

RESEARCH ARTICLE

Modelling pollinator trends using multi-scale environmental data from the UK Pollinator Monitoring Scheme

Claire Carvell¹  | Nick J. B. Isaac¹ | Martin C. Harvey¹ | Robin Hutchinson^{1,2} | Nadine Mitschunas¹ | Christopher Andrews³ | Angus Garbutt⁴ | Lucy E. Ridding¹  | Helen E. Roy^{1,2}  | Richard F. Comont⁵ | Richard Fox^{2,6}  | Dawn E. Balmer⁷ | Rachel Richards⁸ | Rowan Edwards⁹ | Alfried P. Vogler^{10,11} | William E. Kunin¹² | Michael P. D. Garratt¹³  | Simon G. Potts¹³ | Paul Woodcock¹⁴ | Francesca Mancini¹ 

¹UK Centre for Ecology & Hydrology, Wallingford, UK; ²Centre for Ecology and Conservation, University of Exeter, Penryn, UK; ³UK Centre for Ecology & Hydrology, Edinburgh, UK; ⁴UK Centre for Ecology & Hydrology, Bangor, UK; ⁵Bumblebee Conservation Trust, Beta Centre, Stirling University Innovation Park, Stirling, UK; ⁶Butterfly Conservation, Manor Yard, East Lulworth, Dorset, UK; ⁷British Trust for Ornithology, The Nunnery, Thetford, UK; ⁸Buglife, Peterborough, UK; ⁹Hymettus Ltd, Carron Lane, Midhurst, UK; ¹⁰Natural History Museum, London, UK; ¹¹Imperial College London, London, UK; ¹²University of Leeds, Leeds, UK; ¹³Centre for Agri-Environmental Research, School of Agriculture, Policy and Development, University of Reading, Reading, UK and ¹⁴Joint Nature Conservation Committee, Quay House, 2 East Station Road, Fletton Quays, Peterborough, UK

Correspondence

Claire Carvell

Email: ccar@ceh.ac.uk

Funding information

UK Centre for Ecology & Hydrology (UK Pollinator Monitoring Scheme (PoMS) Partnership); Joint Nature Conservation Committee (UK Pollinator Monitoring Scheme (PoMS) Partnership); Natural Environment Research Council (NC-UK programme), Grant/Award Number: NE/Y006208/1; Natural Environment Research Council (UK-SCAPE Programme), Grant/Award Number: NE/R016429/1

Handling Editor: Rodrigo Barahona-Segovia

Abstract

1. Declines in pollinating insects are a cause for concern, yet modelling abundance trends remains challenging and most species are not covered by long-term standardised monitoring
2. We produce new metrics of change for insect pollinators which incorporate multi-scale environmental variables into the modelling process to account for various sources of noise and potential bias. Data were generated from three surveys under the UK Pollinator Monitoring Scheme (PoMS) over 5- and 6-year periods, measuring (i) insect abundance and species richness of bees and hoverflies from pan traps across a network of 1 km squares; (ii) insect abundance from Flower-Insect Timed Counts (FIT Counts) in the same 1 km squares and (iii) FIT Counts by citizen scientists in self-selected locations, especially gardens ('public' FIT Counts).
3. We compare five models containing different sets of environmental variables across insect groups from the three surveys. Our 'full' model, including both large-scale spatial and temporal environmental variables combined with local-scale survey variables, had the best fit, highest R^2 and lowest residual variance among sites in 31 of the 35 modelled datasets.
4. The full model estimated declines in 'all insect' abundance between 2017 and 2022 of 38% (average annual decline of 8.5%) from pan traps, and 33% (average annual decline of 7.4%) from 1 km FIT Counts. This reflected declines in hoverflies, 'other

This is an open access article under the terms of the [Creative Commons Attribution](https://creativecommons.org/licenses/by/4.0/) License, which permits use, distribution and reproduction in any medium, provided the original work is properly cited.

© 2026 The Author(s). *Ecological Solutions and Evidence* published by John Wiley & Sons Ltd on behalf of British Ecological Society.

flies' and wasps on both the 1 km surveys, and bumblebee declines on 1 km FIT Counts, while solitary bee abundance showed no change. There was no change in overall insect abundance between 2018 and 2022 from public FIT Counts but hoverflies declined and several other groups increased. Given the short time series, these trends should be interpreted with caution.

5. **Solution.** PoMS represents a step change in evidence on UK pollinating insects. Our study demonstrates the value of including environmental variables to improve models of temporal trends in pollinator abundance and richness from standardised annual monitoring. Inclusion of these variables does not result in dramatic changes in estimated trends, which tend to be robust across model variants. The proposed metrics could help target conservation actions for different species groups or contribute to improved national biodiversity indicators.

KEYWORDS

bees, biodiversity indicators, citizen science, hoverflies, insect trends, monitoring, pollinators

1 | INTRODUCTION

Monitoring biodiversity is essential to understand the effects of different drivers of change on ecosystem function and human health (Pocock et al., 2018). Robust metrics or indicators are also critical to enable a common understanding of species statuses and trends and track responses to interventions or environmental changes over time (Burns et al., 2023; Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services (IPBES), 2016). However, for many species, our knowledge of the magnitude of changes in abundance or diversity is limited by a lack of high-quality data (Cooke et al., 2025; Thomas et al., 2019). Here we present insights from 6 years of data collected using standardised surveys under the UK Pollinator Monitoring Scheme (PoMS). For the first time, we generate national-scale metrics of change across a wide range of insect pollinator groups which incorporate both large-scale and local-scale environmental variables into the modelling process.

Insects are the most diverse and abundant animal group, supporting many ecosystem functions, including pollination (Noriega et al., 2018). Pollinating insects (especially bees but including flies, wasps, beetles, butterflies and moths) have received much recent attention in the scientific literature and global media (Cardoso & Leather, 2019; Saunders et al., 2019; Stout & Dicks, 2022). Insect pollination is vital to both wild plant communities (Ollerton et al., 2011) and agricultural productivity (Klein et al., 2007), yet pollinators face a range of threats, including habitat loss, disease, climate change, invasive species and exposure to pesticides (Vanbergen et al., 2013; Wagner et al., 2021). There is growing evidence for declines in pollinators in some parts of the globe (Kerr et al., 2015; Potts et al., 2010). However, most studies describe a complex picture with both winners and losers (Fox et al., 2014; Powney et al., 2019; Tordoff et al., 2022; van Klink et al., 2020), and contrasting patterns between different regions (Biesmeijer et al., 2006) or land-use types (Mancini et al., 2023). Furthermore, many species remain data-deficient (Nieto

et al., 2014), prompting calls for more robust, large-scale data to understand long-term (more than 10-year) changes in insect populations (Stout & Dicks, 2022; Thomas et al., 2019; Wagner et al., 2021).

Much evidence for long-term insect trends has been derived from analysis of presence-only records of species occupancy (Fox et al., 2014; Soroye et al., 2020), which lack structured sampling design and contain forms of temporal and spatial bias (Boyd et al., 2024). While occupancy-detection models have become widely used to estimate changes in species distribution (Mancini et al., 2023; Powney et al., 2019; Van Strien et al., 2013), abundance data provide a more sensitive measure of change and link directly to functional significance, in this case the delivery of pollination services (Garibaldi et al., 2020). Insect abundance also affects many other species that depend on insects in the ecosystem (Bowler et al., 2019; Evans et al., 2026). Thus, there is an urgent need for investment in standardised monitoring to assess the abundance of insect populations, specifically of insect pollinators (Breeze et al., 2021).

Monitoring and modelling the abundance trends of insects presents several challenges compared with other taxonomic groups (Cooke et al., 2025; Didham et al., 2020). Their rapid life-history and short lifespan mean that the true population sizes of most insects are in constant flux, violating the assumption of closure (Pryke et al., 2024). Insects experience substantial population fluctuations within and between years, often driven by their sensitivity to environmental factors, such as weather (Fox et al., 2019; Müller et al., 2024; Roy et al., 2001), requiring more time points to detect long-term trends in abundance and separate signal from noise than for vertebrates (Aldercotte et al., 2022; White, 2019). Local variation in activity levels of flower-visiting insects, influenced by weather conditions or floral resources, can also add substantial measurement error. Finally, species presence and abundance may be further dependent on a combination of large-scale drivers, including latitudinal gradients, climate (Vasiliev & Greenwood, 2021), the availability of suitable habitat or the heterogeneity of the surrounding landscape

(Carvell et al., 2011; Steffan-Dewenter et al., 2002). Thus, monitoring schemes for pollinating insect abundance must be designed with these challenges in mind.

Between 2012 and 2017, each UK nation published a pollinator strategy (Defra, 2014; National Biodiversity Data Centre, 2015; The Scottish Government, 2017; Welsh Government, 2013), recommending actions to encourage pollinator-friendly habitat management and improve evidence on the status of pollinators through long-term monitoring. While butterflies, moths and bumblebees are monitored systematically in the UK (Thomas, 2005; Whitehorn et al., 2022), most flower-visiting insects remain overlooked due to taxonomic challenges, particularly the limited possibilities for species-level identification in the field, and the time, cost and expertise required to collect, process and identify specimens of diverse groups (Breeze et al., 2021; Rondeau et al., 2023; Shortall et al., 2009). For example, the UK supports 59 butterfly species and 24 bumblebee species, but around 250 species of solitary bee and more than 280 hoverfly species. To address this gap, a partnership of scientists, amateur experts, conservation NGOs and government stakeholders developed a monitoring scheme designed to detect national-scale trends in insect pollinator abundance and diversity across the UK (Carvell et al., 2016). The process included consideration of the effectiveness, feasibility and cost of different sampling designs (with bees and hoverflies as the key focal groups on account of their importance as pollinators), combinations of participants (volunteers or professionals, non-experts or experts) and the metrics that would be generated, at a given taxonomic resolution (Breeze et al., 2021; O'Connor et al., 2019).

The resulting PoMS, established in 2017, has two novel features. First, it consists of three parallel surveys with complementary design, conducted by a combination of volunteers and professionals: pan traps on a stratified network of 1 km squares, Flower-Insect Timed Counts (FIT Counts) on the same network, and FIT Counts carried out in ad hoc locations. Second, PoMS includes collection of local-scale data describing both weather conditions (e.g. wind speed and amount of sunshine during the survey), and the availability and diversity of floral resources at the survey location (UK Pollinator Monitoring Scheme, 2025c). These local environmental variables could help explain some of the observed variation in insect population dynamics, but there is limited understanding of how including such variables in the modelling process affects the calculation of trend metrics or the uncertainty of predictions (Johnson et al., 2024).

In this paper, we introduce the PoMS survey approaches and datasets, presenting results from the first 5 or 6 years of data (depending on survey) from sites in Great Britain. Recognising the limitations of measuring trends from this relatively short time series (Didham et al., 2020), we focus on exploring different modelling approaches to best fit the data. We compare a series of statistical models incorporating different environmental variables to answer the following questions: (a) Does integrating large- and local-scale environmental variables (Table 1) improve the fit of models of pollinator abundance and species richness? (b) Which sets of variables

TABLE 1 Sets of models fitted to all response variables in the three Pollinator Monitoring Scheme (PoMS) survey datasets and the predictor variables included in each.

Model name	Predictor variables
Base model	Year (spline) + Month (categorical) + Site (random effect)
Spatial model (large-scale)	Base + Landscape heterogeneity + Mean seasonal temperature
Temporal model (large-scale)	Base + Annual seasonal temperature anomaly + local temperature anomaly
Survey model (local-scale)	Pan trap model ^a Base + Total flower count (spline) + Habitat class (categorical) + Flower richness + Sun exposure* + Wind speed* FIT Count model ^a Base + Flower structure + Total flower count + Habitat class (categorical) + Floral context + Sun exposure (categorical) + Wind speed (categorical)
Full model	Base + spatial + temporal + survey model predictors

Note: All variables were modelled as linear continuous effects unless stated. All continuous variables were centred on zero except those marked with an asterisk.

^aSurvey models fitted to the pan trap and FIT Count data are slightly different as the two protocols collect different variables.

are more important in explaining variability in the data? and (c) How do the direction, magnitude and uncertainty of the estimated trends change with the different sets of variables included in the models? We further assess whether answers to these questions differ across the three PoMS surveys. We anticipate that including environmental variables will improve the model fit, reduce uncertainty in the model predictions and produce more useful metrics of change that separate underlying trends in pollinating insects from short-term fluctuations, without oversimplifying those trends.

2 | MATERIALS AND METHODS

2.1 | Survey design and sampling methods

UK PoMS includes three surveys: (a) pan traps on a network of 1 km × 1 km squares across England, Scotland and Wales (pan traps), (b) FIT Counts carried out during pan trap survey visits (1 km FIT Counts) and (c) FIT Counts at locations that are self-selected by volunteer citizen scientists ('public' FIT Counts).

The PoMS 1 km square survey in Great Britain was established in 2017 across a network of 75 randomly stratified 1 km squares (Figure 1), based on a power analysis using existing data (Breeze

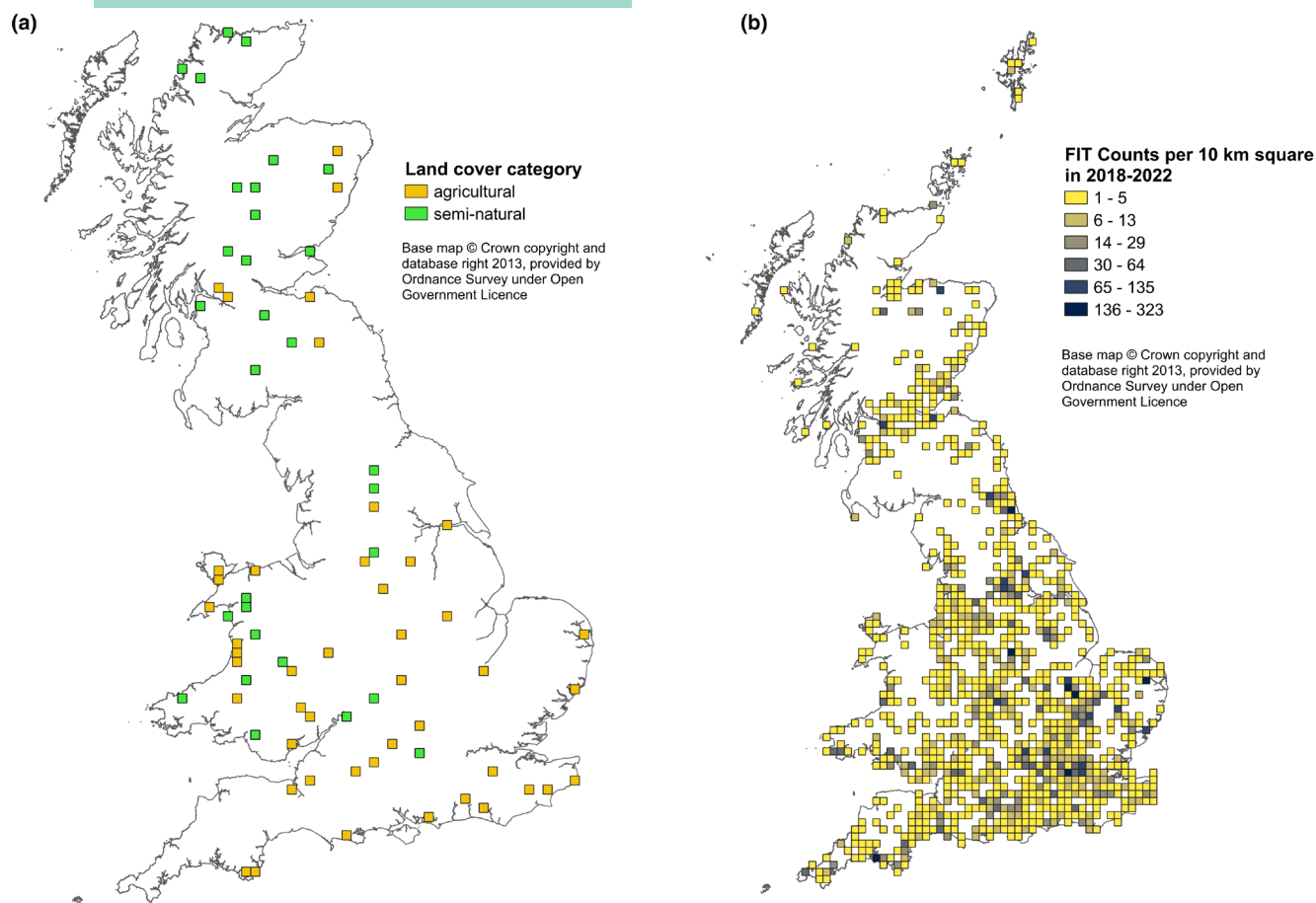


FIGURE 1 Maps showing (a) the location of PoMS 1km survey squares in England, Scotland and Wales with data collected between 2017 and 2022. Each 1km survey square is shown as a 10km square and coded according to whether it has predominantly agricultural (greater than 50% land cover within the arable and horticultural or improved grassland UKCEH Land Cover Map class [Marston et al., 2022]), or predominantly semi-natural land cover (greater than 50% cover within the woodland; rough, neutral, calcareous or acid grassland; fen, marsh; heather; bog or montane Land Cover Map classes). Note there are no 1 km survey squares located on Shetland and Orkney; and (b) locations of 'public' FIT Counts submitted between 2018 and 2022. FIT Count locations are aggregated as 10km squares and coded according to their relative density.

et al., 2021). Full details of the site selection and stratification procedure are given in [Supporting Information](#) (Methods).

2.1.1 | PoMS survey protocols on 1 km squares

PoMS surveys on the 1km square network comprise two protocols implemented on the same day by non-experts (full details in [Supporting Information](#) [Methods]). The first uses pan traps (sets of three coloured bowls filled with water and left for 6h at five fixed stations along a diagonal of each square, each set producing a 'sample'; O'Connor et al., 2019). During the trapping period, surveyors collect data on local weather conditions, floral resources and habitats surrounding the pan trap stations (Table 2). All bee and hoverfly specimens are identified to species by expert taxonomists (on account of being the initial key focal groups for the scheme), while other taxa are individually counted and classified to high-level taxonomic group (Table S1).

We retained the following insect groups for analysis of the pan trap data: bumblebees, solitary wild bees, honeybees, an 'all bees' group (the sum total across all three bee groups), hoverflies, other flies, wasps, beetles and 'other insects'. Counts from remaining groups were included in the total sum of all insects per trap station, per survey (Table S1). From the species-level identifications, we calculated five different variables representing species richness according to their group: number of bumblebee species (*Bombus* spp.), solitary bee species (all non-*Bombus* and non-*Apis* bees), richness of all bees (including the honeybee), number of hoverfly species (Syrphidae) and total species richness of all bees and hoverflies per sample.

The second protocol uses FIT Counts, which involve counting all insects that land on flowers within a 50cm×50cm quadrat over a period of 10 min, ideally of a particular 'target' plant taxon (Table S2, [Supporting Information](#) [Methods]). Surveyors complete at least two FIT Counts within the 1 km square per survey visit, identifying insects to broad taxonomic groups (bumblebees,

TABLE 2 Variables included in the models described in Table 1.

Variable (type, model)	Description	Survey
Month (categorical, all models)	Month in which the survey was conducted. One of: April, May, June, July, August, September. Data source: PoMS	Pan trap and FIT Counts
Landscape heterogeneity (numerical, spatial and full model)	An index quantifying the landscape heterogeneity in an area of 3×3 km centred on the 1 km site in which the survey was conducted. The metric is based on the number of land cover classes and their area within this 3×3 km zone and calculated as the inverse Simpson Index, where a higher value denotes higher diversity. See Supporting Information (Methods) S3 for a description of this variable and Figure S1a (Supporting Information tables and figures) for plots showing its distribution across sites on each survey. The variable was centred around the mean, divided by the standard deviation and modelled as a linear effect. Data source: the UKCEH Land Cover Map 2021	Pan trap and FIT Counts
Mean seasonal temperature, MST (Numerical, spatial and full model)	Mean monthly temperature (April to September) calculated for each 1 km site across all years, centred on zero. See Supporting Information (Methods) S3 for a description of all temperature metrics and Figure S1b for plots showing its distribution on each survey	Pan trap and FIT Counts
Annual seasonal temperature anomaly, ASTA (numerical, temporal and full model)	For each 1 km site, the relative temperature for the year in question (using data for April to September), calculated as the difference between the average temperature at a site in each year and the average temperature at the same site across all years (2017–2022 for pan traps and FIT Counts on the 1 km square survey and 2018–2022 for the public FIT Counts— Figure S1c in SI [tables and figures]). The variable was modelled as a linear effect. Data source: HAD UK	Pan trap and FIT Counts
Local seasonal temperature anomaly, LSTA (numerical, temporal and full model)	This is the residual temperature anomaly at each 1 km site, after accounting for the mean seasonal temperature and annual seasonal temperature anomaly (Figure S1d).	Pan trap and FIT Counts
Flower count (numerical, survey and full model)	For pan trap data, this is the total number of floral units counted by the surveyor within a 2 m radius of the pan trap station (Figure S2a in SI [tables and figures]). The variable was logged, centred around the mean and divided by the standard deviation. We modelled the effect of this variable as a spline to account for a potential non-linear relationship with insect abundance (European Commission: Joint Research Centre, 2024). For FIT Count data, this is the number of floral units of the target species counted in the 50×50 cm patch where the survey was conducted (Figure S3a). The variable was logged, centred around the mean and divided by the standard deviation. We modelled the effect of this variable as linear. Data source: PoMS	Pan trap and FIT Counts
Flower richness (numerical, survey and full model)	The number of plant species in flower counted within a 2 m radius of the pan trap (Figure S2b). The variable was centred around the mean, divided by the standard deviation and modelled as a linear effect. Data source: PoMS	Pan trap
Flower structure (categorical, survey and full model)	The structure of the target flower on which the FIT Count was conducted (Figure S3c and Table S2 , Supporting Information [tables and figures]). One of: open or closed floral structure. Data source: PoMS	FIT Counts
Flower context (categorical, survey and full model)	The category of flower context in which the FIT Count was conducted (Figure S3b). One of: growing in a larger patch of many different flowers, growing in a larger patch of the same flower, or more or less isolated. Data source: PoMS	FIT Counts
Habitat type (categorical, survey and full model)	Broad categorisation of local habitat type (Figure S4). For pan trap data, one of: semi-natural or agricultural. For FIT Count data, one of: semi-natural, agricultural, garden or urban (UK Pollinator Monitoring Scheme, 2025a). Data source: PoMS and Land Cover Map 2007.	Pan trap and FIT Counts

(Continues)

TABLE 2 (Continued)

Variable (type, model)	Description	Survey
Sunshine (categorical, survey and full model)	An estimate of amount of sunlight falling on the 50×50 cm quadrat during the 10-minute count (Figure S3d). One of: entirely in sunshine, partly in sun and partly shaded, or entirely shaded. Data source: PoMS	FIT Counts
Sun exposure (numerical, survey and full model)	Estimated % of total trapping time per survey during which the sun was shining (Figure S2c). The variable was modelled as a linear effect. Data source: PoMS	Pan trap
Wind speed (numerical, survey and full model)	Average wind speed on the Beaufort scale during the pan trap survey (Figure S2d, SI [tables and figures]). The variable was modelled as a linear effect. Data source: PoMS	Pan trap
Wind (categorical, survey and full model)	Wind prevalence category during the 10-minute count (Figure S3e, SI [tables and figures]). One of: leaves still/moving occasionally, leaves moving gently all the time or leaves moving strongly. Data source: PoMS	FIT Counts

Note: Data sources for UKCEH Land Cover Map 2021 (Marston et al., 2022) and HAD UK (Hollis et al., 2022).

solitary bees, honeybees, hoverflies, other flies, wasps, beetles, butterflies and moths, and groups for 'other insects' and very small insects <3 mm in length; Table S1, Supporting Information [Methods]). Additional data on local habitat type, number of target flowers within the 50 cm quadrat, context of the flower patch and weather conditions at the time of the FIT Count are also recorded (Table 2).

Each year, approximately 55 survey squares are adopted and surveyed by trained volunteers, with the remainder covered by paid surveyors (UK Pollinator Monitoring Scheme, 2025c). Sites receive up to four survey visits each year, from May to September, with a minimum of 2 weeks between consecutive visits. Between 2017 and 2022, a total of 1129 survey visits were conducted, generating 5612 pan trap samples across the 75-site network, with an average of 188 surveys per year and 2.66 surveys per site. Fewer surveys took place in 2017 due to late setup and in 2020 (during May and June in particular) due to disruption from the COVID-19 pandemic. A total of 2501 FIT counts were submitted from the 1 km square network, averaging 2.5 counts per visit (ranging from 1 to 10) (Figure 1).

2.1.2 | Public Flower-Insect Timed Counts (FIT Counts)

In addition to FIT Counts on the 1 km square network, citizen scientists conduct FIT Counts in self-selected locations between 1 April and 30 September, when weather conditions conform to the criteria for the 1 km survey (Supporting Information [Methods]). Public FIT Count data presented here span 2018 to 2022, with 2017 having been a pilot year for this survey. While counts have been submitted from Northern Ireland (since 2020), the Isle of Man and the Channel Islands, for this paper our analyses are restricted to counts conducted within Great Britain (GB). A total of 9599 public FIT Counts was submitted from within 2330 different 1 km squares across GB,

showing a steady increase in uptake from 585 counts in 2018 to 3171 in 2022 (Figure 1).

2.2 | Modelling approach

Prior to model fitting, we implemented a number of data cleaning and processing steps described in Supporting Information (Methods).

Our first question focuses on the value of integrating large-scale and local-scale environmental variables (described below) into models of pollinating insect abundance and species richness over time. We fit five models containing different sets of these environmental covariates to each of the survey datasets and compare their performance. Table 1 describes the five models fitted to the three survey datasets and the variables included in each of them, with each model operating at the level of the pan trap station or FIT Count. All variables are described in Table 2 and in more detail in Supporting Information (Methods).

The base model mirrors structures used by existing national monitoring schemes, such as the Breeding Bird Survey and UK Butterfly Monitoring Scheme (Dennis et al., 2016; Massimino et al., 2025). It includes the effect of year, modelled using a cubic spline with two degrees of freedom. This form of 'smoothing' is generally applied in indicators of species abundance, especially for insects, as it reduces the impact of interannual fluctuations on resulting estimates, allowing long-term trends to be detected. Unlike many UK indicators of species abundance that apply smoothing to the model predictions as a separate step after fitting the model (Dennis et al., 2016; Massimino et al., 2025), we applied smoothing as part of the model fitting step to simplify the workflow without affecting the statistical output.

The spatial model includes large-scale spatial environmental covariates typically used in species distribution models, for example climate gradients or patterns linked to land use and landscape

heterogeneity. The temporal model includes some climate variables that aim to explain short-term inter-annual fluctuations in insect abundance. The survey model incorporates a suite of local-scale variables captured during sampling, including amounts of sunshine or wind speed and the floral resources available around the survey location, to explain some of the intra-annual variation in insect numbers or behaviours between sites or sampling locations due to specific conditions at the time of the survey. Finally, the full model includes all variables from the base model, large-scale spatial and temporal and local-scale survey models (Table 2).

All models were generalised linear mixed-effect models and were fitted with the R (R Core Team, 2021) package glmmTMB (Brooks et al., 2017). To account for the hierarchical nature of the data, all models included a random effect for the 1 km grid cell in which each FIT Count or pan trap survey was conducted. In all models, we used a negative binomial distribution to account for overdispersion in the insect counts and species richness (Figure S5).

We modelled each insect group separately rather than modelling all data together, because the dispersion parameters differ by group and by fitting separate models, we can explore effects of the environmental variables on different insect groups. In total, 175 models were fitted to 35 datasets (50 for each of the 1 km and public FIT Count datasets that included 10 insect groups per survey, and 75 for the 15 pan trap survey datasets that included 10 insect groups and five species richness variables).

To compare the performance of models with different categories of predictor variables, we used Akaike information criterion (AIC) (Akaike, 1974). For each insect group and survey type, we identified the model that best fitted the data as that with the lowest AIC. For each of the 175 models, we also calculated the marginal R^2 which quantifies the variance explained by the fixed effects. Finally, we extracted the variance of the random effect for survey site as a measure of the amount of variability that remains unmodelled by the fixed effects.

2.3 | Metrics of temporal change

From the model predicted abundance or species richness on each survey, we derived two metrics of change.

- *First-to-last year percentage change in abundance or species richness*: this is the difference between the predicted abundance or species richness in the first and last year of the time series, converted to percentage change:

$$\text{Percentage change} = 100 \times \left(\frac{y_{t=n} - y_{t=1}}{y_{t=1}} \right) \quad (1)$$

where $y_{t=n}$ is the abundance or species richness in the last year and $y_{t=1}$ is the abundance or species richness in the first year.

- *Average annual percentage change in abundance or species richness*: this is the percentage change in abundance or species richness between all consecutive years (calculated using the equation above) and then averaged across the time series.

Confidence intervals for these metrics were derived by bootstrapping: the dataset is resampled 1000 times and the model refitted to produce independent predictions from which the metrics above and their confidence intervals are calculated.

3 | RESULTS

3.1 | Summary of pollinator data generated by the three PoMS surveys

After cleaning, the dataset comprised 5261 pan trap samples from 1087 surveys, totalling 411,668 insects. Of these, 9020 bees (including bumblebees, solitary bees and honeybees) and 9108 hoverflies were identified to 133 and 114 species, respectively, representing on average 3.45 individuals and 2.14 species per sample. Other insect groups sampled included 'other flies' (57.6 individuals per sample), beetles (11.1 per sample), 'other insects' (3.54 per sample) and wasps (2.14 per sample).

Within the 2352 FIT Counts on the 1 km square survey sites (following data cleaning), 24,964 insect flower visits were recorded at an average of 10.61 insects per Count. Bees represented 14% and hoverflies 19% of all insects recorded. The most common insect visitors were 'other flies' (30% of flower visits) followed by small insects (24% of visits). On the 8895 public FIT Counts submitted (following data cleaning), 99,304 insect flower visits were recorded. Bees (including bumblebees 19%, solitary bees 5% and honeybees 16%) represented 41% and hoverflies 15% of all insects recorded, with the 'other flies' comprising 15% and small insects 7% of visits. All raw datasets are available via the NERC EIDC (UK Pollinator Monitoring Scheme, 2025a, 2025b).

3.2 | Effects of integrating large-scale and local-scale environmental variables on model performance

Model selection results for the five fitted model types are summarised in Table 3 with detailed comparisons in Table S3 (Supporting Information tables and figures). The full model has the lowest AIC, indicating best fit, in all but four of the 35 datasets. The exceptions are beetles in the public FIT Counts, bumblebee abundance and species richness and abundance of 'other insects' from the pan traps, where the survey model has the lowest AIC. In most cases the full model fits the data much better than the second-best model, as shown by the large ΔAIC ($\Delta\text{AIC} > 2$ in all cases and > 10 in 23 cases), indicating strong evidence that spatial and temporal variability in

TABLE 3 Results of model selection for the three survey datasets.

Dataset	Best model	Second best	Δ AIC
Public FIT Counts			
All insects	Full	Survey	17.49
Bumblebees	Full	Survey	6.51
Solitary bees	Full	Survey	47.36
Honeybees	Full	Survey	91.40
All bees	Full	Survey	35.03
Hoverflies	Full	Survey	62.33
Other flies	Full	Survey	17.25
Wasps	Full	Survey	18.56
Beetles	Survey	Full	7.46
Small insects	Full	Survey	5.74
1 km FIT Counts			
All insects	Full	Survey	34.57
Bumblebees	Full	Survey	18.62
Solitary bees	Full	Spatial	29.17
Honeybees	Full	Survey	32.19
All bees	Full	Spatial	50.16
Hoverflies	Full	Survey	11.48
Other flies	Full	Survey	5.56
Wasps	Full	Survey	18.02
Beetles	Full	Spatial	22.59
Small insects	Full	Survey	5.44
Pan traps			
All insects	Full	Survey	12.11
Bumblebees	Survey	Full	4.88
Solitary bees	Full	Survey	32.01
Honeybees	Full	Survey	13.71
All bees	Full	Survey	4.65
Hoverflies	Full	Survey	16.25
Other flies	Full	Survey	6.52
Wasps	Full	Survey	13.05
Beetles	Full	Survey	19.90
Other insects	Survey	Full	3.72
Species richness of bumblebees	Survey	Full	7.06
Species richness of solitary bees	Full	Survey	31.96
Species richness of all bees	Full	Survey	5.03
Species richness of hoverflies	Full	Survey	11.64
Species richness of bees and hoverflies	Full	Survey	5.70

Note: For each dataset (based on insect abundance unless stated as species richness), the table shows which of the five model types had the lowest AIC ('best' model) and second lowest AIC ('second' best). Δ AIC is the difference between the AIC of the second best and best model.

insect abundance and richness is best explained by all the selected environmental variables in addition to the base model (Burnham & Anderson, 2002). The survey model, containing local-scale variables collected during each survey, is the second-best model (with next lowest AIC) in 28 of the 31 datasets where it is not top, with the spatial model second-best in the remaining three datasets.

3.3 | Which sets of environmental variables are more important in explaining variability in the data?

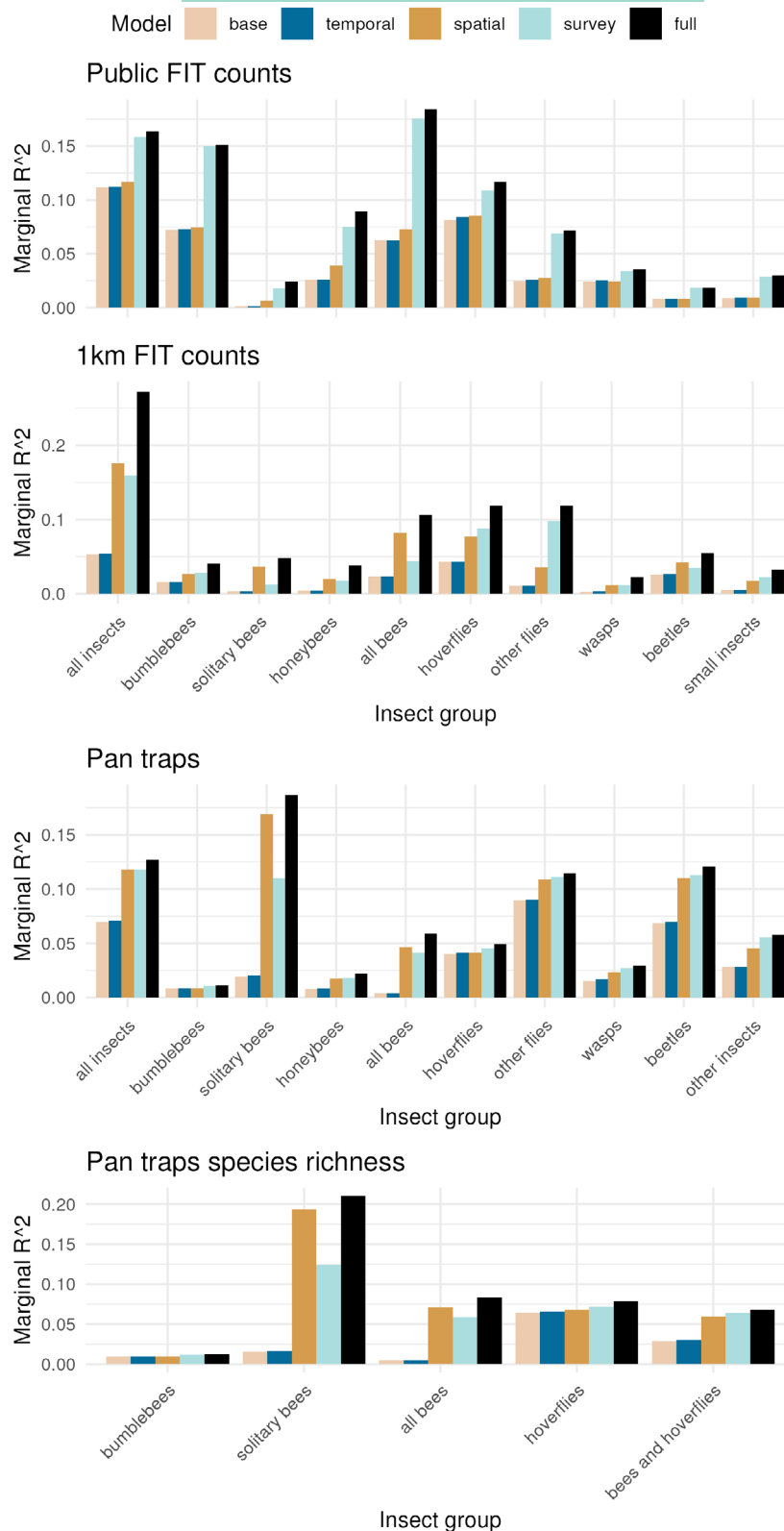
The amount of variability explained by the fixed effects is highest in the full model, as shown by the Marginal R^2 (Figure 2 and Table S3). The variance of the random effect generally decreases when we introduce each set of variables (but not always), and it tends to be lowest in the full model (Table S3). However, variance remains high across all model types, suggesting that the data contain a large amount of between-site variability that is not explained by the modelled variables.

For insect groups in the public FIT Counts, local-scale survey-level variables were the most important in explaining variability in abundance, as shown by the notable increase in marginal R^2 in models containing those variables (Table S3 and Figure 2). In the pan trap and 1 km FIT Count data, models containing the large-scale spatial variables explain a similar amount of variability as the models containing survey-level variables. Survey and large-scale spatial variables are also disproportionately important compared with the other variables in explaining species richness of bees (driven by the solitary bees; Figure 2). This suggests that local environmental conditions at the time of the survey and large-scale spatial variables (here landscape heterogeneity and mean seasonal temperature) are important in explaining some of the fluctuations in insect numbers.

3.4 | Effects of modelled environmental variables on the direction, magnitude and uncertainty of estimated trends in annual abundance and species richness

While the full model is unequivocally the best model from a statistical perspective, the direction and magnitude of changes in abundance and species richness of the different insect groups and the associated uncertainty of the estimated trends do not differ dramatically across the five models (Figures S6 and S7, Supporting Information tables and figures). This is the case for both the first-to-last year and average annual percentage change metric (Table 4). Only in a few cases were the error bars (95% confidence intervals of the percentage change metric) crossing zero in one or more models and not crossing zero in others for the same insect group, signalling the significance of the change over the time series. To provide examples of the trend metrics generated, we here present estimates from the full model fitted to all datasets.

FIGURE 2 Marginal R^2 of the different model variants fitted to group-level abundance and species richness for all insect groups and surveys.



According to the first-to-last year percentage change metric, in the public FIT Count survey, hoverflies declined in abundance between the first and last years in our analysis, while bees, particularly honeybees and bumblebees, other flies, beetles and small insects showed an increase in abundance, and solitary bees, wasps, beetles and the 'all insects' group showed no significant change

(Table 4 and Figure S6). Overall, insects surveyed in the 1km FIT Counts declined in abundance, as did the bees, influenced by the bumblebees, hoverflies, other flies, wasps and small insects, while trends in solitary bees, honeybees and beetles were not significant (Table 4 and Figure S6). We see similar results from the pan trap survey, where the 'all insects' group declined in abundance

TABLE 4 Change metrics estimated from the full model fitted to all datasets.

Dataset	First to last year % change (95% CI)	Average annual % change (95% CI)
Public FIT Counts		
All insects	0.3 (−8.8, 10.6)	0.2 (−2.2, 2.6)
Bumblebees	22.6 (0.1, 48.6)	5.3 (0.5, 10.6)
Solitary bees	−14.6 (−38.4, 18.1)	−3.5 (−10.7, 4.6)
Honeybees	79.2 (39.9, 136.7)	16.8 (9.2, 27.5)
All bees	29.7 (11.1, 52.3)	6.9 (2.7, 11.6)
Hoverflies	−38.3 (−49.3, −25.6)	−10.1 (−14.2, −6.3)
Other flies	25.8 (4.5, 51.2)	6.6 (2, 11.4)
Wasps	42.2 (−1.9, 113.3)	13.9 (1.6, 31.3)
Beetles	43.2 (3.7, 108.4)	9.8 (1.5, 21.3)
Small insects	39.9 (12.6, 77.4)	9.3 (3.6, 15.7)
1 km FIT Counts		
All insects	−32.5 (−41.3, −22.6)	−7.4 (−9.9, −4.7)
Bumblebees	−40.2 (−54.9, −18.9)	−9.4 (−14.3, −3.6)
Solitary bees	−16.5 (−45.3, 29.8)	−2.9 (−10.9, 6.9)
Honeybees	35.6 (−15.8, 117.3)	6.8 (−2.6, 17.9)
All bees	−25.2 (−40.6, −6.1)	−5.5 (−9.8, −0.9)
Hoverflies	−32.6 (−44.8, −18.2)	−6.3 (−10.3, −1.9)
Other flies	−16.9 (−30.8, −1.5)	−3.4 (−6.8, −0.2)
Wasps	−40.6 (−63.2, −5.3)	−9 (−17.4, 0.9)
Beetles	7.9 (−29.5, 64.6)	3.7 (−5.6, 15.8)
Small insects	−50.6 (−64.6, −29.8)	−13 (−18.6, −6.5)
Pan traps		
All insects	−37.8 (−43.6, −31.9)	−8.5 (−10.4, −6.8)
Bumblebees	−2.2 (−18.5, 15.5)	−0.1 (−3.8, 3.5)
Solitary bees	9.9 (−6.4, 29.3)	3.5 (−0.1, 7.7)
Honeybees	43.9 (10.7, 88.2)	8.2 (2.4, 14)
All bees	6 (−6.9, 20.6)	1.9 (−0.8, 4.9)
Hoverflies	−47.9 (−55.8, −39.4)	−12.2 (−14.9, −9.5)
Other flies	−34.1 (−40.4, −27.9)	−7.2 (−9.1, −5.4)
Wasps	−26.8 (−36.5, −16.1)	−4.6 (−7.2, −1.9)
Beetles	−59.5 (−67.5, −48.8)	−16.3 (−19.9, −12)
Other insects	−62.8 (−69, −55.3)	−17.7 (−20.5, −14.7)
Species richness of bumblebees	−2.3 (−16, 11.8)	−0.3 (−3.4, 2.4)
Species richness of solitary bees	11.9 (−2.7, 28.5)	3.6 (0.3, 7.1)
Species richness of all bees	7 (−3.4, 18.6)	1.8 (−0.2, 4)
Species richness of hoverflies	−41.5 (−48.1, −34.6)	−10.1 (−12.2, −8.1)
Species richness of bees and hoverflies	−20.4 (−27, −13.6)	−4.3 (−5.9, −2.7)

Note: For each dataset, the table shows the first-to-last year percentage change and the average annual percentage change with 95% confidence intervals from bootstrapping. Values in bold represent a significantly positive or negative change.

between 2017 and 2022, as did the hoverflies, other flies, wasps, beetles and other insects, while honeybees showed a significant increase (Table 4 and Figure S6). Pollinator species richness from

the pan traps also declined, particularly for hoverflies, with no significant change in bumblebee or solitary bee richness (Table 4 and Figure S6). Overall, confidence intervals around the first-to-last

year percentage change are wide, especially for the bee groups (Table 4 and Figure S6).

Overall, estimates for the average annual percentage change metric across the time periods of each survey were in the same direction as those for the first-to-last year percentage change (e.g. with hoverflies consistently decreasing in abundance and species richness), but they tended to be smaller in magnitude (Table 4 and Figure S7). This is not surprising given that this metric represents an average across the interannual fluctuations. Confidence intervals also tended to be smaller for this metric compared with the first-to-last year percentage change. The two metrics reached slightly different conclusions in only three cases (Table 4).

3.5 | Comparison of trends in pollinator abundance and richness across the three PoMS surveys

We plotted the time series of annual insect abundance and species richness as estimated by the full model and compared this across surveys for the focal bee and hoverfly insect groups, and for the summed abundance of all insects (Figure 3). Abundance per survey is higher in the pan trap surveys than the FIT Counts for all insects and solitary bees, lower for bumblebees, and similar for honeybees and hoverflies, reflecting the differences between survey methods in sampling different insect groups (Figure 3).

We found both similarities and differences in the direction and shape of temporal changes in abundance between the three surveys, (Table 4, Figures 3 and 4). Comparing public FIT Counts with 1 km FIT Counts, 4 out of the 10 insect groups show consistent temporal trends for both metrics. Honeybees and beetles increased in both FIT Count surveys, although the magnitude and significance of estimated changes differed. Both surveys show a decrease in abundance of solitary bees (non-significant) and hoverflies. For all other groups (all bees, bumblebees, other flies, small insects, wasps and 'all insects'), trends estimated by the full model from the public FIT Counts are positive, while trends from the 1 km FIT Counts are negative. Uncertainty is generally higher from the public FIT Counts, especially for wasps and small insects. Only honeybees and solitary bees have less uncertainty in estimated trends from the public than the 1 km FIT Counts (Figure 4).

Comparison between the pan traps and 1 km FIT Counts conducted on the same sites shows agreement in trend direction for four of the six insect groups (Figure 4). Hoverflies and bumblebees show negative abundance trends in both surveys, but with different magnitudes: from the first-to-last year change, hoverflies declined by 47.9% in the pan trap survey and 32.6% in 1 km FIT Counts, and bumblebees declined by 2.2% (non-significant) in the pan traps and 40.2% in the 1 km FIT Count survey. 'All insects' and honeybees show similar changes across both surveys: 'all insects' declined by 37.8% in pan traps and 32.5% in 1 km FIT Counts, while honeybees increased by 43.9% in pan traps and 35.6% (non-significant) in 1 km

FIT Counts. The width of the confidence intervals around these estimates is comparable across surveys (Figure 4), but trends for the solitary bees and honeybees tend to be estimated more precisely by the pan traps. Finally, within the pan trap dataset, both the group-level abundance and species richness of bumblebees and solitary bees follow a hump-shaped trend, increasing towards the middle of the time series to 2020 and decreasing thereafter (Figure 3). Abundance and species richness of hoverflies in pan traps declined in a more linear fashion between 2017 and 2022 (Figure 3), contributing to the greater magnitude of change detected for hoverflies.

4 | DISCUSSION

The UK PoMS represents a step change in the evidence base on UK pollinating insects. Our analysis provides compelling evidence for the inclusion of environmental variables to improve the fit of models of trends in pollinator abundance and species richness. Models combining large-scale and local-scale variables with survey year were the best fit to the data in nearly all cases and explained the highest amount of variability. In contrast, our 'base' model containing only year and month, with a random effect for site, which mirrors the model structures used by current national schemes (Dennis et al., 2016; Massimino et al., 2025) often showed the poorest fit (in 12 of 35 datasets) and explained the lowest proportion of variance (in 31 datasets). However, variance remained high across all models, suggesting the PoMS data contain substantial variability that is not yet explained by this set of modelled variables. In addition, while improving model fit, the inclusion of environmental variables did not have a big impact on the direction and magnitude of the estimated trends and their uncertainty, which remained consistent across model variants.

When assessing population trends and their drivers, especially for insect populations with large year-to-year fluctuations, it is important to partition variance explained by the model into two components: the interannual variability and the long-term trend (Duchenne & Fontaine, 2024; Saunders et al., 2019). Our full model incorporates environmental variables at different scales to reduce interannual variability and improve detection of a signal of temporal change (Didham et al., 2020). While other studies have modelled effects of some variables including temperature on single response measures, such as insect biomass (Müller et al., 2024) or butterfly abundance (Roy et al., 2001), none have integrated this range of environmental variables into national-scale trend models on data for such a wide variety of insect groups. Trend metrics generated over this short time period should be interpreted with caution for reasons explained below. Nevertheless, the significant declines in hoverfly abundance and richness and in abundance of some other pollinator groups across both the observational FIT Count and pan trap surveys provide an early warning for policymakers looking to tailor conservation actions or to meet national-level biodiversity targets (Burns et al., 2023).

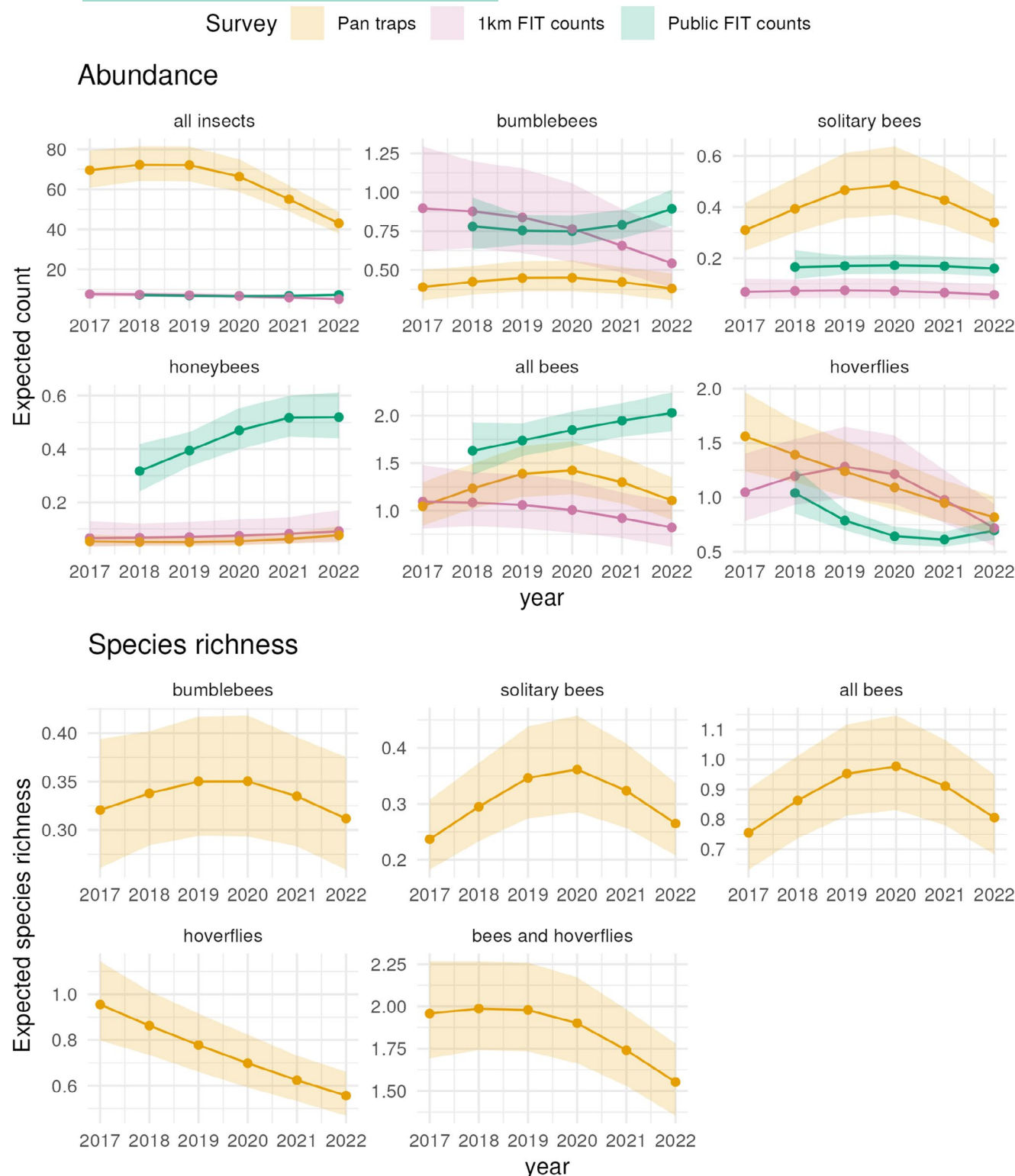


FIGURE 3 Annual insect counts and species richness estimated by the full model for key pollinator groups on the three Pollinator Monitoring Scheme (PoMS) surveys. Points are model estimates and shaded areas are 95% confidence intervals. Note the scale on the Y-axis differs between insect groups. Units are expected number of individuals or species per pan trap station or Flower-Insect Timed Count (FIT Count).

Local-scale variables collected during sampling (including flower abundance and richness, target flower structure, habitat type, sun exposure and wind speed) were important in explaining variability in

pollinator abundance in all surveys, especially the public FIT Count. This was shown by the increase in marginal R^2 in models containing those variables (Figure 2), demonstrating how our approach

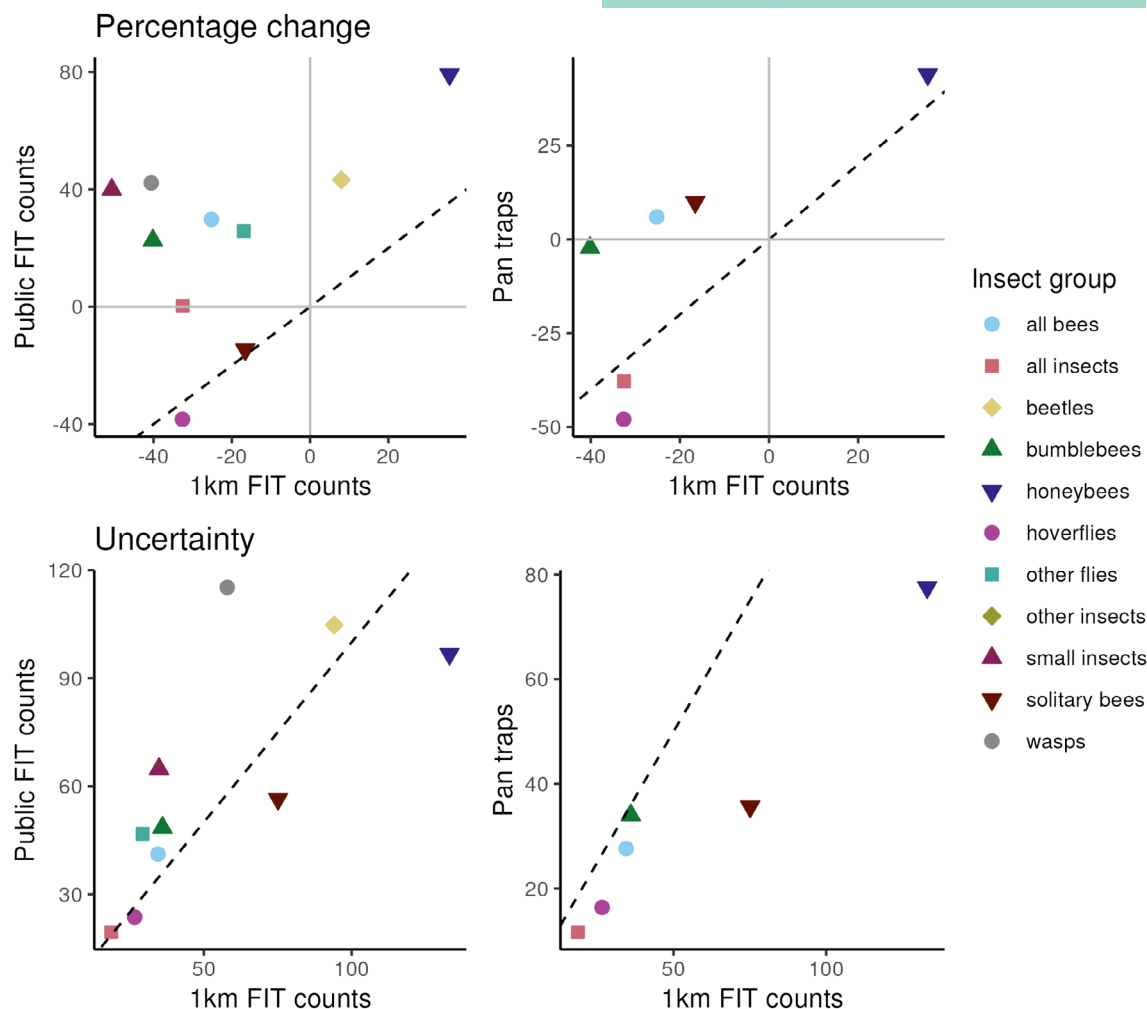


FIGURE 4 Cross-survey comparison of temporal trends in abundance (top panels) and associated uncertainty (bottom panels) estimated by the full model. Symbols represent the percentage change in abundance between the first and last year of each time series (top panels) or width of the confidence intervals (bottom panels). Dashed line is the 1:1 line; diamonds close to the 1:1 line indicate similar trends and uncertainty from the two surveys being compared. We compare the two Flower-Insect Timed Count (FIT Count) surveys (left panels) and the 1 km survey pan traps with the 1 km FIT Counts conducted on the same sites (right panels). Note that a subset of insect groups (all bees, bumblebees, honeybees, solitary bees, hoverflies and all insects) is included in the latter comparison as the other insect groups are not comparable across these two surveys based on the way in which small insects (<3 mm) were categorised.

can reduce noise in the count data created by local conditions on survey days. A previous UK citizen science survey of bumblebees visiting focal plants also found local factors to be more significant than large-scale factors in explaining variation in bumblebee abundance in a single year (Roy et al., 2016). This reinforces the value of participants in large-scale initiatives collecting environmental data alongside biodiversity observations.

Including large-scale spatial variables (landscape heterogeneity within 3×3 km around the centroid of the 1 km site and mean seasonal temperature) explained a similar amount of variability in the pan trap and 1 km FIT Count datasets as the models containing only survey-level variables. This aligns with the 1 km survey network covering a gradient of UK land use types and latitudes, and previous evidence that bee and hoverfly abundance and species richness respond to landscape context at these scales (Carvell et al., 2011; Schirmel et al., 2018; Steffan-Dewenter et al., 2002). However, some

large-scale variables such as seasonal temperature may mask long-term trends in the data. For example, 2022 was a relatively hot year (Figure S1c, Supporting Information [tables and figures]) with a late-summer heatwave, likely affecting some groups more than others. Many hoverfly species have a requirement for damp habitat niches at different lifecycle stages, so may have been disproportionately impacted.

Although the full model was statistically the best of the five tested, there was very little difference across models in the direction, magnitude and uncertainty of the estimated temporal trends in insect abundance and species richness (Figures S6 and S7, Supporting Information [tables and figures]). This suggests the PoMS survey datasets are fairly robust to the choice of environmental variables included in the model, which is important from a policy perspective because it provides confidence that any indicators generated are not overly influenced by methodological decisions. We do not explore in

depth the ecological drivers of abundance and richness within the PoMS datasets here. These warrant future research based on some of the initial effect sizes demonstrated by our models and evidence from other large-scale insect datasets (Didham et al., 2020; Maher et al., 2024).

Our results show a high degree of uncertainty around both change metrics (first-to-last year and average interannual percentage change), likely due to the relatively short time series of PoMS data that were available at the time of developing this modelling framework. This highlights the need for data over a longer time series (>10 years) to more confidently detect changes across these insect groups (Wauchope et al., 2019; White, 2019). Indeed, the power analysis informing design of the scheme was conducted with a 10-year simulation (Breeze et al., 2021), although due to the significant task of sample processing, data validation and cleaning, it will be 2029 before data from a 10-year time series across all three PoMS surveys are available for analysis. While a single metric is desirable for policy and communication reasons, it is not straightforward to summarise a smoothed trend in annual abundance; therefore, the two metrics reported here will inevitably lead to loss of information. First-to-last year percentage change may be a more intuitive metric to communicate (Massimino et al., 2025), but offers only a snapshot comparison of changes in abundance, is sensitive to conditions in the first and last year of the survey, and ignores any changes that happen in the middle of the time series (Didham et al., 2020; Duchenne et al., 2022; Fox et al., 2019). While average annual percentage change is less sensitive to conditions in any specific year, a value close to zero could mask interannual change just because the negatives and positives balance each other out. Furthermore, this metric could be misinterpreted as being cumulative over the time series. Overall, the first-to-last year percentage change is likely to be a more intuitive metric to communicate, as evidenced by other long-running national monitoring schemes (Massimino et al., 2025). Using a smoother to estimate annual abundance helps minimise sensitivity to particular years by smoothing out much of the interannual variability. With a longer PoMS time series, it may be feasible to omit the first and last year as described by Massimino et al. (2025), or calculate change between an average of the first two and last 2 years, as there is greater uncertainty at the ends of the smoother.

Comparing trends predicted by the full model across the three PoMS surveys reveals some important differences. Predictions from the two FIT Count surveys align in direction for 4 of 10 groups (including hoverflies and solitary bees, both key target groups for PoMS) while for all other groups the direction of the trend differs (Figures 3 and 4). This probably reflects the two surveys sampling a different mix of habitats and target flowers, and differences in their size and spatial distribution. Most 1 km FIT Counts (on which abundance of most groups decreased) occur in habitats classified as semi-natural (75%) or agricultural (20%) within each square in the wider countryside (Figure S4, Supporting Information (tables and figures)), where declines in UK pollinator biodiversity have been documented (Mancini et al., 2023). In contrast, public FIT Counts spanning more than 2300 sites across the time series (on which bumblebees,

honeybees, other flies, beetles and small insects increased) were mainly conducted in gardens (50%, including allotments; Figure S4). While increasing urbanisation tends to negatively impact pollinator richness, especially for hoverflies (Ellis et al., 2025), UK gardens have been shown to act as pollinator hotspots (Baldock et al., 2019). Globally, the variance in biodiversity value across urban habitats suggests that targeted conservation measures (such as planting for pollinators which may be a feature in the gardens of FIT Count participants) can succeed in urbanised environments (Sanllorente et al., 2025). However, we should be cautious in interpreting trends from the public FIT Counts given that the selection of sites is not a random sample of the population of interest and that there is an increase in participation through time.

Modelling adjustments could be made to better understand the apparent differences in trends between the two FIT Count surveys. Separate smoothers fitted for each habitat type or target flower, given sufficient sample size, could investigate their impacts within the model. The higher proportion of bees observed in the public FIT Count (41%) than the 1 km FIT Count (14%) may reflect public participants paying more attention to bees than other insect groups. Equally, the lower proportion of flies in the public FIT Count dataset could be due to the sample of target flowers selected by public observers (especially in gardens) being less likely to attract large numbers of flies than those that are more prevalent as target flowers in the 1 km FIT Count (e.g. Ivy, Hogweed, Hawthorn, Buttercup; see Table S2 for the full list of target flower types; Orford et al., 2015). As mentioned above, public FIT Counts show a southern bias (Figure S1b) and increasing participation over time, suggesting sample adjustment may be needed to ensure the inferences drawn from the survey are representative of national-level trends (Boyd et al., 2024). Levels of recorder experience may also be important (Vallecillo et al., 2021), particularly if this changes as volunteers become more familiar with the survey method. Model estimates from the 1 km FIT Counts carried out by more experienced volunteers were more precise than those from the public FIT Counts, especially for the wasps and small insects which could be considered more challenging groups to identify or count accurately. This could be addressed by integrating the public FIT Count dataset with the 1 km FIT Counts to produce a composite trend estimate, or further testing the accuracy of public FIT Counts in the field.

Abundance trends generated from the pan trap and 1 km FIT Count surveys align in direction for 'all insects' and four of the six insect groups, and in magnitude for two groups (all insects and honeybees; Figure 4). Both surveys are conducted on the same sites and days, so the uncertainty of the predicted trends is similar for most insect groups, except the honeybees and solitary bees, where uncertainty is higher for the 1 km FIT Counts. This likely reflects differences in the effectiveness of the two methods in detecting these species groups. Pan traps may be less effective for sampling bumblebees than observational counts, but more effective for solitary bees, hoverflies and other flies in northern Europe (European Commission: Joint Research Centre, 2024; O'Connor et al., 2019). Overall, the FIT Count survey is an effective method of generating

observational data on insect abundance which, while only broadly resolved to taxonomic group level, correlate closely with equivalent annual measures from pan trap surveys. We recommend using more than one survey approach in national-level pollinator monitoring schemes to both reach a wider pool of volunteer participants (Roy et al., 2016) and adequately sample different elements of the pollinator community.

Our results for hoverflies indicate significant interannual and overall declines in both abundance and species richness, consistent with European trends (Barendregt et al., 2022; Powney et al., 2019) highlighting concern for these key providers of pollination and natural pest control services (Toivonen et al., 2022). Further analyses exploring these trends should be a priority, for example looking at differences among hoverfly guilds by comparing primarily migratory with non-migratory species or aphidophagous hoverflies with saprophagous feeders. The 'other flies' (all non-syrphid Diptera) and wasps represent a larger and potentially even more significant proportion of PoMS records than the hoverflies and bees, in terms of their relative abundance, likely species richness and functional importance (Orford et al., 2015). Both groups increased in the public FIT Counts but declined on both 1km square surveys, and indeed patterns of change in the 'all insects' metric are likely to strongly reflect changes in the 'other flies' and wasps. The current processing pipeline for PoMS pan traps does not allow for the non-bee and hoverfly specimens to be identified to species level. However, molecular DNA technologies or image recognition approaches could significantly enhance the potential of the PoMS sample archive for monitoring these hyper-diverse and yet understudied insect groups (Liu et al., 2021; van Klink et al., 2022).

An increase in honeybee abundance since 2017 was a consistent trend across surveys (but particularly the public FIT Count) and models (Figures 3 and 4). We retained honeybees as a defined group in our analysis given their role as pollinators and prevalence in all PoMS survey datasets either as part of the flower-visiting insect community in FIT Counts or within pan trap samples. However as most honeybees in the UK are managed, their abundance largely reflects local hive presence. We would therefore caution against over-interpretation of trend metrics for the aggregate 'all bees' group and suggest that future indicators intended to reflect trends in wild bees exclude honeybees. Previous studies suggest that honeybee dominance can reduce wild bee species richness (Weekers et al., 2022), but there is potential for habitat management that increases wild-flower diversity to limit resource competition and disease transmission between pollinators via shared floral use (Doublet et al., 2022). Our results suggest that both the group-level and species-level datasets generated by PoMS provide an important opportunity to monitor potential future changes in wild and managed pollinators and their interactions at a national scale.

In conclusion, our study provides evidence that the inclusion of both large-scale and local-scale environmental variables improves the fit of models on noisy citizen science datasets of annual insect abundance or species richness, reducing uncertainty in model predictions and enabling production of metrics that separate underlying

national trends from short-term fluctuations. As the PoMS time series is extended, such metrics can inform the development of Official Statistics (UK Statistics Authority, 2025) and Biodiversity Indicators to support policy makers. These must meet stringent codes of practice and will rely on the sustainability of cost-effective structured insect monitoring schemes with transparent protocols and data pipelines, such as PoMS (Breeze et al., 2021; Levenson et al., 2024; UK Pollinator Monitoring Scheme, 2025b). Our results have wider relevance for targeting conservation actions towards species groups showing the greatest declines. PoMS pan trap and FIT Count surveys may not take a traditional species-centred approach but serve to better understand changes in the abundance, status and population drivers of a wide range of currently understudied pollinating insect groups and the ecosystem functions they provide.

AUTHOR CONTRIBUTIONS

Claire Carvell, Helen E. Roy, Nick J.B. Isaac, Martin C. Harvey, Nadine Mitschunas, Christopher Andrews, Angus Garbutt, Lucy E. Ridding, Richard F. Comont, Richard Fox, Dawn E. Balmer, Rowan Edwards, Alfred P. Vogler, William E. Kunin, Michael P. D. Garratt, Simon G. Potts and Paul Woodcock conceived and designed the study; Francesca Mancini and Nick Isaac developed the modelling framework and conducted the analyses; Martin Harvey coordinated the volunteer network and data entry and provided the maps in Figure 1; Nadine Mitschunas led delivery of the 1km square survey and sample processing; Robin Hutchinson and Martin Harvey curated the data; Lucy E. Ridding derived 1km square site locations and land cover data; Claire Carvell and Francesca Mancini led the writing of the manuscript. All authors provided comments on drafts of the manuscript and gave final approval for publication.

ACKNOWLEDGEMENTS

The UK Pollinator Monitoring Scheme (PoMS) is a partnership funded jointly by the UK Centre for Ecology & Hydrology (UKCEH) and Joint Nature Conservation Committee (JNCC—through funding from the Department for Environment, Food & Rural Affairs, Scottish Government, Welsh Government and Department of Agriculture, Environment and Rural Affairs for Northern Ireland). UKCEH's contribution is part-funded by the Natural Environment Research Council formerly as part of the UK-SCAPE Programme (award NE/R016429/1) and now as part of the NC-UK Programme (award NE/Y006208/1) delivering National Capability. UK PoMS is coordinated by UKCEH, with the following delivery partners: Bumblebee Conservation Trust, Butterfly Conservation, British Trust for Ornithology, Buglife, the Royal Horticultural Society, DAERA and Hymettus, and academic partners the Natural History Museum, University of Reading and University of Leeds. PoMS is indebted to the many volunteers who carry out surveys and contribute data to the scheme, as well as the landowners who allow access to their land for surveys. Thanks to Miranda Bane, Richard Dawson, Catherine Jones, Katty Baird, Fiona Montgomery, Tereza Kocarkova, José van Paassen, Eleonora Fitos, Fiona Everingham, Ellen Lamborn and Jan Winder for conducting surveys and training volunteers; Liam

Crowley, Richard Dawson, Ellen Lamborn, Alice Parfitt, Steven Falk, Nigel Jones and Ivan Wright for identifying specimens and Mike Edwards for additional taxonomic support. We also thank Mark Stevenson, Adam Vanbergen, Rory O'Connor, David Roy and members of the PoMS core team and Steering Group (past and present) for contributions to the scheme.

CONFLICT OF INTEREST STATEMENT

The authors report no conflict of interests.

PEER REVIEW

The peer review history for this article is available at <https://www.webofscience.com/api/gateway/wos/peer-review/10.1002/2688-8319.70327>.

DATA AVAILABILITY STATEMENT

Data are available from the NERC Environmental Information Data Centre: <https://doi.org/10.5285/699f2172-88c1-44b7-a8f5-a22296a9e2cb> (UK Pollinator Monitoring Scheme, 2025a). <http://doi.org/10.5285/4a565007-d3a1-468d-9f84-70ec7594fafa> (UK Pollinator Monitoring Scheme, 2025b). Model code has been published on Zenodo (Mancini, 2026).

ORCID

Claire Carvell  <https://orcid.org/0000-0002-6784-3593>

Lucy E. Ridding  <https://orcid.org/0000-0003-3141-8795>

Helen E. Roy  <https://orcid.org/0000-0001-6050-679X>

Richard Fox  <https://orcid.org/0000-0001-6992-3522>

Michael P. D. Garratt  <https://orcid.org/0000-0002-0196-6013>

Francesca Mancini  <https://orcid.org/0000-0003-4085-4978>

REFERENCES

- Akaike, H. (1974). A new look at the statistical model identification. *IEEE Transactions on Automatic Control*, 19, 716–723.
- Aldercotte, A. H., Simpson, D. T., & Winfree, R. (2022). Crop visitation by wild bees declines over an 8-year time series: A dramatic trend, or just dramatic between-year variation? *Insect Conservation and Diversity*, 15, 522–533.
- Baldock, K. C. R., Goddard, M. A., Hicks, D. M., Kunin, W. E., Mitschunas, N., Morse, H., Osgathorpe, L. M., Potts, S. G., Robertson, K. M., Scott, A. V., Staniczenko, P. P. A., Stone, G. N., Vaughan, I. P., & Memmott, J. (2019). A systems approach reveals urban pollinator hotspots and conservation opportunities. *Nature Ecology & Evolution*, 3, 363–373.
- Barendregt, A., Zeegers, T., van Steenis, W., & Jongejans, E. (2022). Forest hoverfly community collapse: Abundance and species richness drop over four decades. *Insect Conservation and Diversity*, 15, 510–521.
- Biesmeijer, J. C., Roberts, S. P. M., Reemer, M., Ohlemüller, R., Edwards, M., Peeters, T., Schaffers, A. P., Potts, S. G., Kleukers, R., Thomas, C. D., Settele, J., & Kunin, W. E. (2006). Parallel declines in pollinators and insect-pollinated plants in Britain and The Netherlands. *Science*, 313, 351–354.
- Bowler, D. E., Heldbjerg, H., Fox, A. D., de Jong, M., & Böhning-Gaese, K. (2019). Long-term declines of European insectivorous bird populations and potential causes. *Conservation Biology*, 33, 1120–1130.
- Boyd, R. J., Stewart, G. B., & Pescott, O. L. (2024). Descriptive inference using large, unrepresentative nonprobability samples: An introduction for ecologists. *Ecology*, 105, e4214.
- Breeze, T. D., Bailey, A. P., Balcombe, K. G., Brereton, T., Comont, R., Edwards, M., Garratt, M. P., Harvey, M., Hawes, C., Isaac, N., Jitlal, M., Jones, C. M., Kunin, W. E., Lee, P., Morris, R. K. A., Musgrove, A., O'Connor, R. S., Peyton, J., Potts, S. G., ... Carvell, C. (2021). Pollinator monitoring more than pays for itself. *Journal of Applied Ecology*, 58, 44–57.
- Brooks, M. E., Kristensen, K., van Benthem, K. J., Magnusson, A., Berg, C. W., Nielsen, A., Skaug, H. J., Maechler, M., & Bolker, B. M. (2017). glmmTMB balances speed and flexibility among packages for zero-inflated generalized linear mixed modeling. *R Journal*, 9, 378–400.
- Burnham, K. P., & Anderson, D. R. (2002). *Model selection and multi-model inference: A practical information-theoretic approach* (2nd ed.). Springer-Verlag.
- Burns, F., Mordue, S., al Fulaij, N., Boersch-Supan, P. H., Boswell, J., Boyd, R. J., Bradfer-Lawrence, T., de Ornellas, P., de Palma, A., de Zylva, P., Dennis, E. B., Foster, S., Gilbert, G., Halliwell, L., Hawkins, K., Haysom, K. A., Holland, M. M., Hughes, J., Jackson, A. C., ... Gregory, R. D. (2023). *State of nature 2023*. The State of Nature Partnership.
- Cardoso, P., & Leather, S. R. (2019). Predicting a global insect apocalypse. *Insect Conservation and Diversity*, 12, 263–267.
- Carvell, C., Isaac, N. J. B., Jitlal, M., Peyton, J., Powney, G. D., Roy, D. B., Vanbergen, A. J., O'Connor, R. S., Jones, C. M., Kunin, W. E., Breeze, T. D., Garratt, M. P. D., Potts, S. G., Harvey, M., Ansine, J., Comont, R., Lee, P., Edwards, M., Roberts, S. P. M., ... Roy, H. E. (2016). Design and testing of a national pollinator and pollination monitoring framework. Final summary report to the Department for Environment, Food and Rural Affairs (Defra), Scottish Government and Welsh Government: Project WC1101. <https://randd.defra.gov.uk/ProjectDetails?ProjectID=19259>
- Carvell, C., Osborne, J. L., Bourke, A. F. G., Freeman, S. N., Pywell, R. F., & Heard, M. S. (2011). Bumble bee species' responses to a targeted conservation measure depend on landscape context and habitat quality. *Ecological Applications*, 21, 1760–1771.
- Cooke, R., Outhwaite, C. L., Bladon, A. J., Millard, J., Rodger, J. G., Dong, Z., Dyer, E. E., Edney, S., Murphy, J. F., Dicks, L. V., Hui, C., Jones, J. I., Newbold, T., Purvis, A., Roy, H. E., Woodcock, B. A., & Isaac, N. J. B. (2025). Integrating multiple evidence streams to understand insect biodiversity change. *Science*, 388, eadq2110.
- Defra. (2014). The National Pollinator Strategy: for bees and other pollinators in England. <https://www.gov.uk/government/publications/national-pollinator-strategy-for-bees-and-other-pollinators-in-england>
- Dennis, E. B., Morgan, B. J. T., Freeman, S. N., Brereton, T. M., & Roy, D. B. (2016). A generalized abundance index for seasonal invertebrates. *Biometrics*, 72, 1305–1314.
- Didham, R. K., Basset, Y., Collins, C. M., Leather, S. R., Littlewood, N. A., Menz, M. H. M., Müller, J., Packer, L., Saunders, M. E., Schönrogge, K., Stewart, A. J. A., Yanoviak, S. P., & Hassall, C. (2020). Interpreting insect declines: Seven challenges and a way forward. *Insect Conservation and Diversity*, 13, 103–114.
- Doublet, V., Doyle, T., Refoy, I., Hedges, S., Carvell, C., Brown, M. J. F., & Wilfert, L. (2022). Increasing flower species richness in agricultural landscapes alters insect pollinator networks: Implications for bee health and competition. *Ecology and Evolution*, 12, e9442.
- Duchenne, F., & Fontaine, C. (2024). Weather explains inter-annual variability, but not the temporal decline, in insect biomass. *Insect Conservation and Diversity*, 17, 932–937.
- Duchenne, F., Porcher, E., Mihoub, J.-B., Lois, G., & Fontaine, C. (2022). Controversy over the decline of arthropods: A matter of temporal baseline? *Peer Community Journal*, 2, e33.

- Ellis, E. E., Campbell, S. A., & Edmondson, J. L. (2025). Drivers of nocturnal and diurnal pollinating insect declines in urban landscapes. *Proceedings of the Royal Society B: Biological Sciences*, 292, 20250102.
- European Commission: Joint Research Centre. (2024). *Refined proposal for an EU pollinator monitoring scheme*. Publications Office of the European Union.
- Evans, L. C., Burgess, M. D., Potts, S. G., Kunin, W. E., Fox, R., Powell, K. E., Boughhey, K., Harrower, C. A., Bourhis, Y., Martay, B., & Oliver, T. H. (2026). Assessing direct effects of insect change on insectivore populations in the United Kingdom. *Biodiversity and Conservation*, 35, 134.
- Fox, R., Harrower, C. A., Bell, J. R., Shortall, C. R., Middlebrook, I., & Wilson, R. J. (2019). Insect population trends and the IUCN Red List process. *Journal of Insect Conservation*, 23, 269–278.
- Fox, R., Oliver, T. H., Harrower, C., Parsons, M. S., Thomas, C. D., & Roy, D. B. (2014). Long-term changes to the frequency of occurrence of British moths are consistent with opposing and synergistic effects of climate and land-use changes. *Journal of Applied Ecology*, 51, 949–957.
- Garibaldi, L. A., Sáez, A., Aizen, M. A., Fijen, T., & Bartomeus, I. (2020). Crop pollination management needs flower-visitor monitoring and target values. *Journal of Applied Ecology*, 57, 664–670.
- Hollis, D., McCarthy, M., Kendon, M., & Legg, T. (2022). *HadUK-grid grid-ded climate observations on a 1 km grid over the UK, v1.1.0.0 (1836–2021)*. NERC EDS Centre for Environmental Data Analysis.
- Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services (IPBES). (2016). <http://www.ipbes.net/>.
- Johnson, T. F., Beckerman, A. P., Childs, D. Z., Webb, T. J., Evans, K. L., Griffiths, C. A., Capdevila, P., Clements, C. F., Besson, M., Gregory, R. D., Thomas, G. H., Delmas, E., & Freckleton, R. P. (2024). Revealing uncertainty in the status of biodiversity change. *Nature*, 628, 788–794.
- Kerr, J. T., Pindar, A., Galpern, P., Packer, L., Potts, S. G., Roberts, S. M., Rasmont, P., Schweiger, O., Colla, S. R., Richardson, L. L., Wagner, D. L., Gall, L. F., Sikes, D. S., & Pantoja, A. (2015). Climate change impacts on bumblebees converge across continents. *Science*, 349, 177–180.
- Klein, A.-M., Vaissière, B. E., Cane, J. H., Steffan-Dewenter, I., Cunningham, S. A., Kremen, C., & Tscharntke, T. (2007). Importance of pollinators in changing landscapes for world crops. *Proceedings of the Royal Society B: Biological Sciences*, 274, 303–313.
- Levenson, H., Du Clos, B., Smith, T., Jepsen, S., Everett, J., Williams, N., & Woodard, S. (2024). A call for standardization in wild bee data collection and curation. *Journal of Melittology*, 123, 4–16. <https://doi.org/10.17161/jom.vi123.22533>.
- Liu, H., Riccomagno, S., Vogler, A. P., Read, D. S., & Carvell, C. (2021). Pollinator-plant interactions and insect community dynamics: DNA Centre of Excellence project as part of the Pollinator Monitoring and research partnership 2019–2020. Report to the Department for Environment, Food & Rural Affairs: BE01132.
- Maher, S., Kelly, R., Hodge, S., O'Hara, E., Ruas, S., Rotches-Ribalta, R., Lee, A., White, B., Gormally, M., Moran, J., Ó Huallacháin, D., & Stout, J. (2024). Pollinator responses to farmland habitat features: One-size does not fit all. *Journal of Pollination Ecology*, 35, 29–46.
- Mancini, F. (2026). FrancescaMancini/poms_paper: Initial release. Zenodo.
- Mancini, F., Cooke, R., Woodcock, B. A., Greenop, A., Johnson, A. C., & Isaac, N. J. B. (2023). Invertebrate biodiversity continues to decline in cropland. *Proceedings of the Royal Society B: Biological Sciences*, 290, 20230897.
- Marston, C., Rowland, C. S., O'Neil, A. W., & Morton, R. D. (2022). Land cover map 2021 (10m classified pixels, GB). NERC EDS Environmental Information Data Centre (Dataset).
- Massimino, D., Baillie, S. R., Balmer, D. E., Bashford, R. I., Gregory, R. D., Harris, S. J., Heywood, J. J. N., Kelly, L. A., Noble, D. G., Pearce-Higgins, J. W., Raven, M. J., Risely, K., Woodcock, P., Wotton, S. R., & Gillings, S. (2025). The breeding bird survey of the United Kingdom. *Global Ecology and Biogeography*, 34, e13943.
- Müller, J., Hothorn, T., Yuan, Y., Seibold, S., Mitesser, O., Rothacher, J., Freund, J., Wild, C., Wolz, M., & Menzel, A. (2024). Weather explains the decline and rise of insect biomass over 34 years. *Nature*, 628, 349–354.
- National Biodiversity Data Centre. (2015). *All-Ireland Pollinator plan 2015–2020*. National Biodiversity Data Centre Series No. 3. <https://pollinators.ie/working-together-for-biodiversity/about-the-aipp-2015-2020/>
- Nieto, A., Roberts, S. P. M., Kemp, J., Rasmont, P., Kuhlmann, M., García Criado, M., Biesmeijer, J. C., Bogusch, P., Dathe, H. H., De la Rúa, P., De Meulemeester, T., Dehon, M., Dewulf, A., Ortiz-Sánchez, F. J., Lhomme, P., Pauly, A., Potts, S. G., Praz, C., Quaranta, M., ... Michez, D. (2014). *European Red List of bees*. Publication Office of the European Union.
- Noriega, J. A., Hortal, J., Azcarate, F. M., Berg, M. P., Bonada, N., Briones, M. J. I., Del Toro, I., Goulson, D., Ibanez, S., Landis, D. A., Moretti, M., Potts, S. G., Slade, E. M., Stout, J. C., Ulyshen, M. D., Wackers, F. L., Woodcock, B. A., & Santos, A. M. C. (2018). Research trends in ecosystem services provided by insects. *Basic and Applied Ecology*, 26, 8–23.
- O'Connor, R. S., Kunin, W. E., Garratt, M. P. D., Potts, S. G., Roy, H. E., Andrews, C., Jones, C. M., Peyton, J. M., Savage, J., Harvey, M. C., Morris, R. K. A., Roberts, S. P. M., Wright, I., Vanbergen, A. J., & Carvell, C. (2019). Monitoring insect pollinators and flower visitation: The effectiveness and feasibility of different survey methods. *Methods in Ecology and Evolution*, 10, 2129–2140.
- Ollerton, J., Winfree, R., & Tarrant, S. (2011). How many flowering plants are pollinated by animals? *Oikos*, 120, 321–326.
- Orford, K. A., Vaughan, I. P., & Memmott, J. (2015). The forgotten flies: The importance of non-syrphid Diptera as pollinators. *Proceedings of the Royal Society B: Biological Sciences*, 282, 20142934.
- Pocock, M. J. O., Chandler, M., Bonney, R., Thornhill, I., Albin, A., August, T., Bachman, S., Brown, P. M. J., Cunha, D. G. F., Grez, A., Jackson, C., Peters, M., Rabarijaon, N. R., Roy, H. E., Zaviezo, T., & Danielsen, F. (2018). Chapter six—A vision for global biodiversity monitoring with citizen science. In D. A. Bohan, A. J. Dumbrell, G. Woodward, & M. Jackson (Eds.), *Advances in ecological research* (pp. 169–223). Academic Press.
- Potts, S. G., Biesmeijer, J. C., Kremen, C., Neumann, P., Schweiger, O., & Kunin, W. E. (2010). Global pollinator declines: Trends, impacts and drivers. *Trends in Ecology & Evolution*, 25, 345–353.
- Powney, G. D., Carvell, C., Edwards, M., Morris, R. K. A., Roy, H. E., Woodcock, B. A., & Isaac, N. J. B. (2019). Widespread losses of pollinating insects in Britain. *Nature Communications*, 10, 1018.
- Pryke, J. S., Samways, M. J., New, T. R., Cardoso, P., & Gaigher, R. (2024). *Routledge handbook of insect conservation* (1st ed.). Routledge.
- R Core Team. (2021). *R: A language and environment for statistical computing*. R Foundation for Statistical Computing. <https://www.R-project.org/>
- Rondeau, S., Gervais, A., Leboeuf, A., Drapeau Picard, A.-P., Larrivé, M., & Fournier, V. (2023). Combining community science and taxonomist expertise for large-scale monitoring of insect pollinators: Perspective and insights from Abeilles citoyennes. *Conservation Science and Practice*, 5, e13015.
- Roy, D. B., Rothery, P., Moss, D., Pollard, E., & Thomas, J. A. (2001). Butterfly numbers and weather: Predicting historical trends in abundance and the future effects of climate change. *Journal of Animal Ecology*, 70, 201–217.
- Roy, H. E., Baxter, E., Saunders, A., & Pocock, M. J. O. (2016). Focal plant observations as a standardised method for pollinator monitoring: Opportunities and limitations for mass participation citizen science. *PLoS One*, 11, e0150794.

- Sanllorente, O., Blanco-Urdillo, E., Sánchez-Tójar, A., & Diego Ibáñez-Álamo, J. (2025). A systematic review and meta-analysis on urban arthropod diversity. *Insect Conservation and Diversity*, 18, 447–464.
- Saunders, M. E., Janes, J. K., & O'Hanlon, J. C. (2019). Moving on from the insect apocalypse narrative: Engaging with evidence-based insect conservation. *Bioscience*, 70, 80–89.
- Schirmel, J., Albrecht, M., Bauer, P. M., Sutter, L., Pfister, S. C., & Entling, M. H. (2018). Landscape complexity promotes hoverflies across different types of semi-natural habitats in farmland. *Journal of Applied Ecology*, 55, 1747–1758.
- Shortall, C., Moore, A., Smith, E., Hall, M. J., Woiwod, I. P., & Harrington, R. (2009). Long-term changes in the abundance of flying insects. *Insect Conservation and Diversity*, 2, 251–260.
- Soroye, P., Newbold, T., & Kerr, J. (2020). Climate change contributes to widespread declines among bumble bees across continents. *Science*, 367, 685–688.
- Steffan-Dewenter, I., Munzenberg, U., Burger, C., Thies, C., & Tschertke, T. (2002). Scale-dependent effects of landscape context on three pollinator guilds. *Ecology*, 83, 1421–1432.
- Stout, J. C., & Dicks, L. V. (2022). From science to society: Implementing effective strategies to improve wild pollinator health. *Philosophical Transactions of the Royal Society, B: Biological Sciences*, 377, 20210165.
- The Scottish Government. (2017). Pollinator Strategy for Scotland 2017–2027. <https://www.nature.scot/doc/pollinator-strategy-scotland-2017-2027>
- Thomas, C. D., Jones, T. H., & Hartley, S. E. (2019). "Insectageddon": A call for more robust data and rigorous analyses. *Global Change Biology*, 25, 1891–1892.
- Thomas, J. A. (2005). Monitoring change in the abundance and distribution of insects using butterflies and other indicator groups. *Philosophical Transactions of the Royal Society of London. Series B, Biological Sciences*, 360, 339–357.
- Toivonen, M., Karimaa, A.-E., Herzon, I., & Kuussaari, M. (2022). Flies are important pollinators of mass-flowering caraway and respond to landscape and floral factors differently from honeybees. *Agriculture, Ecosystems & Environment*, 323, 107698.
- Tordoff, G. M., Dennis, E. B., Fox, R., Cook, P. M., Davis, T. M., Blumgart, D., & Bourn, N. A. D. (2022). Inconsistent results from trait-based analyses of moth trends point to complex drivers of change. *Biodiversity and Conservation*, 31, 2999–3018.
- UK Pollinator Monitoring Scheme. (2025a). *Flower-insect timed count data from the UK Pollinator Monitoring Scheme, 2017–2022*. NERC EDS Environmental Information Data Centre.
- UK Pollinator Monitoring Scheme. (2025b). *Pan-trap survey data from the UK Pollinator Monitoring Scheme, 2017–2022*. NERC EDS Environmental Information Data Centre.
- UK Pollinator Monitoring Scheme. (2025c). *The UK PoMS annual report 2024*. UK Centre for Ecology & Hydrology and Joint Nature Conservation Committee.
- UK Statistics Authority. (2025). Code of practice for statistics.
- Vallecillo, D., Gauthier-Clerc, M., Guillemain, M., Vittecoq, M., Vandewalle, P., Roche, B., & Champagnon, J. (2021). Reliability of animal counts and implications for the interpretation of trends. *Ecology and Evolution*, 11, 2249–2260.
- van Klink, R., August, T., Bas, Y., Bodesheim, P., Bonn, A., Fossøy, F., Høye, T. T., Jongejans, E., Menz, M. H. M., Miraldo, A., Roslin, T., Roy, H. E., Ruczyński, I., Schigel, D., Schäffler, L., Sheard, J. K., Svenningsen, C., Tschan, G. F., Wäldchen, J., ... Bowler, D. E. (2022). Emerging technologies revolutionise insect ecology and monitoring. *Trends in Ecology & Evolution*, 37, 872–885.
- van Klink, R., Bowler, D. E., Gongalsky, K. B., Swengel, A. B., Gentile, A., & Chase, J. M. (2020). Meta-analysis reveals declines in terrestrial but increases in freshwater insect abundances. *Science*, 368, 417–420.
- Van Strien, A. J., van Swaay, C. A. M., & Termaat, T. (2013). Opportunistic citizen science data of animal species produce reliable estimates of distribution trends if analysed with occupancy models. *Journal of Applied Ecology*, 50, 1450–1458.
- Vanbergen, A. J., Baude, M., Biesmeijer, J. C., Britton, N. F., Brown, M. J. F., Brown, M., Bryden, J., Budge, G. E., Bull, J. C., Carvel, C., Challinor, A. J., Connolly, C. N., Evans, D. J., Feil, E. J., Garratt, M. P., Greco, M. K., Heard, M. S., Jansen, V. A. A., Keeling, M. J., ... Initiative, I. P. (2013). Threats to an ecosystem service: Pressures on pollinators. *Frontiers in Ecology and the Environment*, 11, 251–259.
- Vasiliev, D., & Greenwood, S. (2021). The role of climate change in pollinator decline across the Northern Hemisphere is underestimated. *Science of the Total Environment*, 775, 145788.
- Wagner, D. L., Grames, E. M., Forister, M. L., Berenbaum, M. R., & Stopak, D. (2021). Insect decline in the Anthropocene: Death by a thousand cuts. *Proceedings of the National Academy of Sciences*, 118, e2023989118.
- Wauchope, H. S., Amano, T., Sutherland, W. J., & Johnston, A. (2019). When can we trust population trends? A method for quantifying the effects of sampling interval and duration. *Methods in Ecology and Evolution*, 10, 2067–2078.
- Weekers, T., Marshall, L., Leclercq, N., Wood, T. J., Cejas, D., Drepper, B., Hutchinson, L., Michez, D., Molenberg, J.-M., Smagghe, G., Vandamme, P., & Vereecken, N. J. (2022). Dominance of honey bees is negatively associated with wild bee diversity in commercial apple orchards regardless of management practices. *Agriculture, Ecosystems & Environment*, 323, 107697.
- Welsh Government. (2013). *The action plan for pollinators in Wales*. Biodiversity Team, Biodiversity and Nature Conservation Branch. <https://www.biodiversitywales.org.uk/en/our-work/wales-action-plan-for-pollinators/>
- White, E. R. (2019). Minimum time required to detect population trends: The need for long-term monitoring programs. *Bioscience*, 69, 40–46.
- Whitehorn, P. R., Seo, B., Comont, R. F., Rounsevell, M., & Brown, C. (2022). The effects of climate and land use on British bumblebees: Findings from a decade of citizen-science observations. *Journal of Applied Ecology*, 59, 1837–1851.

SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

Figure S1. Large-scale environmental covariates included in the spatial, temporal and full model.

Figure S2. Local-scale covariates included in the survey and full models for pan trap data from the PoMS 1 km square survey network.

Figure S3. Local-scale covariates included in the survey and full models for FIT Count data.

Figure S4. Number of FIT Counts (public and 1km) and pan trap stations in different habitat classes (note pan trap stations were classified as located in either predominantly agricultural or semi-natural habitats only).

Figure S5. Histograms of insect and species numbers per pan trap station or FIT Count.

Table S3. Model comparison for all 35 datasets, ordered by survey type.

Figure S6. Percentage change in abundance and species richness between the first and last year of each time series (2017 to 2022 for pan traps and 1 km FIT Counts; 2018 to 2022 for public FIT Counts) estimated by the five model types for each of the datasets.

Figure S7. Average annual percentage change in abundance and species richness (from 2017 to 2022 for pan traps and 1 km FIT Counts; from 2018 to 2022 for public FIT Counts) estimated by the five model types for each of the datasets.

Table S1. Insect groups recorded on PoMS and their assignment within the pan trap and FIT Count protocols.

Table S2. Target flowers for Flower-Insect Timed Counts and flower structure categories assigned for analysis.

How to cite this article: Carvell, C., Isaac, N. J. B., Harvey, M. C., Hutchinson, R., Mitschunas, N., Andrews, C., Garbutt, A., Ridding, L. E., Roy, H. E., Comont, R. F., Fox, R., Balmer, D. E., Richards, R., Edwards, R., Vogler, A. P., Kunin, W. E., Garratt, M. P. D., Potts, S. G., Woodcock, P., & Mancini, F. (2026). Modelling pollinator trends using multi-scale environmental data from the UK Pollinator Monitoring Scheme. *Ecological Solutions and Evidence*, 7, e70327. <https://doi.org/10.1002/2688-8319.70327>