 2022), which was on average 19.2 km away from the centroid location of the sites, ranging from 9.4 km to 26.1 km.

2.7. Vocal activity models

Data analysis was conducted in R v.4.2.3 (R Core Team, 2023). The relationships between bird (whole community and FBI species) and bat vocal activity with hedge age, hedge and other habitat characteristics, and weather conditions (Table 2) were examined using generalized additive models (GAM) with negative binomial error distribution with restricted maximum likelihood (gam in mgcv, Wood and Wood, 2022). GAMs are a generalization of Generalized Linear Models that can include flexible, non-parametric smoothing splines to capture trends of the data (Hastie and Tibshirani, 1990). Thus, the models included spatially explicit terms for the ARUs location (a tensor product smoother of their coordinates, obtained using the te function) to account for the spatial relationships among them (Fang and Chan, 2015; Wood, 2017; Viana et al., 2022). Hedgerow age category and month of recording were included in the models as categorical variables, while continuous predictors of hedgerow condition (length, connectivity, ground floral diversity and woody species diversity), landscape (distance to the nearest watercourse, number of trees in 100 m radius buffer, and woodland cover in a 250 m radius buffer), and hourly weather predictors (air temperature, wind speed, rainfall) were included as parametric linear predictors. Collinearity of linear parametric predictors was checked with Pearson's correlation coefficient for each pair of variables ($|r| < 0.55$, Appendix C). All continuous predictors were standardised for effect size comparability.

3. Results

3.1. Overall bird and bat activity

A total of 4466 h were recorded over 30 days, 2609 h during bird dawn chorus, and 1985 after sunset for bats. BirdNET found 874,598 bird matches from a total of 114 bird species. 87 % of these species, which corresponded to 98 % of total bird sounds, were classified as abundant, common, or fairly common according to regional census definition (Cumbria Biodiversity Data Centre, 2015; Cumbria Bird Club, 2022, Appendix D). However, 92.4 % of the bird matches had a confidence score < 0.5 after pooling and smoothing. The remaining 7.6 % of matches were attributed to 83 different species, 12 of which were classified as farmland specialists. The average total number of bird matches per hedgerow was 36,442 (±10,312). Bird vocal activity did not change significantly between 3 am and 7 am and averaged 335 (±282) matches per hour. After removing confidence scores <0.5 the average bird species number per hour was 2.75 (±1.65).

Kaleidoscope Pro found 24,210 bat matches, 27 % of which were not identified to species. The remaining 73 % were attributed to 12 species, with the vast majority belonging to *Pipistrellus pygmaeus* ($n = 8159$), *P. pipistrellus* ($n = 6926$) and *Nyctalus noctula* ($n = 2078$), which together

Table 1
Average values (±standard deviation) of the hedgerow and landscape characteristics included in the models. Different letters indicate statistically significant differences ($p < 0.05$), no letters indicate no statistically significant differences among the hedge age categories.

Age class	Height (cm)	Sig.	Width (cm)	Sig.	Length (m)	Sig.	Connectivity	Herb. diversity	Woody diversity	Trees (n)	Dist. to water (m)	Woodland (%)
New	135 (±48)	b	84 (±42)	b	132 (±59)	b	3.13 (±0.83)	0.79 (±0.01)	0.27 (±0.21)	4.4 (±5.2)	448 (±312)	4.2 (±5.2)
Young	213 (±42)	a	164 (±33)	a	195 (±149)	ab	3 (±1.07)	0.83 (±0.05)	0.14 (±0.16)	3.4 (±2.4)	310 (±197)	3.3 (±4.4)
Old	214 (±54)	a	188 (±40)	a	268 (±109)	a	2.75 (±0.71)	0.78 (±0.04)	0.30 (±0.29)	2.9 (±1.9)	447 (±255)	4.2 (±5.8)

Table 2
Variables included in the bird and bat vocal activity models and the reason for their inclusion.

	Variable	Unit	Reason for inclusion in the model
Hedgerows	Age class	New/Young/Old	Birds and bats: Time since hedgerow planting.
	Length	Meters	Birds: Resource provision, nesting habitat (Parish et al., 1995; Chamberlain and Wilson, 2000; Grüebler et al., 2008). Bats: Resource provision, navigation using ecolocation (Jensen et al., 2005; Schweiger et al., 2005; Grüebler et al., 2008).
	Connectivity	Number of nodes	Birds and bats: Dispersal and movement in the landscape, as hedgerows serve as landscape corridors and habitat (Davies and Pullin, 2007; Froidevaux et al., 2017).
	Herb. spp. diversity	Simpson index	Birds and bats: Resource provision (Hinsley and Bellamy, 2000; Schweiger et al., 2005; Froidevaux et al., 2019).
	Woody spp. diversity	Simpson index	
Landscape	Distance to water	Meters	Birds: Riparian areas supply food resources and habitat (McCracken et al., 2012). Bats: Distance to foraging areas (Davidson-Watts et al., 2006; Nicholls and Racey, 2006).
	Trees, including hedgerow trees	Number in a 100 m buffer	Birds: Trees can affect positively the abundance and diversity of birds in hedgerows, but negative impacts have been also shown (Green et al., 1994; Hinsley and Bellamy, 2000; Walker et al., 2018). Bats: Presence of trees in hedgerows generally shows a positive influence on bat activity (Russ and Montgomery, 2002; Boughey et al., 2011; Lacoeuilhe et al., 2018).
	Woodland	Percentage cover in a 250 m buffer	Birds and bats: The cover of semi-natural habitat in an agricultural matrix affects many farmland species (Heim et al., 2015; Duflot et al., 2018).
Season/ weather	Month	June; July	Birds and bats: Timing of breeding season.
	Temperature	Celsius	Birds and bats: Insect prey availability (Grüebler et al., 2008).
	Wind speed	mph	Birds and bats: Flying conditions and insect prey availability (Grüebler et al., 2008).
	Rainfall	mm/h	

represented 97 % of the matches. 4.96 % of total bat matches ($n = 1202$) originated for the same species within a one-minute window and we never observed more than two matches per minute for the same species. The average total number of bat matches per hedgerow was 1053 (±486). Most bat vocal activity, regardless of species, occurred in the first hour after sunset (average 19.0 ± 13.4) and decreased by 49.7 % ($p < 0.001$) and then a further 18.1 % ($p < 0.001$) during the second and third hours of recordings.

3.2. BirdNET match precision and species precision

BirdNET performed well in identifying bird vocalisations from other audible signals, as match precision in the 408 individual 3 s recording sample was 5.8 %, with 90 % of false discoveries occurring with a confidence score < 0.5. However, 77 % of true positive matches also occurred with a confidence score < 0.5. 62 % of false discoveries occurred during wind gusts, 20 % with no discernible background noise, and 16 % with livestock sounds (cows and sheep). BirdNET species precision instead was much lower, with 46.6 % of matches not being correctly identified to species. Species precision was strongly improved by setting a confidence threshold, as 97 % of misidentifications occurred with a confidence score < 0.5, and 80 % with a confidence score < 0.25. 62 % and 34 % of correct species IDs occurred with confidence score < 0.5 and < 0.25, respectively.

3.3. Drivers of birds and bats activity around hedgerows of different ages

The GAMs of all birds, FBI birds, and bats indicated a significant increase in vocal activity in Young and Old hedgerows compared to New ones. The three models showed significantly higher activity in Young hedgerows and Old hedgerows compared to New ones, with Young hedges showing the highest effect estimate (Fig. 2).

Overall bird community ($R^2 = 0.51$) and farmland bird species

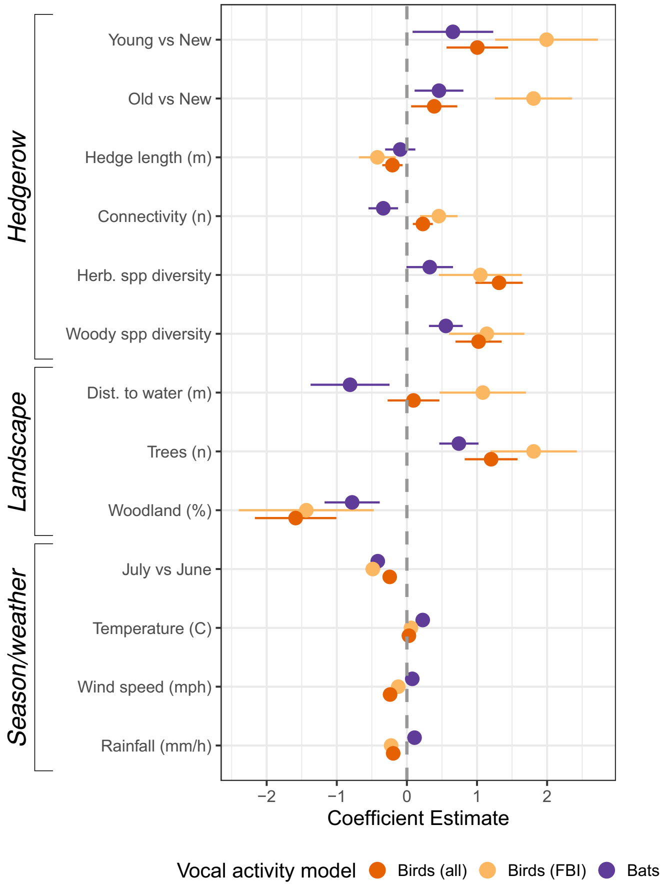

Fig. 2. Effect sizes of hedgerow characteristics, landscape variables, and weather conditions on the vocal activity of the whole bird community, of FBI bird species, and of bats with bootstrapped 95 % confidence intervals. Effect sizes are significant only when confidence intervals do not overlap with the dotted line indicating zero.

($R^2 = 0.34$) vocal activity was higher in hedgerows with greater connectivity, greater woody plant species diversity, and greater herbaceous plant species diversity in their understory. Longer hedgerows were associated with lower bird vocal activity, while greater bird vocal activity was associated with a higher number of trees in the surrounding area, but lower woodland cover. While distance to the nearest watercourse did not appear to affect overall bird vocal activity, the farmland birds model suggested that their vocal activity was higher around hedgerows farther away from watercourses. With the end of breeding season for most species, July was characterized by a decrease in vocalisations for birds. Weather was also shown to affect vocalisations, with greater vocal activity in drier and less windy conditions.

The model for bat vocal activity ($R^2 = 0.23$) showed that the diversity of hedgerow woody species was positively associated with the number of matches, while hedgerow connectivity was negatively associated with it. Of the landscape variables, bat vocal activity decreased with increasing distance to water. As for bird activity, a higher number of matches were recorded around hedgerows with a greater number of trees in the surrounding areas, and a lower proportion of woodland cover. Bat vocal activity decreased in July compared to June. All weather variables showed a significant positive association on bat vocalisations, as Kaleidoscope Pro recorded more matches in association with higher temperature, precipitation, and wind speed, although the latter had a small effect size (full model results shown in Appendices E–G).

4. Discussion

4.1. BirdNET vocal activity and species-level precision

The use of BirdNET in the literature has been rapidly growing in popularity, but the number of field studies utilising this software to identify vocalisations in recordings is still very limited (Darras et al., 2019; Pérez-Granados, 2023). This is one of the first studies to use BirdNET in a real-world scenario while assessing its performance and our results show that BirdNET successfully discerns bird vocalisations within a farmland soundscape, while the overall precision in species ID was low. From our subsample of manually checked IDs, we found that the software had a high capacity to recognise the presence of a bird vocalisation in the recordings, with a match precision of 94.8 %. Thus, our results indicate that BirdNET can be used to measure the vocal activity of the entire bird community in the field without having to set a minimum confidence threshold.

BirdNET species precision (53.4 %) was much lower than match precision. However, our results show that smoothing the confidence scores and limiting matches to those with $\geq$0.5 confidence removed a large amount of false positive species IDs. Although undoubtedly needed to increase precision, our results show that this process likely removed many true species IDs, as over half of these occurred with confidence $<$0.50. Further research supported by expert validation of the results is needed to investigate the nature of these true positives with low confidence scores, which may be due, for example, to softer vocalisations (Arif et al., 2020). The process of filtering matches by confidence scores decreased by 27 % the suggestions of identified species (114 to 83), in line with the results of (Cole et al., 2022) who found a 62 % decrease when limiting observations to those with $\geq$ 0.9 confidence (104 to 39) and reduced the sample size by 92 %. The consequence of this strong decrease in sample size is evident in the FBI bird species model, which showed much wider errors than the model of total bird vocal activity. However, one of the main advantages of PAM is the capacity to collect very large amount of field data with relatively small effort (i.e. regularly changing batteries and replacing storage), and in a cost-effective way depending on the survey conditions (Markova-Nenova et al., 2023). Thus, substantially increasing the sample size within species-specific studies should not represent a major obstacle to future studies. Increasing the sample size will also maximise the chances of detecting more species in the absence of visual surveys (Kułaga and Budka, 2019; Wood et al., 2021).

It is possible that BirdNET performance in species ID accuracy may improve if used outside of dawn chorus hours, when many species overlap their song leading to a cacophonous chorus (Farina et al., 2015; Gil and Llusia, 2020). Arif et al. (2020) tested 205 recordings and found that the loudest species were identified with greatest confidence, suggesting that the simultaneous vocalisation of several, potentially loud individuals might be detrimental to the ID process. Kahl et al. (2021) proposed increasing the sensitivity parameter and the overlap between prediction segments to improve the species ID. Due to the scarcity of quantitative studies on BirdNET ID of field recordings, in this study, we opted to use the software standard parameters.

4.2. Vocal activity around hedgerows from planting to maturity

Our results indicate that vocal activity of birds and bats was higher in Young and Old hedgerows than in New ones. These findings applied to the entire bird and bat community, as well as FBI species, which often rely on hedgerow presence for nesting, particularly in arable landscapes (Broughton et al., 2021). Thus the results of our space-for-time substitution approach suggest that, within an intensive dairy farming landscape, biodiversity benefits of planting hedgerows, in terms of vocal activity of birds and bats, can be achieved within a decade. While the effect of other metrics (e.g. hedge height and width) on biodiversity have been assessed previously, little is known about the trends in farmland biodiversity with hedgerow age, particularly from the early stages of planting (Kremen and M'Gonigle, 2015; Sybertz et al., 2020; Tresise et al., 2021b; Litza et al., 2022) and our results contribute towards filling this research gap.

The models indicated that the vocal activity of birds and bats did not keep increasing with hedgerow age, as the highest vocal activity was associated with Young hedgerows, likely due to a mix of resource availability distribution, hedge management cycles, and study design. Other studies have found that the association between hedgerow age and biodiversity is not linear. For example, similarly to our study, a two-year field case study in North America found that both 15–20 year old hedgerows and 40 year old ones had higher bird abundance than recently planted ones, and that abundance was comparable between the two older age categories (Sibbald and Terpsma, 2016; Schlechtleitner and Bondar, 2017). This similarity could be explained by invertebrate prey availability, as hedgerow age has been shown to have a weak effect on the abundance of invertebrates after around a decade post-planting. For example, Deeming et al. (2010) found lower invertebrate abundance in $\leq$ 5 year old than 50+ year old hedgerows, and Bennett (2016) found the same invertebrate abundance on the ground and in the canopy in 15 year old hedges compared to 50+ year old ones. The results from these two studies suggest that, while invertebrate abundance in New hedges was likely lower, it was comparable between Young and Old hedgerows, rendering both age categories suitable to provide invertebrate food to breeding birds and bats.

Management regime may explain why vocal activity was higher in Young hedges than Old ones, as these age categories differed in the stage of their management cycle. Young hedges were not significantly different to Old ones in terms of their size or any other hedgerow or habitat characteristic included in the study (Tables 1). However, they had not yet entered the regular management cycle typical of UK hedges, which consists in trimming every 1–3 years and laying every 15–30 years. This management regime results in differences in the woody biomass of Young and Old hedgerows (5.62 vs 12.8 Mg dry biomass km^{-1}, Biffi et al., 2023). Other studies have shown that differences in hedgerow woody structure and cutting regime can influence bird and bats by affecting resources availability and habitat quality (Hinsley and Bellamy, 2000; Froidevaux et al., 2019). As hedges in this study are managed intensively, as typical for most UK hedgerows (Carey et al., 2007), untrimmed, Young hedges may have provided better habitat than Old ones in our study area. It should also be noted that the distribution of Young hedgerows among farms was more clustered than the other age categories, potentially biasing their estimated effect compared to Old hedgerows. Finally, it should also be noted that our results represent associations between vocal activity and hedgerow age over a month, and that applying automated PAM over longer periods of time and different seasons might highlight changes in the relationships that we found.

Although shifts in individual species activity are beyond the scope of this study, it should be noted that old hedgerows may have the potential to attract more specialist species than young ones. For example, remnant hedgerows support greater populations of forest specialist plants (Clements and Alexander, 2009; Kremen and M'Gonigle, 2015; Litza et al., 2022) and previous avian studies have linked the loss of old hedgerows to the mating structure simplification of hedgerow specialist species (Bishton, 2001; Browne and Aebischer, 2004). Thus, preserving existing old hedgerows is crucial to support biodiversity in farmed landscapes.

4.3. *Other drivers of vocal activity around hedgerows*

Accounting for both local and landscape scale effects when evaluating the effects of individual hedgerows on biodiversity measures is crucial (Railsback and Johnson, 2014; Sullivan et al., 2017; Heath et al., 2017; Lacoeuilhe et al., 2018), and we found hedgerow and habitat characteristics to have multiple and sometimes diverging effects on vocal activity of birds and bats. Our results are largely in agreement with findings of previous studies on bird and bat abundance in relation to hedgerow and adjacent landscape characteristics (Newton, 2017; Hinsley and Bellamy, 2019). However, it should be noted that the goodness of fit for the bat model was low, suggesting that the model did not capture some factors that were controlling most of their activity.

4.3.1. *Hedgerow and habitat drivers*

We found that hedgerow length was negatively associated with bird activity. Although total hedgerow length (density), is known to affect bird communities at regional scales (Fuller, 2000; Whittingham et al., 2009), our results suggest that, for individual hedgerows, bird vocal activity increases with greater hedgerow connectivity rather than with length per se. We found a stronger effect size of connectivity on FBI species compared to the entire bird community, which agrees with findings of other studies reporting the importance of hedgerow connectivity for the movement of bird species that are less dependent on woodland cover (i.e., not forest specialists) within the agricultural landscape (Mortelliti et al., 2010; Gil-Tena et al., 2014). By contrast, hedgerow connectivity was negatively associated with bat vocal activity, a result in accordance with Frey-Ehrenbold et al. (2013) who found no effect of connectivity on mid-range echolocator species, and an increased activity of *P. pipistrellus* with decreasing connectivity and increasing linearity of hedgerows. As linear features are important for bats with structure-bound ecologies to navigate the landscape when commuting between roosts and foraging areas (Downs and Racey, 2006; Froidevaux et al., 2017), it is possible that vocal activity was lower around hedgerows with higher connectivity due to a dilution effect (Fahrig, 2003), where less activity is found over abundant hedgerow networks, which offer more complex navigation routes, and higher activity around more isolated hedgerows, which are influential features of reference in the landscape.

The diversity of both herbaceous and woody species in hedgerows were positively linked to the vocal activity of both birds and bats, while distance to the nearest water course had opposite effects on them. Greater diversity in floral resources in and around hedgerows has been linked to the abundance and diversity of insect communities in farmed landscapes (Maudsley, 2000; Morandin and Kremen, 2013; Holden et al., 2019), which, in turn, supports higher predator abundance (Froidevaux et al., 2019). For example, wildflower diversity has been positively associated with bat foraging activity over agricultural fields (Peter et al., 2021). Given the importance of riparian habitats in the foraging behaviour of several UK bat species (Nicholls and Racey, 2006; Downs and Racey, 2006), it was not surprising that bat activity declined as distance from water courses increased. We found higher bird vocal activity away from water courses. Although distance to water can be important to some bird species found in farmland, as shown by Jungandreas et al. (2022) for endangered species in Germany, most species commonly found in UK's grassland habitats are not strongly dependent on proximity to water habitats during breeding season (Radović et al., 2013; Rosin et al., 2016; Jungandreas et al., 2022).

We found the number of trees to be positively associated with both bird and bat vocal activity. The effect of trees on bird abundance has been found to vary from species to species, with territory occupancy of generalist species such as greenfinch (*Chloris chloris*) being positively affected by trees, while, for example, yellowhammer (*Emberiza citrinella*) territory number can be negatively affected by the presence of hedgerow trees (Tresise et al., 2021a). Bats generally benefit from hedgerow trees and isolated trees, as they provide shelter from predators and from the elements, for example, by reducing wind speed (Verboom and Spoelstra, 1999; Nicholls and Racey, 2006; Boughey et al., 2011; Lima and O'Keefe, 2013). Trees can also represent hotspots of insect prey, as they provide diverse microhabitats (Merckx et al., 2009; Lacoeuilhe et al., 2016). We found instead that woodland cover had a negative effect on bird and bat vocal activity. This was surprising, particularly for bats, as woodland cover or nearness to woodland have been found to have a positive effect on several UK species (Davidson-Watts et al., 2006; Nicholls and Racey, 2006; Boughey et al., 2011; Frey-Ehrenbold et al., 2013). However, woodland vegetation type has a strong impact on bat activity, with *Pipistrellus* spp. favouring low tree densities with an open understory and thus higher activity has generally been recorded around grazed grassland than woodland (Fuentes-Montemayor et al., 2013). Thus, the combination of woodland type and the predominantly grassland landscape surrounding the hedges may explain the negative association between activity and woodland cover we found in this study.

4.3.2. *Seasonal and weather conditions*

The month of recording and weather conditions also presented multiple associations with vocal activity. Activity during July was always lower than in June, which represents the peak of nesting and breeding season for many bird and bat species in the UK. Weather conditions are known to affect the availability of insect prey in agricultural landscapes, with the negative effect of wind and rain being most evident at lower temperatures (Grüebler et al., 2008). While bird vocal activity was negatively affected by rainfall and wind speed, we found a positive association of bat vocal activity with precipitation and wind speed. Heavy rainfall has been shown to negatively affect bat vocal activity (Perks and Goodenough, 2020) but rainfall during the study was not heavy (0.1 ± 0.7 mm/h on average), with only 6 h (0.3 %) above 5 mm/h across the entire recording period. Thus, one explanation for this positive association may be that during rainfall events below a certain intensity, foraging is not compromised by the increased energetic cost of thermoregulation. It should be noted, however, that the rainfall data was collected from the nearest weather stations, thus, on-site conditions may not have been fully captured in the analysis. We found that most bat vocal activity occurred shortly after sunset and at warmer temperatures, as bat foraging activity (particularly *Pipistrellus* spp.) is known to peak shortly after sunset (Catto et al., 1995; Newson et al., 2015; Perks and Goodenough, 2020).

4.4. *Incorporating automated PAM in agri-environment schemes design*

With the rapid advances of digitisation in agricultural practices and policy (Ehlers et al., 2022), PAM using automated vocalisation ID is an opportunity to integrate large-scale, community-level monitoring into biodiversity conservation goals (Müller et al., 2022). Our results show that the simple metric of overall bird and bat vocal activity can be used to monitor bird and bat activity changes following hedgerow planting in AES. This relatively simple and cheap monitoring technique can be beneficial in the context of result-based schemes or hybrid schemes, where farmers may be expected to monitor and report the outcomes of AES on their own farms (Natural England, 2019) with a set of indicators that are often developed at the species-level (Elmiger et al., 2023). While species-level monitoring using PAM (i.e. requiring expert evaluation of the recordings) is not always cost-effective compared to human observations (Markova-Nenova et al., 2023), our results show that expert evaluation is not needed when considering the vocal activity of the wider bird or bat community. As ARUs can be purchased at low costs (e.g. Hill et al., 2019) and automated software for species ID are becoming widely available, community-level vocal activity could drastically reduce monitoring costs. Thus, vocal activity is a suitable candidate indicator for the design of future AES that are aimed at improving the provision of semi-natural habitat in agricultural land to benefit multiple species and taxa, such as hedgerow planting. Future hybrid hedgerow planting AES options, for example, could encompass a one-off action-based payment to compensate farmers for the costs incurred by planting hedges (e.g. currently UK farmers are paid £22.97 per meter of hedgerow planted, RPA, 2022), as well as a result-based annual payment tied to the delivery of increased vocal activity of all birds, farmland birds, and bats, as measured with automated PAM.

Incorporating automated PAM in the design of new hybrid schemes may provide an incentive for farmers to continuously manage the hedgerow in a biodiversity-friendly way, as well as planning the spatial placement of hedgerows with conservation explicit goals to benefit the wider bird and bat community. The effectiveness of AES placement and management in delivering ecosystem services is not usually considered by farmers across Europe when adopting AES (Bartkowski et al., 2023) and the management of hedgerows is essential to their continued ecological functioning within the farmed landscape (Staley et al., 2015). As hedgerow management is key to support birds and bats (Froidevaux et al., 2019; Staley et al., 2023), tying a fraction of AES payments to demonstrated increases in vocal activity may encourage farmers to adopt management practices that ensure the hedgerow remains in good quality, such as hedgerow rejuvenation and incremental trimming. Similarly, the incentive to demonstrate AES effectiveness may support farmer decision-making in the spatial planning of hedgerow placement. Our results show that hedges that are more connected, more diverse, and are accompanied by trees support greater bird and bat vocal activity. Thus, future hedgerow planting AES should promote the planning, development, and monitoring of hedgerow networks at the farm and landscape-scale that can subscribe to these characteristics (Staley et al., 2023), leaving to farmers the possibility to use their experience and local knowledge to achieve the targeted outcomes (Burton and Schwarz, 2013).

For automated PAM to be used as a monitoring tool in AES, further research should be conducted to establish trust in the application of this technology, so that it can be accepted and legitimized by ornithology and chiroptology experts, farmers, and the public. Firstly, clear guidance should be given on how to collect sound recordings within AES. Good-practice guidelines for PAM have been recently proposed in the UK (Metcalf et al., 2023); however, these highlight how many aspects of PAM have not been quantified or fully assessed yet. Importantly, research should inform the development of standard methods for the deployment of recorders, for calibrating the ARUs, and for ensuring a homogenous and replicable automated processing of the audio data (Pérez-Granados and Traba, 2021; Yip et al., 2021). For example, a hybrid approach that utilises PAM and occasional point count surveys has been proposed to deliver ground-truthing when relating vocal activity to abundance (and thus calibrate the recordings, Doser et al., 2021). In the case of bird monitoring, the continued refinement of BirdNET since its recent development (Kahl et al., 2021; Wood et al., 2022) suggests that in the coming years the software will be improved further. Future studies could use expert-labelled training data produced from different context-specific habitats, potentially improving species-level predictability by turning BirdNET from a (virtual) worldwide generalist birder to a well-versed (virtual) local field ornithologist that could be used to monitor AES practices that are targeting individual species. However, our results show that BirdNET already has a very high match precision, rendering it suitable for the assessment of community-level vocal activity for AES that deliver habitat improvements for many taxonomic groups, as with hedgerow planting.

Secondly, as both hedgerow and landscape characteristics strongly influence vocal activity of birds and bats, the analysis of automated PAM outputs should take into consideration hedgerow condition, as well as landscape composition and configuration (Batáry et al., 2020) in the statistical analysis of audio data. Robust and unbiased statistical analysis of automated PAM outputs is crucial in the case of result-based and hybrid AES, as their entire or partial compensation is tied to the proven positive outcome of the AES, also in light of concurring drivers at the landscape level (Concepcion et al., 2012). For example, individuals can move among and along hedges and the spatial range of vocal activity of birds and bats differ, as most breeding bird species in agricultural landscapes are most vocal within a small home range (McHugh et al., 2017; Loretto et al., 2019), while bats are vocal over much greater distances covered when foraging (Robinson and Stebbings, 1997; Froidevaux et al., 2017). Accounting for spatial autocorrelation and recording soundscapes over extended periods of time is essential when conducting automated surveys (Furnas and Bowie, 2020). We addressed the issue of spatial configuration of hedgerows using GAMs, and our results show that, although it is difficult to exclude some degree of correlation among pairs of ARUs, it is possible to measure differences in vocal activity between different hedge age categories.

5. Conclusions

Our results show that the application of PAM with automated vocalisation ID can be used to monitor simple metrics of bird and bat community-level changes following hedgerow planting. We found BirdNET to be a suitable tool to obtain measures of bird vocal activity without setting a minimum confidence threshold; instead, we highlight that species-level metrics obtained with BirdNET should be considered carefully, unless a confidence threshold of 0.5 is applied. However, setting this limit will also remove many true observations from the dataset. The results of this study suggest a positive effect of hedgerows on bird and bat vocal activity a decade after hedgerow planting, indicating a relatively short timeframe in which measurable differences in wildlife activity could be expected following large-scale hedgerow planting efforts within AES. We propose automated PAM as a simple and cost-effective monitoring tool that can be incorporated in the design and implementation of future result-based or hybrid AES, in which farmers may be asked to monitor and report indicators on their own land. Integrating automated PAM methodology in AES design and establishing trust in the outputs of this monitoring tool could be beneficial to encourage farmers to plant hedgerows with structural and spatial characteristics that can maximise biodiversity benefits. While we have used automated PAM to monitor the response of biodiversity to hedgerow planting, this novel technology could be applied to other interventions within AES, such as buffer strips, flower margins, or creation of ponds. Automated PAM is a rapidly developing tool that has the potential to play a central part in facilitating the cost-effective monitoring of the biodiversity response to AES and other restoration and conservation projects. However, further research is needed to establish trust with this practice and achieve its full potential.

CRediT authorship contribution statement

Sofia Biffi: Writing – review & editing, Writing – original draft, Visualization, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Pippa J. Chapman:** Writing - review & editing, Methodology, Project administration, Conceptualization. **Jan O. Engler:** Writing – review & editing, Methodology, Formal analysis. **William E. Kunin:** Funding acquisition, Conceptualization. **Guy Ziv:** Writing - review & editing, Methodology, Funding acquisition, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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Appendix A. Species identification similarity between pairs of ARUs

Methods

To check if pairs of ARUs closer to each other were likely to be recording vocalisations from the same individuals, we separately assessed the similarity of bird and bat species matches between all pairs of ARUs on each farm within a one-minute window. This time window was chosen as to account for potential drift in the internal clock of individual ARUs, as well as potential short-distance movements of bats and birds. To do this, for each ARU in a pair of ARUs, using Python v.3.9.0 we computed a matrix with species as columns and number of matches per minute as rows. We counted the number of overlapping matches (i.e. matches by the same species within the same one-minute window) by species using ARU1matrix.combine (ARU2matrix, numpy.minimim), taking the smaller of the two values within the one-minute window. The total number of matches was determined using ARU1matrix.combine(ARU2matrix, numpy.add). We computed the proportion of overlapping matches by species by dividing the number of overlapping matches by the total number of matches. The distance (m) between each pair of ARUs was calculated using *pointDistance* in **raster** (Hijmans, 2023). 'NoID' bat matches were excluded. Finally, we calculated the Spearman correlation between the proportion of overlapping matches per minute and the distance between ARU pairs.

Results

The similarity of species matches across all ARU pairs was low, with 73 % of one-minute windows of bird matches and 93 % of bat matches showing no overlap in species ID (Fig. 1). The correlation between the proportion of same species matches per minute and the distance between ARU pairs on the same farm also suggested low overlap ($|r|birds = -0.06$, $|r|bats = -0.05$). On average, the proportion of same species matches did not increase with total matches number for birds, while for bats same species ID occurred more likely at low number of matches per minute. For both bats and birds, there was a trend of decreasing similarity with increasing distance between ARU pairs (Fig. 1). However, the proportion of overlapping species matches remained low and across all ARU pairs that were ≤ 200 m apart, only 30 % of one-minute window with non-zero total bird matches showed any amount of overlap in species ID. This proportion was lower for bat matches (10 %). The ARU pair with the highest proportion of overlap in species matches was not the closest pair (52 m), but a pair 103 m apart for birds (17.5 %) and 73 m apart for bats (18.7 %).

Discussion

The overlap in species ID within a one-minute window was generally low, suggesting that we were not usually recording the same individual simultaneously. In birds, we found that similarity did not increase with the total number of matches, suggesting high diversity in species vocal activity also between ARU pairs that were closer. However, this result should be considered carefully in the light of the low accuracy in species ID by BirdNET. In bats, similarity in species ID increased when the number of matches was low, independently to distance between ARUs. This suggests that different ARUs were recording the same species at the same time, but not necessarily the same individuals. This is not surprising, as bats tend to forage in groups.

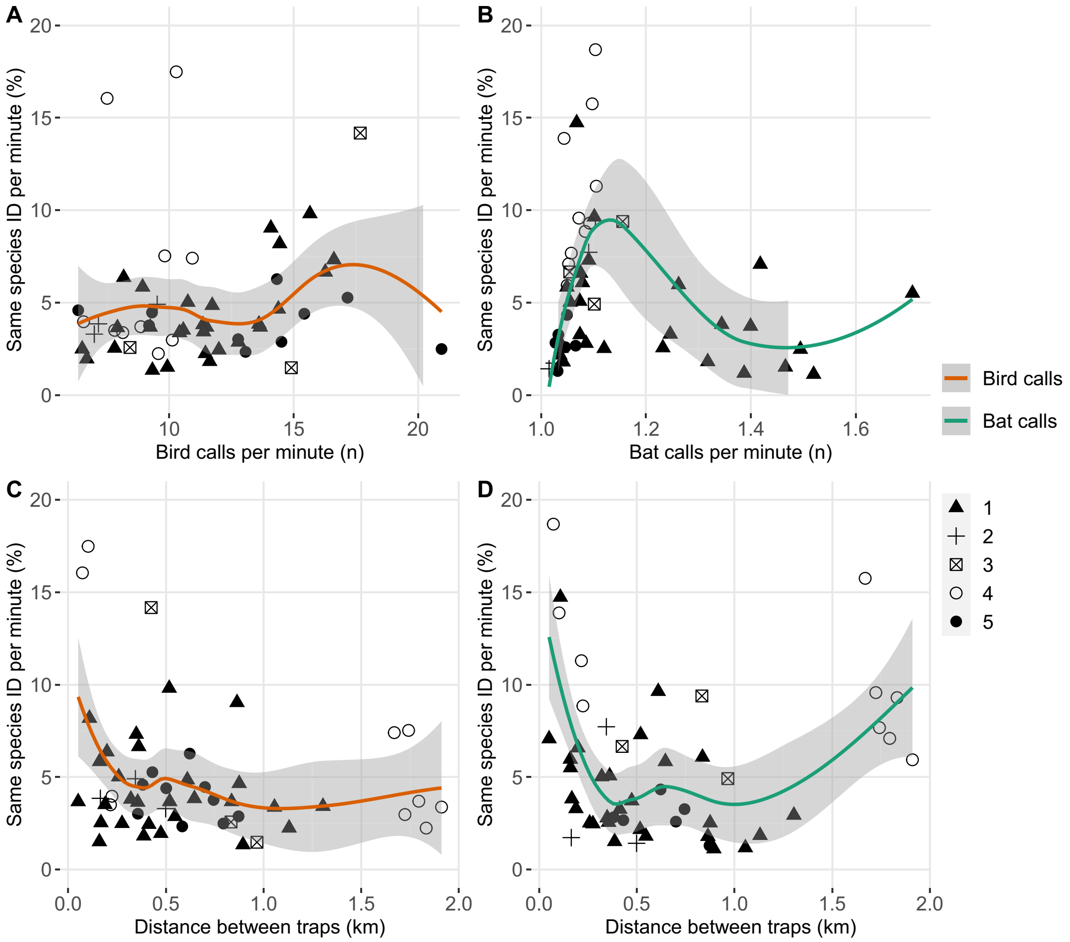
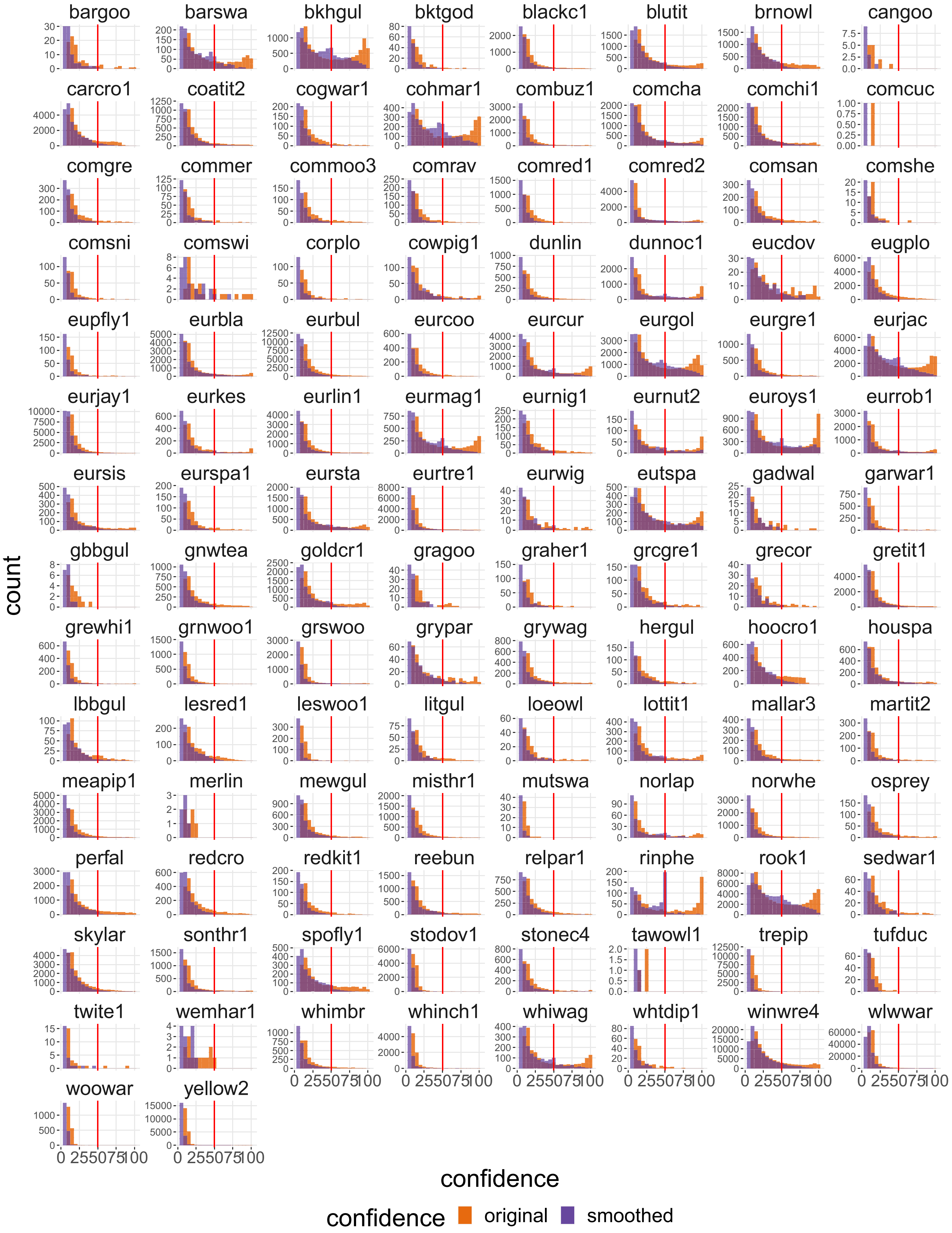


Fig. 1. Scatter plots and loess regression curves with 95 % confidence intervals visualizing the average proportion of identification of the same species for each ARU pair within a farm as a function of the total number of matches (A - birds and B - bats), and as a function of the distance between ARUs (C - birds and D - bats).

Appendix B. BirdNET confidence scores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coatit2
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comchi1
comcuc
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commer
commoo3
comrav
comred1
comred2
comsan
comshe
comsni
comswi
corplo
cowpig1
dunlin
dunnoc1
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eurcoo
eurcur
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eurjay1
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grecor
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grypar
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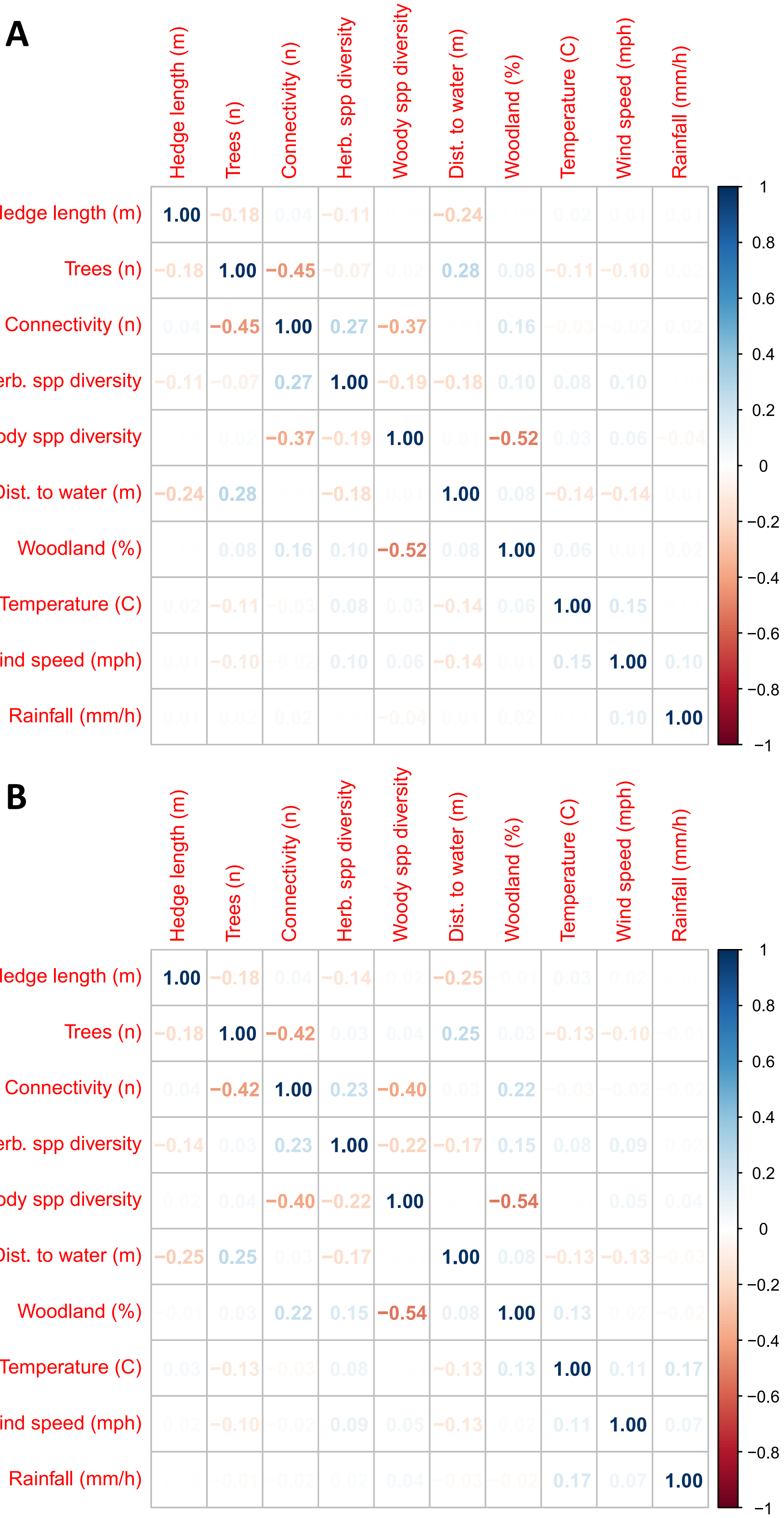
hergul
hoocro1
houspa
lbbgul
lesred1
leswoo1
litgul
loeowl
lottit1
mallar3
martit2
meapip1
merlin
mewgul
misthr1
mutswa
norlap
norwhe
osprey
perfal
redcro
redkit1
reebun
relpar1
rinphe
rook1
sedwar1
skylar
sonthr1
spofly1
stodov1
stonec4
tawowl1
trepip
tufduc
twite1
wemhar1
whimbr
whinch1
whiwag
whtdip1
winwre4
wlwwar
woowar
yellow2
count
0 25 50 75 100
confidence
confidence
original
smoothed

Fig. 1. Distribution of raw BirdNET confidence scores and confidence scores after smoothing and pooling with a moving exponential average window. The red vertical line marks the 50 % confidence threshold used for species IDs. Species codes are shown, for species common and scientific names see Appendix D. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Appendix C. Correlation plots



A

	Hedge length (m)	Trees (n)	Connectivity (n)	Herb. spp diversity	Woody spp diversity	Dist. to water (m)	Woodland (%)	Temperature (C)	Wind speed (mph)	Rainfall (mm/h)
Hedge length (m)	1.00	−0.18	0.04	−0.11		−0.24		0.02	0.01	0.01
Trees (n)	−0.18	1.00	−0.45	−0.07	0.02	0.28	0.08	−0.11	−0.10	0.02
Connectivity (n)	0.04	−0.45	1.00	0.27	−0.37		0.16	−0.03	−0.02	0.02
Herb. spp diversity	−0.11	−0.07	0.27	1.00	−0.19	−0.18	0.10	0.08	0.10	
Woody spp diversity		0.02	−0.37	−0.19	1.00	0.01	−0.52	0.03	0.06	−0.04
Dist. to water (m)	−0.24	0.28		−0.18	0.01	1.00	0.08	−0.14	−0.14	0.01
Woodland (%)		0.08	0.16	0.10	−0.52	0.08	1.00	0.06	0.01	0.02
Temperature (C)	0.02	−0.11	−0.03	0.08	0.03	−0.14	0.06	1.00	0.15	
Wind speed (mph)	0.01	−0.10	−0.02	0.10	0.06	−0.14	0.01	0.15	1.00	0.10
Rainfall (mm/h)	0.01	0.02	0.02		−0.04	0.01	0.02		0.10	1.00

B

	Hedge length (m)	Trees (n)	Connectivity (n)	Herb. spp diversity	Woody spp diversity	Dist. to water (m)	Woodland (%)	Temperature (C)	Wind speed (mph)	Rainfall (mm/h)
Hedge length (m)	1.00	−0.18	0.04	−0.14	0.02	−0.25	−0.01	0.03	0.02	
Trees (n)	−0.18	1.00	−0.42	0.03	0.04	0.25	0.03	−0.13	−0.10	−0.01
Connectivity (n)	0.04	−0.42	1.00	0.23	−0.40	0.03	0.22	−0.03	−0.02	−0.02
Herb. spp diversity	−0.14	0.03	0.23	1.00	−0.22	−0.17	0.15	0.08	0.09	0.02
Woody spp diversity	0.02	0.04	−0.40	−0.22	1.00		−0.54		0.05	0.04
Dist. to water (m)	−0.25	0.25	0.03	−0.17		1.00	0.08	−0.13	−0.13	−0.03
Woodland (%)	−0.01	0.03	0.22	0.15	−0.54	0.08	1.00	0.13	0.02	−0.02
Temperature (C)	0.03	−0.13	−0.03	0.08		−0.13	0.13	1.00	0.11	0.17
Wind speed (mph)	0.02	−0.10	−0.02	0.09	0.05	−0.13	0.02	0.11	1.00	0.07
Rainfall (mm/h)		−0.01	−0.02	0.02	0.04	−0.03	−0.02	0.17	0.07	1.00

Fig. 1. Correlation matrix of the environmental variables used for modelling vocal activity of (A) birds and (B) bats.

Appendix D. Bird species identified by BirdNET

Table 1

List of the 114 bird species identified by BirdNET in the recordings and their proportion in the dataset. The presence of each species in the region is classified according to regional census (Cumbria Biodiversity Data Centre, 2015; Cumbria Bird Club, 2022). FBI = Farmland Bird Indicator species. Presence in region is coded as: A = abundant, C = common, F = fairly common, U = uncommon, R = rare.

Species code	Common name	Scientific name	FBI	Proportion IDs (%)	Presence in region
wlwwar	Willow Warbler	*Phylloscopus trochilus*		18.6	A
winwre4	Eurasian Wren	*Troglodytes troglodytes*		11.2	A
rook1	Rook	*Corvus frugilegus*	Yes	7.2	A
eurjac	Eurasian Jackdaw	*Corvus monedula*	Yes	5.2	A
eurbul	Eurasian Bullfinch	*Pyrrhula pyrrhula*		3.9	C
eurjay1	Eurasian Jay	*Garrulus glandarius*		3.3	C
eurgol	European Goldfinch	*Carduelis carduelis*	Yes	2.7	A
carcro1	Carrion Crow	*Corvus corone*		2.4	A
yellow2	Yellowhammer	*Emberiza citrinella*	Yes	2.4	A
eugplo	European Golden-Plover	*Pluvialis apricaria*		2.2	A
skylar	Eurasian Skylark	*Auleda arvensis*	Yes	1.9	A
eurcur	Eurasian Curlew	*Numenius arquata*		1.9	A
gretit1	Great Tit	*Parus major*		1.9	A
trepip	Tree Pipit	*Anthus trivialis*		1.9	C
eurbla	Eurasian Blackbird	*Turdus merula*		1.8	A
eurtre1	Eurasian Treecreeper	*Certhia familiaris*		1.7	C
meapip1	Meadow Pipit	*Meadow Pipit*		1.3	A
comred2	Common Redstart	*Phoenicurus phoenicurus*		1.3	A
eurlin1	Eurasian Linnet	*Linaria cannabina*	Yes	1.2	A
perfal	Peregrine Falcon	*Falco peregrinus*		1.2	F
bkhgul	Black-headed Gull	*Chroicocephalus ridibunduns*		1.2	A
stodov1	Stock Dove	*Columba oenas*	Yes	1.2	C
comcha	Common Chaffinch	*Fringilla coelebs*		1.1	A
goldcr1	Goldcrest	*Regulus regulus*		1.0	A
eurrob1	European Robin	*Erithacus rubecula*		1.0	A
comchi1	Common Chiffchaff	*Phylloscopus collybita*		1.0	A
blutit	Eurasian Blue Tit	*Cyanistes caeruleus*		0.9	A
dunnoc1	Dunnock	*Prunella modularis*		0.9	A
whinch1	Whinchat	*Saxicola rubetra*		0.9	F
brnowl	Barn Owl	*Tyto alba*		0.8	F
eursta	European Starling	*Sturnus vulgaris*	Yes	0.8	A
norwhe	Northern Wheatear	*Oenanthe oenanthe*		0.8	A
combuz1	Common Buzzard	*Buteo buteo*		0.8	C
euroys1	Eurasian Oystercatcher	*Haematopus ostralegus*		0.8	A
blackc1	Eurasian Blackcap	*Sylvia atricapilla*		0.7	A
grswoo	Great Spotted Woodpecker	*Dendrocopos major*		0.6	C
eurmag1	Eurasian Magpie	*Pica pica*		0.5	A
reebun	Reed Bunting	*Emberiza schoeniclus*	Yes	0.5	C
misthr1	Mistle Thrush	*Turdus viscivorus*		0.5	A
coatit2	Coal Tit	*Coal tit*		0.4	A
sonthr1	Song Thrush	*Turdus philomelos*		0.4	A
eurgre1	European Greenfinch	*Chloris chloris*	Yes	0.4	A
mewgul	Mew Gull	*Larus canus*		0.4	A
cohmar1	Common House-Martin	*Delichon urbicum*		0.4	A
gnwtea	Green-winged Teal	*Anas carolinensis*		0.4	A
comred1	Common Redshank	*Tringa totanus*		0.4	A
eutspa	Eurasian Tree Sparrow	*Passer montanus*	Yes	0.3	C
hoocro1	Hooded Crow	*Corvus cornix*		0.3	U
relpar1	Red-legged Partridge	*Aectoris rufa*		0.3	A
whimbr	Whimbrel	*Numenius Phaeopus*		0.3	U
grnwoo1	Eurasian Green Woodpecker	*Picus viridis*		0.3	F
houspa	House Sparrow	*Passer domesticus*		0.3	A
redcro	Red Crossbill	*Loxia curvirostra*		0.2	U
grywag	Gray Wagtail	*Motacilla cinerea*		0.2	C
dunlin	Dunlin	*Calidris alpina*		0.2	U
spofly1	Spotted Flycatcher	*Muscicapa striata*		0.2	A
woowar	Wood Warbler	*Phylloscopus sibilatrix*		0.2	F
whiwag	White Wagtail	*Motacilla alba*		0.2	A
eurkes	Eurasian Kestrel	*Falco tinnunculus*	Yes	0.2	C
stonec4	European Stonechat	*Saxicola rubicola*		0.2	F
garwar1	Garden Warbler	*Sylvia borin*		0.2	A
lottit1	Long-tailed Tit	*Aegithalos caudatus*		0.2	A
eursis	Eurasian Siskin	*Spinus spinus*		0.2	C
eurcoo	Eurasian Coot	*Fulica atra*		0.2	C
barswa	Barn Swallow	*Hirundo rustica*		0.1	A
mallar3	Mallard	*Anas platyrhynchos*		0.1	A
grewhi1	Greater Whitethroat	*Sylvia communis*		0.1	A
comsan	Common Sandpiper	*Actitis hypoleucos*		0.1	C
comgre	Common Greenshank	*Tringa nebularia*		0.1	F

(*continued on next page*)

Table 1 (*continued*)

Species code	Common name	Scientific name	FBI	Proportion IDs (%)	Presence in region
lesred1	Lesser Redpoll	*Acanthis cabaret*		0.1	C
rinphe	Ring-necked Pheasant	*Phasianus colchicus*		0.1	A
eurnig1	Eurasian Nightjar	*Caprimulgus europaeus*		0.1	U
martit2	Marsh Tit	*Poecile palustris*		0.1	F
eurnut2	Eurasian Nuthatch	*Sitta europaea*		0.1	C
cogwar1	Common Grasshopper-Warbler	*Locustella naevia*		0.1	F
grcgre1	Great Crested Grebe	*Podiceps cristatus*		0.1	F
leswoo1	Lesser Spotted Woodpecker	*Dryobates minor*		0.1	R
comrav	Common Raven	*Corvus corax*		0.1	F
osprey	Osprey	*Pandion haliaetus*		0.1	U
eurspa1	Eurasian Sparrowhawk	*Accipiter nisus*		0.1	C
hergul	Herring Gull	*Larus argentatus*		0.1	A
redkit1	Red Kite	*Milvus milvus*		0.1	U
commoo3	Eurasian Moorhen	*Gallinula chloropus*		0.1	A
cowpig1	Common Wood-Pigeon	*Columba palumbus*		<0.1	A
lbbgul	Lesser Black-backed Gull	*Larus fuscus*		<0.1	A
graher1	Gray Heron	*Ardea cinerea*		<0.1	F
grypar	Gray Partridge	*Perdix perdix*		<0.1	F
norlap	Northern Lapwing	*Vanellus vanellus*	Yes	<0.1	A
commer	Common Merganser	*Mergus merganser*		<0.1	C
eupfly1	European Pied Flycatcher	*Ficedula hypoleuca*		<0.1	C
comsni	Common Snipe	*Gallinago gallinago*		<0.1	A
litgul	Little Gull	*Hydrocoloeus minutus*		<0.1	U
sedwar1	Sedge Warbler	*Acrocephalus schoenobaenus*		<0.1	C
corplo	Common Ringed Plover	*Charadrius hiaticula*		<0.1	F
eucdov	Eurasian Collared-Dove	*Streptopelia decaocto*		<0.1	A
tufduc	Tufted Duck	*Aythya fuligula*		<0.1	C
bktgod	Black-tailed Godwit	*Limosa limosa*		<0.1	F
whtdip1	White-throated Dipper	*Cinclus cinclus*		<0.1	C
loeowl	Long-eared Owl	*Asio otus*		<0.1	U
eurwig	Eurasian Wigeon	*Mareca penelope*		<0.1	U
grecor	Great Cormorant	*Phalacrocorax carbo*		<0.1	C
gragoo	Graylag Goose	*Anser anser*		<0.1	C
bargoo	Barnacle Goose	*Branta leucopsis*		<0.1	A
gadwal	Gadwall	*Mareca strepera*		<0.1	F
mutswa	Mute Swan	*Cygnus olor*		<0.1	F
comshe	Common Shelduck	*Tadorna tadorna*		<0.1	C
comswi	Common Swift	*Apus apus*		<0.1	C
twite1	Twite	*Linaria flavirostris*		<0.1	U
gbbgul	Great Black-backed Gull	*Larus marinus*		<0.1	F
cangoo	Canada Goose	*Branta canadensis*		<0.1	C
wemhar1	Eurasian Marsh-Harrier	*Circus aeruginosus*		<0.1	U
merlin	Merlin	*Falco columbarius*		<0.1	U
tawowl1	Tawny Owl	*Strix aluco*		<0.1	C
comcuc	Common Cuckoo	*Cuculus canorus*		<0.1	C

Appendix E. Results of GAMs on all bird vocal activity

Table 1

Result of GAM model of all bird vocal activity using both parametric terms and a non-parametric smooth tensor product of latitude and longitude of the recording units. Hourly data was used in the analysis.

Component	Term	Estimate	Std error	t-Value	*p*-Value
A. Parametric coefficients	Intercept	5.27	0.12	45.12	***
	Age class: Young	1.00	0.22	4.49	***
	Age class: Old	0.39	0.17	2.32	*
	Hedge length	−0.21	0.07	−2.80	**
	Connectivity	0.23	0.07	3.12	**
	Herbaceous spp. diversity	1.31	0.17	7.63	***
	Woody spp. diversity	1.02	0.17	6.07	***
	Distance to water	0.09	0.19	0.50	
	Trees	1.20	0.19	6.25	***
	Woodland	−1.59	0.30	−5.35	***
	Month (July vs June)	−0.25	0.03	−8.32	***
	Temperature	0.03	0.02	1.91	
	Wind speed	−0.24	0.01	−17.36	***
	Precipitation	−0.20	0.01	−14.86	***

Component	Term	edf	Ref. df	F-value	*p*-Value
B. Smooth terms	*te*(Lat, Long)	13.69	13.94	996.85	***

Adjusted R-squared: 0.51, deviance explained: 0.469.

[*] P < 0.05.

[**] P < 0.01.

[***] P < 0.001.

Appendix F. Results of GAMs on FBI species vocal activity

Table 1

Result of GAM model of Farmland Bird Indicator species vocal activity using both parametric terms and a non-parametric smooth tensor product of latitude and longitude of the recording units. Hourly data was used in the analysis.

Component	Term	Estimate	Std error	t-Value	*p*-Value
A. Parametric coefficients	Intercept	−0.65	0.19	−3.34	**
	Age class: Young	1.99	0.37	5.32	***
	Age class: Old	1.81	0.28	6.43	***
	Hedge length	−0.42	0.13	−3.15	**
	Connectivity	0.46	0.14	3.34	**
	Herbaceous spp. diversity	1.05	0.30	3.48	**
	Woody spp. diversity	1.14	0.27	4.16	***
	Distance to water	1.08	0.31	3.44	**
	Trees	1.81	0.31	5.75	***
	Woodland	−1.43	0.49	−2.92	**
	Month (July vs June)	−0.49	0.05	−8.91	***
	Temperature	0.06	0.03	2.17	*
	Wind speed	−0.12	0.03	−4.60	***
	Precipitation	−0.23	0.03	−6.84	***

Component	Term	edf	Ref. df	F-value	*p*-Value
B. Smooth terms	*te*(Lat, Long)	13.64	13.92	515.58	***

Adjusted R-squared: 0.34, deviance explained: 0.322.

[*] P < 0.05.

[**] P < 0.01.

[***] P < 0.001.

Appendix G. Results of GAMs on bat vocal activity

Table 1

Result of GAM model of Farmland Bird Indicator species vocal activity using both parametric terms and a non-parametric smooth tensor product of latitude and longitude of the recording units. Hourly data was used in the analysis.

Component	Term	Estimate	Std error	t-Value	*p*-Value
A. Parametric coefficients	Intercept	2.17	0.14	15.03	***
	Age class: Young	0.66	0.29	2.24	*
	Age class: Old	0.46	0.18	2.58	*
	Hedge length	−0.09	0.11	−0.86	
	Connectivity	−0.34	0.11	−3.12	**
	Herbaceous spp. diversity	0.33	0.17	1.92	
	Woody spp. diversity	0.56	0.12	4.52	***
	Distance to water	−0.81	0.29	−2.82	**
	Trees	0.74	0.14	5.20	***
	Woodland	−0.78	0.20	−3.89	***
	Month (July vs June)	−0.42	0.05	−8.41	***
	Temperature	0.23	0.03	8.40	***
	Wind speed	0.08	0.02	3.47	**
	Precipitation	0.11	0.02	5.19	***

Component	Term	edf	Ref. df	F-value	*p*-Value
B. Smooth terms	te(Lat, Long)	11.84	12.26	367.71	***

Adjusted R-squared: 0.23, deviance explained: 0.236.

[*] P < 0.05.

[**] P < 0.01.

[***] P < 0.001.

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