Jersey Bat Survey - Understanding the potential of an island-wide static acoustic monitoring system to generate bat population trends

William H. Glynn and Kate E. Jones

Centre for Biodiversity and Environment Research, Department of Genetics, Evolution and Environment, University College London Gower Street, London, UK WC1E 6BT.

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Executive Summary

Report objectives: The Government of Jersey is signatory to a number of multi-lateral environmental agreements, for which ongoing monitoring of protected species constitutes a vital part of the reporting requirements. Bat populations form an important component of these legal requirements due to their sensitivity to environmental change, and their role as bioindicators for wider environmental health. However, despite a wealth of bat survey activity in Jersey, including acoustic driven transects for the Indicator Bats Programme (iBats), robust population trends are absent for many species. In this report, we describe the design and implementation of an island-wide static acoustic monitoring system for Jersey and, by analyzing data gathered from two pilot surveys (July 2018 & 2019), we assess its potential for generating long-term population trends for a wide range of bat species. Finally, we suggest a number of recommendations for the development of a bat population monitoring programme in Jersey.

***Summary of findings*:** Implementing a static sensor network that uses low cost audio sensors (**AudioMoths**) and efficient open-source automated acoustic machine learning algorithms (**BatDetect** and **BatIdentify**), enables a large amount of occupancy and activity data to be collected across a range of available habitats and species on a landscape scale. Results from two pilot surveys where sensors were set to record continuously during the night in 1 km grids (July 2018 – 90 sensors were placed in five habitat types in proportion to habitat type availability; July 2019 –50 sensors were equally placed in five habitat types, 10 in each) suggest the following:

1) The performance of **BatDetect v.2** to find calls of all bat species in Jersey in audiomoth recordings as determined by False Positive Tolerances, FPTs through manual verification is high (FPT95 - <5% of classifications are likely false). However, the accuracies of species classifications are more variable, with one resident (*Pipistrellus kuhlii*) and two vagrant (*Hypsugo savii, Myotis emarginatus)* Jersey bat species not included in the **BatIdentify v.2** training set and cannot therefore be identified. However, classifications are accurate enough (FPTs >50) to generate robust data for five species/species groups (*Eptesicus serotinus*, *M. nattereri*, *P. nathusii/kuhlii*, *P. pipistrellus* and *Plecotus spp.*), with classifications of *E. serotinus*, *P. nathusii/kuhlii*, and *P. pipistrellus* being especially accurate (FPT90 - <10% of classifications are likely false). FPTs for other species were low, including surprisingly a widespread and common species in Jersey with a distinctive call (*P. pygmaeus*). Including missing species and increasing examples of existing species into **BatIdentify** would improve classifier accuracy. Additionally, increasing the sample sizes of the manually verified calls would add clarity of the FPT analyses.
2) Using the five species with FPTs >50, analysis of occupancy, Ψ and detection, p using data across 2018-19 suggested that *P. pipistrellus* had the highest occupancy across the island ($\Psi \sim 1$), followed by *Plecotus spp.* ($\Psi = 0.95$-0.83), *P. nathusii/kuhlii* ($\Psi = 0.88$-0.75), and *M. nattereri* ($\Psi = 0.22$). *E. serotinus* occupancy estimates were more variable and ranged from 0.99-0.31 across a range of FPT thresholds. For species with lower FPTs their occupancy and detection estimates should be used cautiously. For widespread and common species where variation in occupancy is low, other metrics such as abundance (measured as relative abundance of acoustic activity) may be more useful to detect population changes.

3) Our results using the occupancy and detection estimates from the 2019 survey in Jersey and those from the UK (for species we did not have reliable values for), indicate that 90 sites will be sufficient to detect a 25% change in occupancy with high confidence ($\alpha = 0.05$) of *Pipistrellus pipistrellus*, *P. pygmaeus and Plecotus spp*. Therefore, future surveys should cover at least 70 sites for five non-consecutive nights but aim to cover 90 sites per season in order to maximise power. This level of survey effort is likely achievable with the assistance of citizen scientists in Jersey as there was great interest in volunteering for the 2019 survey. None of the other species managed to approach the 80% power threshold through any feasible combination of survey design and the number of sites surveyed, except the *Pipistrellus nathusii/kuhlii* species group which needed a minimum of 120 sites. Our estimates are subject to revision using a more accurate classifier, more comprehensive FPTs testing, more complete information on the occupancy and detection of Jersey bat species and the exploration of different metrics such as abundance to calculate population trends.

Key recommendations:

- Data collection from a network of static acoustic sensors using citizen scientists is a feasible and economical method for future monitoring of bats in Jersey and seems worthwhile pursuing in conjunction with existing monitoring programmes (e.g. Indicator Bats Programme).
- Improvements to the **BatIdentify** algorithm are needed for the development of future monitoring programmes and to utilize more effectively the data collected from existing acoustic monitoring programmes. Efforts should focus on collecting species reference calls so **BatIdentify** can retrained on more comprehensive datasets and species which are recorded in Jersey. In particular, data collection and retraining should focus on *Pipistrellus kuhlii* and the two *Plecotus* species as these are of high regional importance to Jersey.
- Estimating False Positive Tolerances (FPTs) is a useful technique to assess false positive classification error in species classifications, but the manual verification dataset used here was rather limited and these analyses should be repeated with a more comprehensive set of data. Additionally, manual verification ideally should be carried out independently by more than one expert.
- Using changes in occupancy to monitor populations is a powerful technique and further improvements which incorporate error rates, habitat variables, and other data sources should be carried in order to better understand future survey effort and design. For some widespread and common species, estimating population trends with measures of abundance should be considered to compliment the results presented here.
- The detection of some bat species, even with improved information, may be insufficient for this method to produce long-term robust population trends, so therefore a multi-disciplinary approach is required to encompass the full range of bat species found locally, and the methods described here should be used in conjunction with other surveys.
- Scaling up the pilot surveys into a monitoring programme will also require a strong volunteer network of motivated and trained citizen scientists and a robust digital infrastructure to store and analyse large volumes of acoustic data. The resources required to accomplish this should be given careful consideration.

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Section 1. Introduction and Report Scope

Monitoring changes in the abundance and occupancy patterns exhibited by species is a vital step in understanding their conservation status and to inform the prioritisation of effective conservation actions. Bat populations form an important component of ecosystems across the planet, providing services such as pest control, pollination and reforestation. Their high trophic position and varied life history traits, in terms of reliance on different habitat and prey types, also makes them useful indicators of wider environmental health. Their sensitivity to local environmental changes combined with slow breeding rates also makes bat populations vulnerable to rapid changes in land usage and climate. As such, long term monitoring is a vital to understand changes to bat populations, and to deploy appropriate conservation actions where necessary.

To date, 18 species of bats have been recorded in Jersey, with 8 species confirmed as breeding locally (**Table 1.1**). Due to their uncertain conservation status, all of bat species found locally are legally protected under the Conservation of Wildlife (Jersey) Law 2000 and are covered by a Species Action Plan as part of the Biodiversity Strategy for Jersey (2000). Protection of biodiversity in general, and bats specifically, is also seen as a key consideration in individual and strategic development planning through the Planning and Building (Jersey) Law 2002 and the Jersey Island Plan (2011). Furthermore, Jersey is signatory to a number of multilateral environmental agreements (e.g. the Bern Convention on the Conservation of European Wildlife and Natural Habitats, the Bonn Convention on the Conservation of Migratory Species of Wild Animals, and the EUROBATS Agreement on the Conservation of Populations of European Bats) which place monitoring and protection of bats as a high priority for member states.

Table 1.1 ***Bat species found in the UK and Jersey.*** *Status represents whether these species have been recorded in UK/Jersey, where unknown or unknown [vagrant] represents species which have only been recorded once, or from unconfirmed acoustic or roost records, and * indicates species for which the acoustic classifier BatIdentify cannot currently recognise.*

Species	Common name	UK Status	Jersey Status
Barbastellus barbastellus	Barbastelle	Resident	Not recorded
Eptesicus serotinus	Serotine	Resident	Resident
*Hypsugo savii**	Savi's pipistrelle	Not recorded	Unknown [vagrant]
Myotis alcathoe	Alcathoe bat	Resident	Resident
Myotis bechsteinii	Bechstein's bat	Resident	Not recorded
Myotis brandtii	Brandt's bat	Resident	Unknown
Myotis daubentonii	Daubenton's bat	Resident	Unknown
*Myotis emarginatus**	Geoffroy's bat	Not recorded	Unknown [vagrant]
Myotis mystacinus	Whiskered bat	Resident	Unknown
Myotis nattereri	Natterer's bat	Resident	Resident
Nycatlus leisleri	Leisler's bat	Resident	Unknown [vagrant]
Nyctalus noctula	Noctule	Resident	Unknown
*Pipistrellus kuhlii**	Kuhl's pipistrelle	Not recorded	Resident
Pipistrellus nathusii	Nathusius' pipistrelle	Resident	Resident [vagrant]
Pipistrellus pipistrellus	Common pipistrelle	Resident	Resident
Pipistrellus pygmaeus	Soprano pipistrelle	Resident	Resident
Plecotus auritus	Brown long-eared bat	Resident	Resident
Plecotus austriacus	Grey long-eared bat	Resident	Resident

Rhinolophus ferrumequinum	Greater horseshoe bat	Resident	Unknown
Rhinolophus hipposideros	Lesser horseshoe bat	Resident	Unknown

Bat population monitoring in Jersey is currently carried out since 2011 by Government of Jersey's Natural Environment Team in the Department of Growth, Housing and Environment through the Indicator Bats programme (iBats) (an annual Passive Acoustic Monitoring, PAM scheme which records acoustic surveys along a driven transect), and through a roost monitoring scheme led by the Jersey Bat Group. Analysis of 5 years of iBats data generated population trends for the common (*Pipistrellus pipistrellus*) and soprano (*P. pygmaeus*) pipistrelle bat, indicating an increase of 34% and 51%, respectively between 2012 and 2015 (Hawkins *et al.*, 2016; Williams *et al.,* 2019). Indicator Bats was unable to produce robust trends for a wider range of bat species during this period due to an inherent sampling bias towards species which make frequent use of roads and edge habitats, and also because of the limited timespan of the data series. However, inclusion of data collected since 2015 into the analysis of trends may change this picture. The use of roost data for determining trends in bat populations has been limited due to difficulties obtaining repeat access to known roosts, and low reporting rates of new roosts. As such, there remain a number of questions about the status of Jersey's bat populations, further hindered by a limited understanding of local species diversity and ecology.

Following nearly 10 years of the iBats programme with driven road transects, the Government of Jersey are investigating alternative monitoring strategies capable of producing population trends for a wider range of bat species. Although PAM is widely regarded as the best technique for gathering bat activity data on a wide scale, the widespread use of PAM techniques for monitoring in Jersey has been limited by the high cost of equipment and lack of resources to analyse the large volume of data collected by this method. However, the increased availability of cheap, open source acoustic sensors and development of automated machine learning techniques for detecting and classifying bat calls mean that collection and analysis of large amounts acoustic data over a wide area is now a feasible option. Indeed, a new survey deploying a network of static acoustic sensors (AudioMoths Hill *et al*., 2018) and using detection (Mac Aodha *et al.*, 2018) and classification (Fairbrass *et al*., 2018) algorithms to automatically analyse acoustic data is in development to monitor bats in the UK by The Bat Conservation Trust's British Bat Survey (Fairbrass *et al*., 2018). However, there are some questions that need to be answered in order to understand the potential of a such a scheme in Jersey.

This report, commissioned by the Government of Jersey, considers the following questions which are critical to the application of the proposed methodology: 1) are the automated call detection and classification algorithms developed for UK species suitable for use in Jersey; 2) what is the occupancy and detection of bat species in Jersey; and 3) are the methods proposed capable of producing robust long term trends in bat populations? To answer these questions, we report on the design, data collection and analyses of two years of pilot surveys in Jersey building our previous research (Glynn 2018) and make recommendations for the potential of this methodology to improve the monitoring of bat populations in Jersey.

Section 2. 2018-19 Pilot survey design and data collection

For the pilot surveys, 1 km^2 ordnance survey grid was used as a basis for site selection in order to remain consistent with ongoing local, national and international monitoring schemes for other taxonomic groups. Habitat availability is known to influence bat species' activity and occupancy; as such the Phase 1 Habitat Survey of Jersey (2011) was used to select 5 key habitat types representative of the island (Agricultural/Arable, Grassland, Urban, Woodland and Water, Figure 1). The amount of area of each habitat within each 1 km grid square was calculated and used to threshold the grids as to whether they were representative of the habitat of interest and to determine the locations for acoustic sensor placement (survey sites), following 2 different sampling regimes (one in 2018 and the other in 2019) designed to provide different information regarding the suitability of the methodology.

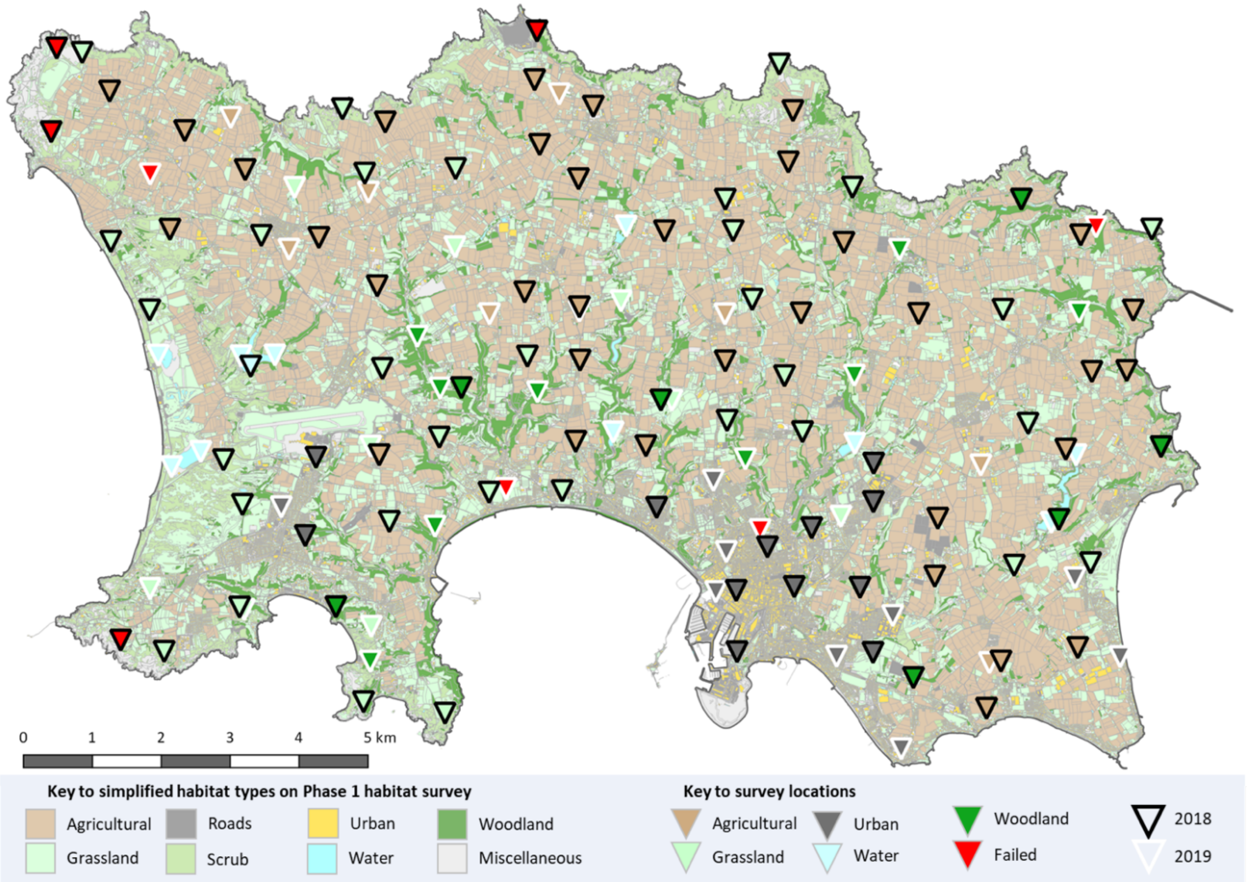

Figure 2.1. Distribution of pilot survey locations across Jersey for 2018-19. *Triangles represent survey locations; triangle and background map colours correspond to habitat types simplified from the Phase 1 habitat survey of Jersey.*

In 2018, 90 survey sites were selected following a random stratified approach in order to sample habitats in a way representative of habitat availability across the island (i.e. if 60% of the island is agricultural, 60% of the acoustic sensors were placed in agricultural land; Figure 2.1, Table 2.1 and Supplementary Table S1). This method provides an overview of bat activity relative to habitat availability which is useful in determining strategic landscape scale conservation actions. However, in 2019 50 sites were randomly selected equally within each of the five habitat types, with 10 acoustic sensors placed in each habitat (Figure 2.1, Table 2.2 and Supplementary Table S1). This enables a more detailed comparison of detection rates for different bat species in different habitats which may influence the optimum survey design. Specific locations within each grid were selected in 2018 by starting at the centre of the square and working outwards until an area of suitable habitat was identified, and in 2019 a desk based random selection was used based on the Phase 1 Habitat Survey. In both years, acoustic data was collected in July, to coincide with the period when bat activity is at its highest, but before the young of the year are flying. This provides the optimum time for data collection with a high probability of encountering bats, whilst avoiding a temporary peak in the population when young pups are first active away from the roost.

Table 2.1. Summary of survey visits and bat activity by habitat type from the pilot survey 2018-19. *n(sites) refers to the number of survey sites per habitat; n(fails) number of unsuccessful surveys; n(visits) number of times the site was surveyed; n(files) number of 10 second duration files generated across all visits; n(files w/bat) number of 1 minute files containing a bat call; n(call) number of bat calls across all surveys; and mean(calls) relates to the average number of calls recorded in each habitat per visit (i.e.* $n_{(calls)}/n_{(visits)}$*). Bat activity (number of calls of all species) were estimated using the BatDetect algorithm (*Mac Aodha *et al.*, 2018*).*

2018 - Proportional representation of habitats

Habitat	$n_{(sites)}$	$n_{(fails)}$	$n_{(visits)}$	$n_{(files)}$	$n_{(files\ w/\ bat)}$	$n_{(calls)}$	$mean_{(calls)}$
Arable	34	0	101	242,748	43,243	862,217	8,537
Grassland	32	0	95	228,533	24,529	319,657	3,365
Urban	12	0	36	84,447	12,389	299,432	8,318
Water	1	0	3	7,085	1,892	29,689	9,896
Woodland	7	0	21	50,810	16,694	387,083	18,433
Total	**86**	**0**	**256**	**613,623**	**98,747**	**1,898,078**	**7,414**

2019 - Equal representation of habitats

Habitat	$n_{(sites)}$	$n_{(fails)}$	$n_{(visits)}$	$n_{(files)}$	$n_{(files\ w/\ bat)}$	$n_{(calls)}$	$mean_{(calls)}$
Arable	10	1	26	60,825	2,595	25,603	985
Grassland	10	1	31	88,423	11,107	58,141	1,876
Urban	10	1	37	73,132	7,850	238,229	6,439
Water	10	0	31	71,369	22,157	970,955	31,321
Woodland	10	1	33	77,969	10,811	204,441	6,195
Total	**50**	**4**	**158**	**371,718**	**54,520**	**1,497,369**	**9,477**

A single acoustic sensor was deployed at each survey location, each location was surveyed 3 times on non-consecutive nights in 2018 and left in place for between 3 - 6 nights in 2019 (start and end time 20:30:00-05:30:00; sample rate 384 kHz; medium gain; recording intervals of 10 seconds with no sleep duration). The acoustic sensors used for this study - the first generation of AudioMoths (Hill *et al.*, 2018) were selected because their low price enabled deployment of a large network of sensors. To protect the sensors from the weather, they were housed in an acrylic case and the internal microphone shielded by an acoustic vent which allows sounds to pass through. There is some evidence to suggest that this type of weatherproof housing somewhat negatively affects the detection rates and higher quality recordings might be achieved using other housing designs.

One of the key considerations when designing a monitoring scheme, is the sustainability of the scheme enabling repeat surveys year on year. As such, many monitoring schemes employ volunteer citizen scientists to share out the survey work, spreading the resources required for data collection. In order to explore whether this model is suitable for the proposed methodology, we recruited 5 volunteers to assist with sensor deployment in 2018, and 28 in 2019. Overall, this was a success with the majority of volunteers successfully managing one or more survey sites following a short training session with very few issues reported. The main issues surrounded the setup of the AudioMoths highlighting the need for more robust training, or automated systems for configuring the devices. Other issues which led to survey failure included equipment faults and sensors being moved after deployment, both of which are commonplace issues in large scale monitoring and which can be accounted for.

In both surveys, once each sensor had completed a deployment it was retrieved, and the data downloaded and backed up onto two hard disk drives. The audio files were then moved to a secure server at University College London before being processed by the automated detection and classification algorithms. Data collected in 2019 was recorded across consecutive nights, which violates the assumptions of the occupancy models used later in the analysis. To avoid this, a summary of the visits made in 2019 was used to subset the complete dataset so that only data collected on non-consecutive nights were included in the analysis.

Section 3. Suitability of bat detection and classification algorithms for Jersey Data

3.1. Background

The rise of remote sensor technologies in wildlife monitoring has driven a need for tools which can process large volumes of data quickly, efficiently and accurately, and acoustic surveys of bats are frequently limited by the amount of data that can be processed manually. For example, the data collected in the 2018 pilot survey alone amounted to 4.5 TB, consisting of over 600,000 sound files representing ~1700 hours of recordings. There is a great deal of interest in the development of automated systems for classifying bat calls to species, many of these based around measuring and comparing parameters known to be representative for different species (e.g. peak/start/end frequency, inter-pulse interval). This approach often requires the bat calls to be located and parameterised within the sound files using specialist software, necessitating significant manual input.

A new approach becoming widely adopted by ecologists across a range of disciplines, is the use of machine learning to classify species automatically. With this approach, an algorithm is trained using a set of labelled data to recognise certain features which are distinctive between different species. When applied to new data, the algorithm identifies these distinctive features and determines the probability of the unknown data and matches to those species in the training set. Two new machine learning algorithms in particular are of interest here, as these automatically detect (or isolate) bat calls within an audio file (B**atDetect**; Mac Aodha *et al.*, 2018, Fairbrass *et al*., 2018), and subsequently classify calls to different species (**BatIdentify**; Fairbrass *et al*., 2018). **BatDetect** was trained on data collected from a wide range of locations around the world as part of the iBats Programme, using files with a wide variety of call structures and background noises present. As such it achieves very high success rates in detecting bat calls within a file (Mac Aodha *et al.*, 2018). **BatIdentify** is still in the developmental stages, and so far has been trained on recordings collected from bats leaving roosts where the species is known, or from bats which have been caught, light tagged, and released (avoiding release calls which are not necessarily representative of echolocation in normal flight).

Currently, **BatIdentify** is trained solely to classify search phase echolocation calls and largely trained on labelled data collected in the UK (although recordings from Jersey have been used for grey long-eared bats, *Plecotus austriacus*). Bats alter the structure of their search phase calls based on the surrounding environment and their current activity (e.g. commuting between areas compared to actively foraging within an area) and intersperse regular search phase calls with other call types (e.g. feeding buzzes, and social calls). This high level of variability within species' call characteristics leads to a large degree of overlap in the parameters used to identify between species. This causes difficulties (sometimes insurmountable) in distinguishing between species even for a highly experienced human expert. For an automated species identification algorithm to be successful, it must be trained on the full range of possible call types for a species, requiring a large amount of data to be collected and correctly labelled. With enough training data these algorithms can achieve high levels of success, however it is important to understand that there will always be a level of error. Error can be introduced through high frequency calls produced by nocturnal insects (e.g. bush-crickets and some moths) and small mammals (e.g. shrews), and abiotic sounds produced by passing vehicles, electric fences, and the acoustic sensors themselves. Furthermore, Jersey is home to at least one and possibly up to three bat species not found in the UK and not included in the current classifier (e.g. Kuhl's pipistrelle, *Pipistrellus kuhlii*), and has not recorded some species found in the UK which are included in the current classifier (e.g. western barbastelles, *Barbastellus barbastellus*). In the case of *P. kuhlii*, the algorithm would classify these calls to the most similar species in the training set (in this case *P. nathusii),* leading to artificially high error in calls classified as *P. nathusii*.

Understanding how well the existing algorithms perform for detecting and classifying different species is essential in interpreting data processed using these methods. For Jersey, it is also important to assess whether a system trained on bats in the UK is suitable for local use, given different species assemblages. Here, we report on the success rates achieved by both **BatDetect** and **BatIdentify** based on manual verification of a subset of calls. We then provide details of a tool for thresholding classifications based on confidence levels provided for each call by **BatIdentify**, which facilitates downstream analysis and interpretation of the results.

3.2. Methods

The audio files for 2018 and 2019 were processed through **BatDetect v.2** (Mac Aodha *et al.*, 2018; Fairbrass *et al*., 2018) and **BatIdentify v.2** (Fairbrass et al., 2018) (Supplementary Table S2 -S4). For the following verification analysis, we used data from 2018 and only retained calls detected with greater than 50% confidence score. A random sample of 200 classifications per confidence level (at 0.1 intervals from 0.5-0.9) were selected for manual verification for the **BatDetect** analysis, and up to 15 classifications per classifier confidence level (at 0.1 intervals from 0.1 - 0.9) per species were selected for the **BatIdentify** analysis (Supplementary Table S2). The order in which the files were analysed was randomised, and the automatic classifications hidden to avoid any influence. Manual verification was carried out by H. Glynn using Kaleidoscope version 5.1.9g (Wildlife Acoustics), based on call parameters described in Barataud (2015), Russ (2012) and Middleton *et al.* (2014). For the **BatDetect** analysis, manual classifications of sounds were made to non-bat/bat and for the **BatIdentify** analysis, classifications were made to species. Sounds which were could not be categorised to non-bat/bat or species were discounted from the analysis. Although this has the potential to bias the classification success rates by only considering calls that can be confidently identified, this was a pragmatic approach.

Following manual checking, the automated and manual classifications were compared, and each call assigned a score of 1 (successful classification) or 0 (false classification). For the **BatIdentify** analysis, this was firstly done for each individual species, and then again with a condensed species list grouping similar species together (Supplementary Table S3). *P. kuhlii* was not in the training data for **BatIdentify** so cannot be classified and would be likely be confused with a species (*P. nathusii*) with similar call characteristics. Therefore, these species were grouped together. Out of five *Myotis* species assessed, *M. nattereri* enjoyed substantially greater success than the others. As such *M. nattereri* was assessed as an individual species, whereas the other *Myotis* species were grouped together.

We ran logistic regressions for non-bat/bat or each species/species group, to compare the false positive rates at different levels of classifier confidence (Supplementary Table S2 and S3). For each species/species group, we adopted the approach of Barré *et al.* (2018) and used these models to predict the confidence level at which each species achieved a known false positive rate ranging from 50% to 10%. The error rate at each of these levels is also known and was used as a tool to threshold the data based on False Positive Tolerances (FPTs) between FPT50 and FPT90 (known error rate = 50% and 10% respectively). Using the automated species classifications as a baseline, we extracted each pairwise combination of automated versus manual classification, and then calculated the proportion of times each combination occurred within the data; i.e. given the automated species classification, how often was the classification correct (true positive) and how often did the call belong to a different species (false positive). This is represented as a confusion matrix, which highlights where there are common misclassifications between species.

3.3. Results

3.3.1. BatDetect

The **BatDetect** algorithm had an average success rate of 95% true positive identifications of bat calls from a subset of 1000 files analysed across a range of confidence levels (0.5-0.9) (Figure 3.1).

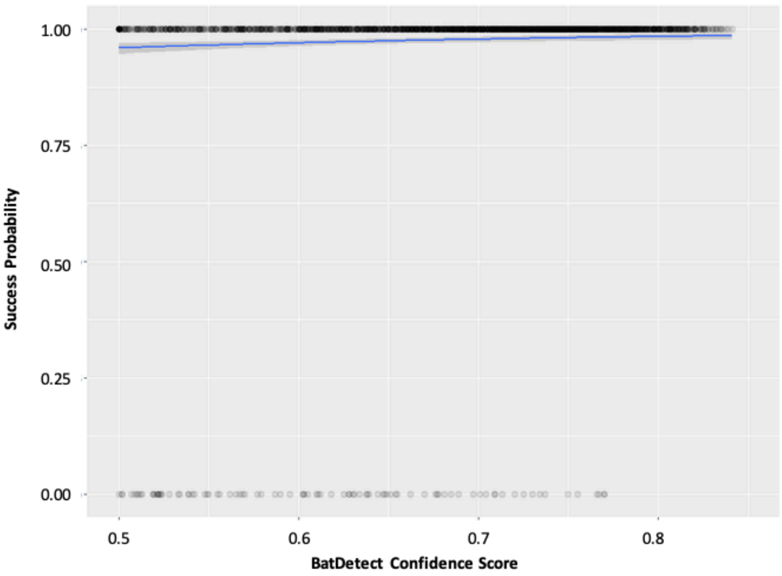

Figure 3.1 Performance of BatDetect algorithm. *Black dots represent classifications, and blue line represents the logistic regression of success probability (0,1) over a range of classifier confidence intervals.*

3.3.2. BatIdentify

When assessed as individual species, only *P. pipistrellus* and *E. serotinus* met the highest threshold for error (FPT90) (Figure 3.2, Figure 3.3, Table 3.1, Supplementary Table 2). *Myotis nattereri*, *P. nathusii* and *Plecotus austriacus* reached FPT50 – FPT60 (Figure 3.2, Table 3.1). *Myotis daubentonii*, *Nyctalus leisleri*, *N. noctula*, *P. pygmaeus* and *P. auritus* all showed low thresholds for false positives. The remainder of automated species classifications (*Barbastellus barbastellus*, *M. alcathoe, bechsteinii* and *brandtii*, and *Rhinolophus ferrumequinum*) proved to be false positives, mostly due to confusion with other bat species, other nocturnal wildlife and abiotic noises (Supplementary Figure 1, Figure 3.3). Analysis of the species groups showed *P. nathusii/kuhlii* achieving FPT90, the *Plecotus* group FPT60, but *Myotis* and *Nyctalus* groups both failed to achieve the lowest FPT (FPT50).

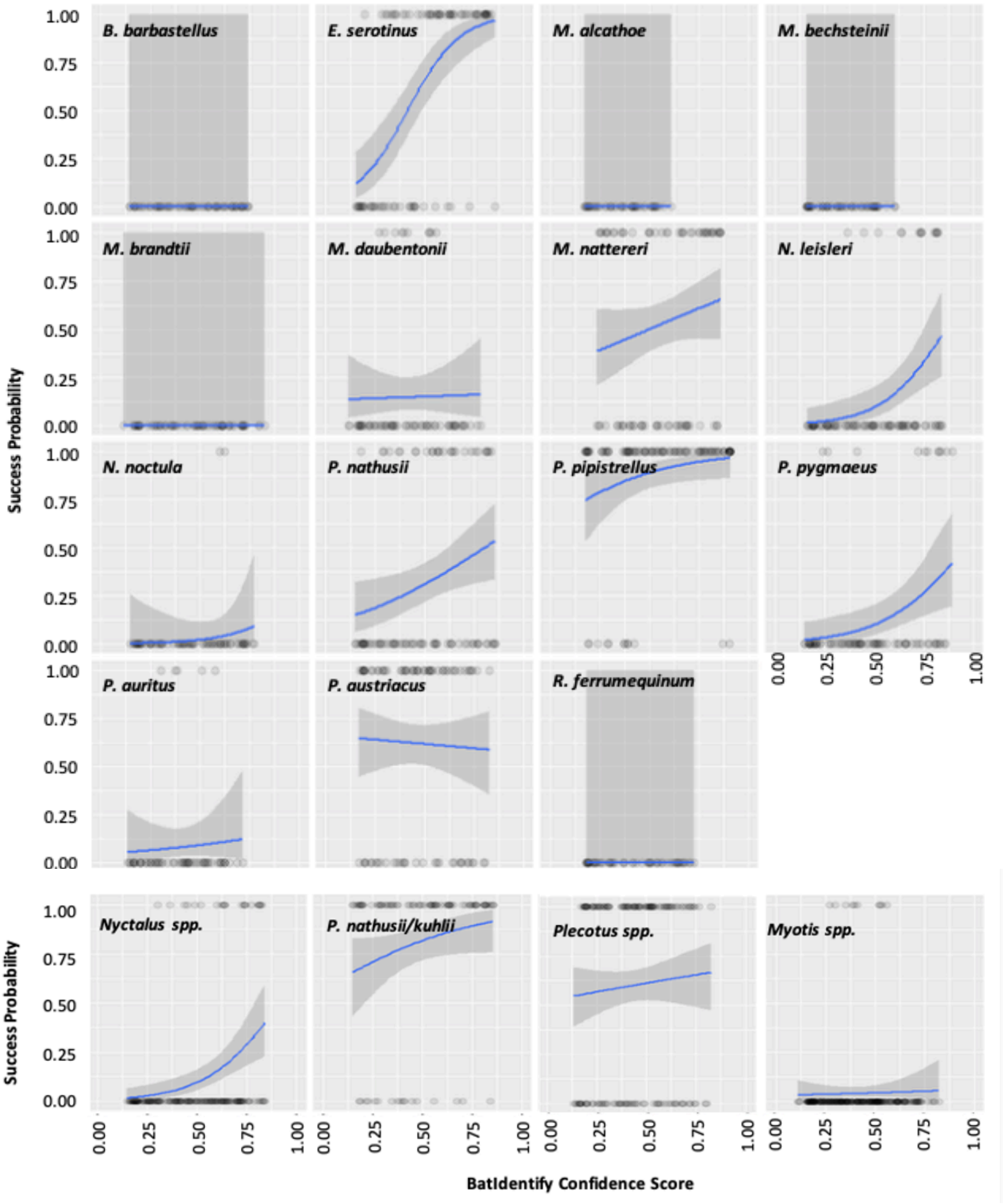

Figure 3.2 Performance of BatIdentify algorithm for species and species groups. *Black dots represent classifications, and blue line and shaded grey represents the logistic regression and confidence intervals of success probability (0,1) over a range of classifier confidence scores.*

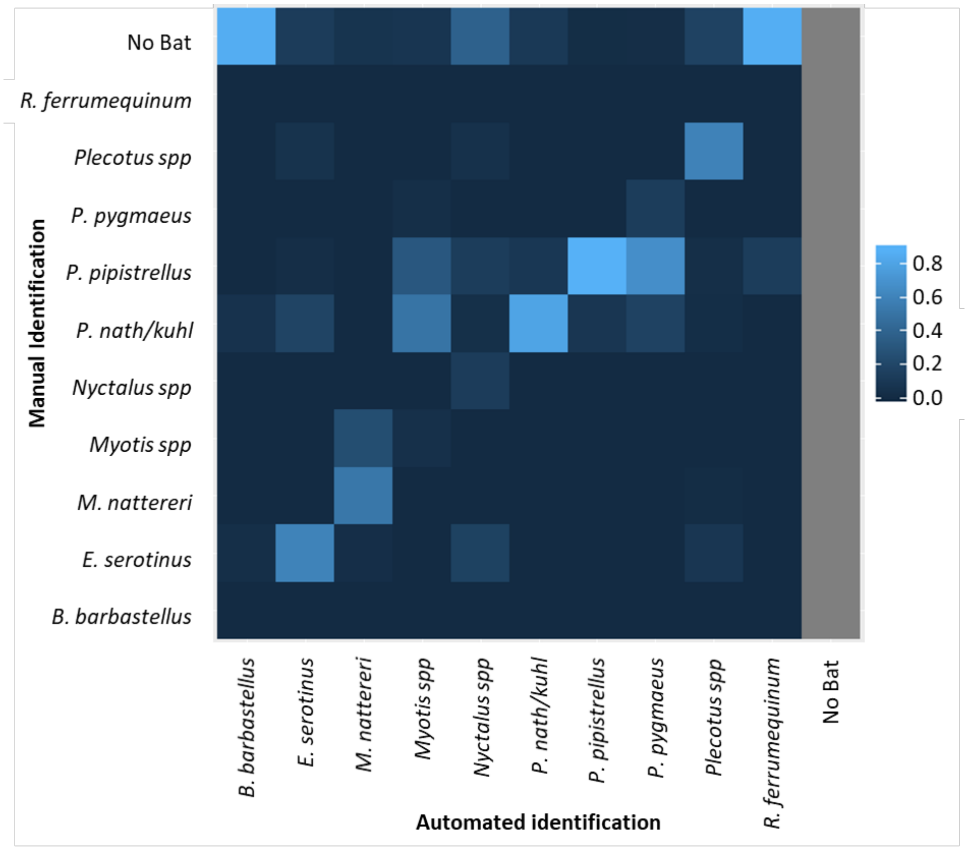

Figure 3.3. Confusion matrix showing the proportion of correct and incorrect species classifications. ***BatIdentify*** *is unable to assign a 'no bat' classification indicated by the grey bar. The 'No Bat' row highlights where confusion with non-bat noises frequently occurred.*

Table 3.1. Summary of results from the logistic regression analysis assessing success rates in BatIdentify using 2018 pilot data from Jersey. *Classifier confidence scores represent upper values meeting the false positive tolerance (FPT) thresholds, and n_{check} represents the total number of files manually checked.*

	Model Results		**FPT50**	**FPT60**	**FPT70**	**FPT80**	**FPT90**	
Species	*Intercept*	*Estimate*			*Classifier Confidence Score*			n_{check}
Barbastellus barbastellus	-26.57	0.00	-	-	-	-	-	72
Eptesicus serotinus	-3.15	7.64	0.41	0.47	0.52	0.59	0.70	88
Myotis nattereri	-0.88	1.76	0.50	0.73	0.98	-	-	76
Myotis spp	-2.98	0.36	-	-	-	-	-	252
Nyctalus spp	-4.92	5.37	0.92	0.99	-	-	-	169
Pipistrellus n/k	0.29	2.44	0.00	0.05	0.23	0.45	0.78	87
Pipistrellus pipistrellus	0.54	3.09	0.00	0.00	0.10	0.27	0.54	105
Pipistrellus pygmaeus	-4.57	4.75	0.96	-	-	-	-	83
Plecotus spp	0.32	0.52	0.00	0.16	-	-	-	147
Rhinolophus ferrumequinum	-26.57	0.00	-	-	-	-	-	60

3.4. Discussion

Our analysis shows that the performance of **BatDetect** to find calls of all bat species in Jersey in AudioMoth recordings is high but the species identifications are more variable. One resident (*Pipistrellus kuhlii*) and two vagrant (*Hypsugo savii, Myotis emarginatus)* Jersey species not included in the **BatIdentify** training set and therefore cannot be identified and may be confused with other species. However, the classifications for other species are accurate enough to generate robust data for five species/species groups (*Eptesicus serotinus*, *M. nattereri*, *P. nathusii/kuhlii*, *P. pipistrellus* and *Plecotus spp*), with classifications of *E. serotinus*, *P. nathusii/kuhlii*, and *P. pipistrellus* being highly accurate (FPT90 - <10% of classifications are likely false).

Pipistrelle species tend to be more readily separated by their calls as there is little overlap between their call characteristics, particularly with regard to the frequency of maximum energy (FMaxE). Furthermore, with the exception of *P. kuhlii*, this genus is widespread and frequently encountered in the UK, allowing for the development of larger reference call libraries to be used in training the classifier. *Pipistrellus pipistrellus* demonstrated the highest levels of success in the automated classification process, fostering a higher level of confidence in downstream analyses for this species. In contrast to previous analyses (Hawkins *et al*., 2016), the classifier failed to produce high success rates for *P. pygmaeus*. This species is encountered in Jersey infrequently but can be distinguished from other pipistrelles based on their use of higher frequency calls (FMaxE > 52 kHz). The reasons for the low success rates observed here are unclear, however there are unverified reports of *P. pipistrellus* making use of higher frequencies in Jersey which if accurate could affect the success of the classifier.

Manual checking of calls classified to *P. nathusii* identified that many of these belonged to *P. kuhlii*, which shares similar call characteristics (FMaxE 35 – 42 kHz for each). *P. kuhlii* reference calls are not yet included in the training data for **BatIdentify** rendering individual analysis impossible. However, grouping these two species together improved the success rate of the classifier for this call type to around 80%, enabling higher confidence in their identification. It is vital that efforts are made to incorporate *P. kuhlii* into the classifier, as it is important to distinguish between these two species for monitoring and conservation planning. In particular, *P. nathusii* is known as a long-distance migrant, and it is necessary to establish whether they are year-round residents in Jersey or whether the island supports only a migratory population.

The classifier performed well for *E. serotinus* at higher confidence levels. The steep drop in the number of accepted classifications between FPT80 and FPT90, indicates that there may be quick gains by improving the confidence of the classifier with additional training. This would further strengthen confidence in results for this species for ongoing monitoring. Serotines, along with *Nyctalus spp*, emit loud calls ending at lower frequencies (15 – 30 kHz) facilitating clearer recordings of their calls which benefits the classifier. The status of the two noctule species (*N. leisleri* and *N. noctula*) is very uncertain in Jersey, relying largely on old roost records. Positive identifications of both were made during the manual verification of classifications, although for the analyses here they were grouped by genus. Other surveys have failed to detect noctules locally, this may be due to a limited or infrequent local distribution or difficulties detecting these species using other methods. Noctules are less frequently encountered during trapping surveys for example, due to their niche as high flying aerial hawkers. Therefore, continued use of PAM may prove useful in better understanding the local status of these species.

When grouped, the *Plecotus* genus was classified with moderate success. Long-eared bats produce very quiet echolocation calls which are hard to detect and suffer from attenuation at higher frequencies, increasing the difficulty of successfully detecting and classifying calls acoustically. *P. austriacus* is an important flagship species locally, as it widespread, charismatic and Jersey likely supports the largest population in the British Isles. The status of *P. auritus* is less well known locally, although seemingly widespread, few roosts are known. Their echolocation characteristics show a degree of overlap (particularly during commuting flights) but are distinguishable in many cases by lower end frequencies of the first harmonic (Barataud *et al.*, 2015). Development of the classifier for *Plecotus* should therefore be a priority in order to enable better assessment of their status using PAM. Efforts should be focussed on obtaining reference calls from *Plecotus* species emerging from known roosts or during trapping surveys to improve the ability of **BatIdentify** to split this group.

Of the *Myotis* bats, success rates only reached moderate FPTs for *Myotis nattereri* with the classifier showing very limited success for other species. Very little is known about these bats locally, with five new species encountered in the last 7 years. Most *Myotis* species in Jersey are known only from a handful of records, although *M. nattereri* is captured frequently during autumn swarming trapping surveys. This genus is also difficult to identify acoustically as there is a large degree of intraspecific overlap, and interspecific variation in echolocation characteristics depending on their activity and surroundings (Barataud, 2015). The calls of *M. nattereri* span a large range of frequencies and feature a particularly low end frequency (< 20 kHz), making them the most distinctive calls in this genus. This likely explains the relative success of **BatIdentify** for this species compared to others. In developing the classifier for *Myotis* bats, it will be important not only to develop a call library for those species encountered, but also to better understand the status of this genus in Jersey through other means (e.g. trapping and radio tracking).

Before grouping, *M. alcathoe*, *M. bechsteinii* and *M. brandtii* were all identified by the classifier with a 0% success rate. Similarly, *Barbastellus barbastellus* and *Rhinolophus ferrumequinum* were entirely misidentified during the classification process. The misclassifications broadly fell into three groups: other bat calls, other biotic sounds, and abiotic sounds. The majority of *Myotis* misclassifications came from either very steep frequency modulated calls produced by members of the *Pipistrelle* genus in cluttered environments, or the calls made during the terminal phase of approaching prey. Social calls made by other bats were also often a source of confusion for the classifier, particularly in the misclassification of *Nyctalus spp*. The main cause of confusion for *B. barbastellus* was through noises made by bush-crickets and moths, and for *R. ferrumequinum*, constant frequency noises made by the AudioMoths themselves led to the most misclassifications.

The accuracy of **BatIdentify v2** for Jersey as measured by False Positive Tolerances is based on manual verification using reference material and was limited to a small subset of data for each species. Although this method should allow robust results to be obtained from a small sample size (Barré et al., 2019), future assessments of error rates should aim to increase the sample size and be carried out by multiple independent verifiers. Improving **BatIdentify** by increasing both the range of species covered and the number of examples from each species should also be a priority for the Government of Jersey in order to analyse existing data for any future acoustic monitoring programmes and maximising the usefulness of existing ones (e.g. Indicator Bats Programme).

Section 4. Baseline occupancy and detection estimates for Jersey bat species

4.1. Background

Occupancy modelling provides an opportunity to assess the probability of a species of interest being present in a given area, separating this from the probability of detecting that species during surveys. This measure is incredibly useful when studying species distributions and habitat associations, and when measured repeatedly over time can be used to generate trends in changes to patterns of occurrence. Occupancy modelling is especially useful when the difficulties of individual species recognition precludes generating direct estimates of species abundance to monitor trends in population abundance directly, as is the case when monitoring bats acoustically. For example, the Bat Conservation Trust uses occupancy of different species at points along a set transect over time to monitor UK populations (Barlow et al. 2015). It is possible to generate estimates of relative abundance from the amount of acoustic activity but as yet the understanding of the relationship between the number of calls recorded from a static sensor and the individual number of bats present is limited. As such, it is more difficult to make inferences about abundance. However, these data are suitable for use in occupancy modelling and this is a useful place to start analyses of trends.

Here, we use the acoustic data collected across the pilot surveys across Jersey in 2018-2019 to calculate presence or absence of different species of bats to estimate the baseline occupancy and detection probabilities. We also explore the impact of the variation in classification FPTs of the **BatIdentify** algorithm on the occupancy estimates for different species.

4.2. Methods

All the raw audio files for 2018 and 2019 pilot surveys were processed through **BatDetect v.2** (Mac Aodha *et al.*, 2018; Fairbrass *et al*., 2018) and **BatIdentify v.2** (Fairbrass *et al.,* 2018), and classifications were subset for each species/species groups (Supplementary Table S2 and S4). Data were subset per site to only include data from non-consecutive nights. Presence or absence of each of the five species/species groups that had classifications with FPT>50 (Section 3) was then determined within 1 km grids at each FPT (FPT50 – FPT90; Table 4.1). We then generated a single season occupancy model to estimate occupancy (Ψ) and detection (p) (MacKenzie *et al.*, 2018) using the *unmarked* package in R (Chandler *et al.*, 2019) for each species/species group. We explored whether including habitat and weather covariates were informative in the models by including environmental data in the occupancy models. Data from the Jersey Met Office was used to calculate the average nightly temperature (mean = 16.8 ^{o}C, SD = 0.75 ^{o}C), precipitation (mean = 0.01 mm, SD = 0.03 mm) and wind speed (mean = 4.10 ms^{-1}, SD = 1.67 ms^{-1}). These values were standardised using the *vegan* package (Oksanen *et al.*, 2019) and included in initial models as observation covariates as possible influences on detection probability. The habitat defined for each site through the initial site selection process (Supplementary Table 1) was also recorded as a site covariate for occupancy probability. However, early testing of 2018 survey data models showed that these were not informative due to limited variation in the data. As such environmental variables were excluded from the rest of the analysis.

Table 4.1 Summary of the number of calls for five species/species groups in Jersey recorded during 2018-2019 pilot surveys used in the occupancy analysis. *n_{calls} represents the number of calls classified by BatIdentify and n_{occ} represents the number of corresponding occupied grid squares for species across the range of FPTs assessed (50 – 90). Dash represents occasions when thresholding to the each FPT removed all calls, or when occupancy modelling failed to produce a result (see 4.3. Results).*

	Total	**FPT50**		**FPT60**		**FPT70**		**FPT80**		**FPT90**	
Species/Species Group	n_{calls}	n_{calls}	n_{occ}	n_{calls}	n_{occ}	n_{calls}	n_{occ}	n_{calls}	n_{occ}	n_{calls}	n_{occ}
2018											
Eptesicus serotinus	6,803	2,197	73	1,682	70	1,362	64	1,000	49	472	27
Myotis nattereri	1,370	1,113	53	623	40	-	-	-	-	-	-
Pipistrellus n/k	77,059	77,059	-	77,059	-	75,590	-	49,292	90	5,851	76
Pipistrellus pipistrellus	1,778,925	1,778,925	-	1,778,925	-	1,778,925	-	1,774,856	-	1,608,568	-
Plecotus spp	6,596	6,596	-	6,572	86	-	-	-	-	-	-
2019											
Eptesicus serotinus	2,636	575	24	382	19	270	13	129	10	28	7
Myotis nattereri	290	155	13	30	7	-	-	-	-	-	-
Pipistrellus n/k	28,171	28,171	-	28,171	44	28,017	44	14,186	40	747	27
Pipistrellus pipistrellus	1,195,164	1,195,164	-	1,195,164	-	1,195,164	45	1,191,294	45	1,016,081	45
Plecotus spp	1,574	1,574	-	1,571	35	-	-	-	-	-	-

4.3. Results

The highest occupancy and detection estimates in both years and across all FPTs was observed for *Pipistrellus pipistrellus* and *P. nathusii/kuhlii* (Table 4.2, Figures 4.1 and 4.2). In fact, *P. pipistrellus* was detected at every site on every visit at FPT50 - 70 in 2018 and FPT50 - 60 in 2019, and as such the models failed to find any variation in detection history. There was some variation in occupancy observed for *P. pipistrellus* (FPT70 - 90) and *P. nathusii/kuhlii* (FPT60 - 70) in the 2019 data, however large error bars indicate a large degree of uncertainty in this result (Figure 4.1). Occupancy estimates obtained for *P. nathusii/kuhlii* at FPT80 and 90 were relatively high, although the estimate at FPT90 was lower in 2019 compared to 2018 (Figure 4.1). Detection estimates for both of these species remained stable across FPTs, with the exception of a sharp decline at FPT90 for *P. nathusii/kuhlii* (Figure 4.2).

Plecotus species also demonstrated high levels of occupancy in 2018 and 2019 ($\Psi = 0.96$ and 0.70 respectively). The detection probability for *Plecotus* demonstrated a sharp drop between 2018 and 2019 ($p = 0.85 – 0.58$; Figure 4.2). Similarly, *Myotis nattereri* showed a large decrease in occupancy and detection estimates between years, and also between FPT levels (Figures 4.1 and 4.2). Both of these species could only be modelled at moderate FPT levels (FPT50 - 60), and as such should be viewed with caution. *Eptesicus serotinus* was the only species for which occupancy could be modelled at all FPT levels (Table 4.2). In 2018, the occupancy estimate remains relatively stable at lower FPTs ($\Psi = 0.95 – 0.91$), before falling substantially at FPT90 ($\Psi = 0.39$). Conversely, in 2019 the occupancy estimate decreased sharply between FPT50 - 70 ($\Psi = 0.86 – 0.36$) before stabilising at higher FPTs ($\Psi = 0.36 – 0.30$). Detection estimates also followed a different pattern between years; although detection was generally higher in 2018, at moderate FPT levels, estimates in both years were equivalent (Figure 4.2).

Table 4.2. Occupancy and detection estimates from single species, single season occupancy models for five species/species groups in Jersey at different false positive tolerance (FPT) levels. *The proportion of survey squares occupied during each season ($prop_{occ}$) is given along with the occupancy (Ψ) and detection (p) estimates, with upper and lower 95% confidence limits, * represents those which failed to produce estimates.*

2018 - proportional representation of habitats

Species	*FPT*	*$prop_{occ}$*	*Ψ*	*Ψ_{L95}*	*Ψ_{U95}*	*p*	*p_{L95}*	*p_{U95}*	
Eptesicus serotinus	50	0.81	0.93	0.70	0.99	0.50	0.42	0.58	
Eptesicus serotinus	60	0.78	0.95	0.48	1.00	0.44	0.35	0.52	
Eptesicus serotinus	70	0.71	0.91	0.56	0.99	0.40	0.31	0.49	
Eptesicus serotinus	80	0.54	0.79	0.50	0.94	0.32	0.23	0.44	
Eptesicus serotinus	90	0.30	0.39	0.26	0.54	0.39	0.26	0.54	
Myotis nattereri	50	0.59	0.69	0.54	0.80	0.48	0.39	0.58	
Myotis nattereri	60	0.44	0.52	0.39	0.65	0.47	0.36	0.58	
Pipistrellus n/k	50 - 70	1.00	-	-	-	-	-	-	*
Pipistrellus n/k	80	1.00	1.00	0.00	1.00	0.99	0.97	1.00	
Pipistrellus n/k	90	0.84	0.87	0.77	0.93	0.70	0.63	0.76	
Pipistrellus pipistrellus	50 - 90	1.00	-	-	-	-	-	-	*
Plecotus spp	60	0.96	0.96	0.89	0.99	0.85	0.79	0.89	

2019 - equal representation of habitats

Species	*FPT*	*$prop_{occ}$*	*Ψ*	*Ψ_{L95}*	*Ψ_{U95}*	*p*	*p_{L95}*	*p_{U95}*	
Eptesicus serotinus	50	0.48	0.86	0.28	0.99	0.27	0.17	0.40	
Eptesicus serotinus	60	0.38	0.63	0.35	0.85	0.29	0.18	0.44	
Eptesicus serotinus	70	0.26	0.36	0.21	0.56	0.39	0.24	0.56	
Eptesicus serotinus	80	0.20	0.30	0.15	0.51	0.34	0.19	0.54	
Eptesicus serotinus	90	0.14	0.32	0.09	0.69	0.18	0.05	0.47	
Myotis nattereri	50	0.26	0.39	0.21	0.61	0.33	0.18	0.52	
Myotis nattereri	60	0.14	0.23	0.09	0.46	0.29	0.11	0.57	
Pipistrellus n/k	50	1.00	-	-	-	-	-	-	*
Pipistrellus n/k	60	0.88	1.00	0.00	1.00	0.81	0.74	0.86	
Pipistrellus n/k	70	0.88	1.00	0.00	1.00	0.81	0.74	0.86	
Pipistrellus n/k	80	0.80	0.91	0.76	0.97	0.74	0.65	0.81	
Pipistrellus n/k	90	0.54	0.76	0.50	0.91	0.37	0.26	0.49	
Pipistrellus pipistrellus	50 - 60	1.00	-	-	-	-	-	-	*
Pipistrellus pipistrellus	70	0.90	1.00	0.00	1.00	0.92	0.87	0.96	
Pipistrellus pipistrellus	80	0.90	1.00	0.00	1.00	0.92	0.87	0.96	
Pipistrellus pipistrellus	90	0.90	1.00	0.00	1.00	0.92	0.86	0.95	
Plecotus spp	60	0.70	0.83	0.66	0.93	0.58	0.48	0.67	

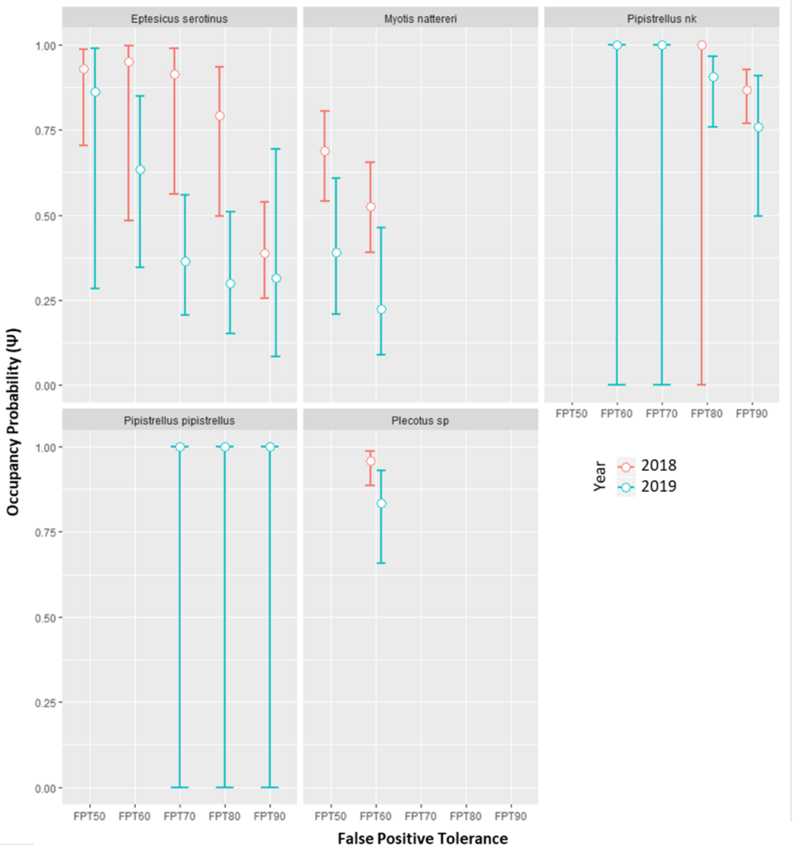

Figure 4.1. Occupancy estimates from single species, single season models for five species/species groups in Jersey at different false positive tolerance (FPT) levels. *Points represent occupancy (Ψ) estimates and whiskers 95% confidence limits, colours represent estimates in each pilot survey year.*

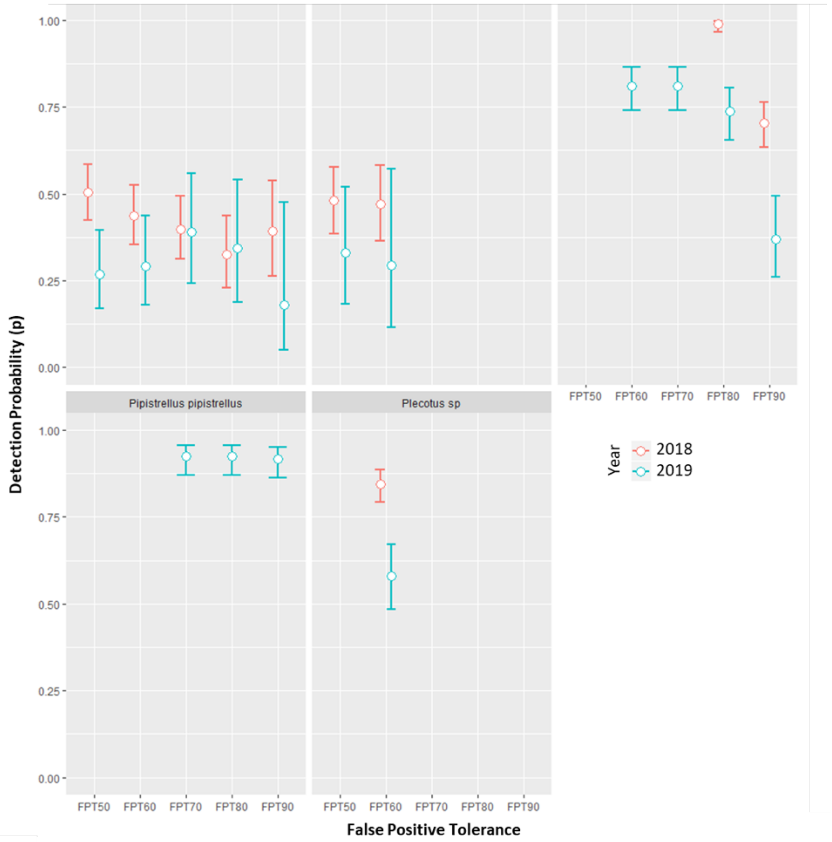

Figure 4.2. Detection estimates from single species, single season models for five species/species groups in Jersey at different false positive tolerance (FPT) levels. *Points represent detection (p) estimates and whiskers 95% confidence limits, colours represent estimates in each pilot survey year.*

4.4. Discussion

Our analysis generated baseline occupancy and detection estimates for five species/species groups of Jersey bat species. *Pipistrellus pipistrellus* was found to be so widespread across Jersey, that it was present at every survey site during each survey in 2018, and in at least 90% of survey squares in 2019. As such the occupancy modelling approach proved to be ineffective, as the models cannot estimate occupancy and detection probabilities with little to no variation in the detection history. The occupancy of *P. pipistrellus* is consistent with other evidence that these species are widespread across Jersey (Hawkins *et al*. 2016; Williams *et al*., 2019). Detection histories of *P. nathusii*/*kuhlii* also showed little to no variation in either year, although, at FPT90 there was enough variation to estimate occupancy and detection probabilities. With such widespread species, other analysis techniques such as estimating relative abundance from acoustic activity might be more appropriate to monitor population trends.

The occupancy of *Plecotus* species was modelled at FPT60 (>40% of classifications are likely false) and inferences on occupancy and detection should be cautious on the basis of this analysis. In particular, the high detection estimate for *Plecotus spp.* in 2018 ($p = 0.85$) is likely to be an overestimate of the true rate. The occupancy estimates for this group ($\Psi = 0.96$ and 0.83 in 2018 and 2019 respectively) also appear high, given that *P. auritus* is usually restricted to woodland habitats, of which there are few locally. However, *P. austriacus* is known from roosts across the island, and a local paucity in their preferred foraging habitats (semi-improved and unimproved grassland) may lead this species to make greater use of the wider agricultural landscape. Less restrictive foraging behaviour enabling *P. austriacus* to access more of the island could explain the seemingly high occupancy estimates. Due to the difference in ecological requirements, and the local and national importance of Jersey's *P. austriacus* population, it is desirable to distinguish between these species for monitoring purposes.

Occupancy estimates were moderate to low for *M. nattereri*, reflective of a likely patchy local distribution restricted to particular habitats (e.g. woodland). The degree of influence habitat availability has on the distribution of *M. nattereri* and other species here should be examined in more depth through the inclusion of appropriate habitat covariates in the modelling process. However, failure to achieve FPTs above FPT60 limits the reliability of the estimates presented, as such these should be used carefully until such time as the classification process is more robust. Increasing FPT levels led to decreasing estimates of occupancy for *Eptesicus serotinus*. This result is expected, as increasing the proportion of false positives in the data is likely to lead to a species being detected at sites where it is not present. However, in 2018, the occupancy estimate remained stable at lower FPTs before dropping substantially at FPT90, whereas in 2019 the occupancy estimate dropped at lower FPTs and stabilised between FPT70 – 90. This may be due to the different site selection processes employed, but comparable estimates at FPT90 for both years indicates that the thresholding approach used is capable of providing consistent results at high FPTs.

The results demonstrate a tendency for occupancy and detection estimates to be lower in 2019 when compared to 2018. Different approaches were taken to site selection in each year: in 2018 habitats were sampled proportionally based on overall island wide availability, and in 2019 habitats were represented equally. Jersey is dominated by its agricultural landscape, comprising a mix of crop, pastoral and grassland therefore, in 2018 over two thirds of the sites surveyed were represented by arable or grassland habitat types. Species which specialise in open agricultural or edge habitats, such as pipistrelles and serotines, are therefore more likely to be encountered during these 2018 surveys, driving higher occupancy and detection estimates. The opposite may be expected for clutter specialists such as *Myotis nattereri* and *P. auritus*, however a similar decrease in occupancy and detection estimates is seen between the two survey years. This indicates that there are processes not encapsulated by this analysis affecting occupancy, and further research should be carried out into the potential for site specific features (e.g. surrounding habitat, distance to roads and water, length of hedgerows) to influence patterns of occurrence. The null models reported here however, provide a generalised view of island wide occupancy which is sufficient as a basis for further research.

The error thresholding approach employed in this study aimed to minimise, or at least help explain, the impact of error in the data on our understanding of bat ecology. However, even at the highest FPT (FPT90) around 10% of the classifications are incorrect. We have used a simple modelling approach to assess occupancy and detection estimates here, but moving forward, the use of occupancy models which explicitly account for false positives and the impact of other environmental variables should be developed, and data collected from other surveys (e.g. roost and trapping surveys) can be included in such models to help account for error. The use of other metrics should also be explored to understand how abundance measures might be estimated from relative acoustic activity to track population trends.

Section 5. Power to detect trends in occupancy of bat species in Jersey over time

5.1. Background

Investment in new wildlife monitoring schemes is often substantial in terms of purchasing equipment, building a volunteer base and committing time and budget over a number of years. A common criticism of monitoring schemes comes when they fail to deliver robust results following significant resource input. It is vital to spend time early on investigating the statistical power of a proposed methodology to deliver the desired results. This should include consideration of the practicalities of particular methods, the ecological metrics of interest, what degree of change in these metrics over time provokes a response, and what this response will be. For example, the Jersey Bat Survey aims to use a network of static acoustic sensors to record bat calls across the island. The degree to which this is achievable will depend on the number of sensors available and the number of sites which can be surveyed (i.e. sufficient volunteer resource). Currently, the metric of ecological interest is occupancy probability which is determined by ecological processes inherent to the life histories of each species and tempered by our ability to accurately detect the presence of a species in a given area. It is these two metrics which will influence the capability of the proposed methodology to deliver robust trends, and resource availability that will constrain survey design.

In order to assess the power of the Jersey Bat Survey methodology to detect a change in the occupancy of bat species, we ran a series of power analyses for various feasible survey designs. Power analyses allow for parameters in the survey methodology (number of sites and visits) and species ecology (occupancy probability) to be varied, assessing the ability (power) of a methodology to detect a pre-determined ecological effect (in this case, a change in occupancy). The results provide an insight into how practical considerations around survey effort and investment may influence the power of the survey and can be used to guide future development of the Jersey Bat Survey.

5.2. Methods

We conducted a series of power analyses designed for use with an occupancy modelling framework based on variations to the survey design (Guillera-Arroita and Lahoz-Monfort, 2012) for the five species/species groups. The scenarios represent practical options for deploying a sensor network locally and cover all combinations of the following: 30, 60, 90 or 120 sites, and 3, 6 or 9 repeat visits. The analyses were parameterised based on detecting a 25% change in occupancy between any two survey seasons, with a significance level of $\alpha = 0.05$ at a power of 0.8. The significance and power levels are based on common practice in power analyses, and the 25% change in occupancy reflects the amount of change required for an amber listing for the Bat Conservation Trust's National Bat Monitoring Programme (Barlow *et al.*, 2015). This method takes the starting parameters and simulates the power achieved across the full range of detection and occupancy probabilities possible (0 – 1). This is then visualised via a contour plot with the occupancy and detection estimates from the occupancy models at the maximum possible False Positive Tolerance to give an approximation of where particular species/species groups are likely to fall. The estimates used were those generated from the 2019 data (Section 4, Table 4.2). As the 2019 data were collected equally over the range of habitats available it gives a generalised overview of occupancy across the island. This is in contrast to a bias towards particularly common habitats (arable and grassland) in the 2018 data.

We also repeated the analyses for species found in Jersey for which occupancy and detection estimates could not be obtained in our study (*Myotis brandtii*/*mystacinus*, *M. daubentonii*, *Nyctalus leisleri*, *N.*

noctula, and *Pipistrellus pygmaeus*) using the estimates presented in Newson (2017). The estimates are based on published values for these bat species in the UK which may not be representative of bats in Jersey, and so the results should be considered provisional until more information is available.

5.3. Results

Carrying out surveys at 30 sites, regardless of the number of visits failed to achieve the power to detect a 25% change in occupancy for any species other than *P. pipistrellus* (Table 5.1, Figure 5.1). Increasing the number of sites to 60 only brought one additional species, *P. pygmaeus (based on data from Newson 2017)*, up to the target of 80% power. *Plecotus spp.* are very nearly encapsulated by 60 sites over 6 visits (power = 0.74), indicating that a small increase in the number of sites may be sufficient to confidently include this group. At 90 sites, *Plecotus spp.* exceeds 80% power with 6 visits, *P. nathusii/kuhlii* now gets close to the threshold (power = 0.68, increasing to 0.78 with 9 visits). However, *P. nathusii/kuhlii* only achieves 80% power at 120 sites with 6 visits (Figure 5.1). This suggests that for species exhibiting lower occupancy estimates, a substantial increase in the number of sites surveyed would be required to achieve the desired power. Of the 10 species included in the analysis, low occupancy estimates for 6 species lead to their failure to achieve the necessary power for any scenario tested (Figure 5.1).

Table 5.1. Results from the power analysis showing the power achieved across a range of survey methodologies comprising of each combination of 30, 60, 90 and 120 sites surveyed, and 3, 6 and 9 repeat visits. *Occupancy (Ψ) and detection (p) estimates used in the power analyses are also given, * indicates species/species groups for which estimates were obtained from Newson 2017.*

	Occupancy Estimates		**Power achieved for different survey strategies (n_{sites} x n_{visits})**					
Species	*Ψ*	*p*	*30 x 3*	*30 x 6*	*30 x 9*	*60 x 3*	*60 x 6*	*60 x 9*
Eptesicus serotinus	0.32	0.18	0.06	0.07	0.09	0.06	0.10	0.13
Myotis nattereri	0.23	0.29	0.06	0.08	0.08	0.07	0.11	0.12
Pipistrellus n/k	0.76	0.37	0.13	0.29	0.34	0.22	0.51	0.59
Pipistrellus pipistrellus	1.00	1.00	0.88	0.88	0.88	0.99	0.99	0.99
Plecotus spp.	0.83	0.58	0.34	0.46	0.46	0.59	0.74	0.75
Myotis brandtii/mystacinus*	0.22	0.83	0.08	0.08	0.08	0.12	0.12	0.12
Myotis daubentonii*	0.32	0.78	0.11	0.11	0.11	0.16	0.17	0.17
Nyctalus leisleri*	0.21	0.86	0.08	0.08	0.08	0.12	0.12	0.12
Nyctalus noctula*	0.42	0.88	0.14	0.14	0.14	0.22	0.22	0.22
Pipistrellus pygmaeus*	0.93	0.96	0.68	0.68	0.68	0.93	0.93	0.93
			90 x 3	*90 x 6*	*90 x 9*	*120 x 3*	*120 x 6*	*120 x 9*
Eptesicus serotinus	0.32	0.18	0.07	0.12	0.17	0.07	0.14	0.21
Myotis nattereri	0.23	0.29	0.08	0.13	0.15	0.10	0.16	0.19
Pipistrellus n/k	0.76	0.37	0.31	0.68	0.76	0.39	0.80	0.87
Pipistrellus pipistrellus	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Plecotus spp.	0.83	0.58	0.76	0.89	0.90	0.87	0.96	0.96
Myotis brandtii/mystacinus*	0.22	0.83	0.15	0.16	0.16	0.19	0.19	0.19
Myotis daubentonii*	0.32	0.78	0.22	0.22	0.22	0.28	0.28	0.28
Nyctalus leisleri*	0.21	0.86	0.15	0.15	0.15	0.18	0.18	0.18
Nyctalus noctula*	0.42	0.88	0.31	0.31	0.31	0.40	0.40	0.40
Pipistrellus pygmaeus*	0.93	0.96	0.99	0.99	0.99	1.00	1.00	1.00

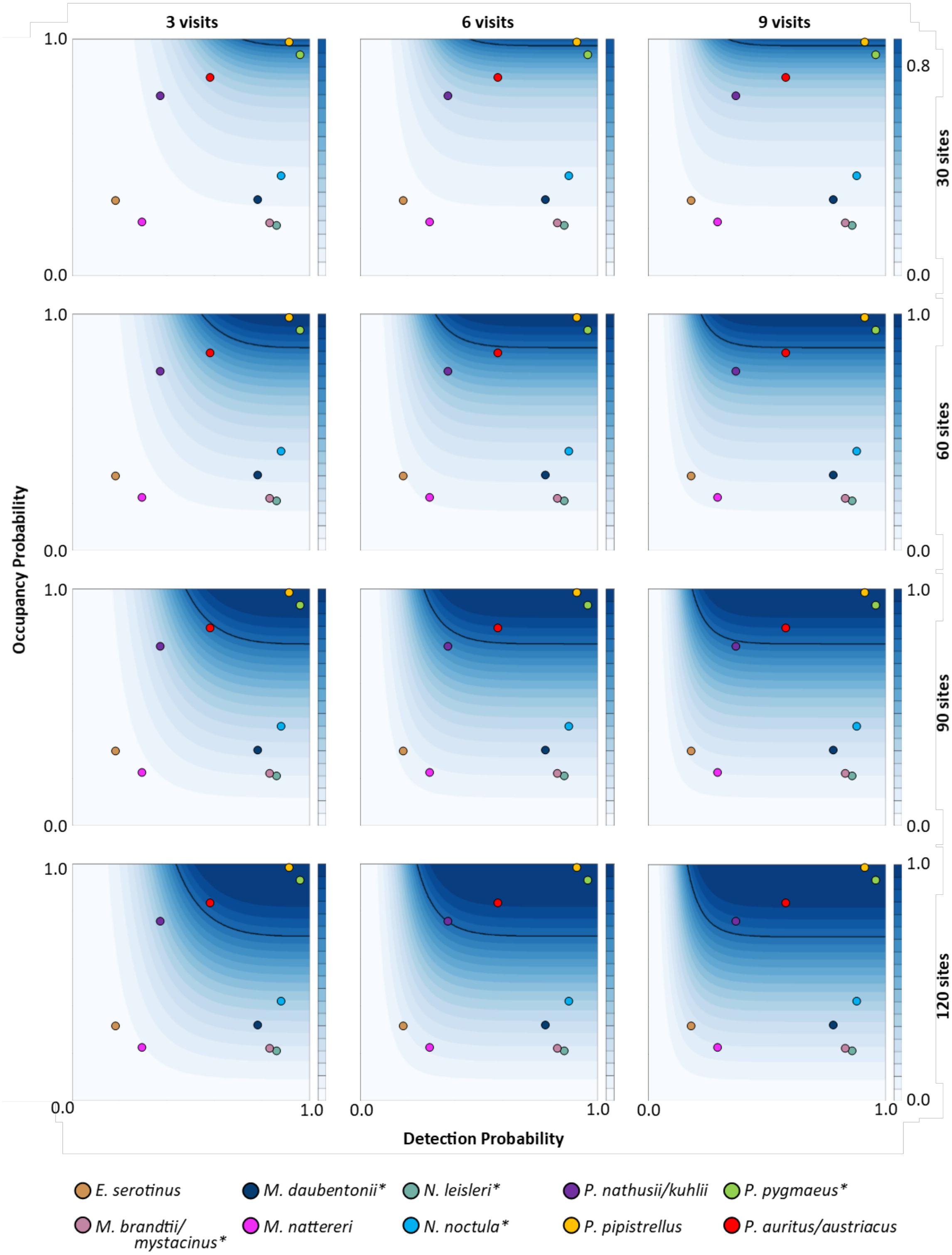

Figure 5.1. Power curves demonstrating the level of statistical power achieved using differing survey methodologies across a range of occupancy and detection probabilities. *Coloured dots represent the approximate position of different species based on occupancy and detection estimates from this study. Where this was not possible estimates from Newson (2017) were used, indicated by *. The solid line indicates the 80% power threshold.*

5.4. Discussion

Our results using the detection and occupancy estimates from the 2019 pilot surveys in Jersey and those from Newson (2017) for missing species, indicate that carrying out surveys at 90 sites will be sufficient for *Pipistrellus pipistrellus*, *P. pygmaeus and Plecotus spp*. Therefore, ongoing surveys should cover at least 70 sites, but aim to cover 90 sites per season in order to maximise power. Each site should be surveyed a minimum of 5 non-consecutive nights per season, in order to fulfil the requirements of the occupancy models and to improve the chances of picking up less detectable species. This level of survey effort is likely achievable with the assistance of citizen scientists in Jersey as there was great interest in volunteering for the Jersey Bat Survey in 2019, and this enthusiasm should be fostered to maintain and enhance the support. Our analysis also suggests that in order to exceed the power threshold for the *Pipistrellus nathusii/kuhlii* species group a minimum of 120 sites should be surveyed. This level of survey input is only likely to be possible in Jersey if there is a substantial increase in the number of volunteer citizen scientists. None of the other species managed to approach the 80% power threshold through any feasible combination of survey design and the number of sites surveyed. Given Jersey's size this means that at present the power of the survey for these other species is limited.

It is important to consider some caveats to our results. Firstly, the information for some of the species presented use estimates come from the UK (Newson 2017). Efforts should be made to include relevant information for Jersey bat populations as previous work has shown that occupancy and detection estimates for bat species tend to be higher in the mainland than in Jersey (Hawkins *et al.*, 2016). Secondly, the power analyses for other species/species groups are ultimately based on the accuracy of the classifier and improved confidence in the classification process will enable development of more accurate occupancy estimates, generating a more robust view of the potential power of this survey. Thirdly, using other metrics such as abundance, rather than occupancy to understand the potential power of the survey should be explored, for example using relative bat acoustic activity as estimates of abundance. This may increase the sensitivity of the survey and reduce the effort needed to produce meaningful trends. Fourthly, analysis has been based on the ability to detect a 25% change in occupancy between any two survey periods. This is in line with the definition used by the Bat Conservation Trust for assessing an amber risk to species (Barlow *et al.*, 2015). However, given Jersey's size, a 25% decline in occupancy of any particular species may represent a substantial impact on local populations. It would be beneficial to consider whether aiming to detect a lower level of change would be more relevant for Jersey, so any decline can be detected before it becomes too severe. Finally, the computing power and storage required for the analysis of the audio data is not trivial. If the survey is to be rolled out on the scale suggested, there needs to be substantial investment in digital infrastructure to manage the project.

Section 6. Synthesis and Recommendations

In our report, we describe the implementation of two pilot surveys in Jersey in 2018 and 2019 using a static sensor network and open-source automated acoustic machine learning algorithms, and then use these data to understand the potential of this monitoring system to generate long-term bat population trends. We conclude that data collection from a network of static sensors deployed using citizen scientists with automated acoustic detection and classification is a feasible and economical method for future monitoring of bats in Jersey and seems worthwhile pursuing in conjunction with existing monitoring programmes (e.g. Indicator Bats Programme).

Our results suggest that the performance of **BatDetect v.2** to find calls of all bat species in Jersey as determined by False Positive Tolerances, FPTs through manual verification is high but the accuracies of species classifications in **BatIdentify v.2** are more variable. Improvements to the **BatIdentify** algorithm are needed for the development of any future acoustic monitoring programmes and also importantly, to better utilize the data collected from existing acoustic monitoring programmes in Jersey. Efforts should focus on collecting species reference calls so **BatIdentify** can be retrained on more comprehensive datasets and species which are representative of Jersey. In particular, data collection and retraining should focus on *Pipistrellus kuhlii* and the two *Plecotus* species as these are of high regional importance to Jersey.

BatIdentify produces classifications accurate enough (FPTs >50) to generate robust data for five species/species groups (*Eptesicus serotinus*, *M. nattereri*, *P. nathusii/kuhlii*, *P. pipistrellus* and *Plecotus spp.*), with classifications of *E. serotinus*, *P. nathusii/kuhlii*, and *P. pipistrellus* being especially accurate (FPT90 - <10% of classifications are likely false). FPTs for other species were low, surprisingly including a widespread and common species in Jersey with a distinctive call (*P. pygmaeus*). Estimating FPTs is a useful technique to assess error in species classifications, but the manual verification dataset used here was rather limited and these analyses should be repeated with a more comprehensive set of data and manual verification should be carried out independently by more than one expert.

Using the five species with FPTs >50, analysis of occupancy, Ψ and detection, p using data across 2018-19 suggested that *P. pipistrellus* had the highest occupancy across the island followed by *Plecotus spp. P. nathusii/kuhlii* and *M. nattereri*, with occupancy estimates of *E. serotinus* less certain. However, for species with lower FPTs these estimates should be used cautiously. Using changes in occupancy to monitor populations is a powerful technique and further improvements which incorporate error rates, habitat variables, and other data sources should be carried out in order to better understand future survey effort and design. For some widespread and common species, estimating population trends with estimates of abundance should be considered to compliment the results presented here.

Our results using the occupancy and detection estimates from the 2019 survey in Jersey and those from the UK , indicate that 90 sites will be sufficient to detect a 25% change in occupancy with high confidence ($\alpha = 0.05$) of *Pipistrellus pipistrellus*, *P. pygmaeus and Plecotus spp*. Therefore, future surveys should cover at least 70 sites for five non-consecutive nights but aim to cover 90 sites per season in order to maximise power. This level of survey effort is likely achievable with the assistance of citizen scientists in Jersey as there was great interest in volunteering for the 2019 survey. None of the other species managed to approach the 80% power threshold through any feasible combination of survey design and the number of sites surveyed, except the *Pipistrellus nathusii/kuhlii* species group which needed a minimum of 120 sites. Our estimates are subject to revision with a more accurate classifier, more comprehensive FPTs testing, more complete information on the occupancy and detection of Jersey bat species and exploring the use of different metrics such as abundance to calculate population trends. The detection of some bat species, even with improved information, may be insufficient for this method to ever produce long-term robust population trends, so therefore a multi-disciplinary approach is required to encompass the full range of bat species found locally, and the methods described here should be used in conjunction with other surveys. Scaling up the pilot surveys into a monitoring programme will also require a strong volunteer network of motivated and trained citizen scientists and a robust digital infrastructure to store and analyse large volumes of acoustic data. The resources required to accomplish this should be given careful consideration.

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Supplementary Information

Supplementary Table S1. Survey locations for 2018 and 2019, including habitat and location information.

2018					2019				
Site	*Habitat*	*Latitude*	*Longitude*	$n_{(visits)}$	*Site*	*Habitat*	*Latitude*	*Longitude*	$n_{(visits)}$
C1	Grassland	49.2051	-2.1684	2	WV5648	Grassland	49.1860	-2.2264	4
C2	Miscellaneous	49.2581	-2.1490	0	WV5650	Water	49.2044	-2.2176	4
C3	Arable	49.2517	-2.1494	3	WV5651	Water	49.2112	-2.2202	2
C4	Arable	49.2433	-2.1484	3	WV5654	Arable	49.2418	-2.2287	0
C5	Arable	49.2240	-2.1514	3	WV5748	Grassland	49.1880	-2.2088	1
C6	Grassland	49.2157	-2.1509	3	WV5750	Water	49.2028	-2.2174	3
C7	Grassland	49.1979	-2.1585	3	WV5751	Water	49.2162	-2.2058	2
C8	Arable	49.2483	-2.1377	3	WV5754	Arable	49.2442	-2.2144	4
C9	Arable	49.2388	-2.1407	3	WV5849	Urban	49.1965	-2.1962	4
C10	Arable	49.2221	-2.1405	3	WV5851	Water	49.2164	-2.2029	2
C11	Arable	49.2152	-2.1404	3	WV5853	Arable	49.2283	-2.1932	4
C12	Arable	49.2046	-2.1412	3	WV5854	Grassland	49.2426	-2.1976	4
C13	Grassland	49.1981	-2.1439	3	WV5947	Woodland	49.1731	-2.1820	4
C14	Arable	49.2320	-2.1236	3	WV5948	Grassland	49.1871	-2.1856	4
C15	Woodland	49.2100	-2.1243	3	WV5950	Grassland	49.2003	-2.1869	4
C16	Arable	49.2040	-2.1273	3	WV5954	Arable	49.2360	-2.1813	2
C17	Urban	49.1960	-2.1251	3	WV6049	Woodland	49.1952	-2.1684	2
C18	Urban	49.1771	-2.1091	3	WV6051	Woodland	49.2087	-2.1660	4
C19	Urban	49.1851	-2.1093	3	WV6052	Woodland	49.2212	-2.1724	4
C20	Urban	49.1908	-2.1031	3	WV6053	Grassland	49.2298	-2.1739	4
C21	Urban	49.1856	-2.0977	3	WV6150	Grassland	49.2016	-2.1537	0
C22	Urban	49.1933	-2.0943	3	WV6152	Arable	49.2247	-2.1547	4
C23	Urban	49.1770	-2.0821	3	WV6251	Woodland	49.2136	-2.1367	5
C24	Urban	49.1855	-2.0847	3	WV6252	Arable	49.2212	-2.1399	2
C25	Urban	49.1967	-2.0820	3	WV6255	Arable	49.2508	-2.1380	2
C26	Grassland	49.2073	-2.1111	3	WV6350	Water	49.2072	-2.1348	4
C27	Arable	49.2151	-2.1115	3	WV6352	Grassland	49.2247	-2.1339	4
C28	Grassland	49.2231	-2.1061	3	WV6353	Water	49.2315	-2.1318	3
C29	Grassland	49.2320	-2.1099	3	WV6448	Urban	49.1856	-2.1113	4
C30	Grassland	49.2361	-2.1114	3	WV6449	Urban	49.1982	-2.1167	4
E1	Grassland	49.2538	-2.1007	3	WV6450	Urban	49.2042	-2.1135	4
E2	Arable	49.2477	-2.0980	3	WV6451	Grassland	49.2088	-2.1212	4
E3	Arable	49.2410	-2.0989	3	WV6452	Arable	49.2239	-2.1188	2
E4	Arable	49.2213	-2.0964	3	WV6548	Urban	49.1898	-2.0974	0
E5	Grassland	49.2131	-2.0997	3	WV6550	Woodland	49.2005	-2.1032	3
E6	Grassland	49.2058	-2.0961	3	WV6647	Urban	49.1748	-2.0856	2
E7	Grassland	49.2377	-2.0861	3	WV6649	Grassland	49.1960	-2.0920	2
E8	Arable	49.2305	-2.0878	3	WV6650	Water	49.2043	-2.0883	4
E9	Urban	49.2017	-2.0819	3	WV6651	Woodland	49.2163	-2.0906	5

E10	Arable	49.2212	-2.0729	3
E11	Arable	49.1945	-2.0692	3
E12	Arable	49.1870	-2.0698	3
E13	Woodland	49.1737	-2.0740	3
E14	Woodland	49.2361	-2.0525	3
E15	Grassland	49.2217	-2.0561	3
E16	Grassland	49.2069	-2.0512	3
E17	Grassland	49.1884	-2.0540	3
E18	Arable	49.1759	-2.0566	3
E19	Arable	49.1697	-2.0595	3
E20	Arable	49.2314	-2.0406	3
E21	Arable	49.2136	-2.0384	3
E22	Arable	49.2035	-2.0437	3
E23	Grassland	49.1691	-2.1672	3
E24	Woodland	49.1944	-2.0451	3
E25	Grassland	49.1887	-2.0388	3
E26	Arable	49.1776	-2.0413	3
E27	Grassland	49.2322	-2.0265	3
E28	Arable	49.2216	-2.0302	3
E29	Arable	49.2137	-2.0315	3
E30	Woodland	49.2038	-2.0247	3
W1	Miscellaneous	49.2558	-2.2447	0
W2	Miscellaneous	49.2449	-2.2458	0
W3	Grassland	49.2552	-2.2396	3
W4	Arable	49.2502	-2.2341	3
W5	Grassland	49.2306	-2.2339	3
W6	Miscellaneous	49.1786	-2.2318	0
W7	Arable	49.2450	-2.2192	3
W8	Arable	49.2322	-2.2221	3
W9	Grassland	49.2217	-2.2261	3
W10	Grassland	49.1771	-2.2231	3
W11	Arable	49.2400	-2.2071	3
W12	Grassland	49.2314	-2.2039	3
W13	Grassland	49.2021	-2.2114	3
W14	Grassland	49.1963	-2.2076	3
W15	Grassland	49.1829	-2.2082	3
W16	Grassland	49.2479	-2.1877	3
W17	Arable	49.2311	-2.1924	3
W18	Urban	49.2025	-2.1930	3
W19	Urban	49.1923	-2.1951	3
W20	Woodland	49.1830	-2.1890	3
W21	Arable	49.2462	-2.1792	3
W22	Grassland	49.2395	-2.1833	3
W23	Arable	49.2248	-2.1808	2
W24	Grassland	49.2141	-2.1798	3
WV6652	Woodland	49.2244	-2.0800	2
WV6746	Urban	49.1663	-2.0744	5
WV6748	Urban	49.1826	-2.0766	5
WV6847	Arable	49.1740	-2.0636	2
WV6850	Arable	49.2042	-2.0577	4
WV6947	Urban	49.1807	-2.0421	5
WV6949	Water	49.1953	-2.0457	2
WV6950	Water	49.2011	-2.0414	5
WV6952	Woodland	49.2193	-2.0474	4
WV7047	Urban	49.1752	-2.0354	4
WV7053	Woodland	49.2277	-2.0280	0

W25	Arable	49.2028	-2.1804	3
W26	Grassland	49.1941	-2.1784	3
W27	Grassland	49.1706	-2.1835	3
W28	Grassland	49.2401	-2.1652	3
W29	Water	49.2143	-2.2060	3
W30	Woodland	49.2116	-2.1640	3

Supplementary Table S2. Summary of the results of the manual checking of automated classifications. n_{raw} is the number of calls automatically classified to each species across the range of classifier confidence in 2018 (0 – 1, reported in 0.1 increments); n_{check} is the number of files manually checked; and n_{fp} the number of false positive classifications in the checked data.

	Upper limit of classifier confidence in automated classification									
	0.1	*0.2*	*0.3*	*0.4*	*0.5*	*0.6*	*0.7*	*0.8*	*0.9*	*total*
Barbastellus barbastellus										
n_{raw}	224	1,069	890	552	364	218	65	-	-	3,382
n_{check}	8	11	10	11	12	11	9	-	-	72
n_{fp}	8	11	10	11	12	11	9	-	-	72
Eptesicus serotinus										
n_{raw}	617	2,191	1,681	832	543	467	366	106	-	6,803
n_{check}	11	10	11	11	12	12	10	11	-	88
n_{fp}	10	9	4	7	1	2	1	1	-	35
Myotis alcathoe										
n_{raw}	220	1,518	1,147	290	53	2	-	-	-	3,230
n_{check}	8	9	10	12	10	1	-	-	-	50
n_{fp}	8	9	10	12	10	1	-	-	-	50
Myotis bechsteinii										
n_{raw}	196	529	576	269	47	3	-	-	-	1,620
n_{check}	12	11	12	11	9	2	-	-	-	57
n_{fp}	12	11	12	11	9	2	-	-	-	57
Myotis brandtii										
n_{raw}	760	4,166	3,978	2,471	1,461	683	113	4	-	13,636
n_{check}	13	9	10	10	10	12	11	1	-	76
n_{fp}	13	9	10	10	10	12	11	1	-	76
Myotis daubentonii										
n_{raw}	150	379	309	147	87	40	8	-	-	1,120
n_{check}	11	11	12	9	11	11	4	-	-	69
n_{fp}	11	9	9	8	7	11	4	-	-	59
Myotis mystacinus										
n_{raw}	-	-	1	-	1	-	-	-	-	2
n_{check}	-	-	-	-	-	-	-	-	-	0
n_{fp}	-	-	-	-	-	-	-	-	-	0
Myotis nattereri										
n_{raw}	-	53	103	101	115	256	466	276	-	1,370
n_{check}	-	10	11	11	10	12	11	11	-	76
n_{fp}	-	4	6	7	6	8	2	3	-	36
Nyctalus leisleri										
n_{raw}	249	1,742	2,177	2,171	1,907	1,408	557	28	-	10,239
n_{check}	12	12	11	12	10	12	12	11	-	92
n_{fp}	12	12	10	11	9	10	8	6	-	78
Nyctalus noctula										
n_{raw}	206	1,399	882	442	276	117	32	-	-	3,354

n_{check}	12	11	9	12	12	11	10	-	-	77
n_{fp}	12	11	9	12	11	10	10	-	-	75
Pipistrellus nathusii										
n_{raw}	560	5,429	14,002	15,322	14,358	12,783	10,719	3,886	-	77,059
n_{check}	12	10	11	11	12	9	11	11	-	87
n_{fp}	11	8	8	9	5	5	7	6	-	59
Pipistrellus pipistrellus										
n_{raw}	448	7,000	34,933	81,644	143,813	293,713	574,780	637,782	4,812	1,778,925
n_{check}	12	11	13	12	11	12	10	12	12	105
n_{fp}	2	3	4		1			1	1	12
Pipistrellus pygmaeus										
n_{raw}	505	1,966	10,848	18,522	9,151	4,611	2,701	687	-	48,991
n_{check}	12	12	10	12	9	8	8	12	-	83
n_{fp}	12	10	10	11	9	8	5	7	-	72
Plecotus auritus										
n_{raw}	59	460	483	263	104	17	3	-	-	1,389
n_{check}	12	10	9	12	11	8	1	-	-	63
n_{fp}	12	10	6	12	9	8	1	-	-	58
Plecotus austriacus										
n_{raw}	250	1,287	1,207	1,021	762	537	140	3	-	5,207
n_{check}	12	12	11	13	12	11	11	2	-	84
n_{fp}	4	5	7	2	3	5	5	1	-	32
Rhinolophus ferrumequinum										
n_{raw}	32	226	21	16	95	243	6	-	-	639
n_{check}	10	10	9	7	9	12	3	-	-	60
n_{fp}	10	10	9	7	9	12	3	-	-	60

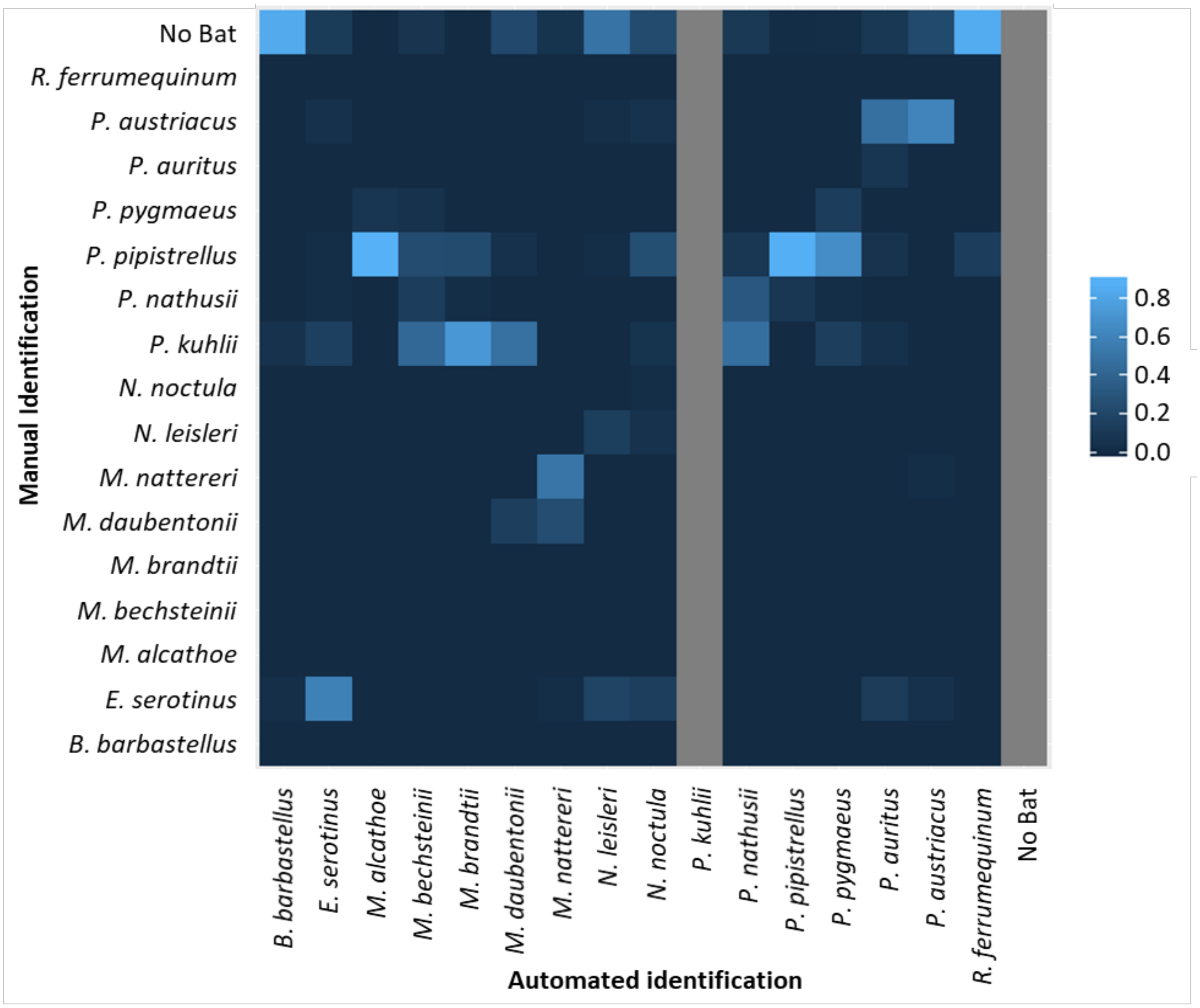
Supplementary Table S3. Summary of the results of the manual checking of automated classifications for subsequently grouped species. n_{raw} is the number of calls automatically classified to each species across the range of classifier confidence in 2018 (0 – 1, reported in 0.1 increments); n_{check} is the number of files manually checked; and n_{fp} the number of false positive classifications in the checked data.

	Upper limit of classifier confidence in automated classification								
	0.1	*0.2*	*0.3*	*0.4*	*0.5*	*0.6*	*0.7*	*0.8*	*0.9*	*total*
Myotis spp **|** *M. alcathoe, bechsteinii, brandtii, daubentonii and mystacinus*										
n_{raw}	1,326	6,592	6,010	3,177	1,648	728	121	4	-	19,606
n_{check}	44	40	44	42	40	26	15	1	-	252
n_{fp}	44	38	41	41	36	26	15	1	-	242
Nyctalus spp **|** *N. leisleri and noctula*										
n_{raw}	455	3,141	3,059	2,613	2,183	1,525	589	28	-	13,593
n_{check}	24	23	20	24	22	23	22	11	-	169
n_{fp}	24	23	19	23	20	20	18	6	-	153
Pipistrellus NK **|** *P. kuhlii and nathusii*										
n_{raw}	560	5,429	14,002	15,322	14,358	12,783	10,719	3,886	-	77,059
n_{check}	12	10	11	11	12	9	11	11	-	87
n_{fp}	2	4	3	4	1	1	1	1	-	17
Plecotus spp **|** *P. auritus and austriacus*										
n_{raw}	309	1,747	1,690	1,284	866	554	143	3	-	6,596
n_{check}	24	22	20	25	23	19	12	2	-	147
n_{fp}	16	15	13	14	12	13	6	1	-	90

Supplementary Table S4. Summary of results of the automated classification of data collected in 2019. Numbers of calls classified to individual species (above) and species groups (below), as well as the number of files without any classified bat calls present.

Upper limit of classifier confidence in automated classification										
0.1	*0.2*	*0.3*	*0.4*	*0.5*	*0.6*	*0.7*	*0.8*	*0.9*	*1*	*total*
-	20	148	65	19	6	-	-	-	-	258
-	132	1,338	555	303	193	91	26	1	-	2,639
-	67	213	86	28	5	1	-	-	-	400
-	27	18	8	3	-	-	-	-	-	56
-	370	2,569	2,558	864	326	200	116	1	-	7,004
-	13	16	20	12	6	2	1	-	-	70
-	-	19	59	59	51	50	50	2	-	290
-	80	4,052	20,785	86,912	105,792	12,799	1,200	59	-	231,679
-	122	1,244	502	176	87	33	13	1	-	2,178
-	64	2,600	7,929	6,181	4,543	3,900	2,587	386	-	28,190
-	417	8,403	39,633	84,848	137,393	230,993	389,212	304,126	311	1,195,336
-	300	2,131	7,072	7,913	5,125	2,999	1,522	366	-	27,428
-	20	217	176	100	39	1	-	-	-	553
-	53	274	297	221	116	42	18	-	-	1,021
-	5	416	50	-	-	-	-	-	-	471
-	477	2,816	2,672	907	337	203	117	1	-	7,530
-	202	5,296	21,287	87,088	105,879	12,832	1,213	60	-	233,857
-	64	2,600	7,929	6,181	4,543	3,900	2,587	386	-	28,190
-	73	491	473	321	155	43	18	-	-	1,574
-	-	-	-	-	-	-	-	-	-	317,198

Species
Barbastellus barbastellus
Eptesicus serotinus
Myotis alcathoe
Myotis bechsteinii
Myotis brandtii
Myotis daubentonii
Myotis nattereri
Nyctalus leisleri
Nyctalus noctula
Pipistrellus nathusii
Pipistrellus pipistrellus
Pipistrellus pygmaeus
Plecotus auritus
Plecotus austriacus
Rhinolophus ferrumequinum
Myotis spp
Nyctalus spp
Pipistrellus NK
Plecotus spp
No Bat



Supplementary Figure S1. Confusion matrix showing the proportion of correct and incorrect species classifications in the subset of data sampled for manual checking. Grey bars indicate classifications which are not assessed by BatIdentify but were identified during manual checks. The 'No Bat' row shows where confusion with non-bat noises frequently occurred.