The Big Scilly Bat Survey – Bats of the Isles of Scilly 2022 to 2024

Technical Appendix

The main reporting for the Big Scilly Bat Survey is presented in the primary document. To maximise readability and accessibility for a wider audience, the details of analytical, data management and statistical methodologies are provided in this supporting document.

This Technical Appendix details the methodology for each section of analysis, beginning from data collection and validation through the questions addressed in the order in which they are presented in the primary document.

Data Collection and Call Analysis

Static detector protocol

Our survey method is based on the Bailiwick Bat Survey[1] and aims to assess the season-wide status of bat species across Scilly. The deployments were undertaken during the main active season from May to October with additional sampling during the winter period in a single location. The long survey season covers the main period of bat activity and allows the entire project area to be surveyed using rotating deployment of the limited number of detectors available.

The protocol enables members of the public to access passive bat recorders which were set out in a stratified array. These detectors automatically trigger and record the calls of bats to a memory card every time a bat passes throughout a night.

Volunteers were deployed to set the detector up as close to selected locations as possible, without targeting specific habitats or landscape features. The detectors were mounted on a 1.5m poles to avoid ground noise and reduce recordings of reflected calls. Guidance was provided to volunteers on the placement of the detector in order to ensure production of good quality recordings – this included positioning the detector at least 1.5m away from vegetation, water or other obstructions.

The bat detectors used were the Song Meter Mini Bat manufactured by Wildlife Acoustics. These were set to switch on and record from 30 minutes before sunset until 30 minutes after sunrise the following day.

Deployment – 2022

Each 1km survey square was surveyed using a detector located in the same position on two separate occasions spaced throughout the season. Each survey covered six nights of deployment.

Deployment – 2023

The locations of the detectors were determined using GIS software to superimpose a 500m x 500m grid on each of the inhabited islands. This was completed for each island independently to correspond with the idiosyncratic shape of each island and minimise the adjustments required.

In situations around the coastline where deployment was not possible, the centre was moved inland to the closest suitable location – examples include around the Garrison to the south-west of St Mary's, the northern edge of Tresco and the north-western edge of St Agnes.

Each location was surveyed on a single occasion for a minimum of 4 nights of deployment. Any variation in deployment length was controlled for during data processing to reflect nightly activity rather than total activity.

For each island, an element of control of timing was introduced, depending on the number of locations to be surveyed. In the case of St Mary's where there were 32 locations, there was a pause of only a day or two between deployments; however for St Agnes with only 11 deployment locations, the detectors were set out every 10-12 days to ensure the full season was represented on each island.

Deployment – 2024

The survey approach in 2024 differed from previous years with long-term deployment in fixed locations rather than maximising geographic range.

Specific locations were selected using the following criteria:

- In order to assess the use of heathland throughout the season, a single location on Chapel Down on St Martin's was selected. The detector was positioned close to an ecotone between gorse scrub and heather but was focussed on the open heathland habitat. A control detector was placed on a rocky shoreline in close proximity to minimise geographical variation but monitor an alternative habitat.
- In order to assess the use of sandy beaches by common pipistrelle, especially with regards to tidal patterns, Little Porth on St Mary's was selected as a sheltered location which has a good tidal range. Abundant hirundine foraging in this location indicated the likelihood of a reliable food supply for aerial hawking species.
- In order to gather further data regarding the distribution of soprano pipistrelles, two locations on St Mary's were selected where they had been previously recorded – Lower Moors and Higher Moors nature reserves. This was intended to assess the frequency of detection in apparently favoured locations and gain further insight into their population.

Detector setup and seasonal deployment were the same as in 2022 and 2023, running from beginning of May to the end of October.

Processing recordings and Species Identification

The detectors used were passive real-time detectors that are triggered when they detect sound within a certain frequency range. Our survey generated a very large volume of recordings (uncompressed wav format), far more than could be feasibly managed if we needed to manually look at each wav file. Instead, we used a semi-automated approach for assigning recordings to species as follows.

After each recording period, the files recorded by the bat detector, as well as associated information on where the recording was carried out, were uploaded to the BTO's Acoustic Pipeline. Volunteers and staff have their own online user account, and desktop software which means they can upload the recordings directly to the cloud-based pipeline for processing. Once analysed, the user is emailed automatically and is then able to download the automated results through their account as a .csv file. These initial results are provided with the caveat that additional manual auditing will be carried out before the survey season's end.

The BTO Acoustic Pipeline applies machine learning algorithms to classify sound events in the uploaded recordings. The classifier allows up to four different "identities" to be assigned to a single recording, according to probability distributions between detected and classified sound events. From these, species identities are assigned by the classifier, along with an estimated probability of correct classification. Specifically, this is the false positive rate, which is the probability that the AP has assigned an identification to the wrong species. However, we scale the probability, so that the higher the probability, the lower the false positive rate. To give an example, given a species identification with a probability of 0.9, there is a 10% chance that the identification is wrong. Based on research into error rates in automated analysis[2], the decision was made that data with probability of less than 0.5 (50%) were discarded.

Verification of species identification was carried out through the manual checking of spectrograms using software SonoBat to provide an independent check of the original species identities assigned by the pipeline. The application of this auditing depended on the species in question and the aims of the project:

- For rarely encountered bats and small mammals where a measure of activity and abundance was desirable, Stuart Newsom manually checked all recordings to confirm identification.
- In the case of common pipistrelle (Pipistrellus pipistrellus), an R Shiny App was used to pull out a random sample of 1,000 recordings for auditing to quantify the likely error rate for this species in the dataset.
- For bush-crickets there can be a large number of recordings, often of the same individual, which precludes use of the data for activity or abundance calculations. Auditing focussed on producing an inventory of species presence instead, where the three recordings with the highest probability for each site and night were selected for auditing.

Common pipistrelle is normally straightforward to identify acoustically, but particular care is needed when considering calls at the low or high frequency end of the range for this species, which could be mis-identified as Nathusius' pipistrelle or soprano pipistrelle respectively. For these it is important to consider the call duration, and not just the peak or end frequency of the calls. For example, considering the possibility for misidentification with soprano pipistrelle in extreme clutter, common pipistrelle typically produces very short calls that are elevated in frequency, where they could be mis-identified as soprano pipistrelle. In addition, where there are multiple individuals of the same species present, there can be frequency-shifting as one or both individuals 'shift' their frequencies to avoid acoustic interference, which again can result in some calls in a sequence that are higher in frequency than would be typical for the species.

It is normally possible to diagnose what is happening in most situations by looking at the sequence of calls, especially when there are other calls (in close time sequence) which are likely to be from the same individual bat. However, there were still some occasions when it was not possible to assign a recording to species.

Data Harmonisation

A harmonised dataset was produced to simplify the dataset and improve computational performance. Individual calls were distributed into 1-minute time bins with the number of detected calls per minute alongside associated temporal and astronomical metrics (sunset, sunrise, and percent through night calculated as a function of these two points).

This dataset was used in subsequent analysis detailed below, unless specified otherwise.

Data Analysis

Unless otherwise specified, all of the analysis in this report including production of plots were undertaken in R v.4.4.2.

Winter Activity

Data sources and structure

Daily weather data for winter 2023 were obtained from the Davis Weather Station running on St Martin's Vineyard within 10m of the detector location. Meteorological variables included temperature, wind speed, humidity, atmospheric pressure and precipitation. For each day, weather variables were available as daily maximum, mean and minimum values.

The response variable was presence/absence of recordings of common pipistrelle on each night between 20th January 2023 and 30th April 2023.

Data preparation and cleaning

The response variable was treated as a binary factor (presence/absence). All weather variables were retained in their original measurement units.

Selection of biologically relevant predictors

From the full set of available variables, predictors were selected to represent distinct physical processes:

- Minimum temperature as a proxy for night-time thermal conditions
- Maximum wind speed to capture exposure to gusts and strong winds
- Maximum humidity as an indicator of atmospheric moisture
- Maximum atmospheric pressure as a descriptor of synoptic conditions
- Daily precipitation total as a measure of rainfall occurrence

This approach avoided redundancy among highly correlated daily summaries.

Statistical modelling approach

The relationship between weather conditions and presence/absence was analysed using a generalised additive model (GAM) with a binomial error distribution and logit link function. GAMs were chosen because they allow flexible, non-linear relationships between predictors and response while remaining interpretable and robust for modest sample sizes.

Each weather predictor was modelled using a penalised smooth term, allowing the data to determine the shape of the relationship while discouraging over-fitting. Model fitting was performed using restricted maximum likelihood (REML).

Model performance was assessed using explained deviance and inspection of smooth terms.

Seasonal Variation: The ‘Bat Year’

Data preparation

Bat activity data were aggregated as call counts per time interval, with each observation associated with a recording date and a metric describing its position through the night, expressed as the percentage of elapsed night time between dusk (0%) and dawn (100%). Observations with missing call counts or missing night-position values were excluded prior to analysis.

Following initial inspection of data collated by calendar month, they were grouped into four seasonal periods reflecting visually distinct behavioural patterns: January–February, March–April, May–July and August–October.

Statistical modelling

Seasonal patterns in nocturnal activity were analysed using generalised additive models (GAMs) fitted to the raw call count data. Call counts were modelled as the response variable using a Poisson error distribution with a log link.

The primary predictor was percentage through the night, included as a smooth term to allow flexible, non-linear variation in activity across the night. Separate smooths were fitted for each seasonal period, allowing the shape of nightly activity to differ between seasonal groups while sharing a common modelling framework. Seasonal group was also included as a categorical term to allow for differences in baseline activity levels.

Models were fitted using REML to provides stable smoothing parameter estimation and guard against overfitting.

Prediction and visualisation

Model predictions were generated over a fine grid spanning 0–100% of the night for each seasonal group. Predicted values represent the expected call rate at a given position through the night, conditional on season. Approximate 95% confidence intervals were derived from the model’s standard errors on the link scale and back-transformed to the response scale.

Results were visualised as smooth curves with shaded confidence bands. For clarity and direct comparison, all plots used identical x- and y-axis scales.

Interpretation framework

The fitted curves are intended to describe how bat activity is distributed across the night within each seasonal period, rather than to estimate absolute abundance or total seasonal call volume. Seasonal differences in total activity arise from changes in both the intensity and duration of activity across the night. By modelling activity as a continuous function of night position, this approach avoids artefacts associated with discrete binning and provides a robust, interpretable summary of seasonal shifts in nocturnal behaviour.

Island Differences

Data Filtering and Preparation

To ensure biologically meaningful and statistically valid comparisons, the dataset was based upon common pipistrelle records for 2022 and 2023 only, excluding winter (January – May) records which were undertaken only on St Martin's. Uninhabited islands were also excluded from the analysis due to lack of replication.

The original data were minute-level observations. To avoid pseudoreplication and ensure valid inference, the data were first aggregated to night-level totals by summing minute-level calls within each recording night. This controls for recording night and ensures that minutes within nights are not treated as independent data. The final dataset included 818 nights across 132 unique sites on 5 islands.

Model Specification

Before model selection, dispersion was assessed and found to be strongly overdispersed (Mean nightly total calls = 430; Variance = 555,819 (Variance $\gg$ Mean, over 1000× larger).

Therefore a Negative Binomial model was selected. To account for repeated sampling at the same sites, a mixed-effects model was used.

Model: total_calls~Island+Year+(1|site_number)

Where:

- Island = fixed effect
- Year (2022 vs 2023) = fixed effect
- Site number = random intercept
- Distribution = Negative Binomial (nbinom2)
- Link function = log

This model accounts for strong overdispersion, repeated measurements within sites, estimates island effects after controlling for site-level variability, and controls for year differences

Model Fit

A likelihood ratio test comparing the models with and without the inclusion of Island as a fixed effect gave the result $\chi^2(4)=27.16$; $p=.0000184$. There is strong evidence that nightly activity differs among islands, even after accounting for site-level clustering and year.

Island Effect

Reference island: Bryher

Island	Multiplicative Effect	Interpretation	Significance
St Agnes	0.76×	~24% lower than Bryher	Not significant
St Martin's	0.90×	~10% lower than Bryher	Not significant
St Mary's	3.03×	~3 times higher	Significant (p = 0.013)
Tresco	4.51×	~4.5 times higher	Significant (p = 0.002)

Random Effect (Site-Level Variation)

Site-level variance (random intercept) = 1.688

Standard deviation = 1.299

This indicates substantial variability among sites, validating inclusion of a site random effect. Without accounting for site-level variation, island differences would be partially confounded with site effects.

Habitat Associations

Data Filtering and Preparation

A total of 90 detector locations were sampled in 2023. For habitat-based modelling, deployments on uninhabited islands were excluded to avoid additional uncertainty associated with isolation and unknown roosting context, leaving 83 locations across the inhabited islands.

Bat activity was quantified using the seasonally normalised nightly activity metric (see below). Each observation represented a single recording deployment and was associated with three ranked habitat categories (see below).

Island identity was initially considered as a potential grouping variable. Exploratory modelling indicated that island did not explain additional variation in activity after accounting for habitat dominance, and it was therefore excluded from the final habitat models.

Seasonal normalisation procedure

To control for seasonal variation in activity across the 2023 dataset, the longitudinal dataset from 2024 using five fixed monitoring sites with near-continuous recording from early May to late October were used to normalise the data. Sites were selected to represent a range of inland and coastal contexts and habitat types across St Mary's and St Martin's. Deployment configuration, recording schedules and acoustic processing matched the 2023 protocol to ensure methodological consistency.

Only common pipistrelle detections were used to derive the seasonal reference curve. Occasional detector outages were not considered materially influential because coverage was near-continuous across multiple sites and the seasonal curve was intended as a broad normalisation index rather than a fine-scale phenological model.

Nightly common pipistrelle activity in 2024 (records per hour) was modelled as a function of Julian day using a locally weighted regression (LOWESS) smoother. A deliberately conservative smoothing span (frac = 0.35) was applied so that each fitted value reflected several weeks of data, suppressing short-term weather-driven peaks and retaining only broad seasonal structure.

The fitted LOWESS curve was rescaled to have a mean value of one, generating a seasonal scaling index. Each 2023 deployment night was matched to the index using Julian day, and observed nightly activity was divided by the corresponding expected seasonal value. This multiplicative correction produced the season-normalised activity metric, which formed the response variable in subsequent habitat analyses.

This approach controls for differences in survey timing across the May–October field season while preserving relative spatial and habitat-associated variation in activity. It is acknowledged that habitat-specific seasonal trends or inter-year variations would not be captured by this normalisation data; however the derived curve is ecologically coherent and fits with wider recorded seasonal trends in the literature.

Habitat data and buffer definition

Habitat composition surrounding each detector deployment was derived from existing habitat mapping provided by David Mawer, originally produced for The New Flora of the Isles of Scilly and based on aerial imagery from 2008, 2010 and 2014.

For each detector location, habitat proportions were calculated within a circular buffer of 150m radius centred on the detector. This buffer was selected to represent consistent local habitat context while remaining ecologically interpretable at the scale of foraging movements.

Detailed habitat classes were aggregated into broader categories to support robust statistical analysis and clearer ecological interpretation. These categories were Built, Scrub & Bracken, Wetland/Freshwater, Grassland & Farmland, Heathland, Coastal Habitats, Woodland and Sea.

Habitat proportions within buffers were subsequently used to derive ranked dominance variables and continuous habitat metrics for modelling.

Encoding of habitat dominance

The three ranked habitat variables (Dom1–Dom3) represent ordered dominance within the buffer and are therefore not independent predictors. To preserve rank information while avoiding pseudo-replication, a dominance-weighted scoring approach was adopted.

Each habitat was assigned a weight according to its dominance rank within an observation: Dom1 = 1.0; Dom2 = 0.5; Dom3 = 0.25.

For each observation, weights were summed within habitat categories to produce a continuous dominance score for each habitat type. This approach retains both presence and relative dominance information in a single modelling framework.

Because dominance scores across habitats sum to a constant within each observation, one habitat category must be treated as a reference to avoid perfect collinearity. Sea was selected as the reference habitat to provide a clear ecological baseline for comparison.

Statistical modelling

Preliminary inspection of the activity response revealed right-skew and heteroscedasticity. To improve statistical stability and interpretability, the response variable was transformed using log(1 + activity). All final inferences are based on the transformed scale.

Habitat associations with bat activity were analysed using linear regression models fitted to the log-transformed response. The general form of the model was:

log(1 + activity) ~ habitat dominance scores (relative to Sea)

Model coefficients therefore represent the expected difference in log(1 + activity) associated with increased dominance of a given habitat relative to Sea-dominant habitat mixes.

Model diagnostics indicated improved residual behaviour on the log scale compared with the raw scale. Model fit was assessed using adjusted R^2 and overall F-tests.

Sensitivity analyses

Wetland/Freshwater occurred infrequently within the top-three dominance ranks. To ensure that inference was not driven by sparse data, additional checks were conducted:

- Comparison of mean log-transformed activity between observations with and without Wetland present in the top three habitats.
- Re-fitting the model with Wetland excluded to assess the stability of other habitat effects.

The principal effects for Woodland and Heathland remained consistent under this sensitivity analysis. Wetland showed a strong positive association with activity but this was interpreted cautiously due to low representation.

Interpretation framework

The fitted model describes associations between relative habitat dominance within 150m of the detector location and local bat activity. Results reflect differences in expected activity conditional on habitat composition and do not estimate absolute abundance or population size.

The dominance-weighted framework provides a transparent and interpretable summary of how ranked habitat structure relates to bat activity while avoiding artefacts associated with treating ranked variables as independent categorical predictors.

Shorelines

Data sources and structure

Minute-level bat activity data for 2024 were derived from static acoustic detectors deployed at three sites: one coastal site (Little Porth) and two inland comparison sites (Porthellick Pool and Lower Moors). Data were restricted to records of common pipistrelle only.

Tide height data for 2024 were obtained from the St Mary's dataset (National Oceanography Centre, Liverpool) at 15-minute resolution and interpolated to 1-minute intervals. These were aligned to detector timestamps and expressed in metres above chart datum.

Extreme tide heights representing sparse boundary observations were excluded to avoid unstable smooth behaviour. Values below the 2nd percentile and above the 98th percentile of tide height were removed (retaining 96% of observations).

Site type was coded as a binary factor (coastal vs inland).

Selection of biologically relevant predictors

- Predictors were selected to represent distinct ecological processes:
- Tide height (m) as a proxy for intertidal habitat exposure
- Proportion through night (0–1) as a descriptor of within-night activity structure
- Survey date as a random effect to account for nightly variation in overall activity

This structure allowed separation of tidal effects from time-of-night effects and from broader nightly fluctuations in activity levels.

Statistical modelling approach – Tide Height

The relationship between tidal height and call activity was analysed using a generalised additive mixed model (GAMM) with a negative binomial error distribution and log link function. Negative binomial errors were selected to account for overdispersion in count data.

The model structure was:

- A penalised smooth for proportion through night
- Separate penalised smooths for tide height at coastal and inland sites
- A random intercept smooth for survey date

Shrinkage smooths were used for tide height terms to reduce the risk of over-fitting and suppress unsupported boundary behaviour.

Model fitting was performed using fREML and was assessed using explained deviance and inspection of smooth term significance.

Predicted tidal response curves were generated at the population level by excluding nightly random effects and averaging across the full range of night progression.

Interpretation of model effects

The final generalised additive mixed model explained 40.5% of the deviance in 5-minute call counts (n = 54,166 intervals after clipping). Overdispersion was accommodated by the negative binomial parameter ($\theta = 0.338$).

All smooth terms were statistically significant ($p < 0.001$).

The smooth term for proportion through night showed a strong non-linear effect (edf = 10.99, F = 691.02), confirming substantial within-night variation in activity.

The tide-height smooth at the coastal site showed a pronounced non-linear relationship (edf = 6.34, F = 591.04), indicating a structured tidal response.

The inland tide-height smooth was weaker and less complex (edf = 3.94, F = 83.66), though still statistically significant.

The random effect for session date (edf ≈ 180) captured substantial night-to-night variation in overall activity levels.

Incorporation of tidal direction

To account for the cyclical nature of tidal dynamics, tidal direction (rising versus falling) was incorporated into the modelling framework for both sites. Tidal direction was derived from the first derivative of tidal height across consecutive 5-minute intervals within each site-night. Height increases between adjacent intervals were classified as rising tide, decreases as falling tide, and near-zero change (< 0.01m per 5 minutes) as slack water. Slack intervals were retained to anchor model estimates at tidal turning points.

Statistical modelling approach – Tidal Direction

Bat activity was modelled using a generalised additive mixed model (GAMM) with a negative binomial error distribution and log link function. The model structure included:

- A penalised smooth of proportion through night to account for within-night temporal structure.
- A shared baseline smooth of tidal height representing the general response to water level.
- Direction-specific deviation smooths of tidal height for rising and falling tides.
- A random intercept for session date to account for nightly variation in overall activity.

Interpretation of tidal direction effects

The resulting model produced two direction-specific response curves for the coastal site, representing predicted activity across the tidal range during rising and falling phases.

The fitted curves indicate a pronounced non-linear response to tidal height during falling tides, with activity peaking at intermediate water levels and declining sharply towards high tide. In contrast, the response during rising tides was flatter and more gradual, with no comparable intermediate peak. Because both curves share a common baseline smooth and converge at tidal turning points, the divergence observed between rising and falling phases represents genuine directional asymmetry rather than independent, unconstrained fits.

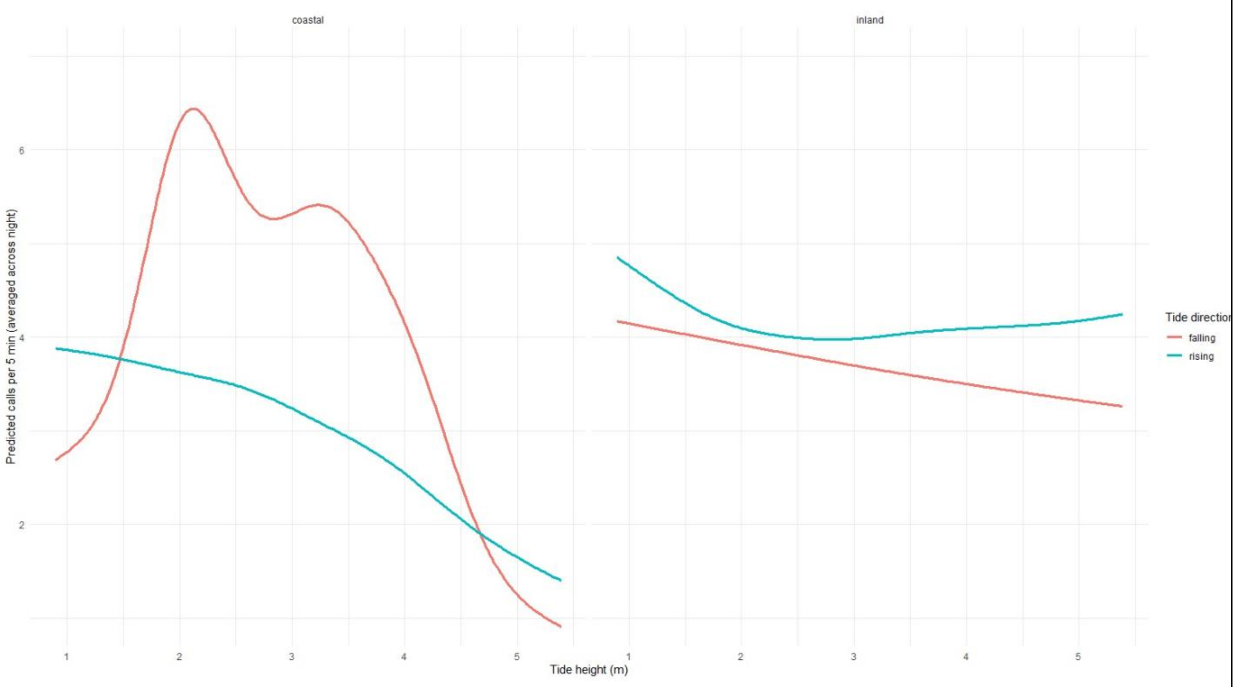


Figure C1 – Showing the results of the fitted models for the Coastal and Inland sites linking bat activity with rising and falling tides.

These results support the interpretation that bat activity at the coastal site is influenced not only by absolute water level but also by the direction of tidal movement, consistent with ecological mechanisms linked to habitat exposure and prey availability during ebbing tides.

Heathland

Data preparation

Acoustic bat activity data were obtained from two static detectors deployed on St Martin's between May and October 2024: a heathland site (Chapel Down) and a nearby rocky shoreline site (Perpitch).

For analysis of overall activity, data were aggregated to nightly totals (total number of classified calls per site per recording date). Nights on which the detector was not operational were excluded; nights with zero calls were retained where deployment was confirmed, ensuring that true zero-activity nights were distinguished from periods without sampling.

For behavioural analyses, call records were further classified into:

- General common pipistrelle calls ("Pippip"),
- Feeding buzzes ("Pippip-buzz"), and
- Social calls ("Pippip-social").

Behavioural proportions were calculated on a nightly basis to account for between-night variation in overall activity.

Overall activity comparison

Differences in nightly activity between sites were analysed using a generalised linear model (GLM) with a negative binomial error distribution and log link. The negative binomial distribution was selected to account for substantial overdispersion in nightly call counts (variance substantially exceeding the mean at both sites).

Nightly total call count was modelled as a function of site (heathland vs shoreline). This model estimates the multiplicative difference in expected nightly activity between sites while accounting for skewness and episodic high-activity nights.

Model estimates indicated that activity at the shoreline site was approximately 6.8 times higher than at the heathland site, and this difference was highly statistically significant ($z = 9.63$, $p < 0.001$).

Seasonal activity patterns

To assess seasonal variation in activity and test whether seasonal trajectories differed between habitats, generalised additive models (GAMs) were fitted to nightly total call counts using a negative binomial error distribution and log link.

Date was included as a smooth term to allow flexible, non-linear seasonal variation. Separate site-specific smooths were fitted using a factor-smooth interaction formulation, allowing the seasonal pattern to differ between the heathland and shoreline sites.

Models were fitted using REML, providing stable smoothing parameter estimation and reducing the risk of overfitting. Overdispersion in nightly call counts (variance substantially exceeding the mean) justified use of a negative binomial distribution rather than a Poisson model.

Results showed:

- A strong overall site effect (shoreline activity significantly higher; $p < 0.001$).
- A statistically significant seasonal pattern at the heathland site (edf = 5.3, $p < 0.001$).
- No statistically significant seasonal deviation at the shoreline site ($p = 0.125$).

This indicates that while shoreline activity remained consistently high across the recording period, heathland activity varied significantly through the season, with a more restricted window of elevated activity in mid-summer.

The model explained approximately 41% of deviance in nightly activity, indicating that site and seasonal structure account for a substantial proportion of observed variation.

Feeding behaviour analysis

To assess habitat differences in foraging behaviour, the proportion of feeding buzzes was analysed using binomial generalised linear models.

For each site and night, the number of feeding buzzes was modelled relative to the number of echolocation calls. A binomial error structure with logit link was used to estimate differences in behavioural composition between habitats.

The shoreline site showed significantly higher feeding buzz proportions than the heathland site (binomial GLM, $z = 12.31$, $p < 0.001$). Model-estimated feeding buzz proportions were 7.7% of calls at Perpitch compared with 2.2% at Chapel Down. This corresponds to a 3.81-fold increase in the odds of foraging behaviour at the shoreline site.

Social call analysis

An equivalent binomial generalised linear model was used to assess differences in the proportion of social calls relative to echolocation between sites. Model-estimated social-call proportions were 4.5% of calls at Chapel Down and 3.5% at Perpitch. The shoreline site exhibited a 24% lower probability of social calls relative to the heathland site (ratio = 0.76; $z = -3.45$; $p = 0.0006$).

Although statistically significant, the absolute difference between sites was approximately one percentage point and small relative to the substantial between-night variability in total activity. Consequently, this effect is minor in ecological magnitude and does not indicate a strong habitat-based difference in social calling behaviour.

Visualisation considerations

Seasonal activity figures were generated from nightly total call counts. For statistical inference, all models were fitted to the full, unmodified dataset.

For graphical clarity, isolated extreme high-activity nights were visually capped at the 95th percentile within each site when producing seasonal trend plots. This adjustment was applied solely for display purposes to reduce the influence of episodic outlier nights on smoothed curves. Statistical analyses were conducted using the uncapped data.

Smoothed curves in figures were produced using locally weighted regression (LOESS) to illustrate seasonal trends. These visual smooths are descriptive and do not form part of the formal statistical testing framework.

Interpretation framework

The modelling framework distinguishes between:

- Overall differences in activity intensity between habitats,
- Seasonal variation in habitat use,
- Behavioural composition (foraging vs general activity).

Together, the analyses indicate that:

- The shoreline site supports consistently higher activity levels;
- The heathland site supports lower overall activity and exhibits a narrower seasonal window of use;
- Foraging behaviour is substantially more prevalent at the shoreline site even after accounting for higher activity levels

These conclusions are statistically supported while remaining ecologically interpretable within the limits of a single paired-site comparison.

Foraging and Socialising

Data preparation

Acoustic bat activity data were obtained from the five static detectors deployed across the Isles of Scilly during the 2024 survey season. Due to extremely low call counts at Chapel Down, seasonal behavioural modelling for this site was excluded, as spline-based seasonal trends could not be reliably estimated. Chapel Down was retained for descriptive context only.

For analysis, records were aggregated to nightly totals (number of classified calls per site per recording date). Nights where detectors were confirmed operational were retained, including nights with zero calls. Non-operational periods were excluded from analysis.

Calls were classified into three behavioural categories using the BTO Acoustic Pipeline:

- General common pipistrelle echolocation calls (“Pippip”)
- Feeding buzzes (“Pippip-buzz”)
- Social calls (“Pippip-social”)

Nightly behavioural proportions were calculated relative to general echolocation calls to account for between-night and between-site variation in overall bat presence.

Overall activity modelling

Nightly echolocation counts were modelled using a generalised linear mixed model (GLMM) with a negative binomial error distribution and log link. The negative binomial distribution was selected to account for substantial overdispersion in nightly counts (variance substantially exceeding the mean) characteristic of episodic high-activity nights.

The model structure was:

echolocation_calls ~ ns(date, 4) + (1 | site_id)

Seasonal variation was modelled using a natural cubic spline with four degrees of freedom, allowing flexible but smooth non-linear seasonal trajectories. Site was included as a random intercept to account for persistent between-site differences in activity intensity.

Model predictions were generated at the population level (excluding random effects) to illustrate overall seasonal trends, with 95% confidence intervals derived from standard errors on the log scale and back-transformed to the response scale.

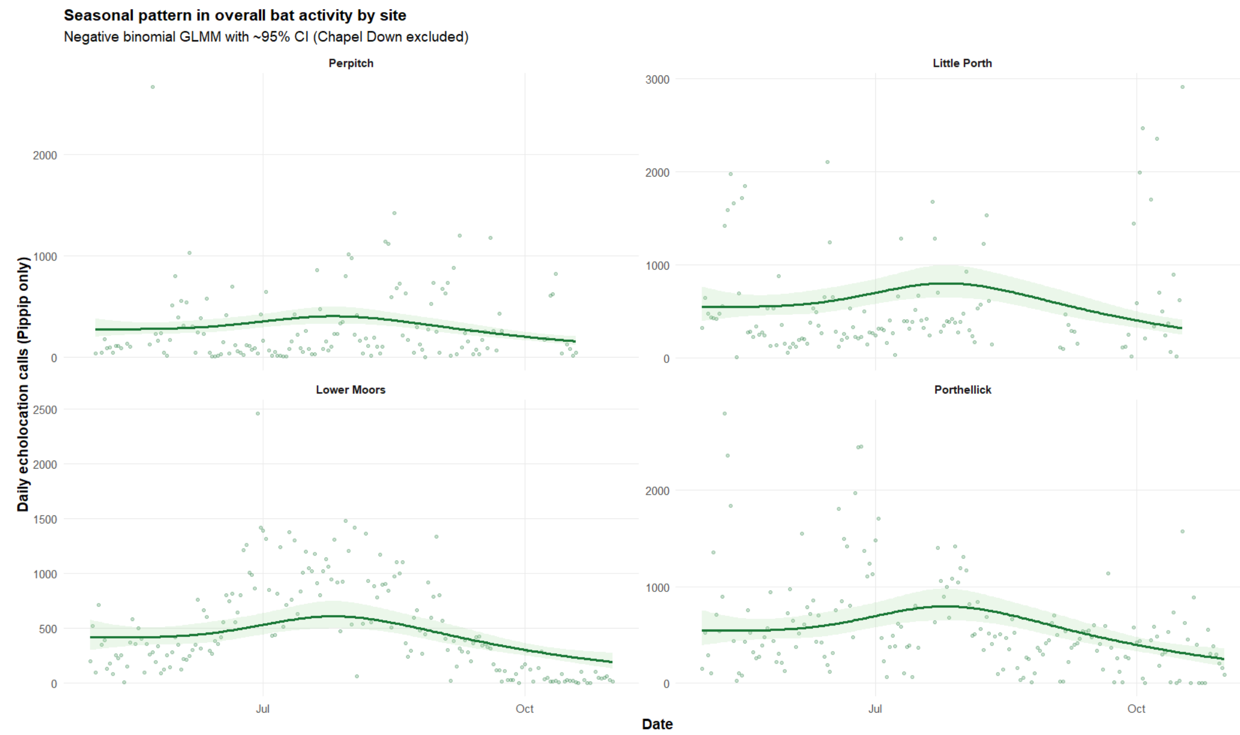


Figure C2 – Showing seasonal patterns in overall bat activity for each site separately.

Social call analysis

Seasonal patterns in social calling were assessed by modelling the proportion of social calls relative to general echolocation calls. For each site and night, the number of social calls was modelled relative to the number of echolocation calls using a binomial GLMM with logit link:

cbind(social_calls, echolocation_calls) ~ ns(date, 4) + (1 | site_id)

This formulation estimates the probability that a given call is social, conditional on bat presence.

Likelihood ratio tests comparing the seasonal model to a null model without the seasonal spline confirmed a highly significant seasonal effect ($p < 0.001$).

To assess whether seasonal trajectories differed among sites, an interaction model was fitted:

cbind(social_calls, echolocation_calls) ~ ns(date, 4) * site_id

Likelihood ratio tests indicated a strongly significant spline × site interaction ($p < 0.001$), demonstrating that seasonal patterns differed between sites.

Model-estimated social call proportions exhibited a highly significant seasonal effect (likelihood ratio test comparing seasonal model to null: $\chi^2(4) = 10{,}794$, $p < 2.2 \times 10^{-16}$).

Across all sites combined, the model-estimated mean proportion of social calls during early summer was 3.4%, increasing to 14.8% at the autumn peak, representing an approximately 4.4-fold increase in social calling intensity relative to baseline activity.

Including site-specific seasonal interactions significantly improved model fit ($\chi^2(16)$ = 1,833, $p < 2.2 \times 10^{-16}$), demonstrating that seasonal trajectories differed among sites. Site-level predictions showed that the pronounced autumn increase was driven primarily by Lower Moors and Little Porth, whereas Porthellick Pool and the St Martin's sites exhibited comparatively weak seasonal change

Confidence intervals were calculated on the logit scale (±1.96 SE) and back-transformed to the probability scale.

Analysis of raw data was also undertaken to ensure that the patterns interpreted from the proportional data was not incorrectly attributing a declining number of echolocation calls for a rise in social calls. The increase in raw numbers of social calls corresponded with the increase in proportion and, as the trends were consistent between approaches, it was decided that controlling for overall activity was the more robust means of representing the seasonal pattern.

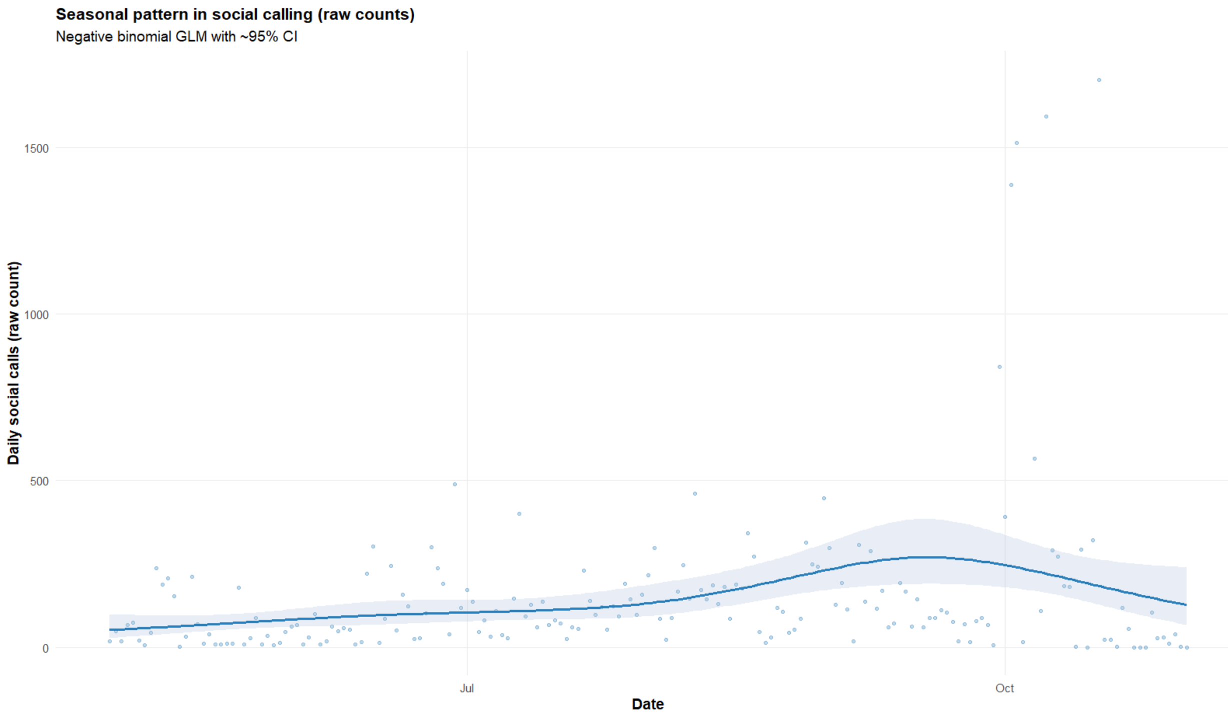


Figure C3 – Showing how the raw count of social calls increases through the season, as well as in proportion to echolocation calls

Feeding buzz analysis

Foraging behaviour was assessed by modelling feeding buzzes relative to echolocation calls.

For each site and night, feeding buzzes were modelled using a binomial GLMM with logit link:

cbind(buzz_calls, echolocation_calls) ~ ns(date, 4) + (1 | site_id)

Likelihood ratio testing against a null model confirmed a highly significant seasonal decline in feeding behaviour ($p < 0.001$).

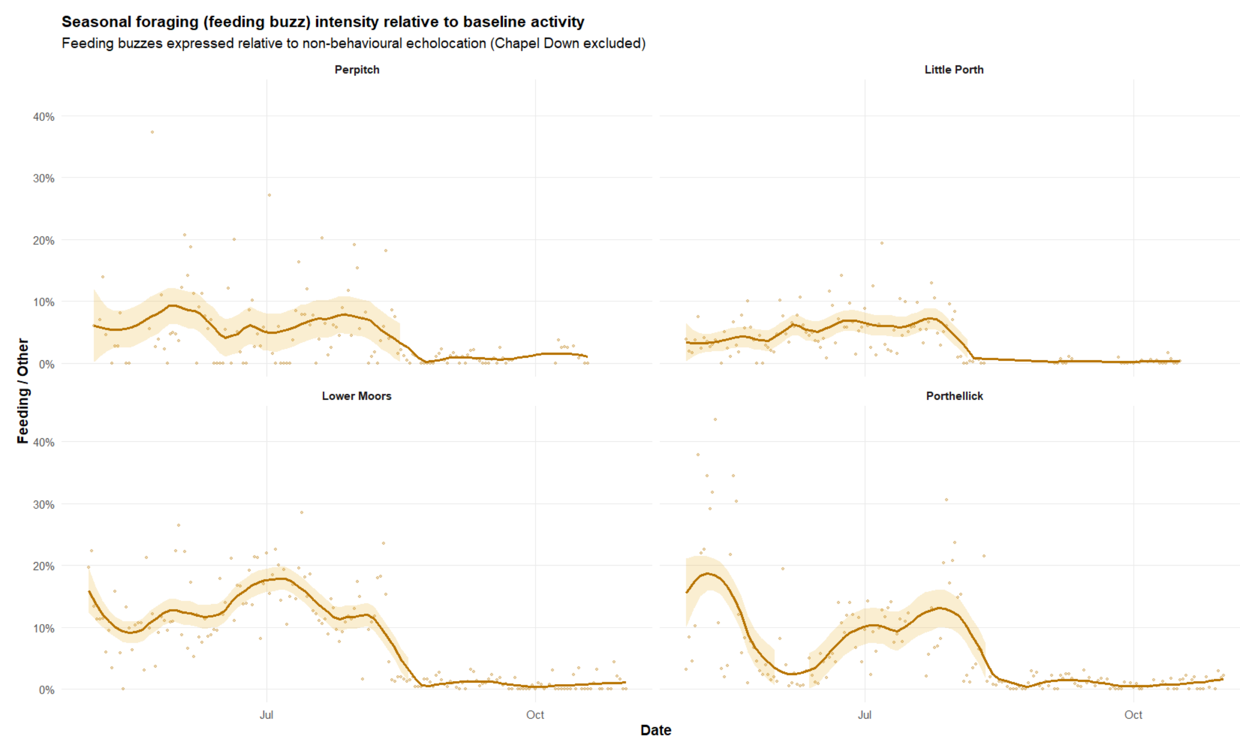
An interaction model including spline × site was fitted to test for between-site differences in seasonal trajectory. This interaction was statistically significant ($p < 0.001$), indicating that the precise seasonal pattern varied among sites. However, the overall declining trend was observed across all sites.

Model-estimated feeding buzz proportions exhibited a highly significant seasonal decline (likelihood ratio test comparing seasonal model to null: $\chi^2(4) = 10{,}794$, $p < 2.2 \times 10^{-16}$).

Across all sites combined, the model-estimated mean feeding buzz proportion during early summer was 7.47%, declining to 0.72% in autumn. This represents a 10.4-fold reduction in the proportion of flight activity associated with foraging behaviour across the survey period.

Including site-specific seasonal interactions significantly improved model fit ($\chi^2(16) = 1{,}833$, $p < 2.2 \times 10^{-16}$), indicating that while the overall declining trend was consistent across sites, the precise seasonal trajectory differed among locations.

Confidence intervals were calculated on the logit scale and back-transformed to proportions.



Seasonal foraging (feeding buzz) intensity relative to baseline activity

Feeding buzzes expressed relative to non-behavioural echolocation (Chapel Down excluded)

Figure C4 – Showing how the proportional number of foraging buzzes decreases through the season as a proportion of echolocation calls

Model comparison and inference framework

All statistical comparisons were conducted using likelihood ratio tests between nested models. Models were fitted using maximum likelihood with Laplace approximation (GLMMs). Statistical significance was evaluated using χ^2 tests on differences in model deviance.

Spline-based seasonal modelling provides flexible representation of non-linear temporal patterns while avoiding overfitting. The chosen four degrees of freedom balance interpretability with flexibility.

Confidence intervals shown in figures represent approximate 95% intervals derived from model-based standard errors on the link scale.

Interpretation framework

The modelling framework distinguishes between:

- Overall activity intensity (echolocation counts),
- Behavioural composition (social and feeding proportions),
- Seasonal trajectories,
- Between-site heterogeneity.

Together, the analyses indicate that:

- Overall bat activity remains broadly present throughout the season, with moderate mid-summer elevation.
- Social calling increases sharply as a proportion of activity in autumn at specific sites.
- Feeding behaviour declines substantially as a proportion of activity across the season at all sites.
- The increase in social calling at selected sites is not driven by a simple reduction in foraging effort.

These conclusions are statistically supported while remaining ecologically interpretable within the limits of a single-season multi-site study.

Uninhabited Islands

Data sources and structure

The analysis of activity levels focused exclusively on recordings of common pipistrelles. Activity was measured as the number of calls per one-minute bin.

Uninhabited islands included in the comparison were Great Arthur, Great Ganilly, Little Ganilly, Nornour and Teän.

Data for these uninhabited islands were compared against seasonally matched recordings from inhabited islands which fell within ±14 days of the sampling window of the uninhabited islands. This ensured comparisons were made within comparable seasonal conditions.

Statistical modelling approach

Activity levels were analysed using a generalised additive mixed model (GAMM) fitted with a negative binomial error distribution and log link function.

The negative binomial distribution was selected following comparison with a Poisson model, which indicated substantial overdispersion in the count data.

The model structure included:

- A fixed effect for an uninhabited vs inhabited island.
- A smooth term for percent through night, allowing for non-linear variation in activity across the night.
- Random-effect smooths to account for repeated measures within nights and sites:
- Night identity (to capture night-to-night variation such as weather) models were fitted using restricted maximum likelihood (fREML).

Statistical results

The estimated rate ratio for uninhabited relative to inhabited islands was 0.85 (95% CI: 0.61–1.20)

This corresponds to an estimated 15% lower activity level on uninhabited islands. However, the confidence interval was wide and included the possibility of both moderately lower and moderately higher activity. A formal comparison between models with and without the uninhabited-island term did not indicate a statistically supported difference. Night-to-night variability was substantial, indicating that recording-level differences were strongly influenced by nightly conditions.

Interpretation

Although raw nightly summaries suggested somewhat lower activity on uninhabited islands, hierarchical modelling of minute-level data showed that differences were small relative to natural variability between nights and sites. Within the limits of the available data, activity levels on uninhabited islands were statistically comparable to those on inhabited islands during the sampled period.

References

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