iBats Jersey: analysis of 10-years of monitoring data

2022 Report and Recommendations

Bat Conservation Trust

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Executive summary

Determining the extent and impact of global and national biodiversity requires systematically collected biodiversity monitoring data. Bats occupy important niches and have been proposed as important biodiversity indicator species. Their use of sound to navigate through emitted echolocation calls makes them ideal species to monitor using passive acoustic surveys. Bat monitoring has been conducted annually on the island of Jersey since 2011 using car driven transects using time-expansion bat detectors using the Indicator Bats Programme (iBats) methodology. Time-expansion detectors were standard use in bat surveys at the start of the survey; however, they do not make continuous recordings. In 2018, full spectrum bat detectors were deployed alongside the time expansion detectors to assess whether future iBats surveys should use these continuously recording sensors in-place of the time-expansion detectors. In addition, advances in static acoustic sensor technology which have reduced device costs mean that an island-wide static survey of bats is now possible. A static passive acoustic survey of bats, the Jersey Bat Survey (JBatS) was piloted in 2018-2020.

In this report we compare bat call and species detection first between full spectrum bat detectors to time expansion detectors in car transect surveys, then between car transect surveys and static passive acoustic surveys. We also use the 10-year iBats time-expansion data to model a bat population trend and compare this trend with like trends from Great Britain and France. We find that more species and more bat calls were detected using full spectrum bat detectors compared to time-expansion detectors on car transects. However, the number of species detected were much greater using the JBatS method. *Pipistrellus pipistrellus* was the most recorded species across all surveys and it was only possible to produce 10-year population trend for this species using the iBats time expansion data. The population trend of this species showed a significant increase, greater than the increase reported from Great Britain.

Finally, we review and recommend methods for future bat surveys in Jersey, including roost counts, genetic analysis, and passive acoustic monitoring, and suggest opportunities for collaboration across organisations in Jersey. Our recommendations for 2022 include prioritising bat echolocation call collection in Jersey for retraining the automated bat call classifier and testing the JBatS static survey method. These recommendations would improve the taxonomic, geographic, and temporal understanding of bat population in Jersey, providing evidence for effective conservation actions.

Contents

1. Introduction

1.1 Scope of the report

This report contains analyses of ultrasonic recordings of bat echolocation calls collected by Government of Jersey Natural Environment Officers and volunteers. These recordings were obtained during both driven transects in July and August between 2011-2020 inclusive, and during pilot static monitoring which took place in July 2020. Data from static recordings made during 2018 and 2019 are not analysed or included in this report due to issues retrieving the data from storage. The aim of this report is to provide recommendations on future passive acoustic monitoring of bats in Jersey, as well as other bat monitoring methods including roost surveys and genetic studies.

1.2 Background

The Government of Jersey (GoJ) undertakes monitoring of bat populations as part of its International, European, and local legislative obligations, with bats representing a key biodiversity indicator. To date, this monitoring has included two passive acoustic survey methods termed iBats (Indicator Bats Programme) (Jones et al., 2013) and pilots of the Jersey Bat Survey (JBatS), a new monitoring scheme for Jersey. Roost surveys were also carried out in collaboration with the Jersey Bat Group; however, analysis of these data is not included in this report. iBats was run on Jersey for 10 years from 2011 to 2020, wherein ultrasonic recordings were made along 11 transect routes driven in July and August (Figure 1). JBatS is a more recent undertaking; a static acoustic monitoring method, with ultrasonic recordings made over a 1km grid across the island in July from 2018 to 2020 (Figure 2). Both methods record bat echolocation calls which can be used to identify bats to species level; these calls can then be geo-referenced, and species' locations determined across the island. Using these data, changes in bat populations and distributions can be assessed over time and the results used to inform decisions on future bat monitoring on Jersey.

In 2011, when iBats started in Jersey, it was standard practice to use time-expansion bat detectors. which record ultrasound and then play back the recordings at frequencies audible to the human ear. During the period of playback, no recording is made, leading to gaps in the recordings, which may cause underestimation of bat species activity and diversity due to missed bat calls. In more recent years, full spectrum bat detectors, which record continuously, have been more widely used in bat surveys. To assess the impact of using time-expansion on estimates of bat activity and species diversity, full spectrum recorders were deployed alongside time-expansion detectors on iBats surveys between 2017-2020.

Eighteen bat species have been recorded in Jersey, including three species not reported in the UK, *Pipistrellus kuhlii*, *Hypsugo savii*, and *Myotis emarginatus*, and eight species breed locally (Glynn & Jones, 2020) (Table 1). Interim analysis of the iBats data collected between 2011 and 2015 found nine species of bat, *Pipistrellus pipistrellus*, *Pipistrellus pygmaeus*, *Pipistrellus kuhlii*, *Pipistrellus nathusii*, *Eptesicus serotinus*, *Nyctalus leisleri*, *Nyctalus noctula*, *Plecotus auritus* and *Plecotus austriacus*, and one species group, *Myotis spp.*, were recorded in Jersey (Table 1). The most commonly recorded species were *P. pipistrellus*, *P. pygmaeus* and *P. kuhlii* (Hawkins et al., 2016). A European-wide bat call identification and classification tool was used to identify bat calls from the recordings, which combined automated echolocation pulse feature extraction, visual inspection, and automated bat call identification (Hawkins et al., 2016; Walters et al., 2012). A proprietary software (Sonobat v.3.1.7p) was used to extract echolocation pulse parameters from the recording, which was found to miss approximately 26% of pulses (Hawkins et al., 2016). The need to visually inspect the echolocation pulses and parameters was manually intensive and not sustainable for long-term passive acoustic monitoring studies (Gibb et al., 2019). Five-year trends in relative abundance were calculated for all bats, *P. pipistrellus* and *P. pygmaeus*, and indicated significant increases, although the confidence intervals around in these trends were large indicating uncertainty (Hawkins et al., 2016).

Table 1: List of species recorded in Jersey, their status, and whether they were reported in the interim iBats analysis in 2016 (Hawkins et al., 2016). The status represents whether the species has been recorded in Jersey. Species that have only been recorded once, from unconfirmed acoustic or roost records are indicated by "Unknown" or "Unknown (vagrant)". Table adapted from Glynn & Jones (2020).

Species	Common name	Jersey Status	Reported in interim iBats analysis
Eptesicus serotinus	Serotine	Resident	Yes
Hypsugo savii	Savi's pipistrelle	Unknown (vagrant)	No
Myotis alcathoe	Alcathoe bat	Resident	Genera level
Myotis brandtii	Brandt's bat	Unknown	Genera level

Myotis daubentonii	Daubenton's bat	Unknown	Genera level
Myotis emargenatus	Geoffroy's bat	Unknown (vagrant)	Genera level
Myotis mystacinus	Whiskered bat	Unknown	Genera level
Myotis nattereri	Natterer's bat	Resident	Genera level
Nyctalus leisleri	Leisler's bat	Unknown (vagrant)	Yes
Nyctalus noctula	Noctule	Unknown	Yes
Pipistrellus kuhlii	Kuhl's pipistrelle	Resident	Yes
Pipistrellus nathusii	Nathusius pipistrelle	Resident (vagrant)	Yes
Pipistrellus pipistrellus	Common pipistrelle	Resident	Yes
Pipistrellus pygmaeus	Soprano pipistrelle	Resident	Yes
Plecotus auritus	Brown long-eared bat	Resident	Yes
Plecotus austriacus	Grey long-eared bat	Resident	Yes
Rhinolophus ferrumequinum	Greater horseshoe bat	Unknown	No
Rhinolophus hipposideros	Lesser horseshoe bat	Unknown	No

In this report, we present analysis of iBats data collected using time-expansion (2011 – 2020) and full spectrum (2018-2020) detectors, and JBatS data collected using AudioMoths in 2020. We compare the performance of time-expansion and full spectrum detectors in recording bat activity and diversity under the driven-transect method. We then compare the estimates of bat activity and diversity from data collected under the driven-transect method and the static survey method. We use the iBats time-expansion data to model a 10-year trend in *P. pipistrellus* relative abundance and compare the trend to the British and French bat trends for this species. We then use iBats data to assess the impact of environmental factors on relative bat activity under a spatially explicit framework. Finally, we use the results of these analysis and outcomes of a consultation with the Jersey Bat Group to provide recommendations for future bat monitoring in Jersey.

2. Methods

2.1 Survey methods

2.1.1 iBats

The Indicator Bats Programme (iBats) recordings were made according to the iBats protocol for car-based acoustic surveying (Jones *et al.*, 2013). Power analysis of iBats surveys conducted 2011 – 2015 on Jersey indicated that surveying 11 transects twice a year would be sufficient to detect significant declines in bat populations over 10-years (Hawkins et al., 2016). Eleven transect routes were determined following roads across Jersey and driven at 15mph for 70 minutes starting 30-45 minutes after sunset. For all ten years (2011-2020) a Tranquillity Transect time-expansion bat detector was used to detect bat echolocation calls and was set to a time expansion factor of 10 with a sample schedule of 320ms sampling and 3.2s playback. This provided seven minutes of time sampled per transect. Sound was recorded to an SD card as a WAV file using either an Edirol R-09HR or Roland R-05 recording device. In addition, full spectrum recordings were made for three years from 2018-2020 using a Pettersson D500x ultrasound recording unit, providing a full 70 minutes of time sampled per transect (Table 2). A GPS track of each transect route was simultaneously recorded using a variety of GPS devices. GPS and recorded detector tracks were started at the same time allowing the position of the car along the transect to be determined at the time of each bat call.

The 11 transect routes were driven twice a year in July and August from 2011 to 2020 inclusive (Figure 1). Surveys were carried out during 'fine' weather only, i.e., when the air temperature was greater than 7°C, and with no more than very light rain or wind. Transects were occasionally repeated a third time due to poor weather conditions during an initial transect, or where battery power was lost during recordings. In such instances, all three recordings have been included in these analyses where possible. Weather conditions were additionally recorded at the beginning and end of each transect. These comprised: temperature (°C), cloud cover (%), rain (dry, drizzle, light), and wind speed (calm, light, breeze). Humidity data was similarly obtained from the

Government of Jersey Department for Environment – Meteorological Section for the beginning and end of each transect.

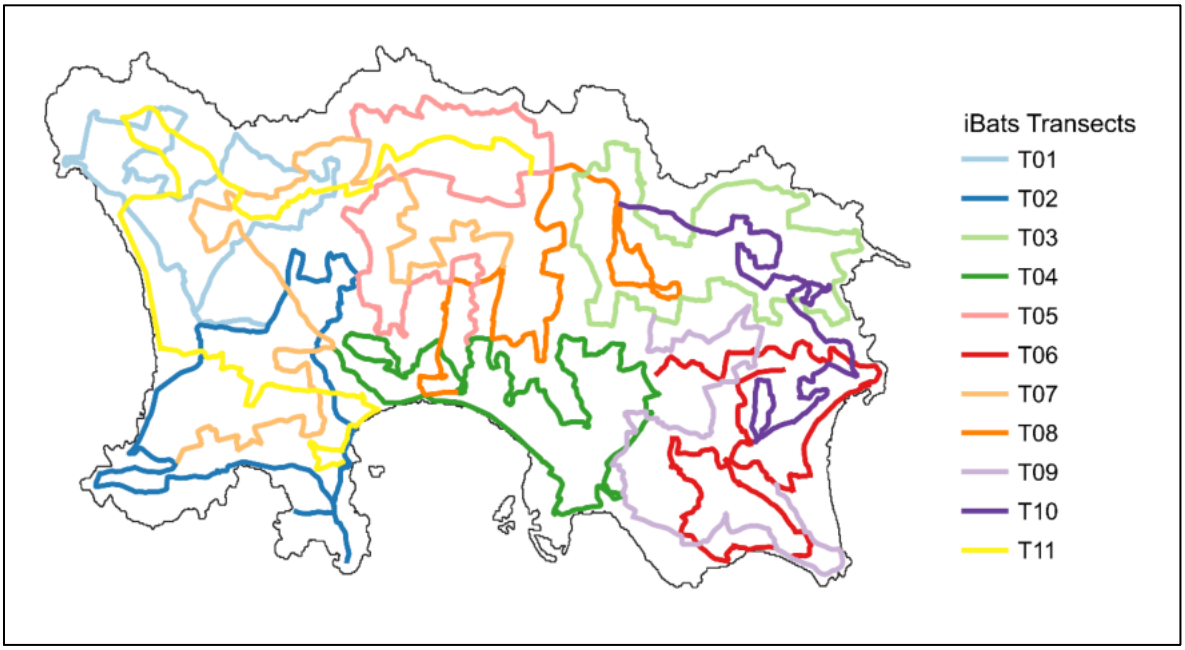

Figure 1. A map of the 11 iBats transect routes in Jersey.

2.1.2 JBatS scheme pilot

The Jersey Bat Survey (JBatS) recordings followed the methodology of the British Bat Survey (Fairbrass et al. 2019; Glynn & Jones, 2020). A 1 km^2 grid was used as a basis for determining static sampling sites, allowing for consistency with ongoing local, national, and international monitoring schemes for other taxonomic groups. A Phase 1 Habitat Survey of Jersey (2011) was then used to select five key habitat types representative of the island: arable, grassland, urban, woodland, and water (Figure 2). Each 1 km^2 grid square was then assigned a habitat type according to area covered within the square.

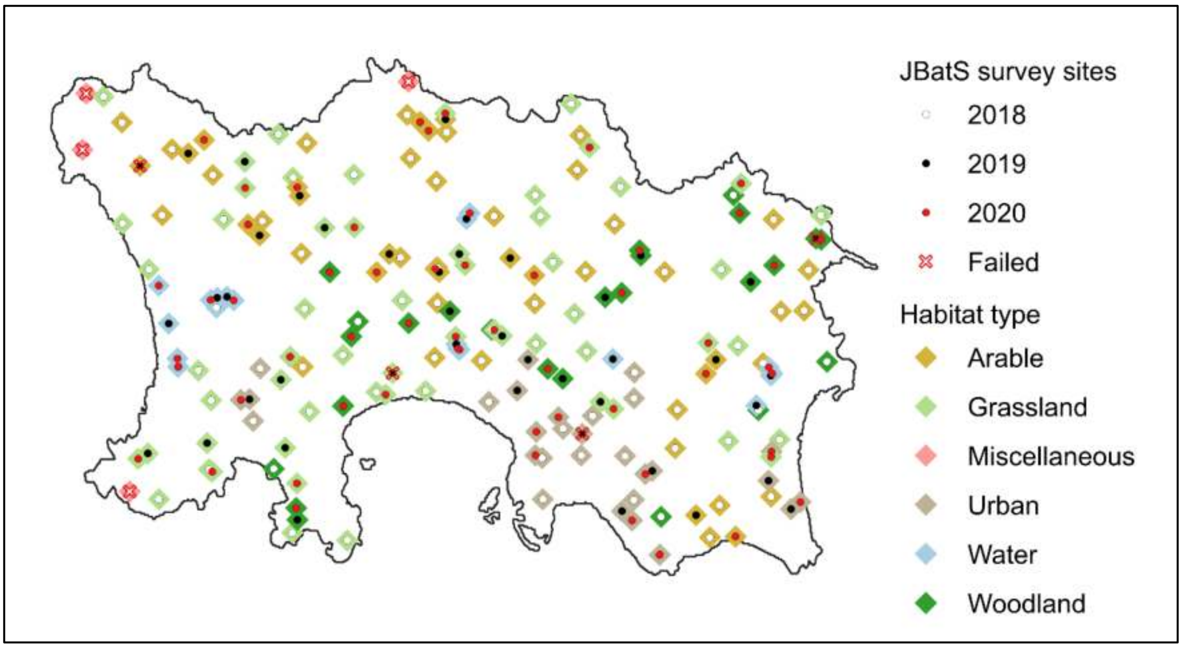

Figure 2. A map of the 140 JBatS survey sites in Jersey.

The number of sites and survey design varied between years. Ninety survey sites were selected in 2018 following a random stratified approach (Buckland et al., 2008), allowing for habitats to be sampled to represent habitat availability across the island (i.e., if 60% of the island is agricultural, 60% of the acoustic sensors were placed in agricultural land) (Glynn & Jones, 2020). Exact locations for sensor deployment within the chosen grid squares were determined by starting at the centre of the square and working outwards until an area of suitable habitat was reached. In 2019, equal representation of habitats was used, and 10 sites were randomly selected within each habitat type, giving a total of 50 survey sites (Glynn & Jones, 2020). In 2019 and 2020, a desk based random selection was used based on the Phase 1 Habitat Survey to select precise deployment sites. Due to the SARS COVID-19 pandemic, in 2020 10 sites were selected based on the random stratification of habitat type. However, these were supplemented by a further 51 sites opportunistically surveyed by citizen science volunteers. This mixed approach was implemented due to constraints brought about by the SARS COVID-19 pandemic. Sites were not lit by artificial light at night, and were at least 1.5m away from vegetation, hard surfaces, and water, to prevent obstruction or distorting of bat calls.

In all years, surveying took place in July with a single first generation AudioMoth acoustic sensor placed at each survey site and housed in an acrylic case for weather protection. In 2018, each location was surveyed for three non-consecutive nights. In 2019, each location was surveyed for 3-

6 consecutive nights (Glynn & Jones, 2020). In 2020, most locations were surveyed for a single night, with a few exceptions where volunteers carried out 2-3 nights of recording. In 2018 and 2019, surveying commenced at 20:30 each night and ceased at 05:30 the following evening, with a sample rate 384 kHz and recording intervals of 10 seconds and no sleep duration. In 2020, the survey regime was adjusted to align with that of the British Bat Survey (BBatS), with sensors set to sample for 10.5 hours from 20:00 – 06:30 BST, and a schedule of 300 seconds' recording followed by three seconds' sleep. A GPS point was recorded at each survey location using a smartphone or GPS device.

Due to the data from 2018 and 2019 being compressed and the large amount of time needed to uncompress the data, only the JBatS data collected in 2020 are analysed here. Data from 2018 and 2019 have been partially classified and will be analysed in October 2022, with results delivered in a supplementary report in December 2022 (Table 2). We therefore here discuss results from 2020 in the context of previous analysis of the 2018 and 2019 data by Glynn and Jones (2020).

Table 2: Passive acoustic surveys carried out on Jersey and the status of the data collected under the indicator bats programme (iBats) using time-expansion (TE) detectors or full spectrum (FS) detectors, and the pilot Jersey Bat Survey (JBatS).

Survey	Years	Survey design	Data status
iBats TE	2011 -2020	Driven transect; roads	Analysed
iBats FS	2018 - 2020	Driven transect; roads	Analysed
JBatS	2018 - 2019	Static; stratified by habitat	Partially classified
	2020	Static; stratified by habitat & unstructured	Analysed

2.2 Data preparation

2.2.1 iBats GPS tracks

GPX track points were extracted from each iBats transect track, and key metadata extracted for each point: coordinates (in WGS84), transect ID (1-11), point ID (sequential numerical values along each transect), date (d:m:y), and time (h:m:s). The start time for each track was then extracted and the time elapsed since the start calculated for each point. It was noted that several track start times fell outside the designated window of 30-45 minutes after sunset; this was discussed with GoJ officers, who advised that such times were the result of differing time zones set on the recording devices and were adjusted accordingly.

Several thousand GPX points with the same transect-date-time value were noticed within the dataset, some with identical coordinates (exact duplicates) and others with differing coordinates (partial-duplicates). Such partial duplicates would cause issues when georeferencing bat calls, as each call must be associated with one point along the transect route according to the time recorded. The distance between these partial duplicates, along with the disparity in point ID (how many points apart) were calculated for each pair/sequence. This confirmed that all partial duplicates were sequential, with a mean of 4m between each pair. This appears to be due to GPX point times being rounded to the nearest second, despite more than one point sometimes being recorded per second. As the distances between such points are negligible, the first instance of each partial duplicate was retained whilst the sequential point/s were removed.

2.2.2 Spatial scale

The scale at which the data were analysed was determined by both ecological relevance and the impact of errors associated with data collection. Firstly, measurement error was calculated by extracting the distance from each GPX point to the planned transect route; this captures any discrepancy caused by interference with satellite signal which would result in incorrect coordinates recorded. Outliers caused by diversions from planned routes were excluded, resulting in a mean measurement error of 2.28m. Secondly, the use of a time-expansion detector results in a time displacement error of approximately 30m when driving at 15mph – this is due to the time associated with each call being recorded during the 32s playback rather than the time the call was produced. Combining these two errors suggests a minimum resolution of 50m^2 for spatial analysis.

2.3 Environmental data

2.3.1. Habitat type

Habitat type (arable, grassland, water, woodland, urban, unclassified) was extracted from a Phase 1 Habitat Survey of Jersey in 2011, provided by the States of Jersey. A 2020 base-map of Jersey was also provided, allowing habitat type to be updated to include any changes in urban extent on the island. This was achieved by 'cutting' the habitat layer around the base-map layer using the *difference* tool in QGIS to remove any overlap, and then joining the two layers together. This combined shapefile was then converted into a $2m^2$ resolution raster layer for each habitat type using the *raster* package in R. Percentage cover of each habitat type was finally calculated for each $50m^2$ grid cell by aggregating the $2m^2$ grid cells in the high-resolution raster.

2.3.2. Boundary features

A shapefile of boundary features in Jersey, also extracted from the 2011 Phase 1 Habitat Survey, was provided by the States of Jersey. Boundary features were then assigned to one of three ecologically relevant categories: 'boundary feature with hedge', 'boundary feature without hedge but with trees', 'boundary feature with no hedge or trees' in R. A $50m^2$ raster layer was then created for each category, representing presence (1) or absence (0) of a boundary feature within each grid cell.

2.3.3. Road type

Road type data were sourced from Williams et al. (2019), wherein transect roads were categorised into three types using definitions in the Phase 1 Habitat Survey: 'Minor', 'Main' and 'Major'. Unlike much of the UK, the roads in Jersey are predominantly small, slow, many are unlit. In addition, minor roads in Jersey are frequently 'Green Lanes', which have a speed limit of 15mph. Williams et al. (2019) created a $50m^2$ raster layer of all cells that intersected transect roads, with values corresponding to the type of road in each cell. Where multiple road types occurred in a single cell, the type covering the greatest area was assigned.

2.3.4. Street lighting

Street lighting data were similarly sourced from Williams et al. (2019) in which streetlights were located along bat transect roads using data compiled from the States of Jersey lighting surveys in 2011 and 2017, and manually ground-truthed. In contrast, Williams et al. (2019) investigated streetlight technologies, updated information on changes to such technologies after 2017 were not available for this analysis. $50m^2$ resolution raster layers displaying the number of each streetlight type in each cell were thus sourced from Williams et al. (2019) and combined into one layer detailing the number of all streetlight types within each cell. This compares both bat activity in lit vs. unlit areas as well as degree of illumination in lit areas.

2.3.5. Weather

Weather data collected at the beginning and end of each transect were averaged to obtain single values for each transect. Cloud cover, rain and wind speed categories were first reclassified as integers to achieve this. The mean values were then assigned to each GPX point along the associated transect.

2.4 Automated sound analysis and manual verification

Audio files from iBats and JBatS 2020 data were processed through BatDetect v.3 (Fairbrass et al., 2018; mac Aodha et al., 2018). We used a random stratification sampling method to select detected pulses from each dataset per species, per 0.1 classification probability score (10 groups of classification scores in total) for manual verification (Barré et al., 2019). Five bat experts were sent a random sample of the selected pulses per dataset and were asked to identify the call to species level if possible, or to genus or species group level. iBats pulses underwent three rounds of verification and JBatS twice due to time constraints. Verified species records were provided for the Jersey Biodiversity Records Centre.

2.5. False-positive tolerance analysis

The automated classifications were compared to the manual classifications, assigning a score of one (success) or zero (failure). Species groups *Myotis* and *Nyctalus/Eptesicus* were defined due to difficulties in manual classification to species and limited training data for the automated classification algorithms. Automated classifications were considered successful in these cases if the genus was correct. As *P. kuhii* was not included in the BatDetect training data, automated classification was not possible, and we grouped manual classifications of this species with *P. nathusii* due to similarities in call characteristics.

The false positive rates at different levels of classifier confidence were compared using logistic regressions for bat/not-bat per species/species group, following the method proposed by Barre *et al.* (2018). The models were used to identify false positive tolerances (FPT) with which to threshold the data per species/species group between FPT50 (50% error rate) and FPT90 (10% error rate).

The predicted classification probability was predicted from each model at which each species/species group achieved false positive rates of 50% to 10%.

2.6. Sequence definition

The number of bat echolocation pulses recorded does not represent the number of bats present and using this metric can cause large overestimation of bat activity or relative abundance. A pulse belongs to a sequence of echolocation calls emitted from an individual bat. Manual classification of bat echolocation call recordings is typically done by assessing the sequence and assigning a species ID based on the sequence (Hawkins et al., 2016; Walters et al., 2012). To automate the process of sequence definition, echolocation call sequences were defined based on the time between detected echolocation pulses. For full spectrum data, if echolocation calls were within 0.4 seconds they were considered part of the same sequence assumed to be emitted by an individual bat. For time-expansion data, a difference between calls of 4 seconds was used. Using species-specific inter-pulse intervals (time between pulses emitted by an individual bat) was considered, but due to the interspecific overlap in intervals defining these explicitly was not possible. The longest mean inter-pulse interval of the recorded species, 0.4 seconds (Russ, 2013), was therefore used. Although this interval is larger than the inter-pulse intervals recorded for several species and did not enable co-occurring, multispecies echolocation call sequences to be detected, this approach was considered robust for most cases as the likelihood of two call sequences being recorded simultaneously was low. Sequences with fewer than three detected pulses were removed from the data to reduce risk of erroneous classification or bat pass detection.

In many cases a sequence contained more than one species according to the classifier output. We explored whether assigning the sequence to the species with the highest classification probability or weighting the per species pulse classification probabilities by the number of calls per species, per sequence resulted in the most accurate species classification. Under the weighted approach, weighting was applied to the species classification probabilities and the sequences was assigned to the species with the maximum weighted probability. We applied the thresholds identified in the FPT analysis per species/species group and where the automated classification probabilities fell below these thresholds the pulse was assigned a weight of zero. Sequences where all pulses were assigned a weight of zero or where the total number of pulses detected was lower than three were removed from the data. We then calculated the number of sequences detected per discrete spatial or temporal unit, depending on the survey type. For the iBats car transect data, the number of sequences per 50 m^2 were calculated to align with the resolution of the GPS data. The time spent per cell was used to control for survey effort in the transect surveys. For the JBatS survey data, the number of sequences per species per minute was used as a measure of relative activity.

2.7 Statistical analyses

Analyses were carried out using Genstat and R (R Core Team, 2020).

2.7.1. iBats: time-expansion vs. full spectrum

The number of bat call sequences and species detected using time-expansion and full spectrum detectors under iBats were first simply compared by plotting the per-minute detected sequences and calculating the ratio. We also used the McNemar's test to assess whether detections were equal from the full spectrum and time expansion data. This test was conducted on a subset of the data from each, where an echolocation call sequence was detected using one method, but not the other. Finally, to assess whether the relative effectiveness of each method varied with other factors (time, route, and year) a binomial general linear mixed model (GLMM) was fit to the pairs of data where a sequence was detected using one method, but not the other (discordant pairs).

2.7.2. Comparing iBats and JBatS

The number of sequences detected per species per night and per hour were used to compare the iBats and JBatS survey methods.

2.7.3. iBats: an assessment of abundance over 10 years

Trends in relative abundance were modelled using a generalised additive modelling approach, as used to produce the reported NBMP trends (Bat Conservation Trust, 2021), following Fewster *et al*. (2000). Models were fitted using the number of sequences detected per 50 m^2. Covariate fixed effects included in the model and identified as being significant by generalised linear mixed modelling were survey start time, mean survey temperature, day of the year. To control for background variation, transect ID was included as a random effect, and time spent per 50m^2 cell was included as an offset in the model to account for the positive relationship between survey length and time per 50m^2 cell. Annual estimates were rescaled to show the index change from a baseline year, set to the second year of the survey, 2012, as per Fewster et al. (2000).

2.7.4. iBats: a comparison of the trend and status of bat species found in Jersey, GB, and France

Population trends from GB were calculated using data collected under the National Bat Monitoring Programme's Field Survey (Bat Conservation Trust, 2021) during the same period as the iBats time-expansion data (2011 to 2020), using GAMs with a baseline of 2012. Bootstrapping was used to calculate the difference in the Jersey and GB trend to assess whether it was significant. French population trends were provided by Vigie-Chiro (Bas et al., 2020). However, the method for producing the French trend was not provided and it was not possible to quantitatively assess the differences.

2.8 Spatial analysis

We assessed environmental correlates of bat occupancy around roads using iBats TE and FS data. We modelled the impact of environmental factors on *P. pipistrellus* occupancy only, due to the high number of zero counts for other species or species groups. However, the number of sequences detected per $50m^2$ grid square was typically low for *P. pipistrellus* in the iBats FS data and rarely greater than one in the iBats TE data. We, therefore, used grid square occupancy in the models, or the presence-absence of *P. pipistrellus* per 50 m^2 grid square.

Spatial analysis of the JBatS data will be completed in October 2022, when classification of the 2018 and 2019 data has been completed. The results of these analyses will be presented in a supplementary report in December 2022.

2.8.1 Environmental data

2.8.1.1 Habitat type

Habitat type (arable, grassland, water, woodland, urban, unclassified) was extracted from a Phase 1 Habitat Survey of Jersey in 2011, provided by the States of Jersey. A 2020 base-map of Jersey was also provided, allowing habitat type to be updated to include any changes in urban extent on the island. This was achieved by 'cutting' the habitat layer around the base-map layer using the *difference* tool in QGIS to remove any overlap, and then joining the two layers together. This combined shapefile was then converted into a $2m^2$ resolution raster layer for each habitat type using the *raster* package in R. Percentage cover of each habitat type was finally calculated for each $50m^2$ grid cell by aggregating the $2m^2$ grid cells in the high-resolution raster. The mean percentage of each habitat class was also calculated for 100 m^2 and 500 m^2 buffers around each $50m^2$ grid cell.

2.8.1.2 Boundary features

A shapefile of boundary features in Jersey, also extracted from the 2011 Phase 1 Habitat Survey, was provided by the States of Jersey. Boundary features were then assigned to one of three ecologically relevant categories: 'boundary feature with hedge', 'boundary feature without hedge but with trees', 'boundary feature with no hedge or trees' in R. A $50m^2$ raster layer was then created for each category, representing presence (1) or absence (0) of a boundary feature within each grid cell. The percentage coverage of each boundary feature was also calculated for 100 m^2 and 500 m^2 buffers around each $50m^2$ grid cell.

2.8.1.3 Road type

Road type data were sourced from Williams *et al*. (2019), wherein transect roads were categorised into three types using definitions in the Phase 1 Habitat Survey: 'Minor', 'Main' and 'Major'. Williams *et al*. created a $50m^2$ raster layer of all cells that intersected transect roads, with values corresponding to the type of road in each cell. Where multiple road types occurred in a single cell, the type covering the greatest area was assigned.

2.8.1.4 Street lighting

Street lighting data were similarly sourced from Williams et al. (2019), in which streetlights were located along bat transect roads using data compiled from the States of Jersey lighting surveys in 2011 and 2017, and manually ground-truthed. Whereas Williams et al. (2019) investigated streetlight technologies, updated information on changes to such technologies after 2017 were not available for this analysis. I$50m^2$ resolution raster layers displaying the number of each streetlight type in each cell were sourced from Williams et al. (2019) and combined into one layer detailing the number of all streetlight types within each cell. This compares both bat activity in lit vs. unlit areas as well as degree of illumination in lit areas.

2.8.1.5 Weather

Weather data collected at the beginning and end of each transect were averaged to obtain single values for each transect. Cloud cover, rain and wind speed categories were first reclassified as integers to achieve this (Table A1.1). The mean values were then assigned to each GPX point along the associated transect.

2.8.1.6 Spatial scale

All environmental data were extracted per 50 m^2 grid square, and within 100 m^2 and 500 m^2 buffers around each grid square. Within buffers, the average value was calculated for the land cover variables, the total number of streetlights and cells with boundary features were calculated, and the mode, or most common, road type was extracted.

2.8.2 Spatial statistical analysis

We used Bayesian hierarchical modelling, under the integrated nested Laplace approximation (INLA) framework, to assess the impact of environmental factors around roads on bat activity at three spatial scales. We used the INLA framework as it allows for robust control of spatial autocorrelation present in the data using the stochastic partial differentiation equation (SPDE) approach (Bakka et al., 2018; Lindgren & Rue, 2015). The presence-absence of *P. pipistrellus* per $50m^2$ grid square was used as the response, assuming a binomial model, with the number of $50m^2$ grid squares per transect as the number of trials. Survey month was included as a random effect, with the year as a replicate. Spatial autocorrelation was controlled for using the SPDE approach. We assessed the impact on model fit of the environmental covariates using the Watanabe-Akaike information criterion, with a lower value indicating improved model fit. This resulted in a reduced set of environmental covariates included in the models: survey mean wind speed, survey mean temperature, road type, boundary features presence, number of streetlights, and proportion of land cover types. To assess the importance of environmental factors on bat occupancy along roads at different spatial scales, we fitted three models per iBats dataset: no buffer, a 100 m^2 buffer, and a 500 m^2 buffer.

3. Results

3.1 Summary of recordings

Overall, there were more bat pulses and bat species recorded and detected using the JBatS method compared to using the iBats survey method. Between 2011 and 2020 there were 230 surveys conducted under iBats using time-expansion detectors, with 37,309 bat pulses detected by BatDetect. Using full spectrum detectors between 2018-2020, 543,591 bat pulses were detected from 70 iBats surveys using BatDetect. In 2020, 2,083,684 bat pulses were detected from JBatS recordings using BatDetect (Table 3).

Table.3: Summary of pulses detected by iBats surveys using time-expansion (TE) (2011 – 2020) and full spectrum (FS) (2017 – 2020) bat detectors and Jersey Bat Survey (JBatS) using AudioMoths (2020).

Survey	n. transects/ sites	n. surveys	n. pulses	Mean detection probability (sd)	Mean classification probability (sd)	n. sequences	n. species/species groups
iBats TE	11	230	37,309	0.65 (sd= 0.09)	0.58 (sd = 0.12)	6713	3
iBats FS	11	70	543,591	0.72 (sd = 0.09)	0.68 (sd = 0.12)	18,202	3
JBatS 2020	61	65	2,083,684	0.66 (sd = 0.09)	0.60 (sd = 0.12)	36,753	9

Bat echolocation call sequences were detected on all iBats transects using time expansion detectors (Figure 3.A) and full spectrum detectors (Figure 3.B). Detections were lower around St Helliers and other urban areas (Figure 3). Bat echolocation call sequences were detected at all

JBatS sites in 2020 (Figure 4). Maps showing individual species detections from the JBatS data are presented in Appendix 2.

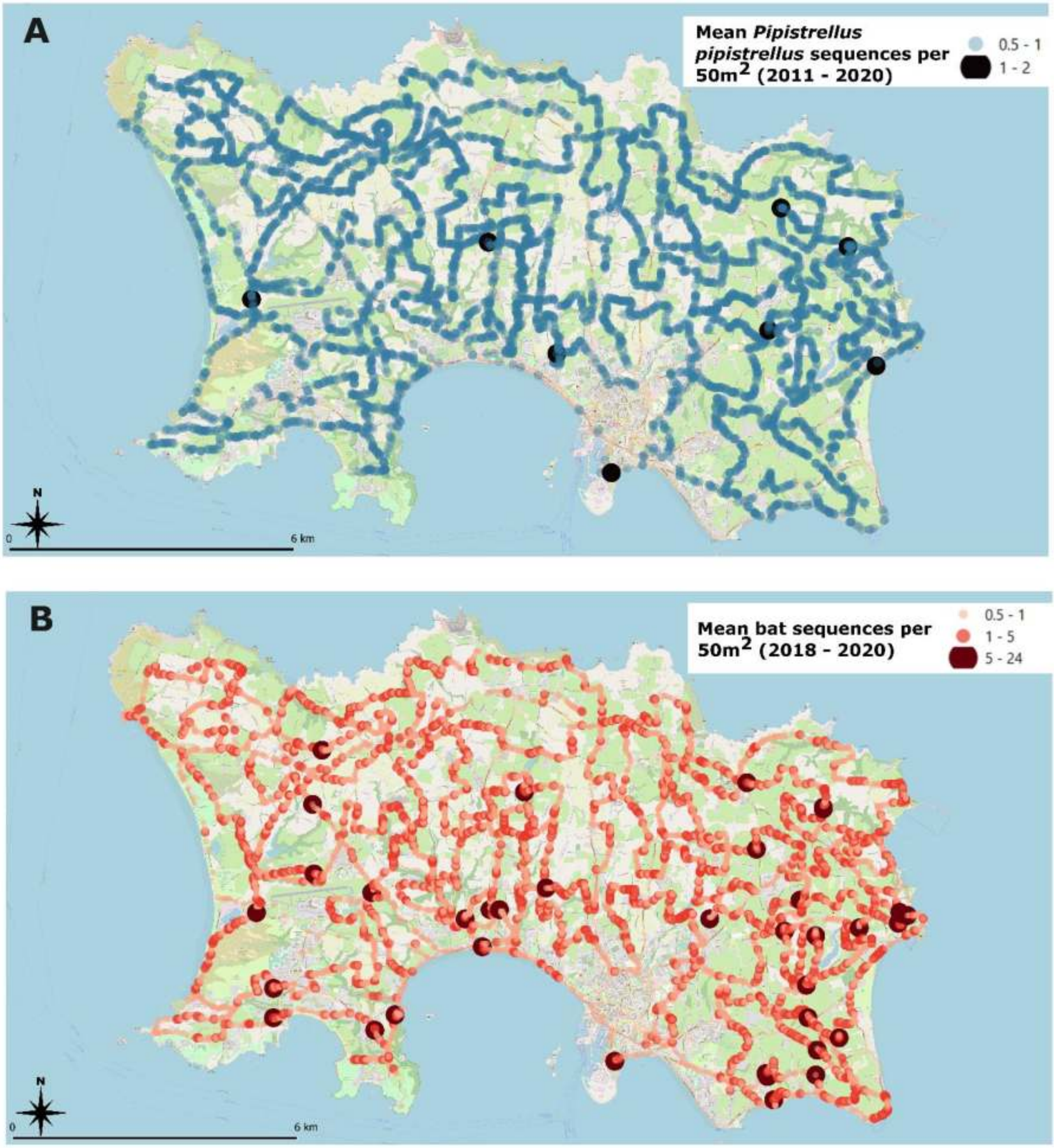

Figure 3: Location and mean number bats echolocation call sequences detected per 50m^2 across Jersey between 2011 and 2020 using time-expansion detectors (A) and between 2018 and 2020 using full spectrum detectors (B). The colour and size of the dots shows the mean number of sequences detected. Background map from OpenStreetMap, © OpenStreetMap contributors, available under the Open Data licence https://www.openstreetmap.org/copyright.

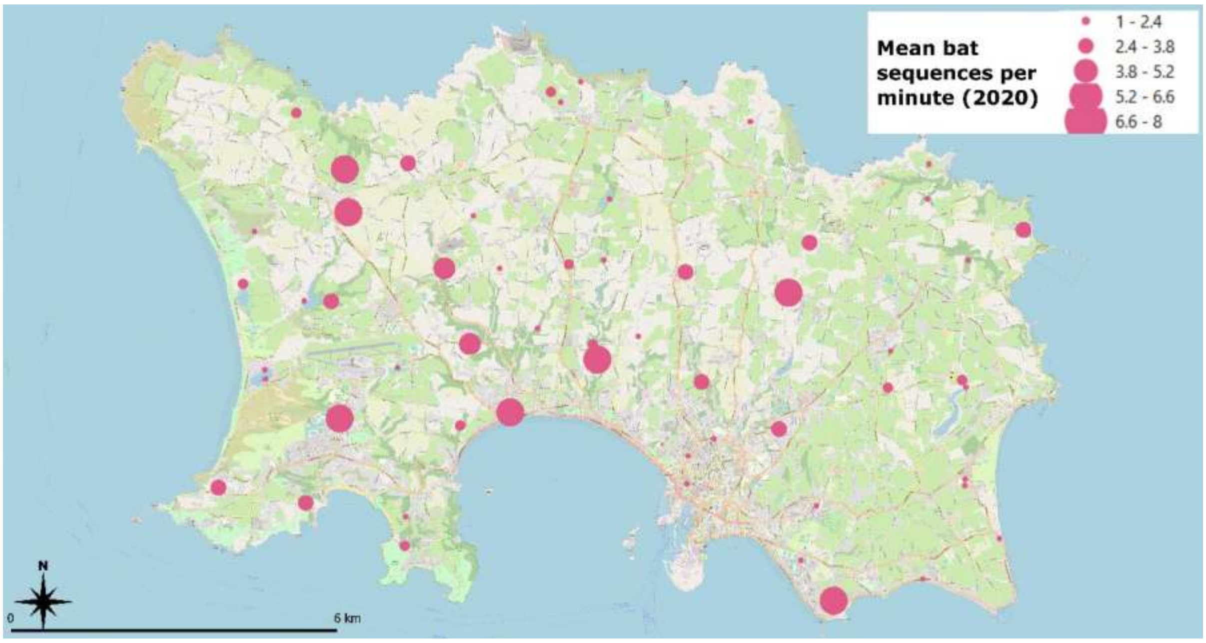

Figure 4: Location and mean number of bat sequences per 50 m² detected under the JBatS 2020 pilot using AudioMoths. The site of the dots represents the mean number of sequences detected. Background map from OpenStreetMap, © OpenStreetMap contributors, available under the Open Data licence https://www.openstreetmap.org/copyright..

3.2 Manual verification

Manual verification of a stratified subset of the iBats TE and FS and JBatS 2020 datasets used for the FPT analysis resulted in 156 verified detections of three species (Table 4): *P. pipistrellus*, *P. pygmaeus*, and *R. ferrumequinum*. Due to verifier disagreement, no detections were verified from the iBats TE dataset. There was consistent disagreement on the classification of *E. serotinus* and *P. austriacus* across verifiers, likely due to the anecdotally reported difficulty in distinguishing long duration *P. austriacus* calls in Jersey. In addition, one verifier returned a low number of verified records as they were not able to confidently provide many definitive classifications. The list of verified species records, including locations, is available in Appendix 3.

Table.4: Number of pulses manually verified per dataset and summary of verified pulses and species where two or more verifiers agreed on species classification.

Survey	n. checked	n. verification rounds	n. verified	n. species verified
iBats TE (2011 – 2020)	277	3	0	0
iBats FS (2017- 2020)	828	3	74	5

JBatS (2020)	905	2	82	3

3.3 False-positive tolerance analysis

Error thresholds varied for most species or species groups between datasets. For the iBatsTE data, *P. pipistrellus*, *Myotis spp.* and *P. austriacus* met the highest threshold for error (FPT90). *P. nathusii/kuhlii*, *Nyctalus/Eptesicus*, and *P. pygmaeus* met lower error thresholds (FPT70 for the former two and FPT60 for the latter (Table 5). For the iBatsFS data, *P. pipistrellus*, *Myotis spp.* and *P. pygmaeus* met the highest threshold for error (FPT90), and *Nyctalus/Eptesicus* met a lower threshold for error (FPT60). For the JBatS data, *P. pipistrellus*, *Myotis spp.*, *P. auritus*, and *R. ferrumequinum* met the highest threshold for error (FPT90), and *P. pygmaeus* and *Nyctalus/Eptesicus* met lower thresholds for error (FPT80 and FPT60, respectively) (Table 5). Where species or species groups did not meet the minimum error thresholds, this was due to either all or most automated classifications being false positives due to confusion with other bat species, nocturnal wildlife, or abiotic sounds.

Table 5: Summary of results from the logistic regression analysis false positive tolerance (FPT) (error rate) per dataset. Dashes indicate that it was not possible to assign a tolerance threshold to that error rate. The number of pulses verified manually per species or species group is indicated by "n. check". Pipistrellus nathusius and Pipistrellus kuhlii were grouped together under Pipistrellus nat/ kuh.

	Species/ species group	Model results		FPT 50	FPT 60	FPT 70	FPT 80	FPT 90	*n. check*
		Intercept	*Estimate*	*Classifier confidence score*					
iBats TE	*Barbastella barbastellus*	-23.57	0.00	-	-	-	-	-	2
	Myotis spp.	-106.76	297.29	0.36	0.36	0.36	0.36	0.37	5
	Nyctalus/ Eptesicus	-0.88	2.18	0.40	0.59	0.79	-	-	101
	Pipistrellus pipistrellus	1.32	1.95	0.00	0.00	0.00	0.04	0.45	68
	Pipistrellus pygmaeus	-1.15	1.60	0.72	0.97	-	-	-	13
	Pipistrellus nat/kuh	-6.25	7.57	0.83	0.88	0.94	-	-	59
	Plecotus austriacus	-638.36	2264.24	0.28	0.28	0.28	0.28	0.28	6
	Plecotus auritus	-25.57	0.00	-	-	-	-	-	19
iBats	*Barbastella barbastellus*	-26.57	0.00	-	-	-	-	-	60
	Myotis spp.	-7.29	16.53	0.44	0.47	0.49	0.53	0.57	114

	Nyctalus/ Eptesicus	-0.71	1.40	0.51	0.80	-	-	-	280
	Pipistrellus pipistrellus	-3.01	16.06	0.19	0.21	0.24	0.27	0.33	90
	Pipistrellus nat/kuh	-1.44	-1.42	-	-	-	-	-	101
	Pipistrellus pygmaeus	-5.85	10.02	0.59	0.63	0.67	0.72	0.80	66
	Plecotus austriacus	-26.57	0.00	-	-	-	-	-	60
	Plecotus auritus	-26.57	0.00	-	-	-	-	-	57
JBatS 2020	*Barbastella barbastellus*	-26.57	0.00	-	-	-	-	-	59
	Myotis spp.	-1.13	3.47	0.33	0.44	0.57	0.73	0.96	219
	Nyctalus/ Eptesicus	-3.58	4.07	0.88	0.98	-	-	-	197
	Pipistrellus pipistrellus	-0.67	3.70	0.18	0.29	0.41	0.56	0.78	82
	Pipistrellus pygmaeus	-3.63	5.57	0.65	0.73	0.80	0.90	-	73
	Pipistrellus nat/kuh	-4.10	3.38	-	-	-	-	-	80
	Plecotus austriacus	-26.57	0.00	-	-	-	-	-	70
	Plecotus auritus	-6.45	11.89	0.54	0.58	0.61	0.66	0.73	65
	Rhinolophus ferrumequinum	-22.11	34.61	0.64	0.65	0.66	0.68	0.70	30
	Rhinolophus hipposideros	-25.57	0.00	-	-	-	-	-	30

After applying the thresholds to the data, 6713, 18,202, and 36,735 sequences remained from the iBats TE, iBats FS, and JBatS data, respectively (Table 3). Three species/ species groups were detected from both iBats datasets, whereas nine species/species groups were detected from the JBatS data. The number of species reported here as detected from the iBats TE data were fewer than the nine species reported as detected in the interim iBats report, which analysed data collected between 2011 and 2015 (Hawkins et al., 2016). This is likely due to a combination of the automated classification algorithm used for these analyses compared to the combination of automated and manual classification method used by Hawkins et al (2016), and the more conservative classification thresholds derived from the FPT used here. However, two additional species, *R. ferrumequinum* and *R. hipposideros*, were detected in the JBatS 2020 data that was not detected in the analysis of the iBats TE 2011-2015 data.

3.4. iBats: time expansion vs. full spectrum

Substantially more sequences were detected using the full spectrum detectors, compared to the time expansion detectors, when deployed concurrently. The full spectrum approach recorded about 7.5 times as many on average (Table 6). There was a positive correlation (0.86) between the number of sequences detected using each detector type (Figure 5). When the number of sequences was larger, the ratio between the number of sequences detected by the full spectrum and time expansion detectors decreased.

Table 6: A: comparison of average detection rates of P. pipistrellus sequences recorded using time expansion (TE) and concurrently deployed full spectrum (FS) detectors between 2018 and 2020.

	Sequences per minute		Percent minutes with species (%)	
	TE	FS	TE	FS
2018	0.388	2.889	37.3	85.5
2019	0.469	3.351	46.7	87.7
2020	0.460	3.451	43.2	87.0
All 3 years	0.438	3.233	42.4	86.7

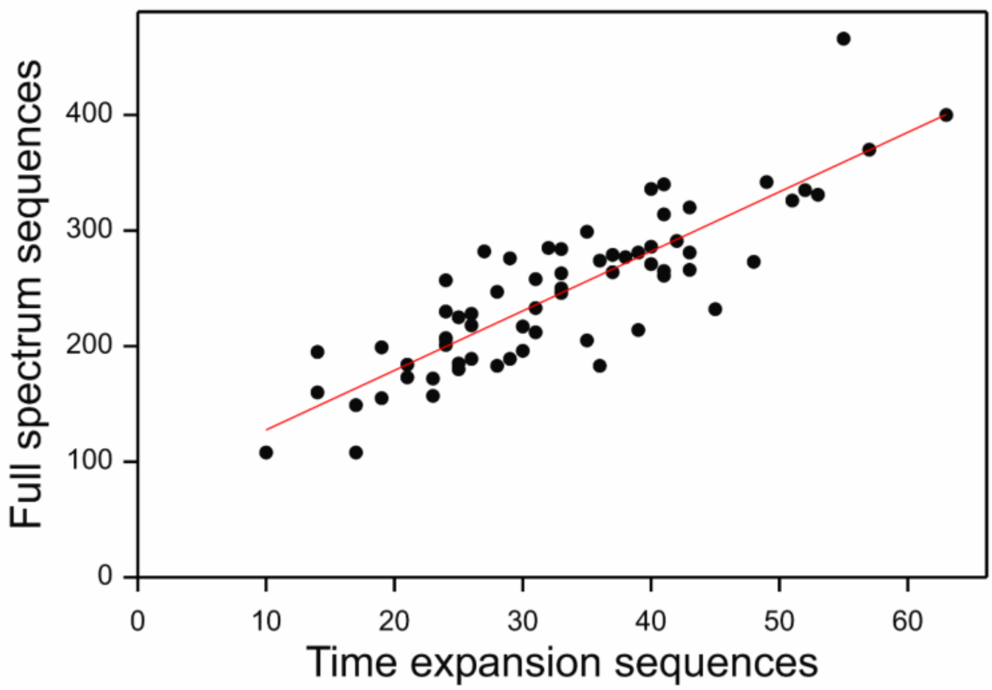

Figure 5: Total numbers of P. pipistrellus sequences detected using time expansion compared to full spectrum detectors. Each point is the total for one survey and the red line is a fitted linear regression line.

The sequences detected by the time expansion detectors were almost always detected by the full spectrum detectors. Where this was not the case, the full spectrum detector always had a positive record for an adjacent minute, suggesting that this is due to a minor difference in the timing of detection, rather than the full spectrum approach missing the bat entirely. There were 2407 minutes where a sequence was detected by the full spectrum detector, but not by the time expansion detector. In contrast, there were 129 minutes where sequences were detected by the time expansion detector but not the full spectrum (Table 7). The results of the McNemar's test showed a significant difference between the methods (P <0.001), indicating that the two methods were not equally effective. The results of the GLMM fit to the discordant pairs indicated no significant differences in relative effectiveness with time (F=0.03 with 1 and 2520 d.f., P=0.87), with route (F=1.18 with 10 and 2520 d.f., P=0.30), or with year (F=0.04 with 2 and 2520 d.f., P=0.26). These results indicate it will be possible to include data from both methods in the same trend model.

iBats surveys conducted using both time expansion and full spectrum detectors overwhelmingly recorded *P. pipistrellus*. Using full spectrum detectors, it was possible to confidently assign sequences to *Myotis* species and *P. pygmaeus*, however these made up <2% of the total number of detected sequences.

Table 7: A two-way table classifying each minute based on whether common pipistrelles were detected. The number of minutes and percentage of the total number of minutes are shown based on 5136 minutes from 67 surveys.

	Full spectrum		
Time expansion	Missed	Detected	All
Missed	552 (10.7%)	2407 (46.9%)	2959 (57.6%)
Detected	129 (2.5%)	2048 (39.9%)	2177 (42.4%)
All	681 (13.3%)	4455 (86.7%)	5136 (100%)

3.5. Comparing iBats and JBatS

3.5.1 Qualitative comparison

iBats and JBatS were passive acoustic surveys, implemented using passive acoustic sensors under different survey designs. Data collected under both surveys were classified using automated bat call detection and classification algorithms to extract bat activity and species presence information. Both surveys can be delivered by volunteers, although iBats has been carried out solely by GoJ, and requires approximately three person hours per survey (Table 8). As a mobile passive acoustic survey implemented using driven car transects, iBats covered a greater spatial area than JBatS, although the total time per year of sampling was greater under JBatS. Data collected under iBats are likely to be biased towards bat species that are tolerant of roads, and other anthropogenic landscape features, such as artificial lighting and buildings (Table 8).

Table 8: Qualitative comparison of iBats and JBatS survey methods.

	iBats	JBatS
Method	· Car-driven acoustic transect survey	· Static acoustic survey
Equipment	· Acoustic sensor - time expansion (e.g., Tranquillity) or full spectrum, (e.g., Pettersson D500x) · Car mounting attachment · Recording device (e.g., Edirol R-09HR) · GPS or smartphone with GPS app · SD card, batteries, cables · Car and warning signs	· Full spectrum integrated acoustic sensor and recorder (e.g., AudioMoth) · Weatherproof case · Mounting pole and attachments · SD card, batteries · GPS or smartphone with GPS app
Current survey effort	· Survey undertaken in July and August. · 11 transects, typically driven once in July and once in August.	· Survey undertaken in July · 2018: one sensor deployed per 1km grid square. 86 1km squares surveyed (proportional representation of habitats), · 2019: 50 1km grid squares surveyed in (equal representation of habitats) · 2020: 65 1km grid squares surveyed (largely opportunistic)

Approximate area sampled*	· Each transect is approximately 25km, giving a coverage of 0.25-5km^2 depending on the species. · Across all transects coverage is approximately 2.75-55 km^2 depending on the species.	· Coverage of each sensor varies from 80m^2 to 0.3km^2 depending on the species. · Across all squares surveyed in 2018 coverage is approximately 0.007-3.3km^2 depending on the species.
Time period sampled per survey	· Transects driven for 70 minutes, starting 30-45 minutes after sunset. · With a time, expansion sensor an expansion factor of 10 is used, with a sample schedule of 320ms sampling, 3.2s playback. This provides seven minutes of sampling per transect, giving 2.6 hours of sampling each year. · Using a full spectrum sensor 70 minutes are sampled per transect, giving 25.7 hours sampling each year.	· Sensors set to sample for 10.5 hours from 20:00 - 06:30 BST, to capture entire period of bat activity. · Sampling is quasi-continuous. Currently a schedule of 300 seconds recording followed by three seconds sleeping is repeated throughout the night. This provides 10.4 hours of sampling per square, and 894.4 hours of sampling each year (assuming the same survey effort as 2018).
Approximate person hours per survey (after route/site has been selected)	· Three hours per survey: checking weather, charging batteries, downloading files, correcting overruns when the stop button didn't work, letting the police know of plans, collecting navigators, driving the route.	· Three hours per volunteer, per site: equipment set up (0.25hr), travel to site (0.5hr), setting up equipment on site (0.5hr), return travel (0.5hr), travel to site to collect equipment in the morning (0.5hr), return travel (0.5hr), returning data and storing equipment (0.25hr)

Habitats surveyed	• All five key habitat types covered (agricultural/arable, grassland, urban, woodland, water), although limited to habitats that occur adjacent to roads.	• All five key habitat types covered
Species coverage	• As an acoustic survey method iBats is most suited to species with loud, distinct vocalisations. • Although many roads in Jersey are minor, where survey transects follow major roads, sampling will be biased towards species more tolerant of lighting/noise/traffic disturbance.	• As an acoustic survey method JBatS is most suited to species with loud, distinct vocalisations.
Data processing	• Automated sound classification with manual verification to assess confidence thresholds and confirm notable records. • Previously, Sonobat, iBatsID, and earlier versions of BatDetect have been used. For this study data have been classified using BCT's automated sound classification system, which incorporates version 3 of BatDetect	• Automated sound classification with manual verification to assess confidence thresholds and confirm notable records. • Previously, earlier versions of BatDetect have been used. For this study data have been classified using BCT's automated sound classification system, which incorporates version 3 of BatDetect
Additional data collected by participants	• Temperature, cloud cover, rain, wind speed, humidity	• No additional data currently collected by surveyors; however environmental data collection could be incorporated in future. Alternatively relevant data can be obtained from third parties

		(e.g., weather station data, landcover data).
Can be delivered by volunteers?	· iBats surveys have been successfully carried out by volunteers in many countries globally; however, this survey approach has not been successful with volunteers in Jersey	· Yes, JBatS and similar surveys have been successfully carried out by volunteers on Jersey and across the UK

** Assuming an omnidirectional microphone and a range of detection distances from 5m (Rhinolophus hipposideros, Myotis species in clutter) to 100m (Nyctalus noctula in open habitat).*

3.3.3 Cost comparison

A comparison of the overall costs of the iBats and JBatS surveys shows that the JBatS survey method is cheaper than iBats (Table 9). A full breakdown of the difference in costs is available in Appendix 5.

Table 9: Cost comparison of iBats and JBatS survey methods.

Survey	Initial equipment cost	Annual project cost	Annual staff cost	Total annual cost	Cost per hour per detection
iBats	£3262.35	£857.50	£2199.90	£3057.40	£119.10
JBatS	£2291.00	£690.80	£1650.00	£2340.80	£1.17

3.3.4 Effectiveness at determining species diversity and distribution

The number of species detected under JBatS was much greater than both the iBats survey methods. Using the car survey method and full spectrum detectors, 99.8% of detections were *P. pipistrellus*, whereas using the static survey method and AudioMoths, this species made up 95% of detections (Table 10). There were also a greater number of species or species groups detected using the AudioMoths and static survey method.

Table 10: Comparison of average detection rates for JBatS and iBats full spectrum (FS) data. Based on 71 nights recording at 64 different sites in 2020 for JBatS and 69 surveys of 11 different routes in 2018-2020 for the full spectrum car surveys. Hourly rates per hour for JBatS are based on the time between sunset and sunrise.

Survey	Species	N present		N sequences		% total sequences
		sites	*nights*	*Per night*	*Per hour*	
JBatS	*Myotis*	19	22	0.79	0.094	0.13
	Nyctalus/Eptesicus	12	16	2.89	0.343	0.49
	Pipistrellus nathusii/P. kuhlii	33	38	13.79	1.639	2.33
	Pipistrellus pipistrellus	64	71	561.35	66.731	95.01
	Pipistrellus pygmaeus	16	19	0.96	0.114	0.16
	Plecotus auritus	5	6	0.39	0.047	0.07
	Plecotus austriacus	19	23	10.45	1.242	1.77
	Rhinolophus ferrumequinum	3	3	0.06	0.007	0.01
	Rhinolophus hipposideros	1	2	0.15	0.018	0.03
iBatsFS	*Myotis*	8	19	0.35	0.275	0.14
	Pipistrellus pipistrellus	11	69	245.17	193.987	99.82
	Pipistrellus pygmaeus	5	6	0.09	0.069	0.04

3.6. iBats: an assessment of abundance over 10 years

Due to the low classification probability scores of species other than *P. pipistrellus* it was only possible to produce 10-year temporal trends for this species. A significant increase of 71.9% (95% CI 54.9-89.2%) in the index of relative abundance of *P. pipistrellus* was found in 2020 from the baseline of 2012. The trend increased steadily from the baseline year (2012), with a mean annual increase of 7.0% and significant increases ($P < 0.05$) annually from 2011 to 2015 and from 2016 to 2018 (Figure 6). As it was only possible to confidently report *P. pipistrellus* echolocation call sequences from the time-expansion data, we were unable to assess changes in diversity between 2011 and 2020.

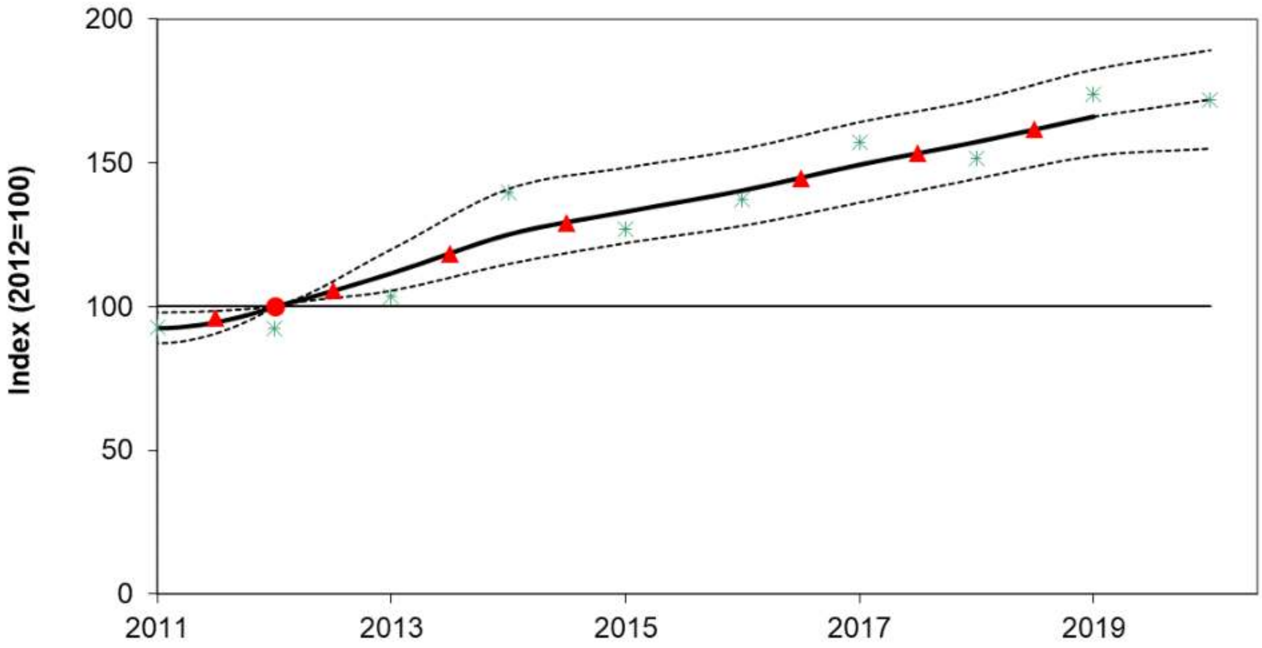

Figure 6: GAM results with 95% confidence limits. Green points are estimated annual means, shown to illustrate the variation around the fitted line. Red circles indicate significant (P< 0.05) change points, where the slope of the smoothed trend line changes. Red triangles indicate that the difference in the smoothed index between consecutive years is statistically significant (P<0.05).

3.7. iBats: a comparison of the trend and status of bat species found in Jersey, GB, and France

As it was only possible to produce a population trend for *P. pipistrellus*, we compared the trends for this species in Jersey, GB, and France. The Jersey *P. pipistrellus* trend increased more between 2012 and 2020, compared to the positive GB trend (Figure 7). The 95% confidence intervals were slightly larger for the Jersey trend than the GB trend, indicating less certainty in the estimate. Bootstrapping the difference between the Jersey and GB showed that the Jersey trend was increasing significantly more than the GB trend from 2013 onwards as the 95% credible intervals did not cross zero (Figure 7c). The Jersey trend qualitatively is clearly different to the French trend, which was relatively stable overtime, with a slight decrease in 2020 (Figure 7d). However, as the method used to produce the French trend was not reported, it was not possible to quantitatively compare the difference. The confidence intervals of the French trend were much narrower than the Jersey and GB trends, which is likely due to the differences in statistical methods used to estimate them. It is important to note that the confidence intervals for the French trend are not scaled to show the confidence in the estimated trend from a baseline year, as for the Jersey and GB GAM trends.

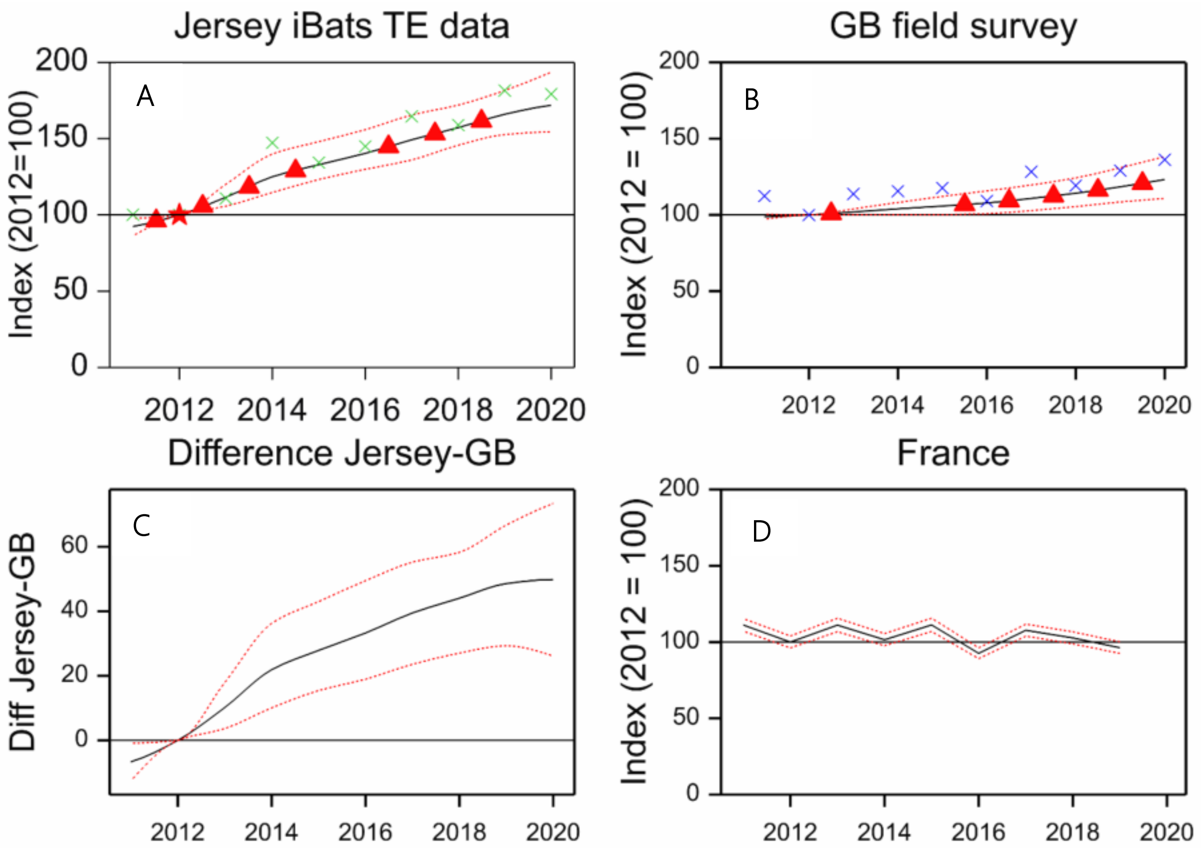

Figure 7: Trends in relative abundance of Pipistrellus pipistrellus between 2011 and 2020 in A) Jersey, B) Great Britain (GB), and D) France. C) shows the difference between the Jersey and GB trends. Red dotted lines are 95% bootstrapped limits for the trendlines (A,B,D) or difference in trends (C). Green (A) or blue (B) crosses are estimated annual means and are shown to illustrate the variation about the fitted line. Red stars indicate significant (P<0.05) change points, where the slope of the smoothed trend line changes. Red triangles indicate that the upward or downward trend is significant between years. Note: the methodology for the French trend is unknown.

3.8 Spatial analysis – effects of environmental features on bat occupancy

Using iBats time expansion and full spectrum data we found mixed effects of environmental features on *P. pipistrellus* occupancy, dependent on spatial scale. We report effects on occupancy as positive or negative if the 95% credible intervals of the estimated covariate coefficients do not include zero. We found consistent negative effects of mean survey temperature and no effect of wind speed on *P. pipistrellus* occupancy using both iBats datasets (Figures 8 & 9).

Assessing iBats time expansion data collected between 2011 and 2020, we found positive effects of all boundary features when no buffer around the road was used. Using a 100 m buffer around the road resulted in a positive effect of higher percentage cover of water on *P. pipistrellus* occupancy. When the environmental features within a 500 m buffer around the road was used, higher proportions of agricultural land, grassland, woodland, and water had positive effects on *P. pipistrellus* occupancy. In contrast, a higher proportion of buildings had a negative effect on *P. pipistrellus* occupancy, as did major roads (Figure 8). The 95% credible intervals around the mean were large for the effects of road types, indicating less certainty in these estimates.

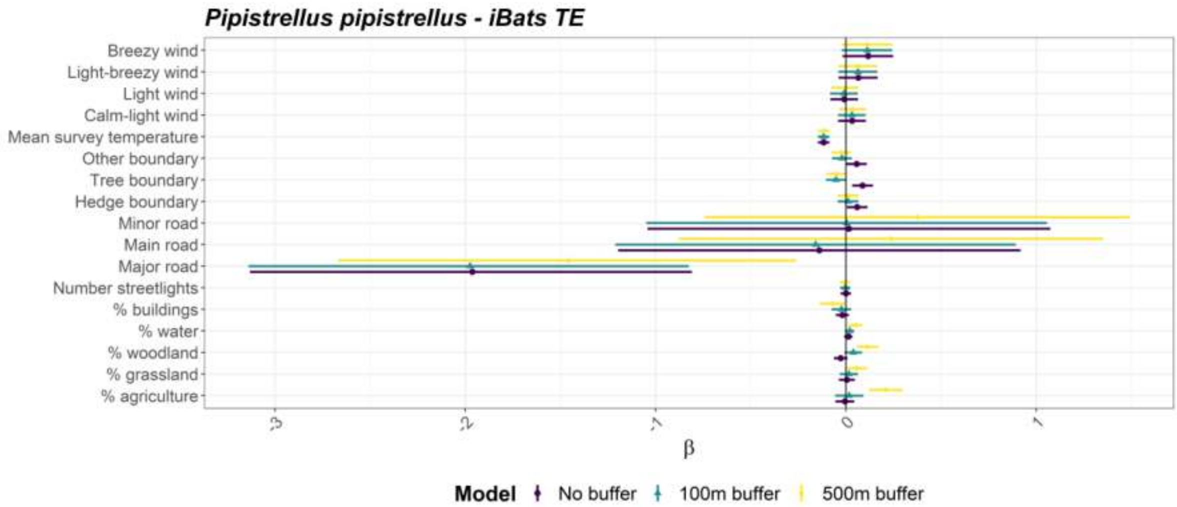

Figure 8: Effects of landscape features on P. pipistrellus occupancy, estimated from iBats time expansion (TE) data. The points show the mean effects and the horizontal lines the 95% credible intervals around the means. Where the 95% credible intervals do not cross the vertical black line at zero the effect is considered strong. The colour indicates the model and size of buffer used around each 50m² grid cell. The effects of wind speed categories are compared to Calm-wind.

The effects of environmental features on *P. pipistrellus* occupancy estimated using the iBats full spectrum data, collected between 2018 and 2020, were broadly the same as for those estimated using the time expansion data, although there were some exceptions (Figures 8 & 9). Within the direct vicinity of the road (no buffer) higher proportions of all land cover types had a negative effect on *P. pipistrellus* occupancy, yet within 100 m and 500 m buffers, all except buildings had positive effects. The opposing effects between buffer sizes is likely due to the small proportions of landcover types within the direct vicinity of the road and we suggest treating the 'no buffer' results of the effects of the landcover type proportions with caution. The converse is likely the case for the effects of boundaries, with the larger buffers containing a small number of boundaries overall, causing wide credible intervals.

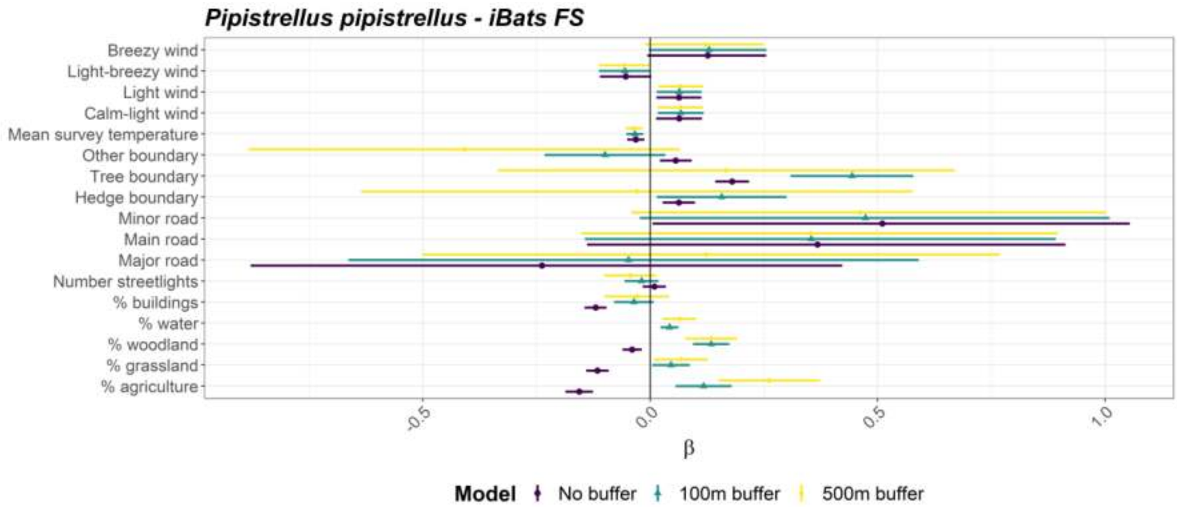

Figure 9: Effect of environmental features on bat occupancy along roads, estimated from iBats full spectrum (FS) data. The points show the mean effects and the horizontal lines the 95% credible intervals around the means. Where the 95% credible intervals do not cross the vertical black line at zero the effect is considered strong. The colour indicates the model and size of buffer used around each 50m² grid cell. The effects of wind speed categories are compared to Calm-wind.

We projected the mean estimated occupancy of *P. pipistrellus* in Jersey across a 500 m² grid using environmental features within a 500 m buffer. We found higher mean occupancy in the east of Jersey and gaps in survey coverage in the west and central eastern regions (Figure 10).

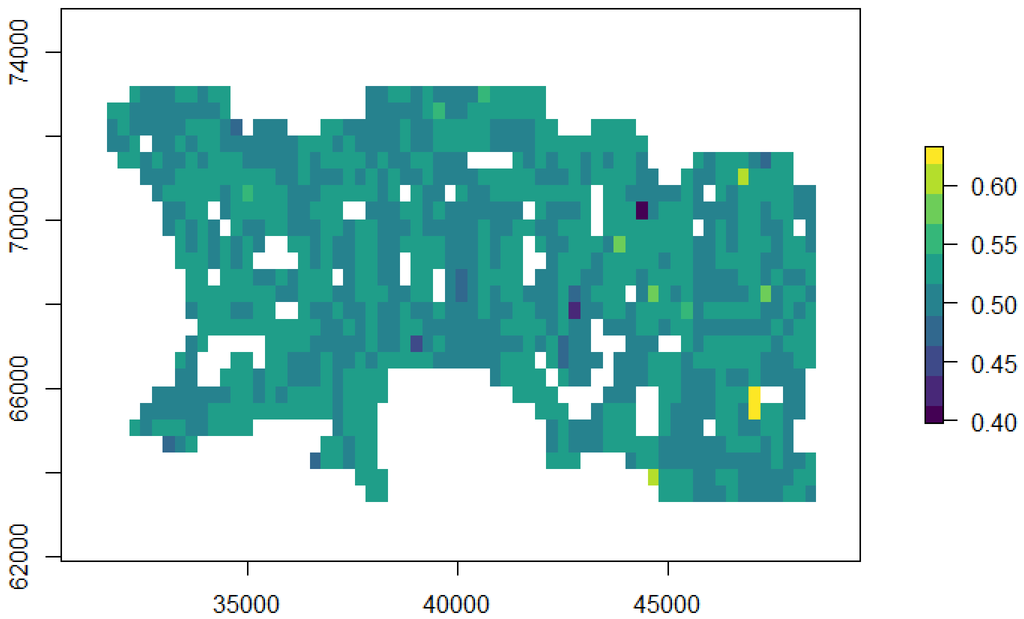

Figure 10: The mean estimated occupancy of P. pipistrellus aggregated to a 500m² scale across Jersey using the iBats TE data and a 500m² buffer around the 50m² road transect survey points. Higher estimated mean occupancy is indicated by yellow and lower by indigo. White squares indicate gaps in survey coverage.

4. Discussion and recommendations

In this section, we discuss the results of the analyses and comparison of different passive acoustic monitoring methods for bats. We consider the effectiveness of the iBats methodology for monitoring bats in Jersey and the use of automated bat call detection and classification tools. We provide recommendations for passive acoustic monitoring surveys in Jersey, as well as identifying other monitoring methods to increase the information for conservation management practices. Finally, we present key recommendations for bat monitoring in 2022 in order of importance.

4.1 iBats: an assessment of the effectiveness of the iBats methodology

The iBats survey methodology was implemented as it enabled a large proportion of the island of Jersey to be surveyed with minimal resources, in terms of human time and bat detector availability (Jones et al., 2013). In terms of survey coverage and consistency it has been hugely successful, with transect routes being repeated annually. Time-expansion bat detectors were standard use for passive acoustic bat surveys at the beginning of the survey; however more recently, full spectrum recorders are preferred as recordings can be made continuously. When deployed concurrently, a greater number of calls and species were detected using the full spectrum bat detectors, although both datasets were dominated by *P. pipistrellus*. The analysis of the iBats data highlighted the limited species coverage of the survey. This was expected due to the known negative impact of roads on many bat species and documented avoidance behaviour (Bennett & Zurcher, 2013; Berthinussen & Altringham, 2012; Claireau et al., 2019; Gaisler et al., 2009; Medinas et al., 2012; Myczko et al., 2017; Zurcher et al., 2010). The static survey method piloted under JBatS enables a greater variety of habitats to be monitored away from areas of high anthropogenic disturbance, increasing the number of species likely to be detected.

P. pipistrellus is a common species that provides an important insect pest control ecosystem service (Jones et al., 2009; Russo & Jones, 2015). It is important to monitor the population of this species as a decline in its population could have a huge impact on ecosystem stability. It was possible to robustly estimate the long-term *P. pipistrellus* population trend from the iBats time-expansion data, revealing a significant increase in the population of this species between 2012 and 2020. The increase in relative abundance was greater in Jersey than in Britain and France. Although the French population trend estimated for *P. pipistrellus* is declining, it should be noted that many of the Vigie-Chiro surveys are conducted in the south of the country (Kerbiriou et al., 2015), where the landscape and climate is markedly different to Jersey and Britain. As such other factors, including poorer legal protection and climate change, may be causing the decline. However, there has been no analysis on the drivers of the French bat population trends to date making it hard to draw conclusions on the parallels with the Jersey trends.

Static surveys, as implemented under JBatS, are also likely to be effective in monitoring this species and are likely to provide greater information on species diversity and enable population trends to be estimated for a greater number of species in the future. However, their recent implementation means that long-term trend estimation for this and other species won't be possible until 10-years of data have been collected. Methods to overlap or integrate data collected using different survey methods should be explored (Freeman et al., 2007; Isaac et al., 2020; Rodhouse et al., 2019) to maintain the long-term population trend of *P. pipistrellus*. Integrating iBats FS and JBatS data may also enable population trends of *P. pygmaeus* and *Myotis spp.* to be estimated sooner.

4.1.1. Drivers of bat population trends in Jersey

The drivers of the increase in relative abundance of *P. pipistrellus* are not clear in Jersey, or the UK. The positive impact of legal protection has been proposed (Browning et al., 2021), as well as the species' ability to adapt to anthropogenic landscapes, such as agricultural and urban areas (Jung & Threlfall, 2015). Spatial analyses of the iBats data support tolerance to agricultural landscapes due to the positive effects of higher proportions of agricultural and grassland, likely primarily used for cattle, on *P. pipistrellus* occupancy around roads. However, a higher proportion of buildings resulted in negative effects on occupancy, indicating that *P. pipistrellus* does not benefit from higher intensity urbanisation (Lintott et al., 2016). Additionally, spatial analysis of the iBats TE data showed the negative effect of major roads on *P. pipistrellus* activity, further highlighting that more intensive anthropogenic landscapes are detrimental to this species.

We did not find an effect of higher numbers of streetlights around roads on *P. pipistrellus*, although we expected a negative effect as found for non-ultraviolet light emitting streetlights from the analysis of the iBats TE data 2011 – 2015 (Williams et al., 2019). Unlike Williams et al. (2019), we did not separate differential lighting type in our analysis due to unavailability of data on changes to street light types since 2017. The grouping of all lighting types, therefore, may explain the neutral effect of street lighting on *P. pipistrellus* occupancy. Assessing the effects of street lighting type on the entire iBats TE dataset, including recent street light type data, would provide valuable information on managing urban areas sympathetically for bats. Positive effects of the presence of tree, hedge, or other boundaries along roads on *P. pipistrellus* occupancy were expected (Boughey et al., 2011; Finch et al., 2020; Froidevaux et al., 2019; Verboom & Huitema, 1997). Bats use linear features for commuting through the landscape, and hedges or trees along roads may provide some shelter from the road, as well as increasing insect occurrence. Increasing boundary features along roads will likely further benefit *P. pipistrellus* populations in Jersey, as would increasing woodland and water cover around roads. Spatial analysis of the JBatS data will provide further insight into the impacts of environmental features on a greater number of species' populations, without the bias of roads.

The negative effect found of higher survey temperature on *P. pipistrellus* occupancy is potential cause for future concern given the increases in temperature already occurring due to climate change. It is possible climate change is playing a role in the declining trend in *P. pipistrellus* found in France, which was estimated from surveys biased towards the south. However, the drivers for this trend have not been conclusively identified and we do not have access to details of how this trend was produced including any investigated covariates. A negative correlation between *P. pipistrellus* occupancy and higher temperatures has important implications for future trends in this species in Jersey.

4.2 Pros and cons of automated call analysis

Advances in passive acoustic sensor technology in the last 10 years has enabled the collection of increasing larger acoustic datasets. Manual detection and classification of target sounds is near impossible as it is very time expensive (Gibb et al., 2019). This is particularly the case when the target sounds are ultrasonic due to having to slow down the recordings so that they are audible to humans. Using automated bat call detection and classification algorithms vastly increases the quantity of data collected under passive acoustic surveys that can be analysed, increasing the temporal and spatial scale of such monitoring projects (Browning et al., 2017). However, although manually less intensive, automated call classification can be computationally intensive on large datasets. A well-designed pipeline for managing, classifying, and storing acoustic data is essential Additionally, automated call classification algorithms rely on representative training data, otherwise their performance will be poor, and species will be misclassified, or calls missed (Barré et al., 2019; Obrist et al., 2004). Training data should be representative taxonomically and regionally, as well as for recording quality. Many proprietary automated bat call classification tools are trained using high quality recordings, and when applied to acoustic recordings made using low-cost devices, such as AudioMoths, their performance is poor and many bat calls are discarded or not detected by the algorithm (Browning et al., 2017). Furthermore, the methods and training data used for many are not published meaning the error rates in call detection and classification are unknown (Gibb et al., 2019).

The BatDetect (Fairbrass et al., 2018; mac Aodha et al., 2018) algorithms used to analyse data collected on Jersey were trained on UK bat call data, which is not wholly regionally representative of Jersey. BatDetect performed well in detecting bat calls from iBats and JBatS surveys, however, species classification was less successful due to poor or no representation of some species in the training data. In particular, *P. kuhlii* is not a resident species in the UK but is present in Jersey. Species with low records in the training data include *P. austriacus*, which is more common in Jersey (*pers. communication* L. Walsh, 2021). A further issue is regional intraspecific call variation, causing misidentification of calls (*pers. communication* L. Walsh, 2021). The BatDetect algorithm could be improved for use on data collected on Jersey by training it with a library of bat calls collected on Jersey, targeting species not currently or under-represented in the existing training set. Training a regionally specific version of the BatDetect classifier for Jersey would thus enable a greater number of species to be monitored in Jersey using passive acoustic monitoring methods.

There are several other, ready-to-use automated bat echolocation call classification tools, some of which are proprietary (e.g., Raven Pro, Kaleidoscope, SonoBat), others have a partial free service (e.g., BTO Acoustic Pipeline). Like BatDetect, they rely on machine learning algorithms of varying complexity and methods to perform the autoID. Many rely on call feature extraction for species classification (e.g., SonoBat, Tadarida, BTO Acoustic Pipeline), which are typically manually defined and not flexible to regional, habitat, or intra-specific echolocation call variation. In addition, many proprietary autoID tools are trained on "perfect" or "best-case" calls, often resulting in poor performance on recordings with background noise or multi-species vocalisations. As the training data, call features, and model parameters used to train the algorithms of most existing bat echolocation call autoID tools are not openly available, it is not possible to determine the cause of poor performance or conduct quantitative comparisons between classifiers. In contrast, BatDetect learns to discriminate calls directly from the raw audio, improving algorithm resilience to variable audio recording quality, location, and background noise. In a comparison with a call feature-based model, the BatDetect model was found to perform better (*pers. communication* Mac Aodha, 2022). To enable others to independently assess model performance, the training data and model for BatDetect will be made open-source on publication of the model (*pers. communication* Mac Aodha, 2022).

4.3 Bat survey recommendations

4.3.1 A comprehensive bat monitoring programme for Jersey

Here we provide options for a comprehensive suite of systematic bat monitoring surveys for Jersey. These options have been selected based on their practicality and ability to simultaneously deliver against multiple monitoring evidence needs in a cost-effective fashion. These are high-level recommendations; a detailed consideration of survey design or a feasibility assessment was beyond the scope of this project. Passive acoustic surveys are considered in more detail elsewhere in this report. These options were developed in consultation with the Natural Environment Team in the Government of Jersey, and Jersey Bat Group, the latter of which also provided input on behalf of the island's amateur and professional bat workers. The consultation began by assessing the evidence needed to monitor the status of bat populations in Jersey, as required by domestic legislation and international agreements. The bat species occurring in Jersey were categorised against these monitoring evidence needs as either having no information, incomplete information, or reasonably complete information. Those evidence needs with no or incomplete information were then prioritised and planned or ongoing work to address these needs were identified. Finally, options to fill the remaining evidence gaps were discussed, which are summarised below.

4.3.2 Passive acoustic monitoring

For species that can be identified with reasonable confidence from acoustic recordings, passive acoustic surveys are a cost-effective means of gathering information on species' presence on the island, their resident status, range, distribution, the location of important foraging areas, migratory movements, relative encounter rate across the island, and changes in species distribution and encounter rate, both within years and between years. This latter metric is commonly used as an indicator of population trend where surveys are well designed and with the important caveat that the link between distribution, encounter rate and population size is not direct, as acoustic surveys cannot distinguish between individual bats. Acoustic surveys can also provide information to target capture/release surveys (see section 4.3.5), for the study of local bat foraging preferences, and can also suggest the location of bat roosts where there are acoustic records from the emergence period. However, information about likely roost locations from acoustic data should not be relied on in isolation and should always be confirmed using other survey methods such as dusk/dawn surveys.

Passive acoustic surveys can take three basic forms depending on whether their focus is on generating public engagement with biodiversity monitoring, providing information about species distribution, or monitoring changes over time (Table 11). These can be run as separate surveys or combined as different 'levels' of participation within a single survey. We suggest incorporating all three forms of acoustic survey into Jersey's bat monitoring programme going forward.

Table 11: Summary of passive acoustic survey goals.

Focus of survey	Frequency of survey	Survey locations
Public engagement	One-off	Selected by survey participants according to their interest. Similar to the BCT NightWatch scheme.
Species distribution	Several surveys over a single year	Distribution of locations is stratified across a grid to provide whole-island coverage.
Population trend monitoring	Several surveys over a year, repeated annually.	A representative network of stratified-random long term monitoring points, the locations of which are precisely identified to enable them to be resurveyed each year. Like for the BBatS survey currently in development at BCT.

There are several considerations to bear in mind given Jersey's particular landscape and size. Jersey is a relatively small island and bats are highly mobile, able to traverse large areas of the island in a single night. This means bat activity at a given location is likely to vary greatly during the night, between nights and over the course of the year. To get a representative picture of species presence and bat activity, detectors need to be in place for multiple nights per survey, and for multiple surveys at different times of the year. This variation in bat activity will create 'noise' in the data but it will not cause a systematic bias, so it is still possible to use this data to estimate robust trends over time given an adequate number of sample locations and sufficient duration of time series, and a representative sample of the island. However, most bat species in Jersey are only rarely encountered, and as a small island, the independence of sample locations will be limited, so it is likely that trends in relative abundance can only be estimated for the few more commonly encountered bat species using acoustic techniques. Trends in occupancy, based on presence/absence may be possible for a larger number of species. These trends are, however, hugely valuable as such information is not available from other sources. Variation in bat activity, together with Jersey's fragmented, fine-scale habitat mosaic, also make analysis of bat habitat associations challenging, but again there should not be any systematic biases, so any habitat associations demonstrated should be robust.

Factors affecting the choice of survey methods and design of an acoustic survey are discussed elsewhere in this report. The available volunteer resource and ability to classify and store the data collected are key considerations, as is the accuracy of classification. Feedback will be key to maintaining participant's enthusiasm. This can be achieved from acoustic data using a sound-classification pipeline, as is currently being developed by the BCT for surveys such as NightWatch and the British Bat Survey. Volunteers would upload their recordings to the BCT sound classification system via a desktop app which is linked to a database of paired volunteer and site location data. Recordings are analysed in the sound classification system, hosted on a cloud-based server and individual feedback reports could be automatically produced, reporting species detected and nightly activity patterns, for example.

To support the development of acoustic surveys the Government could consider developing a central repository for acoustic data that is accessible to all, which could be linked to Digital Jersey. Systematic surveys can be complemented by targeted higher-intensity surveys (e.g., fixed point, transect or dusk/dawn surveys) in particular locations that are underrepresented in existing survey effort, or where other data suggests the presence of species of interest, as per existing surveys undertaken by Jersey Bat Group. The possibility of combining monitoring of multiple taxa at fixed long-term monitoring locations to enhance the value of the dataset and the participant experience should also be explored, similar to the BTO work on Guernsey.

4.3.3. Roost monitoring

The systematic recording of bat roost locations and their attributes provides information about bat species presence, distribution, resident status, and breeding status (where large roosts are present during the breeding season and/or an increase is observed in the number of bats emerging from the roost after the young become volant). It can be used to identify locally important roost sites, provide information for the study of local roosting preferences and it can also provide data to estimate species population trends and a minimum population estimate for species that do not switch roosts frequently and for which sufficient breeding roosts are known (such as *Rhinolophus* species and *Plecotus austriacus*). It should be noted that roost counts may provide negatively biased population trends for species that switch roosts frequently (such as *Pipistrellus* species and *Myotis nattereri*) (Dambly et al., 2021). Bat roost monitoring can also involve different levels of participation (Table 12).

Table 12: Summary of bat roost monitoring survey effort and participation in approximate order of survey effort required.

Information recorded	Survey method
The following survey 'levels' can be undertaken by novices with minimal training:	
1) Roost location	n/a
2) Roost count	An emergence count conducted on two or more nights during the summer, assisted by a bat detector
3) Roost trend	Emergence counts as above, repeated annually.
The following survey methods require the support of experienced bat workers:	
4) Species	Confirmation of species. Method used depends on the species and roost - either visually (daytime roost inspection), acoustically (ultrasound recording during emergence), in the hand (via a capture/release survey) or using genetic tests (via DNA analysis of droppings or environmental DNA collected from air samples).

5) For particularly significant roosts where more information is required	Repeated dusk and dawn emergence surveys, multiple surveyors assisted by bat detectors and night vision/thermal imaging technology

We suggest a coordinated roost monitoring survey (aka 'RoostWatch') incorporating at least levels 1-3 above. This survey could be supported by an online recording form(s) hosted on the Jersey Biodiversity Centre (JBC) website and feeding directly into the JBC archive. Homeowners and consultants could be encouraged to submit information about roosts they are aware of, although we appreciate that for various reasons there may be resistance from some roost owners to sharing details of their roost. We also recommend that support is provided to identify the species occupying the roost where this is unknown, by for example linking with schemes that provide DNA analysis of bat droppings (see section 4.3.4), or to local bat workers that would be able to review acoustic recordings or undertake roost inspections and/or capture/release surveys. We also recommend reviewing existing roost records to establish ownership details for significant roosts, with a view to incorporating these roosts into the survey. This effort would benefit greatly from government support as it can be difficult to establish the current owners of previously recorded roosts.

4.3.4 Genetic monitoring

Genetic material can be obtained in several ways. Here we suggest a focus on bat droppings, as these can be collected using minimally invasive techniques that do not require specialist skills. Genetic material extracted from bat droppings is suitable for species identification, but not for more advanced analyses such as genetic diversity, population structure or effective population size. These latter analyses would be better suited to a post-graduate research study (see section 4.3.7). Genetic analysis of bat droppings can provide information on species presence, resident status, and distribution, and is especially useful for those species that cannot be reliably identified from acoustic recordings. DNA confirmation of species identification is particularly valuable on Jersey given the presence of cryptic species such as *Plecotus austriacus*, and the suggestion that the acoustic parameters used to differentiate *Pipistrellus* species may differ between Jersey and the UK. Confirmation of species-specific roost sites will ensure reliability of bat call library data collection.

The Jersey International Central of Advanced studies has a budget to analyse c. 100 bat droppings from their surveys. We suggest complementing this work by providing additional capacity to analyse droppings and encouraging the submission of droppings via a co-ordinated scheme (aka 'Drop in your droppings'). This scheme could encourage the collection and submission of droppings from individual bats or roosts discovered via other surveys (such as by consultants, capture/release surveys or via a 'RoostWatch' survey), although, as with roost monitoring, we appreciate there may be resistance to this idea from some homeowners. The potential of bat droppings to be used for invertebrate monitoring could also be explored (Hemprich-Bennett et al., 2021; Razgour et al., 2011).

4.3.5. Capture and release surveys

Capture and release surveys using mist nets or harp traps can be used to confirm species presence, resident status and distribution for those species that cannot be reliably identified from acoustic recordings. They also provide the opportunity to collect droppings for DNA analysis (see section 4.3.4) and use radio-tracking to locate roosts. If tagged bats are tracked continuously, radio-tracking can also be used to identify foraging and swarming locations; however, this can be challenging across rough or steep terrain. Capture release surveys are not typically used for systematic surveys due to low capture rates, but they are very valuable when targeted in locations where other data suggests a species of interest may be present. Jersey Bat Group has several capture/release surveys planned or ongoing, and we recommend that the Government continues to build on and support these efforts. Additionally, we suggest sourcing training in attaching radio-tags for Jersey bat workers to enable this technique to be employed more widely.

4.3.6. MOTUS

The MOTUS tracking system provides evidence of species presence, resident status, and migratory movements (see https://motus.org/). A MOTUS receiver on Jersey would make an invaluable contribution to the study of bat migration and links between bat populations on Jersey, France and potentially the UK, currently a key evidence gap. However, projects to tag bats in these locations are currently lacking. We suggest the Government continues to engage with those working towards establishing MOTUS projects in France, Jersey, and the UK (including Paul

Pestana), and facilitates this effort wherever possible with a view to establishing a MOTUS receiver in Jersey when feasible.

4.3.7. Research

There are several monitoring evidence needs that would be best addressed by post-graduate research, including:

- Species distribution modelling, the roosting and foraging preferences of bat species in Jersey, and whether these differ from elsewhere in the species' range.
- Population genetic structure, genetic diversity, and effective population size of Jersey bat populations.
- Genetic differentiation of *Pipistrellus* species in Jersey.
- Viability of using data from the planning process be to indicate trends in roosting habitat availability.
- The success of development mitigation measures.

We suggest facilitating and potentially funding these research projects where possible. The results of these projects should be published in peer-reviewed journals, increasing the scientific evidence base for bat ecology and biology in Jersey.

4.3.8. Data

The role of the Jersey Biodiversity Centre (JBC) is key to a systematic bat monitoring programme. The Centre should be supported to improve its functioning as the central archive for all bat monitoring information in Jersey. To aid this we suggest making (ideally automatically) generated summaries of the bat population information held by JBC publicly available, including information about which species are present in Jersey, their distribution (at a suitable resolution), their resident and breeding status. These reports can be 'peer reviewed' to flag obvious errors, such as the misidentification of soprano pipistrelles. This would also encourage bat workers to keep the reports current by submitting new data. It would be useful to review the recent retrospectives of the bat fauna of Jersey to ensure JBC has a record of all data included in these publications. We suggest reviewing the JBC data submission system to ensure it is user-friendly for large organisations or those that have large amounts of data to submit, and that records are verified in a timely fashion. We would also suggest actively encouraging ecological consultants to submit data and ensuring the submission system meets their needs.

The Bat Conservation Trust will shortly be reviewing guidance for bat recording, validation, verification, and archiving, and we would welcome the Government of Jersey's input into this review. One recommendation likely to arise from this review is to ensure all bat records include the type of record (roost, bat box in flight, capture etc.), how the species was identified (in the hand, via DNA analysis, from a full spectrum acoustic recording etc.) and the type of survey undertaken (dusk emergence count, walked transect, mist net etc). BCT maintains a list of recording categories for this purpose which it can share with JBC. Finally, we suggest that habitat and landcover data held by JBC and elsewhere be assessed for its ability to provide a simple qualitative indicator of trends in bat foraging habitat in Jersey.

4.3.9 Partnership working

We suggest that any new bat survey schemes are developed in partnership with local stakeholders, including Jersey Bat Group, Jersey International Centre of Advanced Studies (JICAS) and the Jersey Biodiversity Centre (JBC), to the extent that stakeholder capacity and resources allow. We also suggest integrating data from existing monitoring projects in Jersey, such as the Jersey Bat Group's long-term woodland monitoring and bat box projects, with data collected under Natural Environment funded projects. Collaborations and data sharing between these entities would add great value to understanding the status of current and future bat populations in Jersey. Creating a centralised list or database of current and planned bat monitoring projects would be a valuable first step, including details of survey protocols and design, and primary contact information. Regular meetings held at least annually between the Natural Environment Team and bat workers on Jersey would be hugely important, providing the opportunities for all parties to update and consult on the following monitoring and research activities:

- Planned or ongoing bat survey projects.
- Results of ongoing or completed work.
- Findings that can be fed back to decision makers to shape conservation strategy and policy.
- Identifying sources of bat monitoring data not currently held by JBC and facilitating their submission.

- Developing future bat monitoring work.
- Opportunities for collaborative working.
- Periodically assessing current and emerging evidence needs, pressures and threats, and considering the future prospects, of bat populations in Jersey.

4.3.10 Links with BCT

The Bat Conservation Trust's new Monitoring Strategy (which runs from March 2022 for five years) includes all of the bat survey methods discussed here, together with emerging monitoring techniques such as radar and eDNA. We would be pleased to develop these approaches collaboratively, sharing knowledge, experience and access to our monitoring IT infrastructure, modelling approaches and data products. We would also be pleased to keep the Government of Jersey up to date with the work of our Conservation Team, for example around the development of favourable population reference values, which can inform discussion of their applicability in the Jersey context.

4.4. Recommended bat monitoring priorities for 2022

In the previous sub-sections, we have outlined different methods for monitoring bat populations in Jersey and the type and use of data collected. Here we identify priorities for 2022 and 2023, which will contribute to a comprehensive, island wide bat monitoring scheme in Jersey.

A key priority for bat monitoring in Jersey is training a regionally representative automated bat call classifier. Differing bat species richness and diversity between Jersey and Britain caused the BatDetect classifier to misclassify or perform poorly on some species such as *P. austriacus* and *P. austriacus*. The collection of known echolocation calls of *P. austriacus*, and *P. kuhlii*, is a priority for improving the performance of the BatDetect classifier in Jersey. The best echolocation calls for training the classifier are collected from roost sites where bats are flying freely. Identifying bat summer roost sites for these species, as well as others, is therefore bound to this priority and should be done as a matter of urgency.

A second priority is to develop and define the survey design of JBatS. Knowledge gaps relate to the number of nights continuous recording per sites required and the sampling regime per night (e.g., one minute recorded per five minutes). The British Bat Survey (BBatS) is also under development (Fairbrass et al., 2018) with a pilot survey planned in summer 2022. Integrating the development of BBatS and JBatS would enable these gaps to be addressed quickly, as well as ensuring data collected under both surveys are comparable.

A final priority is to maintain the long-term population trend of *P. pipistrellus,* currently estimated using iBats TE data. It is possible this trend could be continued using JBatS data, however the method for doing so requires investigation. A potential method is to simply overlay the trends estimated from iBats and JBatS. Overlapping years could be compared and modelled jointly as was done with the Common Bird Count (CBC; 1960s – 2000) and Breeding Bird Survey (BBS; 1994 – present), which ran concurrently between 1994 – 2000 (Freeman et al., 2007). However, the three years of overlap between iBats and J BatS may not be sufficient to assess whether the trends are comparable. A minimum of five years is recommended (*pers. communication* N. Isaac 2022). An alternative is to use data integration methods (Zipkin et al., 2019) to jointly model data collected under using each survey method, which are likely to be more complex. We propose investigating the feasibility of the simpler method employed for the CBC- BBS population trends first and if it is not suitable then investigating the use of a data integration model. Nevertheless, the results of both methods are likely to be more robust with a greater number of overlapping years. Therefore, if resources allow, we recommend continuing iBats surveys in 2022 and 2023.

4.5 Concluding remarks

iBats surveys conducted between 2011 and 2020 provided island-wide data on bat activity in Jersey, enabling a long-term population trend to be estimated for *P. pipistrellus.* However, eighteen bat species are known to occur in Jersey (Glynn & Jones, 2020), and little is known about the population status of most. The recommendations provided in this report will improve the understanding of bat populations in Jersey by expanding the taxonomic, spatial, and temporal scales of bat monitoring. The data collected under the recommended surveys will provide evidence for effective bat conservation measures in Jersey.

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Appendices

Appendix 1

Table A.1: Categories for weather factors cloud-cover, rain and wind, and road type. The levels for the weather variables were assigned by averaging the state at the beginning and end of each transect.

Variable	Levels	Label
Cloud cover	1	0%-30%
	1.5	(0%-30%) - (30%-60%)
	2	30%-60%
	2.5	(30%-60%) – (60%-100%)
	3	60%-100%
Rain	1	Dry
	1.5	Dry-Drizzle
	2	Drizzle
	2.5	Drizzle-Light
	3	Light
Wind	1	Calm
	1.5	Calm-Light
	2	Light
	2.5	Light-Breezy
	3	Breezy
Roads	0	No road
	1	Minor
	2	Main
	3	Major

Appendix 2

Maps showing the locations of individual species or species groups detected by AudioMoths under the JBatS survey in 2020.

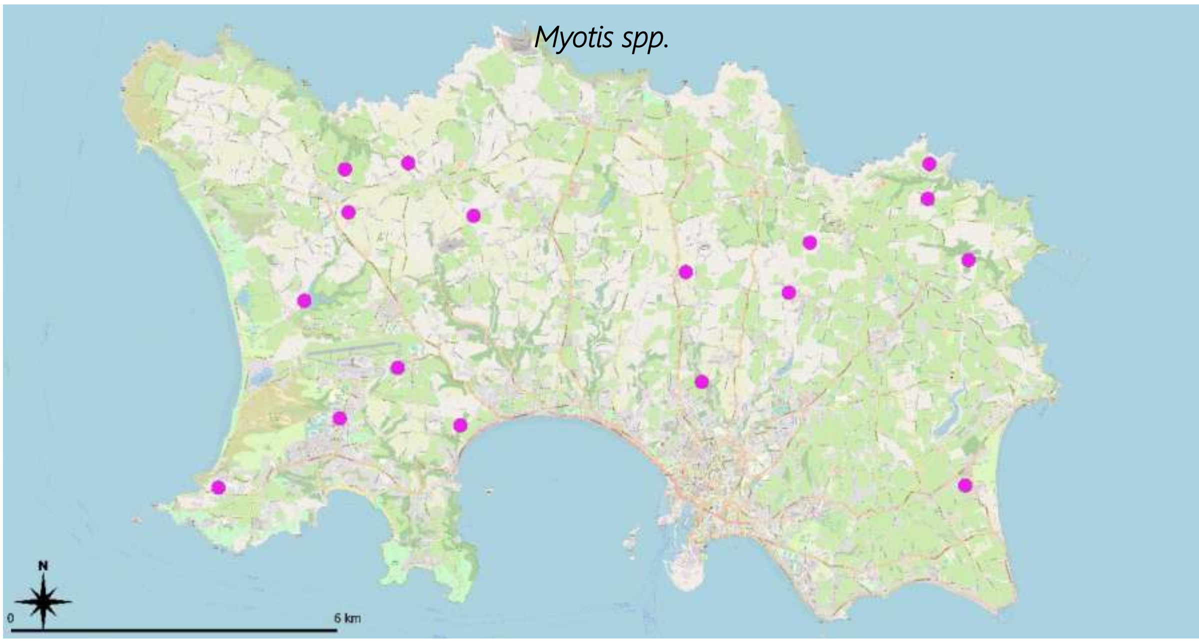


Figure A2.1: Locations of Myotis spp. detections using AudioMoths under the JBatS survey in 2020 in Jersey. Background map from OpenStreetMap, © OpenStreetMap contributors, available under the Open Data licence https://www.openstreetmap.org/copyright.

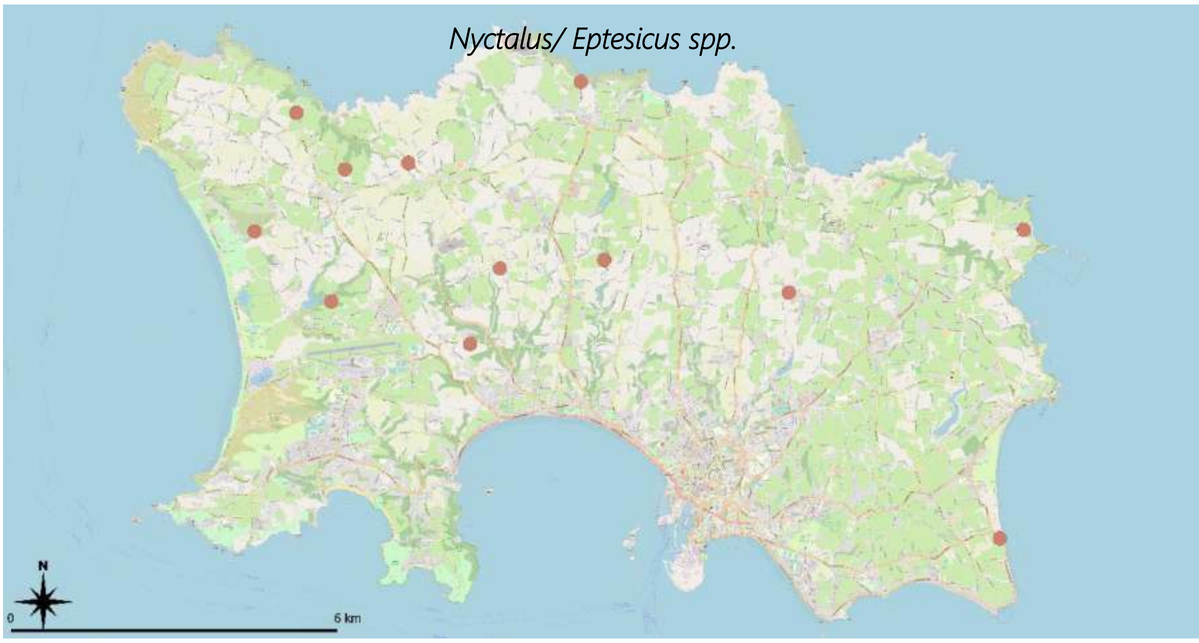


Figure A2.2: Locations of Nyctalus/ Eptesicus spp. detections using AudioMoths under the JBatS survey in 2020 in Jersey. Background map from OpenStreetMap, © OpenStreetMap contributors, available under the Open Data licence https://www.openstreetmap.org/copyright.

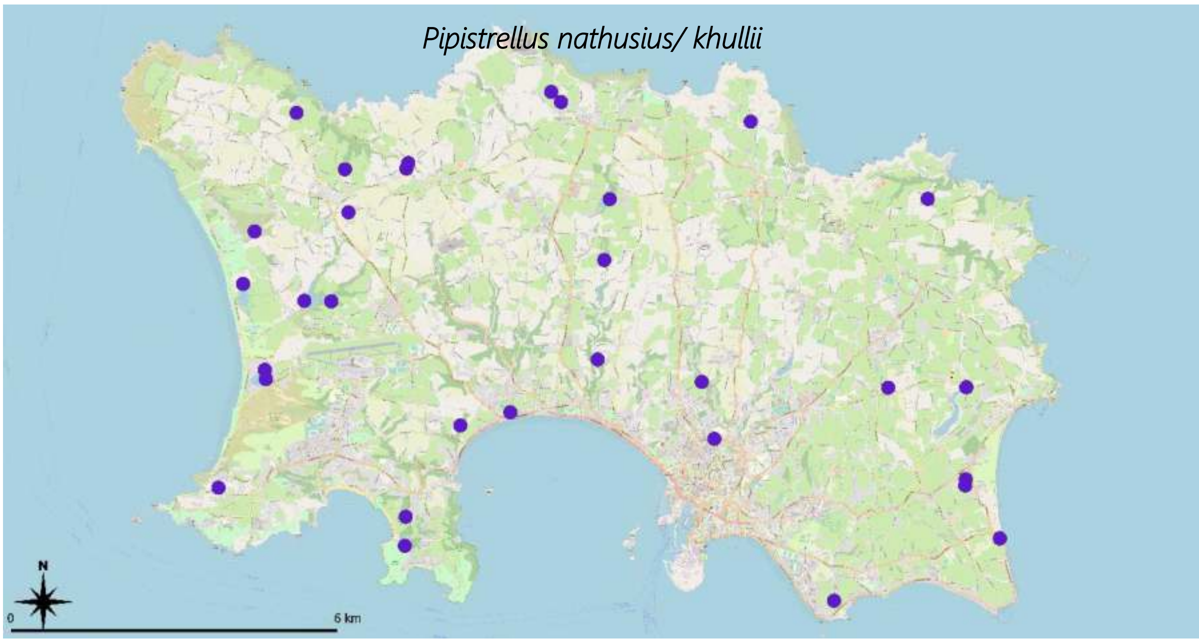


Figure A2.3: Locations of Pipistrellus nathusius/ khulii. detections using AudioMoths under the JBatS survey in 2020 in Jersey. Background map from OpenStreetMap, © OpenStreetMap contributors, available under the Open Data licence https://www.openstreetmap.org/copyright.

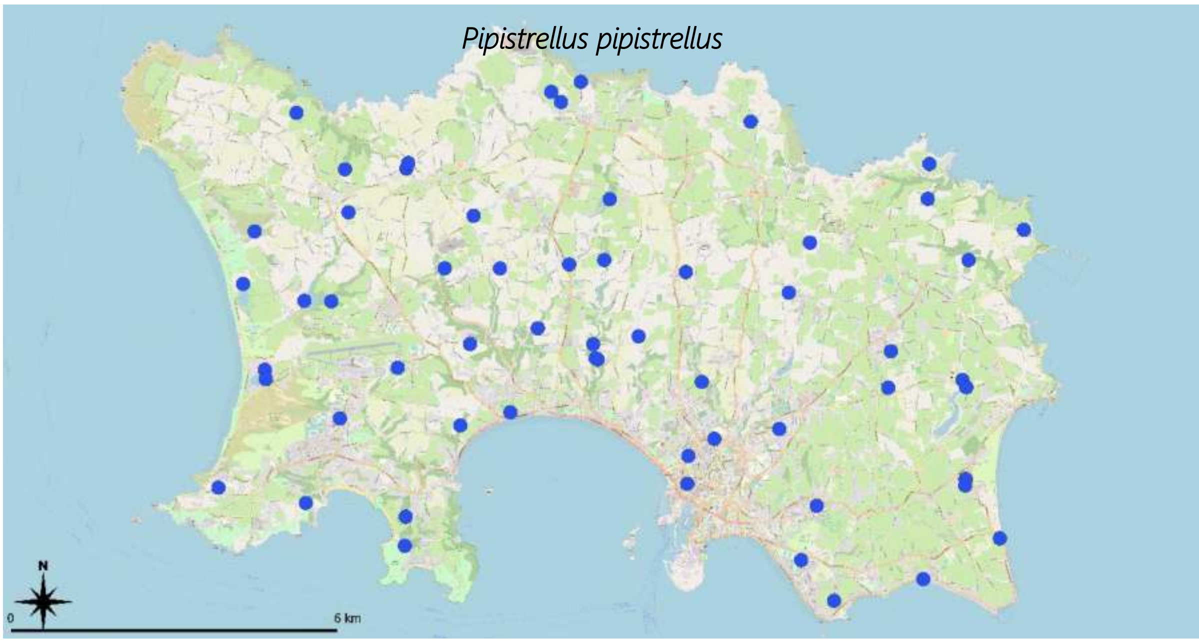


Figure A2.4: Locations of Pipistrellus pipistrellus. detections using AudioMoths under the JBatS survey in 2020 in Jersey. Background map from OpenStreetMap, © OpenStreetMap contributors, available under the Open Data licence https://www.openstreetmap.org/copyright.

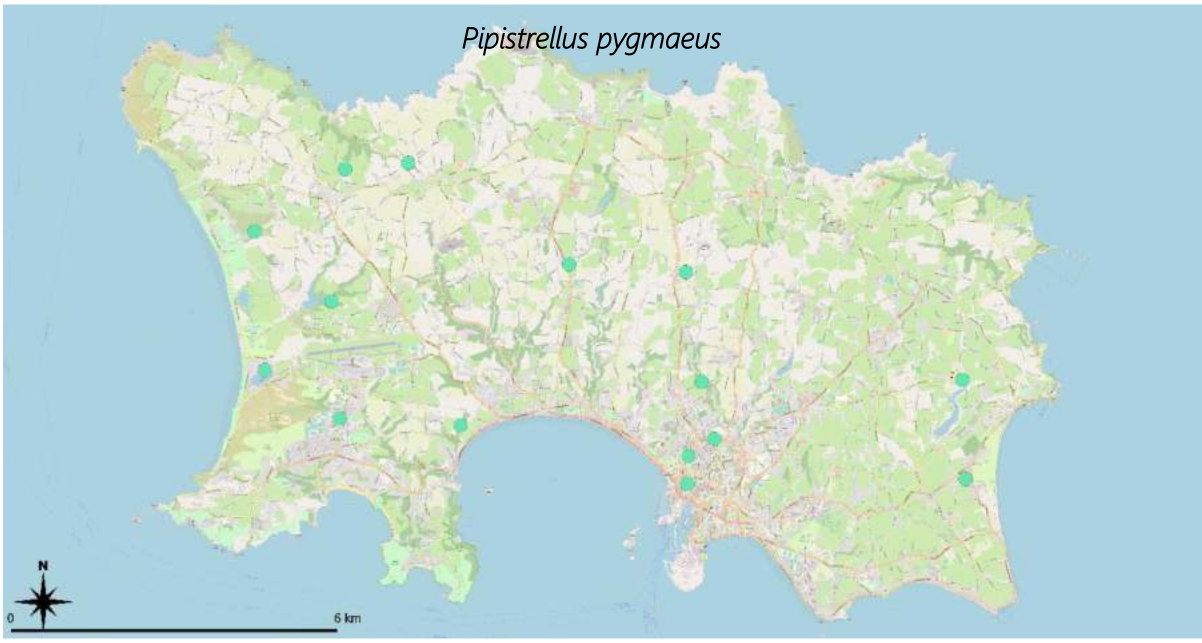


Figure A2.5: Locations of Pipistrellus pygmaeus detections using AudioMoths under the JBatS survey in 2020 in Jersey. Background map from OpenStreetMap, © OpenStreetMap contributors, available under the Open Data licence https://www.openstreetmap.org/copyright.

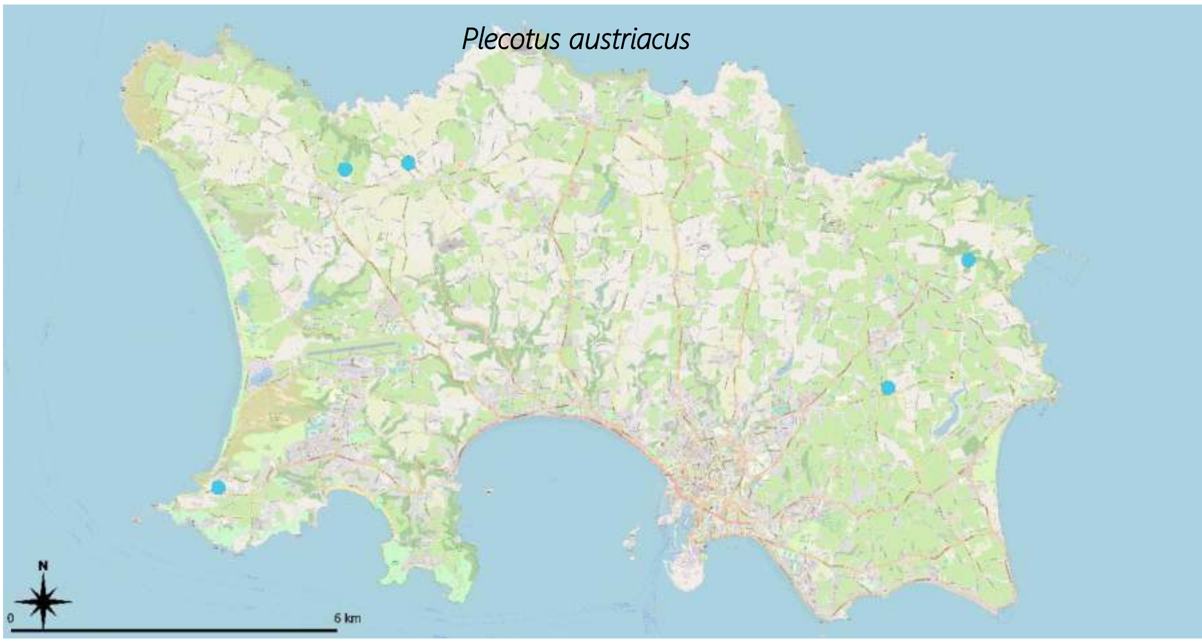


Figure A2.6: Locations of Pleoctus austriacus detections using AudioMoths under the JBatS survey in 2020 in Jersey. Background map from OpenStreetMap, © OpenStreetMap contributors, available under the Open Data licence https://www.openstreetmap.org/copyright.

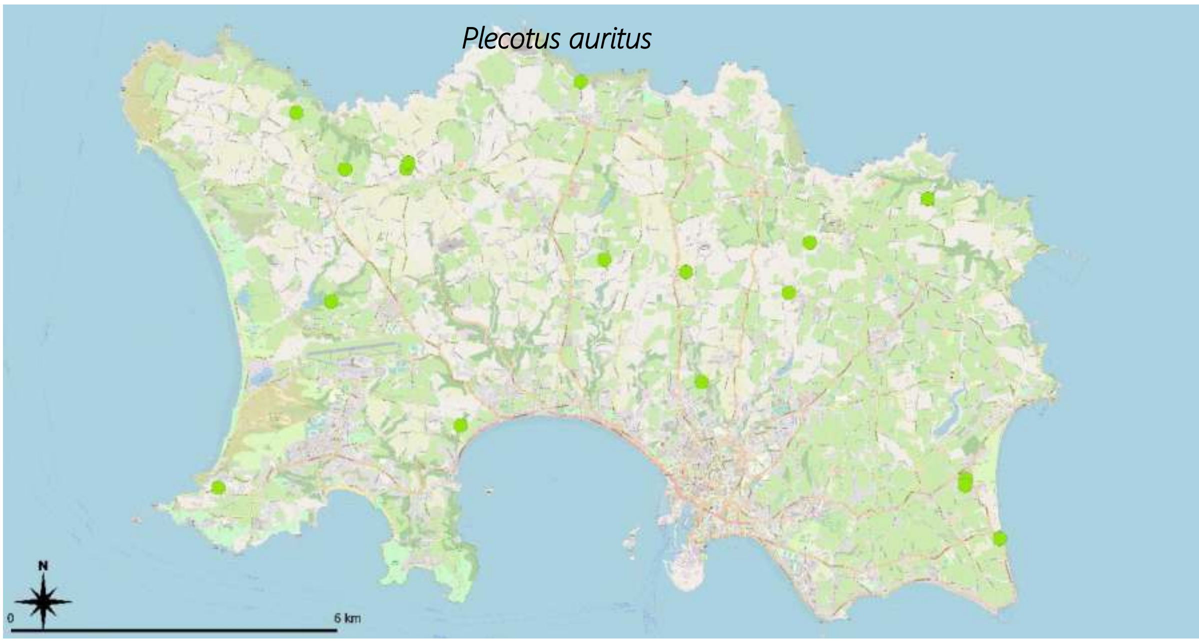


Figure A2.7: Locations of Plecotus auritus detections using AudioMoths under the JBatS survey in 2020 in Jersey. Background map from OpenStreetMap, © OpenStreetMap contributors, available under the Open Data licence https://www.openstreetmap.org/copyright.

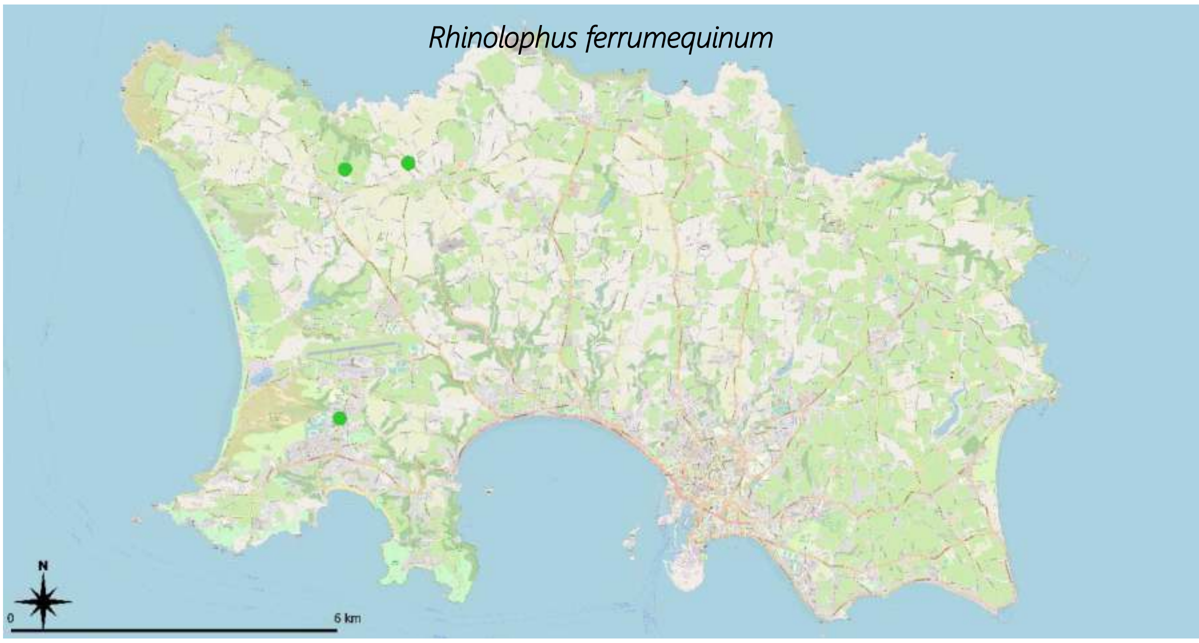


Figure A2.8: Locations of Rhinolophus ferrumequinum detections using AudioMoths under the JBatS survey in 2020 in Jersey. Background map from OpenStreetMap, © OpenStreetMap contributors, available under the Open Data licence https://www.openstreetmap.org/copyright.

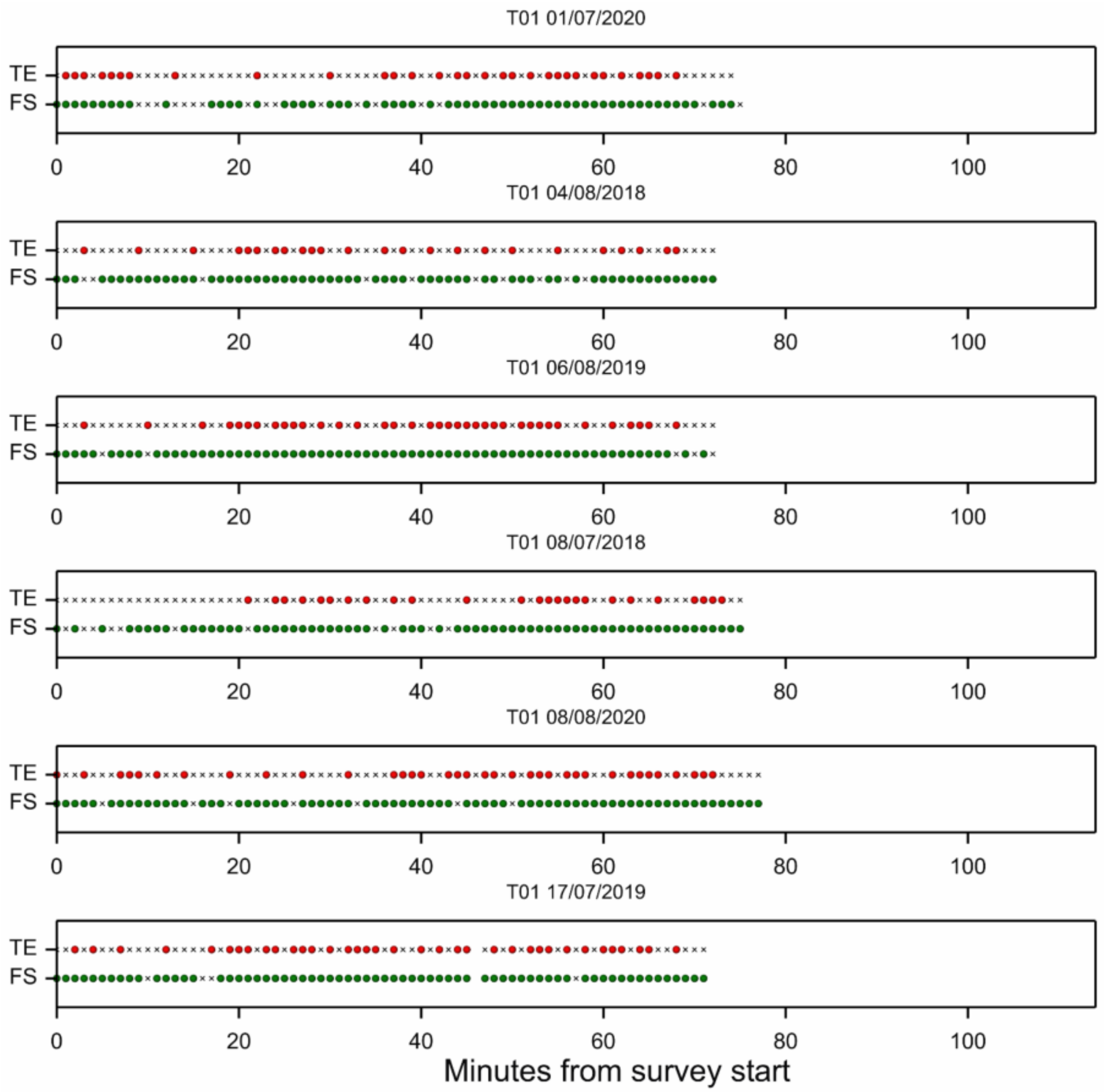
Figure A2.9: Locations of Rhinolophus hipposideros detections using AudioMoths under the JBatS survey in 2020 in Jersey. Background map from OpenStreetMap, © OpenStreetMap contributors, available under the Open Data licence https://www.openstreetmap.org/copyright.

Appendix 3

Manually verified bat call records: Appendix 3_iBats_JBatS_verified_pulses.xlsx

Appendix 4

Example plot showing the minutes in which common pipistrelles were detected in iBats surveys using time expansion detectors (red dots) and full spectrum detectors (green dots).


T01 01/07/2020
T01 04/08/2018
T01 06/08/2019
T01 08/07/2018
T01 08/08/2020
T01 17/07/2019
TE
FS
0
20
40
60
80
100
Minutes from survey start

Appendix 5

Full cost comparison of iBats and JBatS methods: Appendix 5_Cost comparison_iBats_JBats.xlsx