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A novel citizen science approach for large-scale standardised monitoring of bat activity and distribution, evaluated in eastern England

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ABSTRACT

In many countries, bats have high conservation prioritisation owing to their trophic position, habitat associations and threat level, and many have dedicated management plans. However, poor knowledge of species' ecology, identification issues and surveying challenges mean that large-scale monitoring to produce required distribution and abundance information is less developed than for some other taxa. Static detectors deployed to record bats throughout whole nights have been recommended for standardised acoustic monitoring but to date their cost has prohibited wide uptake. Here we describe an extensive survey approach in which members of the public borrowed detectors to participate in a large-scale monitoring and mapping project. Covering a 15% sample of the study area over two years, the survey generated over 600,000 bat recordings. We describe a semi-automated step-wise method for processing this large volume of recordings to assign identity to species or genus level with low error rates. Twelve species were recorded during the survey, ranging from the near ubiquitous Common Pipistrelle *Pipistrellus pipistrellus* to the locally scarce Leisler's bat *Nyctalus leisleri*. We show pronounced patterns of seasonality consistent with post-breeding dispersal and new information on nocturnal activity patterns. Using regression trees we generate new maps of standardised variation in activity which is likely to reflect underlying spatial variation in relative abundance. These reveal hitherto unknown patterns for species of superficially similar status. We conclude that with logistical support and centralised automated species identification it is now possible for the public to contribute to acoustic bat monitoring at an unprecedented scale.

1. Introduction

Biodiversity is facing an unprecedented decline whilst the pressure on the earth's ecosystems continues to grow (Butchart et al., 2010). Recognising the status of biodiversity and its benefit to human well-being, the world's governments committed in 2010 to take effective and urgent action to halt biodiversity loss through the Convention on Biological Diversity's targets (de Heer et al., 2005; Pereira et al., 2010). These targets require monitoring to assess progress towards specific goals. Such large-scale biodiversity assessment calls for methods which are able to provide an understanding of large-scale patterns in species' distributions, abundances and changes over time (Pereira and Cooper, 2006; Jones, 2011). This relies on surveys to collect data that are representative at a regional to national scale, and robust analysis that is able to provide an informed understanding of species' populations (Magurran and Dornelas, 2010).

As a group, bats (Chiroptera) are challenging to monitor because most are nocturnal, wide-ranging and can be difficult to identify. Historically the monitoring of bats in temperate regions has focused on intensive (site-based) visual counts at volunteer-selected winter or summer roosts (Battersby, 2010; Haysom et al., 2014) or capture surveys (Hayes et al., 2009). There is considerable value in these approaches, but it is difficult to confidently infer from these what is happening at a wider population level. For conservation purposes, it is essential that small-scale or local processes be distinguished from processes that may affect populations over larger scales. Therefore, the ability to also assess processes operating at a broader population level is necessary, for which an extensive regional, approach is required.

With developments in passive bat detectors and software for semi-automating the analysis of sound files, there is the potential to provide large-scale representative acoustic monitoring of bat species distribution and activity as a measure of relative abundance (Lintott et al., 2014). Stahlschmidt and Brühl (2012) recently highlighted concerns mirrored in the wider literature (Hayes, 2000; Sherwin et al., 2000; Gannon et al., 2003) that current methodology for monitoring bat populations using acoustic methods often fails to address temporal and spatial variation in bat activity. We would go further to say that more generally, robust information on species occurrence and activity are lacking, with researchers relying on presence-only data, where there is no direct information on absences (strictly absence or non-detection), and which is often obtained through unstructured opportunistic sampling. As a consequence, most recent spatial modelling has used presence-only data (but see Rodhouse et al., 2012; Meyer, 2014).

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The usual argument for using presence-only data has been that large scale presence/absence data and abundance data sets are unavailable or unreliable, but little work has looked at designing work to improve the quality or availability of these data. Clearly a standardised bat survey method using a suitable detector system recording bat activity as a measure of relative abundance and presence/absence is needed. This is particularly important because significant population declines of species of high conservation concern may occur before any reduction in range is observed (Gaston, 2003), where measures of abundance are regarded as the most informative variable for monitoring change in populations and essential for underpinning local and national decision making, targeting of conservation action and providing evidence for biodiversity reporting.

Comparing two widely used methods to survey bat activity, walked line transects and static detectors, Stahlschmidt and Brühl (2012) demonstrated that the use of automatically triggered (often known as passive) real-time bat detectors placed at randomly selected points to record all night, is most likely to produce unbiased standardised data on the relative activity of bats. Whilst this might be ideal, in practice the cost of real-time bat detectors required for this purpose remains high, so this technology and approach has largely been restricted to localised intensive use by environmental consultants or university research groups. In contrast, well developed volunteer-based national or regional bat monitoring programmes typically use simple, tuneable heterodyne detectors that focus on detecting the presence of a small number of relatively easily identifiable species, with the survey methods designed to be as inclusive as possible and using affordable bat detectors to maximise participation and geographical coverage (e.g. the United Kingdom's National Bat Monitoring Programme, NBMP; Barlow et al., 2015). Few species are easily monitored through these methods due to the difficulty in confidently distinguishing the calls of many species, and it is often difficult to produce a standardised measure of bat activity for the suite of species that can be monitored (Walters et al., 2013).

One approach for getting better species coverage and higher quality acoustic data has been the iBats program (www.ibats.org.uk) (Jones et al., 2013), where volunteers across a number of European countries drive along roads at night, using more expensive time-expansion broad-band detectors to record bats. Similar projects are being carried out in other countries (e.g. Ireland, Roche et al., 2011). In doing so, this approach is able to make use of a small number of volunteers and limited equipment to potentially obtain a large volume of data to inform on species distributions. Because of the simplicity of the survey design, the approach is increasing our knowledge of large-scale distribution patterns across a large geographic area, and by making repeat visits to the same transects at the same time of night, it has the potential to provide a robust measure of change in relative abundance on surveyed transects. Assuming that driven transects are faster than a bat can fly, it can also be assumed that recordings relate to different individuals. Its limitations are that it is difficult to compare bat activity directly within and between transects because activity is likely to vary with time of night (Hayes, 2000). In addition, conclusions from a monitoring project based on the road network can only be made in relation to roadside habitats, which may not be representative of wider bat populations (Roche et al., 2011). Similar criticism has been made of the North American Breeding Bird Survey, where restricting bird surveys to roadsides has been shown to limit the representativeness of the data, resulting in skewed abundance, distribution and community composition data (Thogmartin et al., 2006; Betts et al., 2007; Niemuth et al., 2007; McCarthy et al., 2012), reducing the reliability of associated population and trend estimates and distribution models that are developed to guide conservation-related programmes (Bart et al., 1995, 2004; Francis et al., 2005; Sauer et al., 2005).

Clearly for the large-scale monitoring of bat activity there is a need for a standardised survey design. The objectives of this study were to trial the recording of bat activity using passive real-time detectors, to gauge the willingness of members of the public to engage in bat monitoring on a large scale, and to determine the suitability of automated identification routines for processing large volume of citizen-collected recordings. We describe this approach and carry out a critical evaluation of the different stages of the approach, from field deployment to bat identification, and provide provisional results indicating the insights such a scheme can provide for understanding bat status and ecology, and potential for informing conservation planning.

2. Methods

2.1. Norfolk and the Norfolk Bat Survey protocol

Norfolk is a coastal county of 5371 km^2 in eastern England (Fig. 1). It is dominated by arable farmland with scattered woodlands and towns, plus significant wetland-dominated landscapes of international importance (e.g. the Norfolk Broads) and Breckland, an area of sandy heathland and forest (Dymond, 1990). It has not previously been the subject of large-scale bat monitoring, but local studies and ad hoc recordings have to date recorded 12 species (Table 1) including a cryptic species pair where acoustic identification is particularly difficult (Whiskered bat *Myotis mystacinus* and Brandt's bat *Myotis brandtii*). The mixture of landscapes, distribution of observers and local NGOs (see below) made it a good choice for trialling large-scale volunteer-based bat recording.

The Norfolk Bat Survey (www.batsurvey.org) was set up in spring 2013 to enable members of the public to have access to passive real-time bat detectors which they could place in a location of their choice within Norfolk to automatically trigger and record the calls to a memory card every time a bat passes throughout a night. We collaborated with several organisations and local libraries across the county to set up 21 "Bat Monitoring Centres" at existing centres used by the public from which anyone could borrow the equipment for a few days (Wildlife Acoustic SM2Bat+ detector recording in full-spectrum at 384 kHz, see Waters and Barlow, 2013). Microphones were mounted on 3-m poles to avoid ground noise and reduce recordings of reflected calls, and a low pass filter of 8 kHz used to reduce the chance of non-bat noise from triggering the detector. Recording was set to continue until no trigger was detected for a 2.0 second period. Guidance was given to avoid surveying bats in persistent heavy rain, strong wind or if the nightly temperature was predicted to fall well below 7 °C, and on the placement of microphones which should be deployed at least 1.5 m in any direction from vegetation, water or other obstructions. Intensive field trials were carried out prior to the survey season to inform a decision on the survey effort required to provide a reliable representation of species present within a 1-km square (Newson et al., 2014). Based on this, a compromise of three complete nights of recording at three different points located at least 200 m apart within each 1-km square was taken, accepting that species at low density or with a low detection probability may be missed over three nights of recording (see also Skalak et al., 2012). At the end of the three nights of recording, the memory card was returned to the British Trust for Ornithology (BTO) for analyses, along with a completed recording form giving the dates and grid references at which the detector was used. In return for collecting data, participants were sent a summary of the bat species they recorded within a few days of taking part. Using this method, members of the public were given an opportunity to participate in bat surveys and take advantage of bat recording technology that would not normally be available to them. The survey period ran from mid-April to the end of September to cover the core period of bat activity in the UK, and to maximise use of the equipment during the year. Ideally, 1-km squares would be selected and allocated at random to volunteers to ensure representative coverage across the county. In this project we allowed for a free choice of 1-km squares to encourage participant uptake, but on the understanding that we would need to test for and potentially correct for likely bias towards sampling in or near areas of human habitation. Here we make use of data from the first two years of the survey.

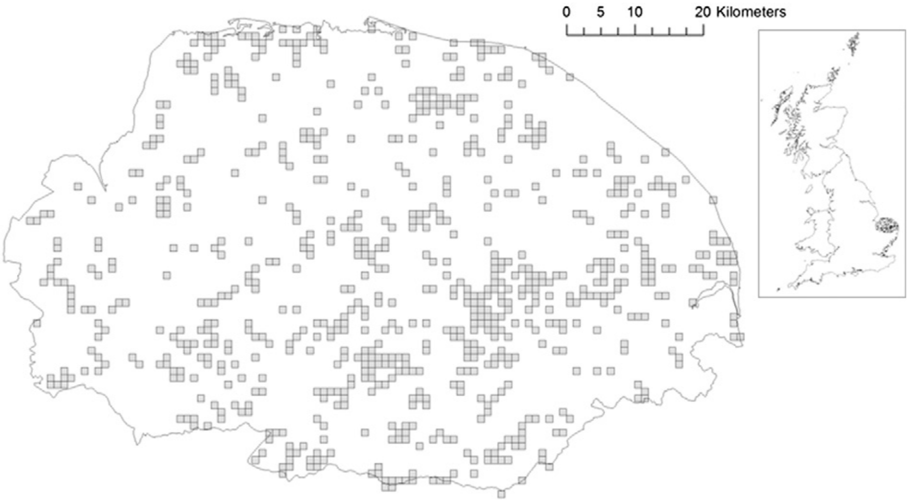

Fig. 1. Distribution of 1-km squares surveyed through the Norfolk Bat Survey and location in relation to Great Britain (inset).

2.2. Semi-automated acoustic identification of bats

Passive real-time detectors are triggered when they detect sound within a certain frequency range. We define this as one recording, and a recording may contain any number of bat calls, or none if triggered by other taxa or ambient high-frequency sounds. Using this technology, bat monitoring on this scale generates an enormous volume of recordings: often over 1000 sound recordings per detector per night. To process such a volume of acoustic data necessitated semi-automated analyses to assign recordings to species and here we assess classification accuracy by additional manual checking.

A first analysis (Step 1) was carried out using the software SonoChiro (www.biotope.fr/fr/innovation/sonochiro) to assign each recording to species. SonoChiro uses a classification tree developed from call measurements taken from an extensive (>250,000) database of recordings of known species recorded on the same detector type to assign identity to all calls in the first 5 s of each recording (Biotope, 2013). From these, recordings not containing bat recordings are identified, and where they do, each is assigned to species and given a confidence index related to the probability of correct classification (as compared with the underlying training database) on a scale of 0–10, but this is poorly defined. It is not linearly related to a probability of correct classification and may be suppressed if acoustically similar species are in SonoChiro's reference sample, even if those species are known to be absent from the study area. Of particular relevance here are Kuhl's Pipistrelle *Pipistrellus kuhlii*, Grey long-eared bat *Plecotus austriacus* and a number of *Myotis* species which are not thought to be present in the survey area, but are similar acoustically to species that are. Owing to these uncertainties we performed additional filtering and manual checking of recordings.

Record filtering (Step 2) was performed in SAS (SAS, 2002) to remove the following recordings: recordings with insufficient acoustic information, here judged to be those containing fewer than three bat calls; those containing sounds from other taxa (e.g. bush-crickets) or other ambient noises; or where the confidence index was zero (typically resulting from poor quality recordings). Recordings, with a confidence index of 1 or 2, judged to have “high” error risk (Biotope, 2013) were reassigned to species group or genus and are not used further in this paper.

Manual checking (Step 3) using software SonoBat (www.sonobat.com) was used as an independent check of the original species identities assigned by SonoChiro (Step 1) and the filtering (Step 2). We manually checked 10,000 of the recordings removed in Stage 2 to determine whether manual analysis would have given a species identity. Next, for 10 of the 12 species, all recordings retained after Step 2 were inspected with SonoBat and identity was checked and re-coded if necessary based on call parameters defined in Russ (2012) and Barataud (2012). For example, a strict criterion for Nathusius' Pipistrelle *Pipistrellus nathusii* identification is for the end frequency of all calls within a recording to fall below 40 kHz (see Table A1 for a summary of important call parameters used in Step 3). The call shape (hockey-stick shaped) and frequencies of Common *P. pipistrellus* and Soprano Pipistrelle *Pipistrellus pygmaeus* are characteristic so discrimination should be good. For Common and Soprano Pipistrelles which made up >95% of all recordings we checked a random sample of 1000 recordings each. Recordings of Whiskered or Brandt's bat were treated from this point as a species pair.

Table 1
Bat species detected by the Norfolk Bat Survey, number of recordings of each species following validation and a summary of the scale of recording.

Species	Species code	No. of recordings following validation	No. of different 1-km squares (% of total)
Daubenton's bat, *Myotis daubentonii*	Mdau	1823	202 (23%)
Whiskered/Brandt's bats, *Myotis mystacinus*/*M. brandtii*	Mmys/Mbra	521	168 (22%)
Natterer's bat, *Myotis nattereri*	Mnat	1112	265 (34%)
Noctule, *Nyctalus noctula*	Nnoc	6377	473 (62%
Leisler's bat, *Nyctalus leisleri*	Nlei	277	78 (10%)
Serotine, *Eptesicus serotinus*	Eser	2406	278 (36%)
Common Pipistrelle, *Pipistrellus pipistrellus*	Ppip	326,008	755 (99%)
Soprano Pipistrelle, *Pipistrellus pygmaeus*	Ppyg	170,938	728 (95%)
Nathusius' Pipistrelle, *Pipistrellus nathusii*	Pnat	916	211 (28%)
Brown long-eared bat, *Plecotus auritus*	Paur	1977	360 (47%)
Barbastelle, *Barbastellus barbastellus*	Bbar	1988	308 (40%)

2.3. Seasonal and nightly patterns of bat activity

To assess how important night-long recording over a long survey season was for effective monitoring, we performed simple summaries of seasonal and hourly presence and activity. Reporting rates were determined for each half-month period and presented according to the percentage of sample squares on which each bat species was detected. Where sample squares were surveyed more than once in a period, we combined data across visits. Activity through the night was analysed by first converting all bat pass times to time since sunset (sunset times from http://data.gov.uk/dataset/uk-sunrise-sunset) and then assessing the frequency distribution of passes relative to sunset for the whole season and in half-month periods.

2.4. Habitat bias

Allowing participants to choose survey squares could have generated geographical bias in coverage, particularly towards areas of habitation. Because environmental bias in datasets can be very influential when predicting spatial patterns of distribution and activity (e.g. Leitão et al., 2011), we evaluated the extent to which the habitat composition of surveyed 1-km squares deviated from a random sample using habitat summarised at a 1-km square resolution and derived from fine-scale remote sensing data made available through the Joint Nature Conservation Committee/Department for Environment, Food and Rural Affairs-funded project "Making Earth Observation Work for UK Biodiversity" (MEOW; Medcalf et al., 2014). In this, Norfolk has been used as pilot for providing habitat mapping for 16 priority habitats and ecosystems for monitoring and reporting against the Habitats Directive and the UK Biodiversity Action Plan. The availability of each habitat type was summarised across 1-km squares in Norfolk, showing that, for example 67% of Norfolk was arable. Ideally, the sample of surveyed 1-km squares would match these values within a margin of error in line with the sample size achieved, which we determined by repeatedly randomly sampling *N* squares, where *N* was the number of squares surveyed. Sampling was repeated 1000 times and the 25th and 975th ranked values of the availability of each habitat across the random samples were found and expressed as a percentage of the actual habitat availability values. A comparison of the habitat coverage achieved compared to these 95% confidence limits indicates which habitats were significantly over- or under-represented in the sample of surveyed squares.

2.5. Spatial models of bat distribution and activity

To evaluate the value of the data collected here for informing our understanding of bat activity and species distributions at a large spatial scale, it was necessary to consider the data in a spatial modelling framework. A number of analytical frameworks are capable of modelling the relationship between species distribution or activity and their environment. We used Generalised Boosted Regression models, which are an ensemble implementation of Regression Trees that have performed well in model comparison studies (e.g. Elith et al., 2006; Prasad et al., 2006; Cutler et al., 2007; Franklin, 2009; Heikkinen et al., 2012). Regression Trees are increasingly being used to predict species distributions, but application to abundance type data is limited to a few studies (Iverson and Prasad, 1998; Moisen et al., 2006; Leathwick et al., 2006; Balmer et al., 2013). For bats we are not aware of any previous study that has attempted to model spatial patterns of activity, and most species distribution modelling has used presence-only data (e.g. Bellamy et al., 2013; Rebelo and Jones, 2010). Presence-only models are useful in their ability to rank sites for their relative suitability. These methods can be informative, where absence data are not available. However where absence data are available, it is recommended that approaches that use these data are prioritised (Brotons et al., 2004; Segurado and Araújo, 2004; Pearson et al., 2006).

Generalised Boosted Regression is a machine learning method that estimates the form of the relationship between a response variable and its predictors without a priori specification of a data model (Elith et al., 2008). This technique estimates a large number of simple models, which are combined to form a final model optimised for prediction, using cross-validation for model building. Models were produced using the R package gbm (Ridgeway, 2013) and using the gbm.step function of Elith and Leathwick (2011) to find the appropriate learning rate and number of trees, with all trees having up to 10 nodes. Models were trained with 10-fold cross validation with a bagging fraction of 0.5 and assessed for predictive performance using either the area under the ROC curve (AUC) for occurrence models or the correlation coefficient between observed and predicted value for bat activity. For evaluation of AUC values, we used the approach recommended by Swets (1988): excellent AUC $>$ 0.90; good 0.80–0.90; fair 0.70–0.80; poor 0.60–0.70; and fail 0.50–0.60 although we accept that these divisions are fairly arbitrary. For occurrence models, data partitioning for cross validation was stratified by prevalence and in all models observations were weighted to account for the post-survey stratification to control for habitat bias, which is described later. For occurrence models we assumed a Bernoulli distribution for the response variable and for activity models, a Poisson distribution.

Before analysis, the bat data used in the models was first standardised. Bat detectors operated all night, but night length varies two-fold over the season, therefore markedly changing effort for detection and the potential number of passes recorded. Based on patterns of activity with respect to sunset time (see Results) we standardised all data by considering only bat passes up to 6 h after sunset. Detectors were usually in situ and recording before sunset and for certain species (e.g. Noctule) some passes occur before sunset but these were a minority (only 0.7% of detected passes were before sunset). Using this ~6 operating hour window we determined presence/absence and the total number of bat passes by species for each visit.

To generalise the recordings at sample locations to the rest of the region we needed to consider factors that are likely to influence bat presence and activity. In terms of covariates included in the models, weather conditions can affect the activity of bats at a given location (e.g. Barlow et al., 2015). For each 1-km square in Norfolk, we extracted hourly minimum temperature, precipitation and wind speed recorded at the closest weather station (MIDAS Land and Marine Surface Stations Data — available from http://badc.nerc.ac.uk/view/badc.nerc.ac.uk__ATOM__dataent_ukmo-midas), and then summarised these for the 6-hour recording window of each visit (minimum temperature, mean wind speed, total precipitation).

Some bat species have precise feeding and roosting requirements so habitat in and around the sampling location is likely to affect the species present. Habitat summarised at a 1-km square resolution was derived using the MEOW dataset containing 16 habitat types and described above. In addition, habitat availability in the wider landscape was quantified because bats forage over a wider area than a 1-km square, although typically within 1–3 km of their roost (Senior et al., 2005). Because habitat data for the 16 priority habitats was only available for Norfolk itself and not for land bordering this, we used satellite-derived land cover data (10 Land Cover Map 2000 aggregate classes, Fuller et al., 2002) to determine the area of each habitat within the 1-km square of interest and its neighbouring squares (9 km^2). Two further larger landscape extents (16 km^2 and 25 km^2) were considered at the beginning of the study, but because landcover variables were strongly correlated across landscape scales ($r > 0.90$), we chose to use a single landscape scale that best fitted known home range sizes. Because bat distribution and activity may vary seasonally, week number was also included as a covariate.

We focus here on 12 species of bat known to occur in Norfolk with Whiskered and Brandt's bats which are difficult to distinguish acoustically treated together as a species pair. Once models had been trained, predictions of occurrence probability and activity (pass frequency) were made for week 27 (mid-season) for each species in every 1-km square across Norfolk, using habitat data for each square and under normal (mean) weather conditions for that time of year. For presentation purposes, activity predictions less than 0.5 passes per night (strictly first 6 h of night) were removed and we only present maps for species where at least 100 grid squares remained. All probability of occurrence maps use the same colour scale, ranging from >0 to 1 in increments of 0.1. Bat activity maps use either a five or a 10-colour scale, where grid cells are placed into bands according to pentiles or deciles of predicted activity. Gini coefficients, which provide a degree of aggregation among a set of values, were used to assess the degree to which bat occupancy and activity were uniform (coefficient tends to 0) or aggregated (coefficient tends to 1) among 1-km squares. Gini coefficients were calculated using the ineq package in R (Zeileis, 2014).

3. Results

3.1. Survey coverage

785 different 1-km squares (15% of Norfolk) were surveyed for bats over the two seasons of 2013 and 2014. This comprises 2653 complete nights of recording, which has resulted in the collection and analyses of over half a million bat recordings from across the county (Fig. 1, Table 1).

3.2. Assigning and validating species identity

Of 611,672 recordings, analysis with SonoChiro successfully assigned 549,863 recordings (90%) to one of the 12 species known to occur in the survey area (Table 2). Of the remaining 10%, 47,006 recordings (8%) were determined as not containing bat calls and 14,803 recordings (2%) were assigned to species not thought to be present in the county. A manual check of 1000 recordings deemed to not contain bat calls revealed mainly bush-crickets and other unidentified noise, and we are confident that few real bat recordings were rejected at this stage.

In Step 2, 41,096 recordings (7%) assigned to bat species were removed where the confidence index produced in SonoChiro was less than 3, or where identity was based on fewer than three calls (Table 2). The proportion of recordings rejected varied among species from 3% of Common Pipistrelles to 67% of Daubenton's. When a random sample of 10,000 of these recordings was analysed manually, less than 5% could be assigned to species. Overall, we estimate that only c. 2000 recordings (0.4%) would have been assigned to species if these recordings had been manually checked.

In Step 3 of the validation the identity of the retained bat recordings were checked manually (Table 2). For most species, the identity assigned automatically by SonoChiro was accepted for over 85% of recordings and less than 1% of all recordings were reclassified to a different species, given the high confidence in the automated procedure. The exception was the cryptic species pair Whiskered/Brandt's bat in which 68% of recordings could be assigned only to the *Myotis* genus, and were thus removed from subsequent analysis. Manual checking of 1000 randomly selected recordings each of Common and Soprano Pipistrelles suggested that only about 1% of recordings were incorrectly assigned, which we deemed an acceptable error rate for these highly abundant species.

3.3. Habitat composition of surveyed squares

Arable habitat availability in the sample of surveyed squares was 83% of the true availability, whereas a random sample of the same size would have yielded 97–103% of the true availability. That the observed coverage fell outside the 95% confidence limits indicates that the choice of squares by Norfolk Bat Survey volunteers resulted in a significant under-sampling of arable habitat (Fig. A1), which is by far the most common habitat type in the survey area (67% of Norfolk). In contrast urban habitat and gardens, which together comprise less than 9% of

Table 2
Results showing the process involved in analysing and validating acoustic bat data collected through this project, and the number of recordings removed or reassigned to genus or species at each step of this process. Species codes as in Table 1.

Identity	Step 1. Initial analysis	Step 2. Secondary recoding		Step 3. Manual analysis of recordings: recordings reassigned							
	Initially assigned to species	Recordings removed (confidence index < 3 and/or < 3 calls)	Confidence index at end of Step 2 (median, range)	Recordings manually checked	% unchanged	*Myotis*	*Nyctalus*	*Nyctalus* or *Eptesicus*	*Pipistrellus*	Reassigned to another species	Reassigned to this species from another spp.
Mdau	5403	3635	3 (3–6)	1768	90%	177	0	0	0	0	232
Mmys/Mbra	3471	1950	3 (3–6)	1521	28%	1049	0	0	2	44	95
Mnat	1793	491	4 (3–10)	1302	85%	169	0	0	0	26	5
Nnoc	8032	785	8 (3–10)	7247	88%	0	217	652	0	0	0
Nlei	673	357	5 (3–10)	316	87%	0	0	19	0	22	2
Eser	4053	1623	4 (3–9)	2430	99%	0	0	10	0	15	0
Ppip	338,260	8969	10 (3–10)	1000 (sample)	99%	0	0	0	0	10	10
Ppyg	179,482	6826	10 (3–10)	1000 (sample)	99%	0	0	0	0	9	9
Pnat	1740	733	5 (3–10)	1007	91%	0	0	0	81	10	0
Paur	4224	2264	5 (3–10)	1960	99%	20	0	0	0	0	37
Bbar	2732	744	8 (3–10)	1988	100%	0	0	0	0	0	0
Bat species (previously unrecorded)	14,803	12,719	3 (3–5)	2084	0%	1855	188	0	0	42	–
Non-bat (bush-crickets, other ambient noise)	47,006	–	–	–		–	–	–	–	–	–

Norfolk, were significantly more likely to be surveyed, as were improved grassland and deciduous woodland (Fig. A1). Of less importance, three very rare habitats, fen, marsh and bog, heathland and semi-improved poor habitat were more likely to be surveyed than expected given a random sample. Whilst free-choice of 1-km squares cannot replace a random sample, to try and control for this bias, we ordered surveyed squares by the percent arable habitat present in the square, for which there was the greatest discrepancy in coverage, and split the squares into two groups containing an equal number of squares (squares containing less or more than 57% arable), which we will refer to here as low arable and high arable. The whole of Norfolk was similarly divided into these strata using the same cut-point, and resampling as before but now within strata. By doing this, the amount of arable sampled by the Norfolk Bat Survey within each stratum, was now not significantly different from a random sample (Fig. A1). The amount of urban habitat and gardens sampled within each stratum remained significantly higher than a random sample, but in all cases represented less than 3% more urban habitat or gardens surveyed than expected from random sample. In the same way that a weighting is included in the analyses of stratified random data to control for unequal representation of different strata (e.g. UK Breeding Bird Survey; Harris et al., 2014), a weighting was calculated here as the inverse of the proportion of the area of each stratum that was surveyed, and included in subsequent modelling of bat distribution and activity.

3.4. Temporal variation in bat occurrence and activity

Examining the nightly activity of bats through the season with respect to sunset time, we found that the core activity of bats occurred in the first 6 h after sunset irrespective of the time of the year, length of night and species (Figs. 2 and A2). However, most species showed some evidence of low levels of activity later into longer nights (Fig. 2), highlighting the need to standardise data prior to analysis when considering nights of variable length. There were large differences between species in the timing of activity. For example Brown long-eared bat *Plecotus auritus* showed little change in activity between 1 and 6 h after sunset, whilst Common and Soprano Pipistrelles were most active shortly after sunset with activity falling thereafter (Figs. 2 and A2). Noctule *Nyctalus noctula* showed the characteristic activity peak in the first 2 h after sunset but we also detected a second smaller peak in the early hours of the morning (Fig. A2). Examining the proportion of squares reporting each species across months showed that the likelihood of detecting some species on a 1-km square was not constant between April and October. Particularly pronounced was an increase in reporting rate of Barbastelle *Barbastellus barbastellus* and Brown long-eared bat post-breeding when presumably individuals disperse or forage further from their roosts and are reported more widely (Fig. 3). In contrast to all other species here, the reporting rate for Nathusius' Pipistrelle was greatest early in the season, with a peak in June.

3.5. Species distribution

Species distribution models and maps of occupancy were produced for all bat species recorded in Norfolk including Whiskered/Brandt's bats as a species pair (Figs. 4 and A3). The learning rate used for each model, number of trees on which the final model was based and AUC values are shown in Table 3. On average, models validated using occurrence data showed fair AUC values (0.70–0.80), with Leisler's bat at the upper end of poor (0.69) and Whiskered/Brandt's bats excellent (0.94). In terms of how aggregated different species are in their distribution, most species showed Gini coefficients of 0.24–0.36, with Serotine *Eptesicus serotinus*, Nathusius' Pipistrelle and Whiskered/Brandt's bats being at the higher end of this range. Common and Soprano Pipistrelles had Gini coefficients that were close to zero reflecting their near ubiquitous distribution across the county. Of the three pipistrelle species, Common and Soprano were near ubiquitous, but Nathusius' was concentrated in the Norfolk Broads with an intriguing secondary hotspot on the coast possibly a sign of immigration.

3.6. Spatial patterns of bat activity

Models of bat activity were produced for all species (Figs. 4 and A3), but maps for Daubenton's, Whiskered/Brandt's and Leisler's bat *Nyctalus leisleri* are not shown because the majority of predictions were less than 0.5 passes per night. The learning rate used for each model, number of trees on which the final model was based and the correlation coefficient between observed and predicted values of bat activity are shown in Table 3. The correlation coefficients averaged 0.28, and ranged from 0.17 for Common Pipistrelle to 0.41 for Noctule. These values are fairly low, but are comparable to or higher than published elsewhere for other analyses of abundance type data and is likely to reflect stochasticity in the survey data (e.g. Johnston et al., 2013). Whereas Common and Soprano Pipistrelles were shown to be near ubiquitous in distribution terms, there were marked differences in spatial patterns of activity which, at this scale, hint at significant spatial variation in abundance, especially around wetlands, major river valleys and forest (Fig. 4). Interestingly, when considering activity and the Gini coefficients, which assess the degree to which bat occupancy and activity were uniform (coefficient tends to 0) or aggregated (coefficient tends to 1) among 1-km squares, some species were particularly aggregated, with a comparatively small number of 1-km squares supporting a large proportion of the recorded activity (Noctule, Nathusius' Pipistrelle and Serotine).

4. Discussion

We present a novel citizen science approach for enabling high-quality extensive standardised recording of bat distribution and activity using passive real-time detectors, where the unit of recording is a complete night of bat recording. The dataset of over half a million bat recordings collected over two seasons, is already one of the most extensive high-quality datasets for bats from anywhere in the world. The value of these data will only increase, as coverage improves and repeat visits to the same sites allow us the potential to monitor and examine questions relating to change in bat populations. At a local scale, the project has improved our understanding of spatial patterns of occurrence and activity of all species from the near ubiquitous Common Pipistrelle to the locally scarce Leisler's bat for which there were previously only ten records of this species for the study area. This demonstrates the cost-effectiveness of setting up a network of centres across a survey area of interest from which anyone can borrow a passive detector for a few days. We chose centres that were open and widely used by the public and that were easily accessible and geographically well-spaced across the county, and through our choice of centres, it gave us the opportunity to work with a wide range of communities and organisations that already had their own network of volunteers or members, and in doing so opened up citizen science to a new set of people.

4.1. Survey recommendations and limitations

Using a single detector type that automatically triggers and records bats removes the need to control for differences in the detection rates of bat detector types, which has been highlighted as a problem elsewhere (Waters and Walsh, 1994; Adams et al., 2012; Barlow et al., 2015). Furthermore, analysing all recordings in-house removes the potential influence of variation in volunteer experience and skills which can affect their ability to detect and identify some species in the field (Barlow et al., 2015), which has been raised as a criticism of citizen science programmes more widely for other taxa (Dickinson et al., 2010). There is tremendous scope for a survey of this design to be used in many countries, with the main constraints being the spatial distribution of observers and a freely available reference library of calls for training identification software.

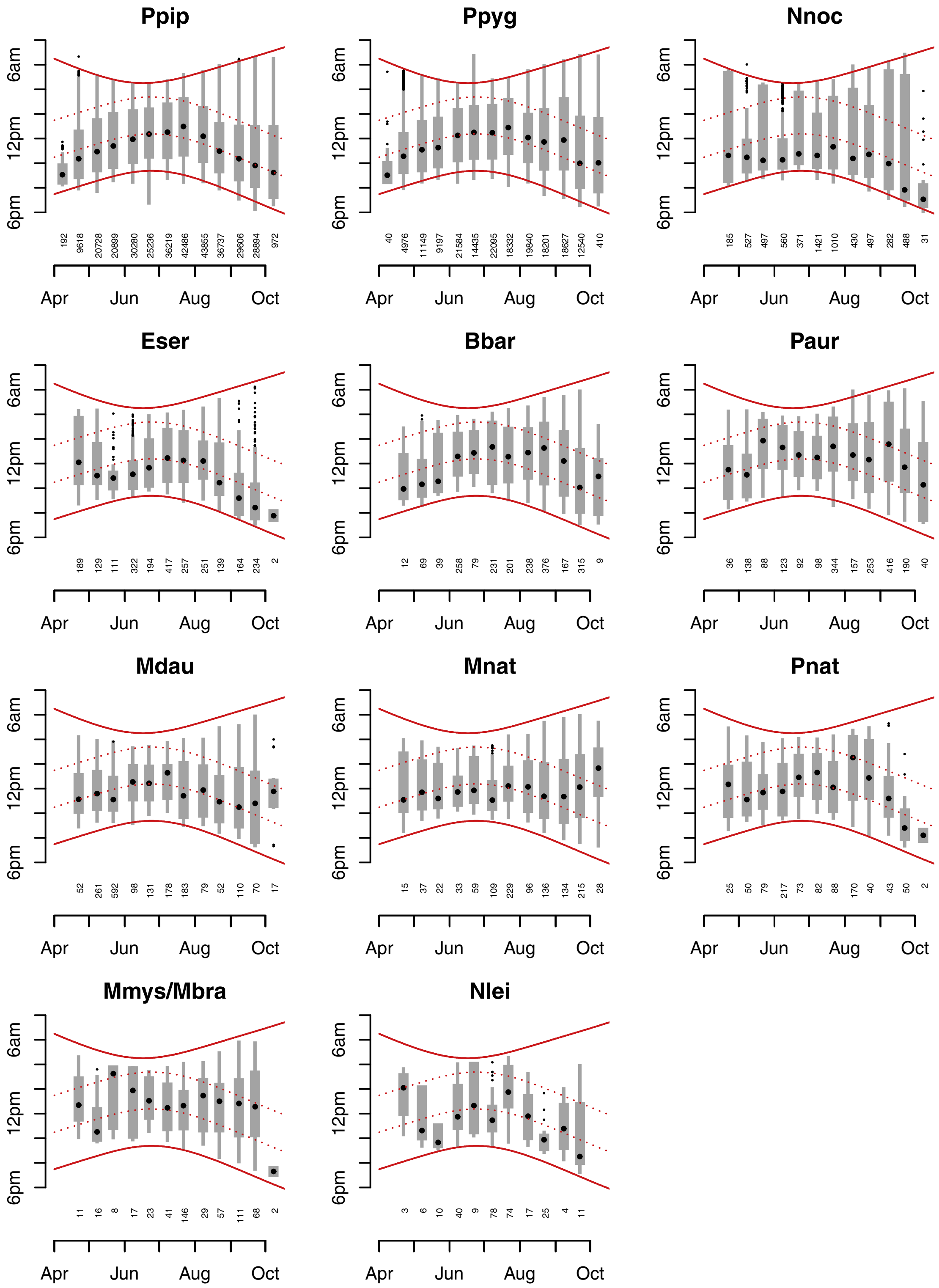

Fig. 2. Patterns of nightly activity through the season with respect to sunset time. Individual box plots summarise the timing of bat passes during half-month periods. The solid curved lines show sunset and sunrise times and the two dashed lines indicate 3 h and 6 h after sunset. For box plots, wide bars show quartiles, lines extend up to 1.5 times the interquartile range, large dots show the median and small dots show outliers. Numbers give the total number of recordings in each period.

The observer network may limit the application of this method in tropical areas, but many pressing problems concerning habitat degradation exist in developed countries (e.g. urbanisation) where bat monitoring is required, and where there are many observers and bat identification software is already advanced.

In relation to acoustic identification of bats there is currently no ideal system but we have shown that the SonoChiro software provides robust results for the majority of the species present in our study area, provided recordings are subsequently filtered to remove low quality recordings and identifications with low confidence. We have taken a conservative approach, minimising the false positive classification rate which we feel is objective and repeatable for our purposes and within the constraints of what current technology and software allow, and practical considering the huge volume of acoustic data collected. Depending on their aims,

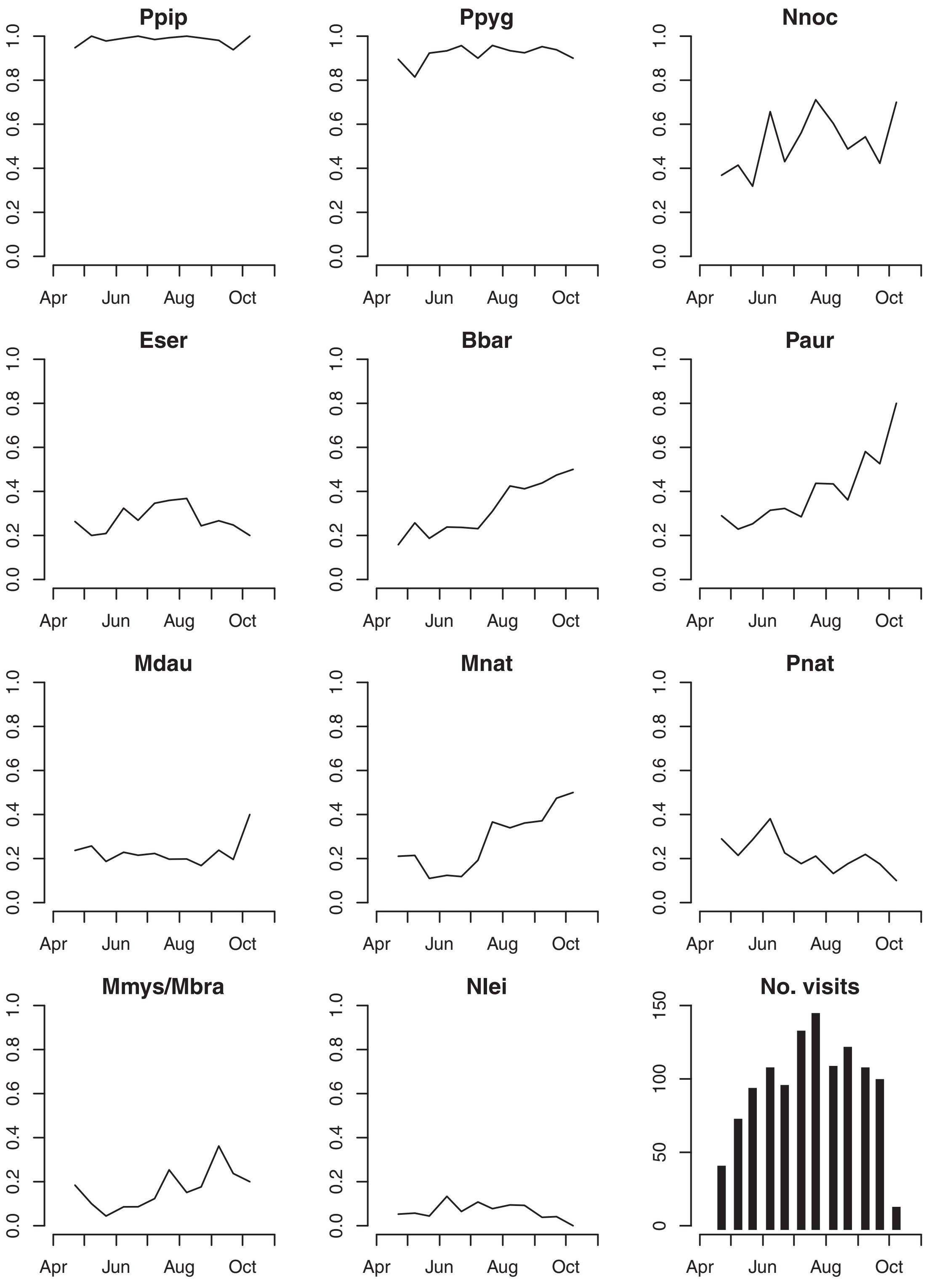

Fig. 3. Reporting rate graphs showing how the proportion of squares at which a species was detected varied through the season (in half-month periods). Species codes as in Table 1. The last graph indicates the number of squares visited per half-month.

future studies should consider whether to optimise false positive or false negative classification rates and may opt for manual validation in a stepwise manner as shown here. The clear habitat associations and seasonality we show for some species suggest that species identification algorithms could perform better if they incorporated survey timing and habitat. This could be accomplished by combining species identification and distribution prediction into a single hierarchical modelling framework, thereby allowing uncertainty to be better reflected in the results.

In terms of the survey design, survey sites would ideally be selected and allocated at random to people wanting to take part, and anyone wanting to set up a similar project should consider this carefully. An important part of this project is engagement, working to encourage people to take part who would not normally participate in biological recording (Newson et al., 2014). In our experience, a purely random design would have significantly reduced uptake among new audiences, so we allowed a free choice of 1-km squares knowing that this was likely to incur costs

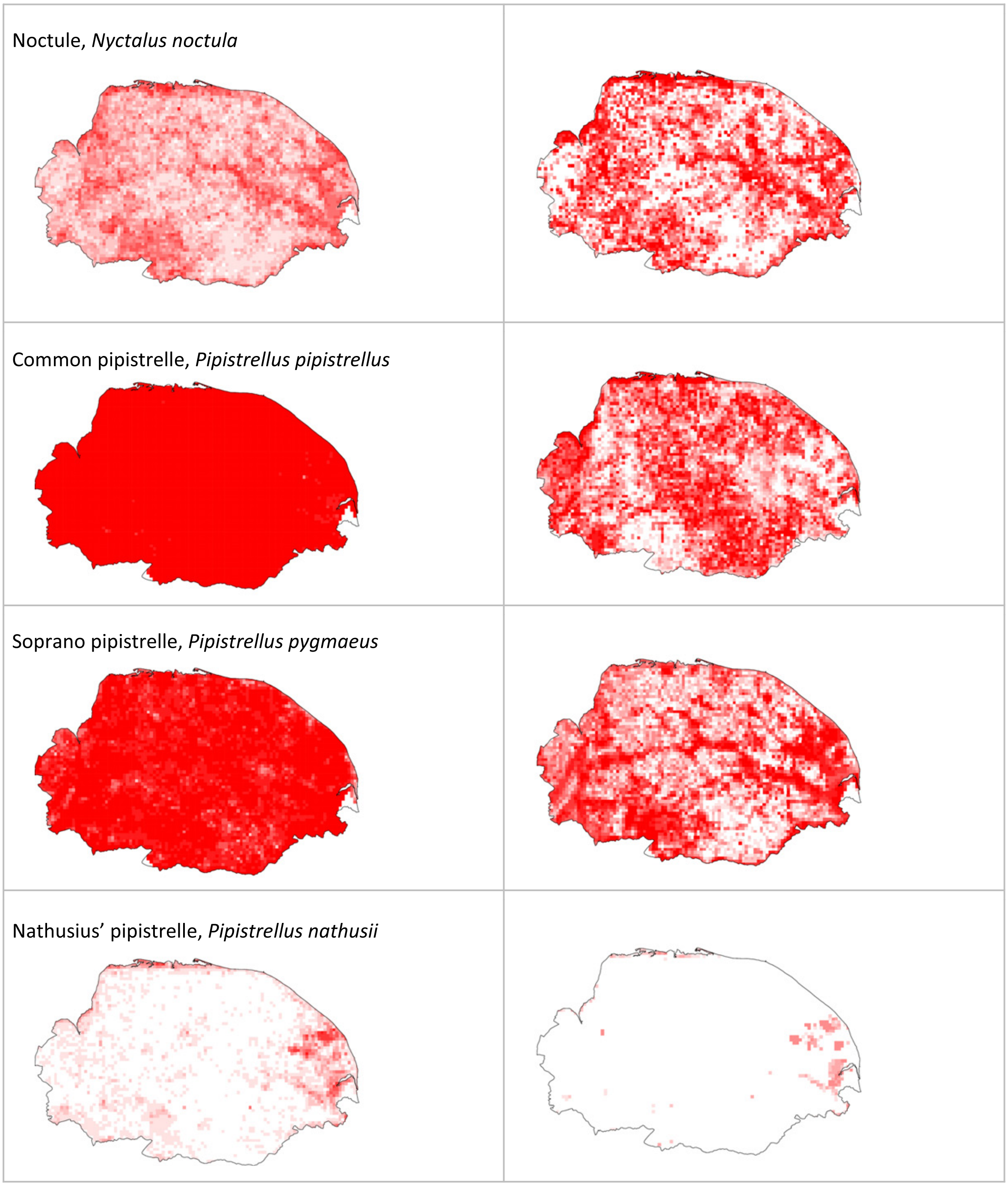

Fig. 4. Maps of predicted occurrence probability (left) and activity which are proxies for abundance (right) for four species of bat (other species shown in Fig. A3). Darker tones indicate higher probability of occurrence or higher activity. Occurrence maps share the same scale (probability in increments of 0.1 from 0 to 1) but the scale for activity maps varies among species.

in terms of any subsequent analysis to control for biases in coverage, in particular towards areas of habitation. Post-hoc stratification reduced but could not entirely eliminate coverage bias. Now that we have a receptive audience, we will be looking into options for reducing bias in subsequent seasons. Potentially this may include having target squares, which are randomly selected to encourage uptake in key areas.

Seasonal and species-specific variation in nightly bat activity (Figs. 2 and A2) highlight the value of designing surveys that provide standardised recording across a night, and reiterates the difficulty highlighted by Stahlschmidt and Brühl (2012) of using walked or driven line-transects for looking at temporal and spatial patterns in bat activity, where the number of bats recorded is so dependent on the time of night. We also demonstrate here that there is real value in designing surveys that record bat activity as a measure of relative abundance, providing far greater resolution for apparently ubiquitous species such as Common and Soprano Pipistrelle, although more work is needed to understand the form of relationship between activity and absolute abundance.

4.2. Modelling considerations

The collection of bat recordings in a systematic and standardised way allows us to consider more powerful analytical techniques such as regression trees of activity rather than rely upon presence-only

Table 3
Results of generalised boosted regression models to predict patterns of bat occurrence and activity. *lr* is the learning rate used for each model and *nt* is the number of trees on which the final model was based. Model performance was assessed by cross-validation and quantified using area under the receiver-operator curve (AUC) for occurrence models and the correlation coefficient between observed and predicted values for relative abundance. Gini coefficients measure the level of aggregation in predicted occurrence or activity.

Species	Occurrence				Activity			
	lr	*nt*	AUC	Gini	*lr*	*nt*	*r*	Gini
Daubenton's bat	0.002	1600	0.70	0.30	0.002	1500	0.22	0.30
Whiskered/Brandt's bat	0.002	1300	0.94	0.35	0.0008	1300	0.36	0.23
Natterer's bat	0.002	2050	0.71	0.27	0.001	2850	0.21	0.28
Noctule	0.005	1350	0.74	0.26	0.009	1550	0.41	0.50
Leisler's bat	0.001	1400	0.69	0.28	0.0008	1050	0.29	0.13
Serotine	0.003	1500	0.73	0.34	0.004	1000	0.28	0.41
Common Pipistrelle	0.001	1350	0.72	0.007	0.001	1000	0.17	0.13
Soprano Pipistrelle	0.004	1100	0.79	0.05	0.002	1350	0.26	0.25
Nathusius' Pipistrelle	0.002	1450	0.71	0.36	0.002	1650	0.31	0.46
Brown long-eared bat	0.004	1250	0.70	0.24	0.003	1350	0.18	0.24
Barbastelle	0.002	1250	0.72	0.31	0.001	1300	0.38	0.29

style analyses. As expected, we were more successful in modelling patterns of species distributions than activity. Poor performance of activity models may be related to unmeasured or unmeasurable variables such as the location of the detector relative to roost sites; a detector on a roost flight-line will record higher activity than one nearby in otherwise identical habitat. Poor performance is also a consequence of high stochasticity in the number of passes of a species made at a site; it is not currently possible to individually identify bats, so a single bat feeding near the detector will cause a large number of detections. The probability of detecting a species given that it is present is also likely to be less than 1. Using acoustic detectors, the issue of imperfect detection is not likely to invalidate the modelling here, but it will affect the interpretation of results. For example, using detection distance tables for the Wildlife Acoustics microphone used here at 20 °C and relative humidity of 50% (Agranat, 2014), and given an estimate of how loud each species is (Sound Pressure Level in db), we expect that the detection distance of Brown long-eared bat will be about 5 m compared with Serotine, which would be detected up to about 35 m. Occupancy modelling (e.g. Royle and Kery, 2007), may provide an alternative framework for developing species distribution models for bats (Rodhouse et al., 2012; Meyer, 2014). In addition, promising analytical approaches for estimating absolute abundance (often referred to as true abundance) are emerging which could be applied to passive bat data. These include extensions to random encounter models (Lucas et al., 2015), which were originally developed for camera trap data, or extensions of occupancy modelling, that allow absolute abundance and detection to be estimated from replicated counts of animals which are not possible to individually identify (e.g. Stanley and Royle, 2005; Guillera-Arroita et al., 2011). This would also have important implications for estimating the population size of bats, which for the UK and most other countries are mainly based on expert opinion (Harris et al., 1995), but more generally for improving our understanding of bats and impacts on bat populations.

4.3. Insights into bat ecology and status

Modelled distribution and activity maps have confirmed suspected patterns but also revealed unexpected differences among species. The maps showing the ubiquity of Common and Soprano Pipistrelles, for example, confirm expectations but are uninformative in identifying important areas for these species, but there are strong indications from the maps of modelled activity that spatial patterns of activity for these two species are very different. For other species like Noctule, where the occupancy and activity maps are visually similar, the comparatively high Gini coefficient from the activity modelling suggests that a high proportion of activity is found at a relatively small number of surveyed sites, which has important implications for the conservation of this species. Examining the activity of different species of bat through the night, there are clearly large differences, which are likely to be related to the diet or biology of the species. Common and Soprano Pipistrelles for example are most active shortly after sunset, which is likely to match the timing of peak availability for small insect prey, whereas more consistent activity of Brown long-eared bat over a night may reflect the behaviour of this species to glean prey directly from foliage and other surfaces which are more likely than small flying insects to be available throughout the night (Harris and Yalden, 2008). Such standardised data over a long survey season can also provide insights into the biology of bats that would be difficult to otherwise obtain at a large-scale. For example an increase in the reporting rate of Barbastelle and Brown long-eared bats post-breeding, may be explained by individuals, which at this time of year would include recently volant juveniles, dispersing or foraging further from their roosts and consequently being detected at a greater proportion of sites at this time. This is supported by limited radio-tracking of these species. Brown long-eared bats in south-east England showed an increase in mean ranging area in August and September, which corresponded with a decrease in the proportion of time spent foraging in woodlands and greater use of hedgerows (Murphy et al., 2012). Radio-tracked non-breeding and post-lactating Barbastelle also travel considerably further to reach their foraging sites (Zeale et al., 2012). Recording of Nathusius' pipistrelle across the whole season, suggests that this species is probably resident in the county, with its stronghold in the Norfolk Broads. However, recording of this species in spring and autumn along the north Norfolk coast, suggests some level of movement, potentially from continental Europe at this time in line with our current knowledge of this species (Russ et al., 2001). There is clearly value in running a project like this over a long survey season for maximising survey coverage, but also in terms of the biological insight that this can give.

4.4. Conclusions

We demonstrate that it is possible to set up a large-scale volunteer-based monitoring programme for bats using static passive real-time bat detectors. We highlight the value of this approach and modelling for improving our understanding of bat status, ecology and to identify important areas for guiding conservation planning for particular species. The use of broadband detectors that provide continuous, full-bandwidth real-time recording is now possible at lower cost, and very likely to become cheaper in the future. There are clearly many questions that could be addressed now with these data, the value of which will continue to increase as we work to improve survey coverage, and encouraging repeat visits to the same sites will allow us to monitor change in bat populations over time. We reiterate the recommendations of Barlow et al. (2015), that there is a huge potential for citizen science to provide extensive high-quality data for bats to inform on bat populations, and that future monitoring should look towards integrating broadband bat detector surveys to increase survey and species coverage and objectivity in species identification. We present a novel citizen science approach to this problem that maximises the use of a limited amount of equipment, with implications for scaling up to a larger regional or national scale.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at http://dx.doi.org/10.1016/j.biocon.2015.06.009.

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