

THE 2023 REPORT

The Bugs Matter Citizen Science Survey

The National citizen science survey of 'bug splats' on vehicle number plates to monitor flying insect abundance.

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Contents

| Summary | 4 |
|---|----|
| Introduction | 5 |
| Methods | 6 |
| Results | |
| National results | 10 |
| Country results | 2] |
| Regional results | 25 |
| County results | 29 |
| Participation in the Bugs Matter Citizen Science Survey | 32 |
| Bugs Matter app development | 36 |
| Synthesis | 37 |
| Suport the survey | 38 |
| References | 39 |
| Appendices | 42 |





Summary

In recent years, scientists, conservation organisations Compared to 2004, the number of insect splats in England and the media have drawn attention to global declines in insect abundance, the consequences of which are potentially catastrophic. Invertebrates are critical to ecosystem functions and services, and without them, life on Earth would collapse.

However, there has been insufficient data to make robust conclusions about trends in insect abundance in the UK, because standardised insect sampling approaches are not widely applied to all insect groups or at a national scale. The Bugs Matter citizen science survey provides a standardised and large-scale approach to monitor the abundance of flying insects over time. The sampling method is analogous to the 'windscreen phenomenon', a term given to the anecdotal observation that people tend to find fewer insect splats on the windscreens of their cars now, compared to in the past. The survey runs every summer and involves citizen scientists across the UK recording the number of insect splats on their vehicle number plates following a journey, having first removed any residual insects from previous journeys.

In this report, the number of insects sampled on vehicle number plates in 2019 (n = 479 journeys in Kent), 2021 (n = 2,918 journeys nationwide), 2022 (n = 4,128 journeys nationwide) and 2023 (n = 4,688 journeys nationwide) are compared with the results of a survey using this methodology led by the RSPB ('Big Bug Count') in 2004 (n = 14,257 journeys nationwide).

The results show that the number of insect splats in the UK has fallen by 77.6% between 2004 and 2023, 13.5% greater than the decrease seen in 2022 (64.1%).

decreased by 82.6% by 2023, 14.2% greater than in 2022 (68.4%). Compared to 2004, the number of insect splats in Scotland decreased by 76.1% by 2023, 39.9% greater than in 2022 (36.2%). In Wales, the number of insect splats recorded decreased by 78.8% in 2023, 7.5% greater than in 2022 (71.3%). In Northern Ireland, a small sample of journeys show that the number of insect splats recorded decreased by 54.4% between 2021 and 2023.

These results are consistent with the declining trends in insect populations widely reported by others, and highlight an urgent need to address the drivers of invertebrate declines - habitat loss and damage, pesticide use, pollution, and climate change. However, these results are based on data with low temporal resolution and consequently we interpret this change with caution. Inter-annual variation in a range of unmeasured factors that could influence flying insect activity or abundance, such as the record-breaking summer temperatures in 2022, could significantly influence the observed pattern. To draw robust conclusions about longterm trends in insect populations in the UK, scientists require data from multiple years, over long time periods, and over large spatial scales - the Bugs Matter citizen science survey has demonstrated that it has the potential to generate such

Introduction

Global insect declines

A growing body of evidence (Fox et al., 2013; Hallmann et al., 2017; Goulson, D. 2019; Sánchez-Bayo et al., 2019; Thomas et al., 2019; van der Sluijs, 2020; Macadam et al., 2020; Outhwaite, McCann and Newbold, 2022) highlights population declines in insects and other invertebrates at UK and global scales. These declines, which are evident across all functional groups of insects (herbivores, detritivores, parasitoids, predators and pollinators), could have catastrophic impacts on the Earth's natural systems and human survivability on our planet. Invertebrates are functionally of greater importance than large-bodied fauna, and in terms of biomass, bioabundance and species diversity, they make up the greatest proportion of life on Earth.

Invertebrates are critical to ecosystem functions and services. They pollinate most of the world's crops including foods and fibers, provide natural pest control services, decompose organic matter and recycle nutrients into the soil. Invertebrates underpin food chains, providing food for larger animals including birds, bats, reptiles, amphibians, fish and terrestrial mammals. Almost all birds eat insects, and many of those that eat seeds and other food as adults must feed insects to their young - it is thought to take 200,000 insects to raise a single swallow chick (Chapman et al., 2013). Without insects, life on Earth would collapse, millions of species would go extinct, and we would be surrounded by the carcasses of dead animals.

Habitat loss and fragmentation has caused declines in biodiversity across the world. The conversion of natural habitats into agriculture, urban areas, and infrastructure development leads to the loss of suitable habitats for insects, making it difficult for them to feed and reproduce. The widespread use of chemical pesticides, including insecticides, herbicides, and fungicides, can have detrimental effects on insect populations. Climate change alters weather patterns, affecting insect life cycles, behaviour, and distribution. Some insects may struggle to adapt to rapidly changing conditions or may lose suitable habitats due to shifting climate zones.

Monitoring global insect populations

Evidence of insect declines comes from targeted surveys using specific sampling techniques aimed at specific target groups. Many of these have generated long-term datasets, such as the Rothamstead Insect Survey of aphids and larger moths, since 1964 (Taylor, 1986), the UK Butterfly Monitoring Scheme, since 1976, (Brereton et al., 2020), and the National Moth Recording Scheme, since 2007 (Fox et al., 2021). These surveys provide a good indication of trends for these target taxa, however generalising national and global trends from surveys which focus on a limited number of insect groups risks only showing part of the picture. Patterns and trends for specific species or species groups are nuanced, and while trends in some insect groups are well understood, there is a paucity of data for many others.

Whilst some survey techniques such as moth trapping and butterfly transects are discriminate in terms of what species they record, there are very few established indiscriminate methods for large-scale monitoring of insect abundance across a broad range of insect groups.

The Bugs Matter citizen science survey

The Bugs Matter citizen science survey uses an innovative method for large-scale indiscriminate monitoring of flying insect populations. Citizen scientists record the number of insect splats on their vehicle number plates following a journey, having first removed any residual insects from previous journeys. It has the potential to provide an efficient, standardised and scalable approach to monitor trends in insect abundance across local, regional and global scales.

The sampling technique is based on the 'windscreen phenomenon' (Wikipedia, 2021), a term given to the anecdotal observation that fewer insect splats appear on the windscreens of cars now compared to a decade or several decades ago. These observations, which have also been reported from empirical data (Møller, 2019), have been interpreted as an indicator of major global declines in insect

The Bugs Matter sampling approach is indiscriminate, such that a wide range of flying insect species can be recorded. Therefore, the survey aims to quantify overall flying insect abundance, rather than the diversity or abundance of target species or insect groups. Adult forms of flying species from the taxonomic groups of Coleoptera, Diptera, Ephemeroptera, Hemiptera, Hymenoptera, Lepidoptera, Megaloptera, Neuroptera, Plecoptera, Trichoptera and Thysanoptera are most likely to be recorded.

The 2023 report

This comprehensive report describes the Bugs Matter citizen science survey in the UK as of December 2023. The methods and any changes to the methods are described. The results of a statistical analysis to determine the annual change in the number of insect splats is presented. The model incorporates a range of independent variables and integrates pre-existing data from 2004, which was collected as part of a national survey using the same sampling method led by the RSPB ('Big Bug Count'), which provides an opportunity to assess invertebrate abundance over a 19-year timeframe (Tinsley-Marshall et al., 2021a, 2021b). Data on the number of journeys, the characteristics and environmental conditions of the journeys, and the number of insects splats are presented, supported by appendices. It is hoped that the Bugs Matter survey will continue every year, providing an increasingly valuable dataset on flying insect abundance in the UK, with promising applications beyond.

Methods

The Bugs Matter app and insect sampling

The Bugs Matter citizen science survey took place throughout the UK between 1st June and 31st August in 2021, 2022 and 2023, using the Bugs Matter mobile application (Figure 1). In 2021 and 2022, users received a standardised sampling grid, termed a 'splatometer', in the post after they had signed up in the application. However, in 2023 the whole number plate was used to count insect splats. Within the app, users add details about the vehicle used for sampling, and vehicle specification information is fetched via an Application Programming Interface (API) number plate look-up service. Here, participants are asked to confirm whether their number plate measures to standard UK dimensions, and if not, asked to manually input the dimensions of their number plate. Multiple vehicles can be added by a single user. Vehicle specification information is used in the analysis to determine if different types of vehicles sample insects differently.

Prior to commencing a journey, citizen scientists clean the front number plate of their vehicle to remove any residual insects. The app requests a checkbox confirmation that the number plate has been cleaned. Upon starting a journey, citizen scientists tap a button in the app to begin recording the journey route using the mobile device's GPS. This provides crucial data on the length, duration, location, and average speed of the journey. Insects are then sampled when they collide with the number plate throughout the duration of a journey. Upon completing a journey, citizen scientists tap a button in the app to finish recording the journey route. They record the number of insect splats on the front number plate of their vehicle. The journey route, the number of insect splats, and a photograph of the number plate are submitted via the app. Citizen scientists were asked to participate only on essential journeys and not to make journeys specifically to take part in the survey.

The 2004 survey took place between the 1st and 30th June in England, Scotland and Wales, whilst the 2019 survey took place between the 1st June and 31st August and was limited to journeys starting in Kent. In 2004 and 2019, a mobile application was not used and the start and end times and locations of the journeys were recorded manually, along with the journey distance from vehicle odometer readings. The mobile application was developed and used for the 2021 survey seasons onwards, where in 2021, 2022 and 2023 journeys were recorded in England, Scotland, Wales and Northern Ireland.

Collating explanatory variables

Time of day was calculated for each journey as the intermediate time between the journey start and end times. As 97.9% of journeys occurred during daytime hours (05:00–21:00), we treated time as a continuous variable. To account for seasonal effects on flying insect abundance, the calendar date of the journey was included in the models. This variable



Figure 1. Promotional image showing screenshots from the Bugs Matter mobile app.

was not included in the 2021 analysis. The average speed of the journey was calculated by dividing the journey distance by the journey duration. The vehicle type, which is acquired in the app via an API, was classified into four categories: car, heavy goods vehicle (HGV), sports utility vehicle (SUV), and van. Data collected in 2004 and 2019 contained only start and end postcodes, so journey routes were obtained from the Google Directions API through the R 'mapsapi' package (Dorman, 2022). The 'sf' package (Pebesma, 2018) in R was used to work with the spatial data.

Mean temperature was calculated for each journey by averaging the intersecting raster cell values from the daily mean temperature from E-OBS, a high resolution daily gridded dataset (Cornes et al., 2018). The mean altitude of each journey was extracted from ASTER Global Digital Elevation Model (GDEM) V2 which has a 30 m resolution. A few journeys were located outside of the extent of the data values in these rasters, and therefore these values could not be calculated. In these instances, the mean temperature of journeys on the same day were used. Similarly, missing altitude values were assigned the mean altitude of all journey routes to avoid these journeys being excluded from the analysis due to the presence of NA values for these independent variables.

Normalized difference vegetation index (NDVI) describes the difference between the visible and near-infrared reflectance of vegetation cover based on chlorophyll content, and can be used as a proxy for vegetation biomass and/or productivity. In previous years, the maximum greenest pixel composites of NDVI values were generated in Google Earth Engine (Gorelick et al., 2017) from MODIS Terra Vegetation Indices 16-Day Global 250 m data (Didan, 2015) for each survey year. This year, NDVI was omitted from our analysis, in favour of data on the proportion of urban or suburban land cover surrounding the journey route, which was collinear with NDVI.

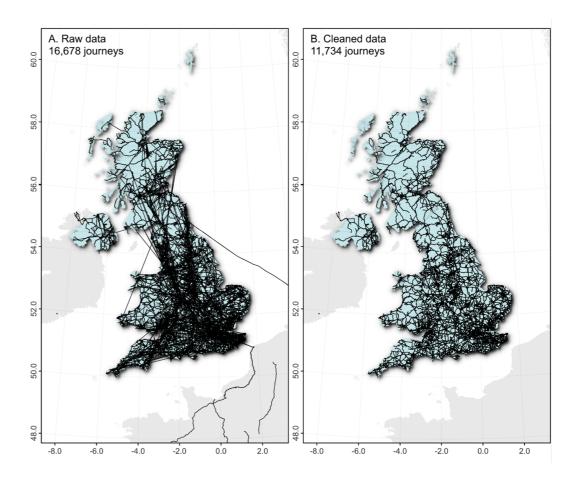


Figure 2. Map showing all journeys recorded in the Bugs Matter app over its lifetime, before (A) and after (B) data cleaning.

The proportions of different land cover types within a 500 m buffer of each journey route were calculated from UKCEH Land Cover Map (LCM) 2020 land parcels data (Morton et al., 2021) by summing the areas of intersecting land cover polygons for each land cover type. Land cover types were consolidated into new categories of arable, modified grassland, natural grassland, broadleaved woodland, coniferous woodland, wetland, coastal and urban land cover types. Including all land cover types in the statistical models would lead to perfect collinearity, so modified grassland was excluded after an inspection of coefficients of a Lasso regression model including the land cover types showed that modified grassland explained the lowest amount of variation in the number of bug splats compared to the other land cover types.

Finally, the proportions of each journey that followed 'primary', 'secondary', 'tertiary' or 'other' road types were extracted for each journey by snapping the journeys to the road network using the Map Matching package in R, which uses the GraphHopper routing engine (Newson et al., 2009). GraphHopper provides the road classification data of the 'snapped' journey in segments and calculates the distance of those segments, which are then aggregated. Journeys mostly followed primary, secondary, and to a lesser extent tertiary roads, with very few on other road types. Only data on the proportion of secondary and tertiary roads were included as variables in the model, as including the proportion of primary roads too would lead to perfect collinearity, due to

the proportions of each road type (primary, secondary, and tertiary) summing to a whole (100%). Collinear independent variables cannot be included in statistical models because it would be impossible to understand how each one individually affects the response variable.

All journeys were assigned to one country, region, and county based on the largest proportion of overlapping journey route. Therefore, our geographically-stratified results are based on journey coverage, rather than where the journey started.

Data cleaning

Prior to the analysis, some steps were taken to clean the data and remove outliers. Some duplicate journeys from 2021 were removed. Overseas journeys or journeys which included ferry crossings were omitted. Journeys recorded outside the June-August survey period were also omitted.

Journeys with GPS errors were removed from the dataset from 2021–2023 (Figure 2). These errors were caused by a drop-out of background tracking due to GPS signal being lost by the device, and they appear as long straight lines between distant locations. All journeys with a 1 km or greater gap between route vertices were omitted. The dataset contained some very short journeys with very high splat counts. Very short journeys of less than 1 mile do not provide a sufficient sampling duration, and the majority are likely the result of GPS errors or incorrect use of the app. Therefore, very short

| | | Journey count | | | | Journey distance (miles) | | | | |
|--|--------|---------------|-------|-------|-------|--------------------------|--------|---------|---------|---------|
| Data cleaning step | 2004 | 2019 | 2021 | 2022 | 2023 | 2004 | 2019 | 2021 | 2022 | 2023 |
| Raw journey count | 17,682 | 626 | 4,431 | 5,488 | 6,667 | 1,115,670 | 10,403 | 179,341 | 202,643 | 201,671 |
| Remove overseas/ferry journeys | 17,652 | 626 | 4,428 | 5,482 | 6,658 | 1,112,524 | 10,403 | 179,144 | 201,185 | 200,273 |
| Remove journeys from outside survey period | 17,649 | 560 | 4,265 | 5,393 | 6,628 | 1,112,318 | 9,469 | 170,532 | 196,551 | 199,023 |
| Remove journeys with GPS errors | 17,649 | 560 | 3,566 | 4,647 | 5,587 | 1,112,318 | 9,469 | 121,725 | 146,267 | 146,216 |
| Remove journeys with length/ distance < 1 mile | 17,541 | 488 | 3,445 | 4,582 | 5,479 | 1,106,480 | 8,094 | 121,704 | 146,245 | 146,163 |
| Remove journeys with duration < 3 minutes | 17,375 | 481 | 3,444 | 4,582 | 5,478 | 1,092,559 | 8,018 | 121,698 | 146,245 | 146,162 |
| Remove journeys with average speed > 70 mph | 17,179 | 480 | 3,442 | 4,581 | 5,477 | 1,072,216 | 8,007 | 121,388 | 146,171 | 145,905 |
| Remove journeys with average speed < 3 mph | 17,133 | 479 | 3,421 | 4,560 | 5,457 | 1,071,375 | 8,004 | 121,175 | 145,846 | 145,514 |
| Remove journeys with splat count > 300 | 17,121 | 479 | 3,421 | 4,560 | 5,454 | 1,069,700 | 8,004 | 121,175 | 145,846 | 145,315 |
| Remove journeys with rain | 14,257 | 479 | 2,918 | 4,128 | 4,688 | 855,531 | 8,004 | 91,571 | 123,321 | 113,839 |

Table 1. The total journey counts and journey distance after each data cleaning step for each survey season.

journeys of less than 1 mile were removed based on both the distance data values and by filtering the line geometry lengths of the journey routes. Similarly, journeys with durations of less than 3 minutes were removed. Journeys with an average speed of over 70 mph or under 3 mph were assumed to result from inaccurate GPS tracking and were omitted. Only journeys that recorded less than 500 insect splats were retained (in 2022 a threshold of 300 insect splats was used), as journeys with more than 500 insect splats have a high probability of containing spurious data. Finally, all journeys during which rainfall occurred were omitted from the dataset due to the high chance that rainfall could dislodge insects from number plates and create inaccurate splat counts.

After data cleaning, 26,470 of 34,894 journeys were retained (Table 1).

Statistical analysis

To begin exploring the data and calculate simple summary statistics, insect splat counts recorded by citizen scientists were converted to a 'splat rate' by dividing the insect splat count by the number plate sampling area and the journey distance, expressed in a unit of 'splats per cm² per mile'. This metric makes the data comparable between journeys and is defined as the number of insects sampled per cm² of the number plate every mile. Differences in insect splat rate between years, countries, regions and counties were visualized in plots. In addition, relationships between other variables, such as how journey distance or the types of vehicles used in the surveys varied between years, were examined visually in boxplots.

We used a zero-inflated negative binomial statistical model to examine the relative effects of survey year, time of day of the journey, calendar date of the journey, average journey temperature, average journey speed, journey distance, vehicle type, elevation, local land cover, and road type, on splat count. The sampling area of the number plate (cm²) multiplied by the journey distance was included in the model as an offset term. Offset terms are included in models of count-derived data to manage counts made over different

| Model | Log.likelihood | AIC | BIC | Likelihood.ratio.test DF.diff. |
|---------|----------------|----------|----------|-----------------------------------|
| Poisson | -146807 | 293663.7 | 293868.3 | 115640.74 , -24 |
| NB | -70944.2 | 141940.3 | 142153.1 | 19123.18 , -24 |
| ZIP | -140235 | 280569.7 | 280978.9 | 95702.42 , -48 |
| ZINB | -70715.8 | 141533.5 | 141950.9 | 9715.31 , -48 |

Table 2. Evaluation metrics from fitting several different models to the data. The ZINB model was found to provide the best fit.

observation periods, which in the case of the Bugs Matter survey was journey distance. This is preferable to using a precalculated splat rate (splats per cm per mile) because by adding the denominator of the ratio (distance) as an offset term, it makes use of the correct probability distributions.

This approach can be thought of as explicitly modelling the expected rate of sampling an insect as distance driven changes. Including offset terms in the model effectively represents the splat rate (splats per cm² per mile), but in a way that is likely to be much more compatible with the data (Coelho et al., 2020).

The response variable (insect count) showed a right-skewed distribution due to the high number of zero and low values, as is typical for count-derived data (Appendix 1). Therefore, several modelling approaches suited to over-dispersed and zero-inflated count data were tested and their performance compared to identify the optimum model to use for this analysis (Yau, Wang and Lee, 2003). A Poisson generalized linear model (Poisson), a negative binomial generalized linear model (NB), a zero-inflated Poisson model (ZIP), and a zeroinflated negative binomial generalized linear model (ZINB) were compared using Log Likelihood, AIC, BIC and Likelihood ratio test statistics (Table 2). Overdispersion was confirmed using a test for overdispersion on a Poisson model (Cameron and Trivedi, 1990), which resulted in a test statistic of c = 15.04 (c = 0 for equidispersion). Therefore, the ZINB model provided the best fit and was subsequently used for the main analysis.

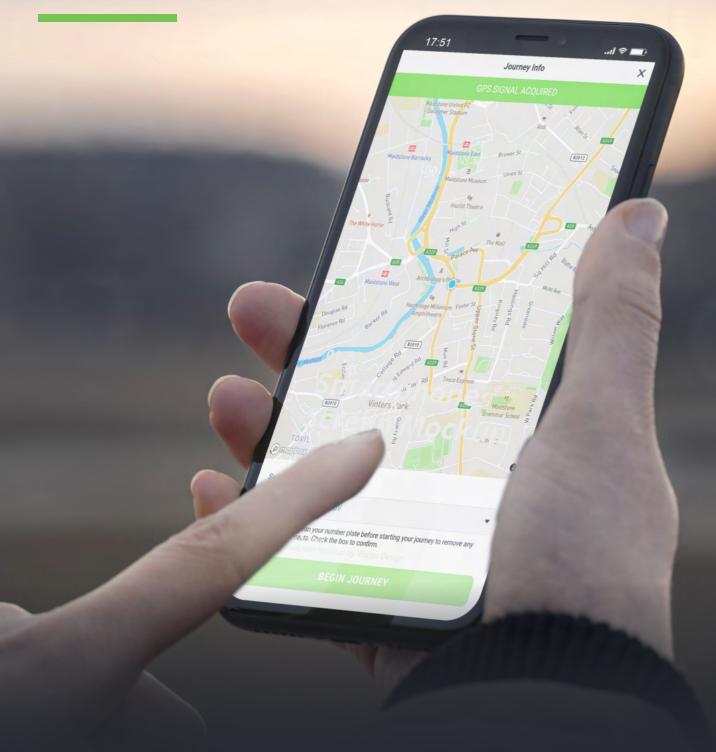
The ZINB model is designed for data that includes excess zeros. The model accepts that there could be additional processes that are determining whether a count is zero or greater than zero and models this explicitly. Whilst the importance of submitting data for zero-count journeys was explained to citizen scientists in all survey years, there may be other unknown processes that result in zero count journeys, for example associated with journey speed, distance or location. The ZINB model has two parts. The first is a binomial model which models the relationship between the independent variables and a binary outcome of zero or greater than zero insect splats. The second part is a negative binomial model to model the count process. The analysis was performed using the MASS package (Venables and Ripley, 2002) and the pscl package (Zeileis, Kleiber and Jackman,

2008) in RStudio (R Core Team, 2022), following established techniques (Sokal and Rolf, 1995; Crawley, 2007).

After running the model, variance inflation factor (VIF) scores were calculated to check for multicollinearity between independent variables. A VIF score greater than 10 indicates high collinearity, when two or more independent variables are correlated with one another. This can cause unreliable predictions and weaken the statistical power of the model. A likelihood ratio test was used to compare a model with only survey year included as an independent variable with the full model containing all survey years to evaluate the contribution of the other independent variables to the model fit. Comparisons of the number of insect splats between 2019, 2021, 2022 and 2023 were achieved by rerunning the models with different reference years.

The results of the ZINB model show the quantity of change in the response variable given a one-unit change in the independent variable, while holding other variables in the model constant. These values are called incidence rate ratios and they can be visualised effectively in a forest plot. Also presented in this report are plots of adjusted predictions of splat count, corrected for number plate sampling area and journey distance, in relation to the survey year and other independent variables. The marginal effects package (Arel-Bundock, 2022) in R was was used. To examine trends at country and regional scales, the analysis was repeated using the data for each country or region separately; adjusted predictions are shown in the same plot. The results of the ZINB zero-inflated model show the change in the odds of a zero-count journey occurring given a one-unit change in the independent variable.

National Results



The number of insect splats recorded in the UK fell by 77.6% between 2004 and 2023, a rate of 43.1% per decade. Between 2022 and 2023, the number of insect splats fell by 37.6%.

National results

In 2023, 19,928 insects were sampled over 4,688 journeys comprising 113,839 miles. In 2022, 8,583 insects were sampled over 4,128 journeys comprising 124,380 miles.

In 2021, 7,839 insects were sampled over 2,918 journeys comprising 91,571 miles. In 2019, 880 insects were sampled over 479 journeys comprising 8,004 miles. In 2004, 190,946 insects were sampled over 14,257 journeys comprising 855,531 miles. (Figure 3, Appendices 2-4).

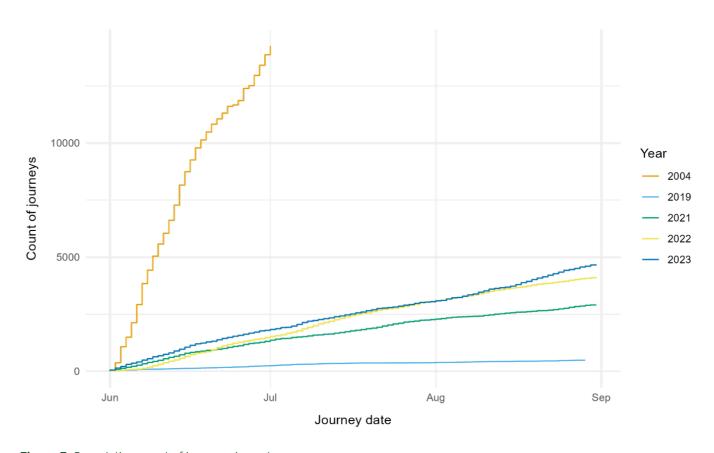


Figure 3. Cumulative count of journeys in each survey year

The results of the zero-inflated negative binomial (ZINB) statistical model show a 77.6% (95% CI [76.4%, 78.8%]) reduction in 2023 (43.1%/decade), a 64.1% (95% CI [62.0%, 66.1%]) reduction in 2022 (35.6%/decade), a 55.5% (95% CI [52.6%, 58.2%]) reduction in 2021 (32.6%/decade), and a 10.8% (95% CI [-6.3%, 25.2%]) reduction in the number of insect splats in the UK in 2019 (7.1%/ decade), compared to 2004 (Figure 4). The ZINB model found the differences were statistically significant (p = < 0.001). The estimate of change in the number of insect splats between 2004 and 2023 (a decrease of 77.6%) has a lower confidence interval of 76.4% and an upper confidence interval of 78.8%, at a 95% confidence level.

This means that if the study was repeated, 95% of the time the estimate of change would be expected to fall between these values. The Likelihood Ratio test statistic was 9,715, and in a model with only year as a predictor it was 6,682. This indicates that the goodness of fit of the model increased substantially (45%) with the addition of the other independent variables. The VIF scores (max VIF = 3.71, mean VIF = 1.61) showed low collinearity between independent variables.

A 37.6% (95% CI [33.5%, 41.4%]) reduction in the number of insect splats was observed between 2022 and 2023 (p < 0.001). A 19.6% (95% CI [13.5%, 25.3%]) reduction was observed between 2021 and 2022, although this reduction was not statistically significant (p = 0.55). The purpose of the ZINB statistical model is to predict splat count while considering all the independent variables such as journey temperature, average speed, and road types. By including journey distance as an offset term, it also corrects the splat count for the journey distance, and effectively models the splat rate (splats per cm per mile). This is best practice, as we explicitly model the splat count as a function of journey distance. However, this means the results are presented as a unit of 'splat counts' (corrected for number plate sampling area and journey distance) rather than the slightly more interpretable 'splat rate' (splats per cm per mile). The predictions of splat count are 7.8 in 2004, 6.6 in 2019, 3.5 in 2021, 2.8 in 2022, and 1.7 in 2023 (Figure 5). The wide confidence interval in 2019 is due to the small sample size from that year. Appendices 8, 10, 12, 14, 15, 17, 19 and 21-28 show the ZINB model predictions of splat count corrected for journey distance in relation to the survey year and the other independent variables.



Image: Silver Y

The results reported here are based on data from only a few points in time with a skewed temporal distribution, and consequently do not constitute a trend. With a low temporal resolution, there is a risk of uncharacteristically high or low insect abundances and splat counts during these sampling years, leading to an apparent change that is in fact unrepresentative of actual insect abundance trends. To accurately estimate change in insect abundance over time, the population needs to be monitored comprehensively at regular intervals over an extended timeframe to reveal the direction and scale of genuine trends.

A statistically significant 37.6% reduction in the number of insects splats in the UK between 2022 and 2023 is a concerning statistic. However, this cannot be considered a reliable estimate of the long-term trend in flying insect abundance. Whilst the journeys appear similar in many respects (speed, distance, time of day, surrounding land cover), the sample size may still be too small to ensure an even and accurate representation of invertebrate populations across the UK for each year.

Assuming the journeys in each year provide similarly representative data, the observed 37.6% decrease between 2022 and 2023 could be the result of both a long-term background rate of decline and short-term reduced insect abundance as a result of the extreme hot and dry climate in the UK in the summer of 2022 and spring of 2023.

Data from future years will help to clarify whether and for how long insect populations are affected by extreme climate events, as well as the long-term rate of change in flying insect abundance.

The results show a reduction in the number of insects sampled on vehicle number plates, consistent with rates of insect abundance decline reported by others (Fox et al., 2013; Goulson, D., 2019; Hallmann et al., 2017). The national rate of change in flying insect abundance that may be inferred by this study, -37.1%/decade, is much higher than the longer term -6.6%/decade rate of annual moth change calculated by Fox et al. (2021). However the figures are similar to more recent trends, such as the change in insect numbers sampled on vehicle windscreens recorded by Møller (2019), on two transects in Denmark between 1997 and 2017 (-40%/decade), and -28.0% decadal change in the biomass of flying insects in malaise traps on nature reserves in Germany between 1990 and 2011 revealed by Hallmann et al. (2017). In contrast, when windscreen splats in Denmark and Spain were compared between 1997 and 2018, there was no significant difference between the two years (Møller, et al. 2021).

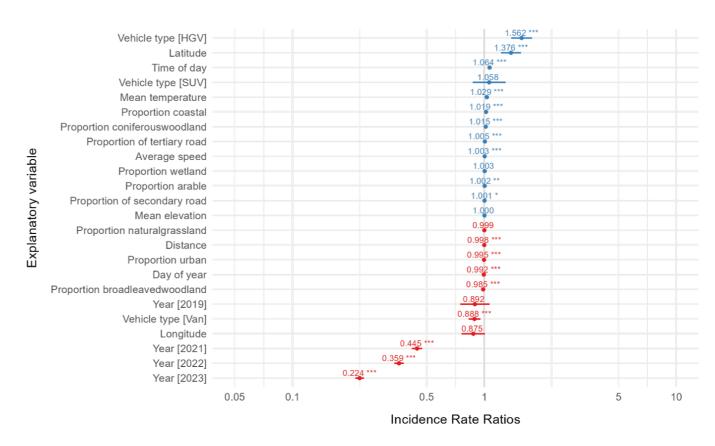


Figure 4. Forest plot of incidence rate ratios from the ZINB negative binomial model of Bugs Matter survey data of insects on car number plates in the UK, showing the quantity of change (a multiplier) in splat rate (splats per mile) given a one–unit change in the independent variable, while holding other variables in the model constant. Significant relationships between splat rate and independent variables are shown by asterisks (* p < 0.05, ** p < 0.01, *** p < 0.001). Vehicle types are compared to the reference category of 'conventional cars'. The reference year is 2004.

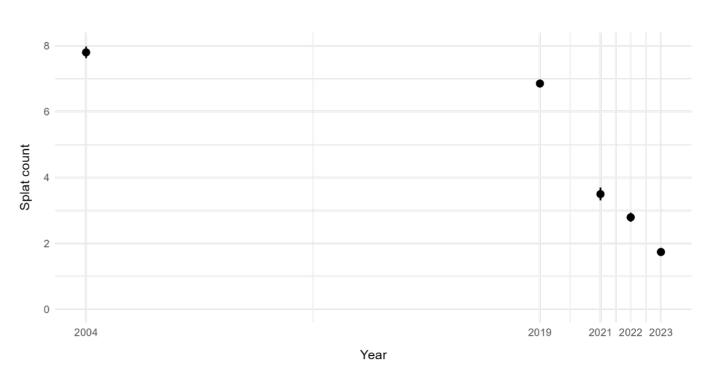


Figure 5. Predictions of splat count (corrected for number plate area and journey distance) by the ZINB model across year values.

The average splat rate was 0.00163 splats per cm per mile in 2004, 0.00074 splats per cm per mile in 2019, 0.00070 splats per cm per mile in 2021, 0.00052 splats per cm per mile in 2022, and 0.00030 splats per cm per mile in 2023 (Figure 6 and Figure 7). As participation in the Bugs Matter survey grows and more citizen scientists record more journeys each year, the mean splat rate will likely stabilize earlier in the survey season (Figure 6). The overall spread of the insect splat rate data is shown in Appendix 5, and the high proportion of journeys with very few bug splats can be clearly seen. The spread of the insect splat rate data for each year is shown in Figure 7, and for each country in Appendix 6. All countries showed decreased mean splat rates from 2022 to 2023. Heat maps show mean splat rates for each year by country (Figure 8), region (Figure 9) and county (Figure 10). It is important to note that simply comparing mean splat rates over time or between countries is not analytically sufficient to draw conclusions, because a range of other climatic and environmental factors, as well as those associated with the sampling methods, are not taken into account. This is one key reason that using statistical modelling for this analysis is important.

Across all years, 24.7% of journeys recorded zero insect splats (Appendix 7). Zero insect splats were sampled in 7.7% of journeys in 2004, 55.1% of journeys in 2019, 42.4% of journeys in 2021, 46.9% of journeys in 2022, and 42.8% of journeys in 2023. For the Bugs Matter survey years, 44.1% of journeys recorded zero insect splats, 17.1% of journeys recorded one insect splat, 10.4% of journeys recorded two insect splats, and 6.9% of journeys recorded three insect splats, whilst 21.5% of journeys recorded four or more insect splats (Figure 11). In 2023, England and Wales recorded the highest numbers of journeys with zero insect splats (Appendix 7).

The proportion of journeys that record zero insect splats in a given year is likely to be related to the abundance or activity of insects, such that low insect abundance or activity will result in more journeys that record zero insect splats. This has implications for the Bugs Matter sampling approach, because at low insect abundances, the probability of insects colliding with number plates decreases. Therefore, the sensitivity of the sampling approach was increased in 2023 in order to detect changes in the abundance of small or reduced insect populations, which may continue to shrink under current rates of biodiversity loss. In 2023, the entire number plate was used to sample insects, which is a standard size in the UK and approximately four times the size of the sampling area than when a splatometer was used in previous survey years (2021 and 2022). Custom number plates, or number plates in other countries which have different dimensions, can still be used, but the dimensions of the number plate must be submitted via the app.

In 2004, the primary method of engagement with citizen scientists was a printed leaflet. The increased prevalence of social media and digital communications in 2019-2023 made it possible for engagement with citizen scientists to be more frequent, targeted and specific. This may have resulted in more effective communication of the importance of submitting journeys that record zero insect splats, and therefore greater frequency of their occurrence in the data. Citizen scientists may also forget to clean their number plate prior to conducting a survey, although the risk of this is now low as the Bugs Matter app requires a checkbox confirmation that the number plate has been cleaned prior to undertaking a journey.

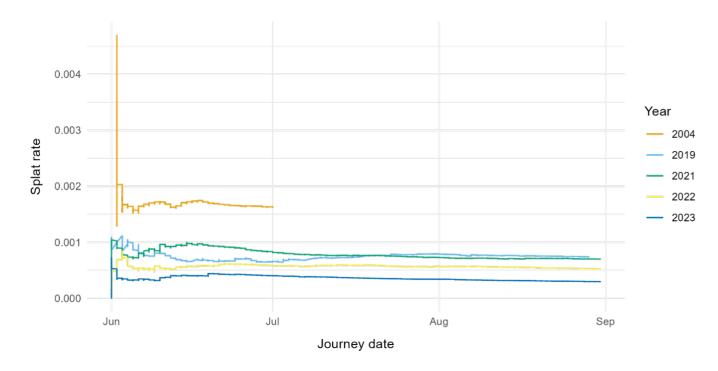


Figure 6. Cumulative mean of insect splat rate in each survey year

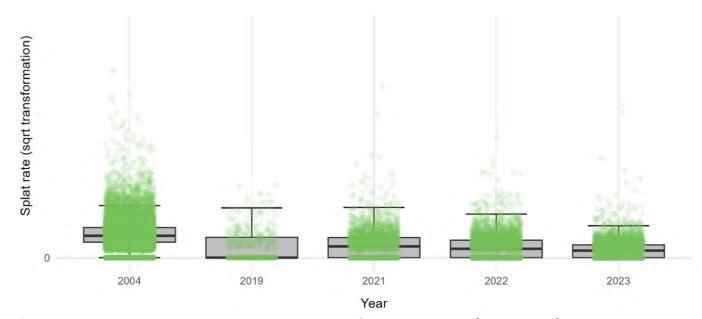


Figure 7. Boxplot with jittered data points showing the spread of the insect splat rate (splats per mile) data. The boxes indicate the interquartile range (central 50% of the data) either side of the median splat rate, which is shown by the horizontal line inside the box. The vertical lines extend out by 1.5 times the interguartile range, and the data points themselves are 'horizontally jittered' so they do not overlap to aid visualization. The thick green line at y = 0 for each year represent the data points for journeys where zero bug splats were recorded.

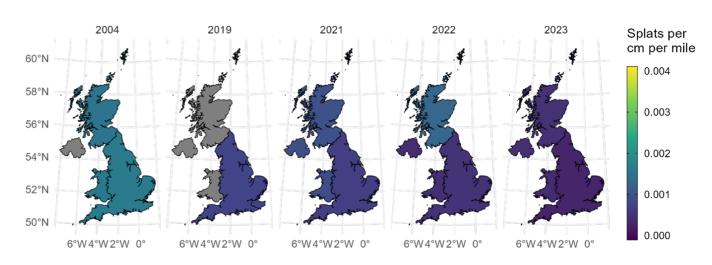


Figure 8. Heat map of mean splat rate for each country across survey years

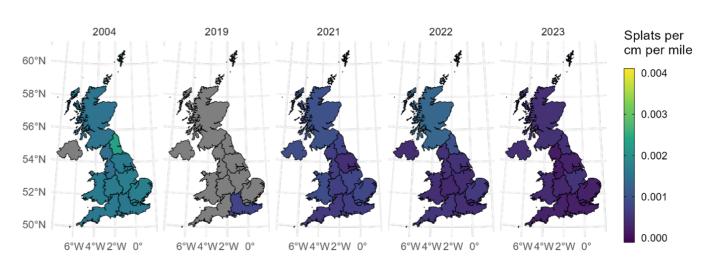


Figure 9. Heat map of mean splat rate for each region across survey years

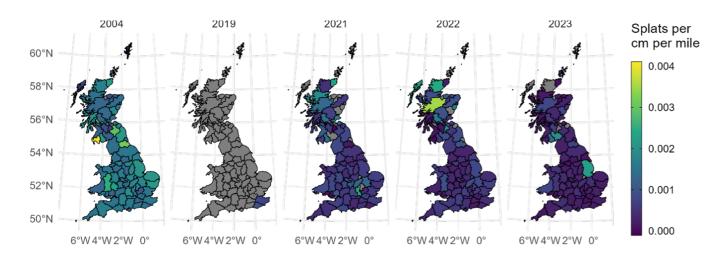


Figure 10. Heat map of mean splat rate for each county across survey years

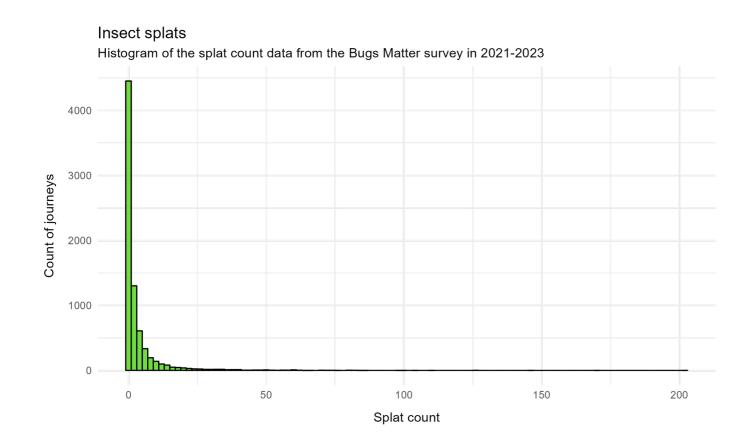


Figure 11. Histogram of the splat count data from the Bugs Matter survey in 2021–2023

Independent variables

Vehicle type

The majority of journeys (94%) were undertaken in a car with the remainder being undertaken in HGVs, SUVs, or vans (Table 3). Very few HGV drivers have recorded journeys in

the Bugs Matter app, indicating a need to encourage greater participation from this important group of road users that contributed significantly during the 2004 survey led by the RSPB.

| Vehicle type | 2004 | 2019 | 2021 | 2022 | 2023 |
|--------------|--------|------|-------|-------|-------|
| Car | 13,310 | 278 | 2,794 | 3,987 | 4,508 |
| HGV | 256 | 66 | 2 | 0 | 0 |
| SUV | 31 | 135 | 16 | 9 | 59 |
| Van | 660 | 0 | 106 | 131 | 120 |

Table 3. The number of journeys undertaken in each vehicle type in each survey year.

The ZINB model results show that compared to conventional cars, splat count was 56% higher for HGVs and 11% lower for vans, but splat count for SUVs did not differ significantly from cars (Appendix 8). Vehicle type is an important variable to include in the analysis, as the differing aerodynamics of different vehicle types could affect the number of insects that are sampled. This hypothesis has however been challenged by an automotive aerodynamics expert with 40+ years of wind-tunnel experience (Vice President for Strategic Fluid Design and Simulation at Altair), who suggested that, "not only has it [license plate aerodynamics] really not changed, it is also placed near the stagnation point on the vehicle or the location the air naturally comes to a stop at the leading edge. In other words, the plates are at the tip of the blunt nose of the aerodynamic teardrop shape, so their experience should be consistent regardless of what happens elsewhere" (pers. comm. Andrew Van Dam, in relation to Van Dam, 2022). If this is the case, then the type of vehicle used to sample insects may have less of an influence on the way insects are sampled than previously assumed.

Journey distance

The average journey distance in 2004 was 60 miles, in 2019 it was 16.7 miles, in 2021 it was 31.4 miles, in 2022 it was 30.1 miles, and in 2023 it was 24.3 miles (Appendix 9). Short journeys in 2019 would be expected due to the survey being focused on Kent. Splat count increased steeply with journey distance, up to a distance of between 20–50 miles, at which point it started to decrease by 0.2% with each mile of journey distance (Appendix 10). This indicates that very short journeys sample zero or very few bugs, presumably because a minimum sampling duration or distance is required before bugs are encountered and sampled.

Conversely, longer journeys sample fewer bugs than expected, and two main factors could be leading to this result. Firstly, longer journeys are more likely to follow motorways, and the results show that fewer bugs are sampled on motorways. Secondly, on longer journeys, sampled insects could be blown off the number plate, especially if the average journey speed is high. The results of the ZINB zero-inflated model showed that the chance of a zero-count journey occurring decreased by 3% with each one-mile increase in journey distance. This shows that despite the splat count decreasing on longer journeys, there is a greater chance that at least one insect will be sampled.

Average speed

The mean average journey speed in 2004 was 37.4 mph, in 2019 it was 23.5 mph, in 2021 it was 28.8 mph, in 2022 it was 29.7 mph, and in 2023 it was 27.8 mph (Appendix 11). Splat count increased by 0.3% with each 1 mph increase in average journey speed (Appendix 12). The average speed of a journey is an uninformative variable, as the number of splats will be greatly affected by the prevailing vehicle speed along different sections of the journey. As it is not possible to know at what point along a journey an insect is sampled, it is not possible to investigate in a meaningful way whether or how speed affects insect sampling.

Road type

Across all survey years, the mean proportion of journeys conducted on primary roads was 59.1%, the mean proportion of journeys conducted on secondary roads was 35.1% and the mean proportion of journeys conducted on tertiary roads was 5.8%. These proportions differed most notably between 2004 and the recent surveys in 2021-2023 (Appendix 13). For each one percent increase in the proportion of journey route that was conducted on secondary roads compared to primary roads, splat count increased by 0.1% (Appendix 14). For each one percent increase in the proportion of journey route that was on tertiary roads, splat rate increased by 0.5% (Appendix 15). This shows that splat rate decreased as the proportion of primary roads in a journey route increased, as the proportions of each road type sum to a whole (100%). As the proportion of tertiary road, and to a lesser extent secondary road, in a journey route increased, the confidence intervals become wider (Appendix 14 and Appendix 15). Therefore, journeys that mostly followed secondary and tertiary roads showed high variation in the number of insects sampled. This may be related to high variation in insect abundance or activity along these roads, or this result may be due to differing speeds at which vehicles travel along these road types. For instance, some tertiary roads may have a speed limit of 20 mph while others may have a speed limit of 60 mph.

Time of day

The average time of day of journeys in 2004 was 13:42, in 2019 it was 12:41, in 2021 it was 13:33, in 2022 it was 13:17, and in 2023 it was 13:06 (Appendix 16). On average, splat count increased by 6% with each hour of the day that passed (97.9% of journeys occurred between 05:00-21:00) (Appendix 17).

Mean temperature

The average journey temperature in 2004 was 15.9°C, in 2019 it was 16.6°C, in 2021 it was 16.5°C, in 2022 it was 17.3°C, and in 2023 it was 16.8°C. The 2004 survey was limited to the month of June, which could partly explain the difference in temperatures. The high average for 2022 reflects the warm weather during that year (Appendix 18). Insects are more active at higher ambient air temperatures which occur later in the day (Mellanby, 1939). Indeed, splat count increased by 3% with each one degree increase in mean daily temperature (Appendix 19). Insects may also be attracted to the light emitted from vehicle headlights and road lighting leading to greater numbers of insects sampled at dusk.

Calendar date

The average calendar date of journeys in 2004 was 165, in 2019 it was 186, in 2021 it was 190, in 2022 it was 194, and in 2023 it was 196 (Figure 3 and Appendix 20). Splat count decreased by 0.8% with each day that passed during the survey season (Appendix 21), and this relationship was strongest in 2004 and 2019. Nonetheless, on average, two fewer insects were sampled at the end of the 2021 and 2022 survey seasons than at the beginning. In 2024, the survey season will start in May and continue until the end of September to provide a more complete picture of insect abundance, especially as many species have flight periods in

Land cover

One aim for the 2023 analysis was to include information about the land cover types surrounding journey routes in the statistical model. The spread of the land cover type data was fairly consistent across all survey years (Figure 12).

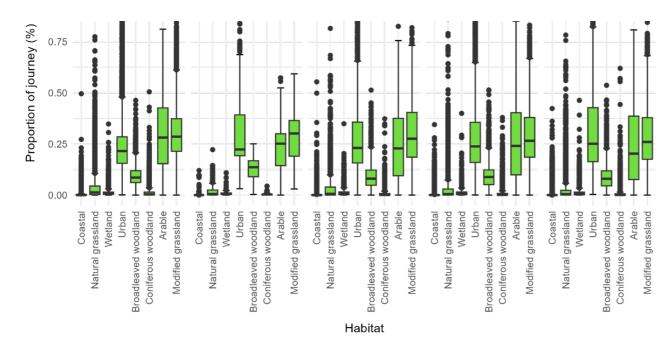


Figure 12. Grouped boxplot showing the spread of the habitat data (the proportions (%) of habitat types along each journey). The boxes indicate the interquartile range (central 50% of the data) either side of the median proportion of journey, which is shown by the horizontal line inside the box. The vertical lines extend out by 1.5 times the interquartile range.

The results show that splat count increased by 1.9% for each 1% increase in coastal land cover surrounding the journey route (Appendix 22). Several factors including amount, type and quality of natural and semi-natural habitats, continuity of habitat over time, and climate may lead to greater insect abundance in coastal areas.

Splat count increased by 1.5% for each 1% increase in coniferous woodland land cover surrounding the journey route (Appendix 23). One reason for this could be that midges and aphids are small flying insects which are well-sampled using the Bugs Matter method, and can be very abundant in plantation conifer forest (Pedley et al., 2014). It should also be considered that, as the roads will be going through or alongside the wooded habitats, the splat rate could be a result of edge-effects - with conifer woodland edges often supporting high species diversity and being rich in invertebrate biomass (Mitchell & Kirby, 1989). Or, alternatively, that the road and verges provides a route through the coniferous woodland, with insects being channeled along the road corridor.

Splat count increased by 0.2% for each 1% increase in arable land cover surrounding the journey route (Appendix 24). Splat count decreased by 0.5% for each 1% increase in urban land cover surrounding the journey route (Appendix 25). Our results show a very slight increase (0.2% for each 1% increase in arable land cover) in insect splats with increasing arable land cover. Using the current dataset and analytical methods it is not possible to provide a comprehensive explanation for this relationship.

However, it may be in part due to the proportional negative relationship between urban and arable land cover types, such that as one increases the other decreases (Pearson r = -0.46). The number of splats increases with increasing coverage of arable land and decreases with increasing coverage of urban land. Furthermore, shorter slower journeys in urban areas splat fewer bugs, as can be seen from low splat counts in London compared to other English regions. And conversely, longer and faster journeys splat more bugs and have higher proportions of surrounding arable land cover. Indeed, we find there is more arable land around journeys that follow primary roads. Longer journeys also encounter more different types of landuse and habitats – so have a wider range of habitats to "sample" from - which may also increase opportunities for splats. This broad scale rural-urban pattern has also been detected in similar studies (Svenningsen et al., 2020).

Splat count decreased by 1.5% for each 1% increase in broadleaved woodland cover surrounding the journey route (Appendix 26). Causation behind this result is unclear, although it could be linked to the impacts of climate-induced shifting woodland phenology on insect populations (Uphus et al., 2023). More data over multiple years is required to better understand the relationships between surrounding habitats and splat rates.

Splat count did not change significantly with changes in wetland (Appendix 27) and semi-natural grassland (Appendix 28) land cover types.



Image: Brimstone butterfly

The high rate of localised extinctions of specialist species, whose habitats are most fragmented, and their replacement with generalist species that are less efficient at converting resources into insect biomass, is thought to be one of the drivers behind widespread reductions in insect biomass (Vasiliev and Greenwood, 2021).

Habitat fragmentation may be affecting the evolution of flying insects. When habitats become increasingly fragmented, dispersal becomes evolutionarily disadvantageous for a species, and the frequency and distances that insects fly decreases (Hill et al., 1999). Eventually the high probability of failure outweighs the benefits of successful dispersal, and so wings shrink, wing muscles atrophy, dispersal reduces (Davies and Saccheri, 2013) and, we assume, long-distance dispersal eventually ceases. The relationship between increasing habitat fragmentation, increasing temperature and reduced wing functionality has been shown in most groups of butterflies including swallowtails (Dempster et al., 1976; Dempster, 1991), skippers (Fenberg et al., 2016), blues (Dempster, 1991; Wilson et al., 2019), and a white and nymphalid (Bowden et al., 2015).

Smaller insect species may be more affected as the cost of flying between fragmented habitats is greater. Shrinking wing size has been observed in small insects such as Spanish wasps (Polidori et al., 2019), German craneflies (Jourdan et al., 2019), and Bornean moths (Wu et al., 2019).

The reductions in the occurrence of insects in traps, on windscreens, and on number plates may be caused, at least in part, by reduced insect activity, flight and dispersal as a response to combinations of the effects of climate change, habitat fragmentation and pesticide-contaminated landscapes that reduce the occurrence of genes associated with long-distance flight. Reduced flying insect activity would itself result in reduced pollination rates of plants at a distance from quality habitats, reduced prey availability for flying insectivores, reduced ability of species to respond to climate change, and reduced ability to recolonize after a local extinction event, and may be associated with declines in insect abundance at a landscape scale.

Insect population dynamics and activity are influenced by a range of natural factors that vary inter-annually and across spatial and temporal scales. These factors add noise to longer-term trends in insect abundance, but can be partly controlled for by measuring these factors and including such measurements in statistical models. For instance, the inclusion of mean temperature, land cover type, time of day of the journey, and calendar date of the journey helps to control for inter-annual and spatial differences in temperature, spatial variation in land, vegetation or habitat cover, seasonal variation in insect abundance or activity, and variation in insect abundance throughout the day respectively, all of which may naturally influence insect abundance and activity.

Whilst the aim of the Bugs Matter survey is to quantify long-term trends in insect abundance, the sampling approach can also be considered to measure the activity-density of insects. Thus, it is conceivable that insects are just as abundant between years but are less active. This may explain the results of this survey at shorter timescales, where insect numbers increase with temperature and time of day, not because there are more insects, but because the

same number of insects are active in a different way. How the activity-density of insects interacts with roads is also unknown. Insect sampling was restricted to transects along the road network, and therefore the spatial coverage of the survey is inherently limited. It could be increased by including other modes of transport such as trains, light aircraft in subsequent survey years.

In addition to natural factors, properties of the insect sampling approach also add noise to longer-term trends in insect abundance, which again, can be partly controlled for. The vehicle type, vehicle speed, journey distance, and types of roads driven all create sampling bias. By measuring these variables and including them in the models, these effects can be controlled for to obtain more accurate estimates of change in the number of insects sampled between survey years. However, there are other important variables that are not yet included in the models. For example, environmental variables with demonstrated lethal and sub-lethal influence on insect population ecology such as pesticide use (Møller et al. 2021a), pollution, and climate change could explain a further proportion of the unexplained variation in the data. Our model also lacks data on several other factors that influence insect abundance and activity, such as variation in habitat management, roadside verge management, disease and predation of insects, weather conditions including humidity or wind, and natural variation in insect lifecycles or



The country which recorded the highest number of journeys via the Bugs Matter app was England, with 2,435 journeys in 2021, 3,296 journeys in 2022, and 3,900 journeys in 2023. The second highest number of journeys was recorded in Wales, followed by Scotland, and finally Northern Ireland (Table 4, Figure 13, Appendix 29). In previous years, on average the longest journeys were conducted in Scotland, however in 2023 journeys were, on average, longer in Northern Ireland (Table 4).

In England, compared to 2004, the number of insect splats recorded on vehicle number plates decreased by 37.9% in 2019, 60.0% in 2021, 69.4% in 2022, and 82.6% in 2023. In Scotland, compared to 2004, the number of insect splats decreased by 48.9% in 2021, 36.3% in 2022, and 76.1% in 2023. In Wales, compared to 2004, the number of insect splats decreased by 47.9% in 2021, 71.3% in 2022, and 78.8% in 2023. The number of insect splats decreased by 21.1% in England, 24.3% in Northern Ireland (not statistically significant) and 45% in Wales, but increased by 24.7% in Scotland (not statistically significant), between 2021 and 2022.

The number of insect splats decreased by 44.8% in England, 35.7% in Northern Ireland, 62.4% in Scotland, and 26.1% in Wales, between 2022 and 2023 (Table 5). Predicted splat counts are shown in Figure 14.

Latitudinal variation in insect declines has been described in previous studies. Annual counts of moths caught in Rothamsted moth traps revealed declining trends in moth abundance in traps in northern and southern Britain between 1968 and 2017 (Fox et al., 2021). However, the reduction was much greater in southern Britain (-39%), almost twice that of northern Britain (-22%). Rothamsted moth trap data is a proxy for moth abundance. The surveyed time period of the decline was much longer than that of the Bugs Matter survey, yet a similar observed pattern of greater rates of loss in the south reinforces concerns that the factors responsible for recent insect declines are acting more strongly in England and/or southern Britain.

| | 2021 | | | | 2022 | | | 2023 | | |
|------------------|------------------|---|--|------------------|---|--|------------------|---|--|--|
| Country | Journey count | Total journey distance (miles) | Mean journey distance (miles) | Journey count | Total journey distance (miles) | Mean journey distance (miles) | Journey count | Total journey distance (miles) | Mean journey distance (miles) | |
| England | 2,435 | 76,547 | 31 | 3,314 | 102,883 | 31 | 3,899 | 95,177 | 24 | |
| Scotland | 165 | 7,119 | 43 | 237 | 8,306 | 35 | 308 | 8,980 | 29 | |
| Wales | 286 | 6,876 | 24 | 497 | 10,670 | 22 | 408 | 7,339 | 18 | |
| Northern Ireland | 29 | 1,018 | 35 | 80 | 2,431 | 30 | 73 | 2,343 | 32 | |

Table 4. Journey summary statistics for each country in the Bugs Matter survey years.

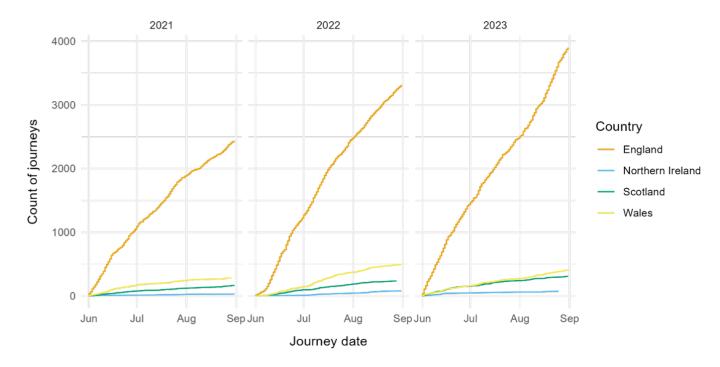


Figure 13. Cumulative count of journeys for each country in each Bugs Matter survey year.

| | | | | | | | | England | Northern Ireland |
|--|------|-------------------------------|-------------------------------|-------------------------------|--|-------------------------------|-------------------------------|-------------------------------|----------------------------|
| | | 2004 | | | | | | Scotland | Wales |
| | 2019 | -37.9*** CI[- 28.5, -45.9] | | 2019 | | | | | |
| | 2017 | | | | | | | | |
| | 2004 | -60.0*** CI[- 57.5, -62.3] | | -35.6*** CI[- 25.4, -44.4] | | 2004 | | | |
| | 2021 | -48.9*** CI[- 36, -59.1] | -47.9*** CI[- 36.1, -57.4] | | | 2021 | | | |
| | 2022 | -68.4*** CI[- 66.6, -70.1] | | -49.2*** CI[- 41.3, -56.0] | | -21.1*** CI[- 15.3, -26.5] | -24.3 CI[-57.5, +34.2] | | 200 |
| | 2022 | -36.3*** CI[- 21.3, -48.3] | -71.3*** CI[- 64.8, -76.6] | | | +24.7 CI[-2.7, +59.5] | -45*** CI[- 32.2, -55.4] | 20 |)22 |
| | 2023 | -82.6*** CI[- 81.6, -83.4] | | -71.9*** CI[- 67.7, -75.7] | | -56.4*** CI[- 53.4, -59.2] | -51.4** CI[-19.1, -71.1 | -44.8*** CI[- 41.3, -48.1] | -35.7* CI[-58.7, +0.4] |
| | | -76.1*** CI[- 71.6, -79.8] | -78.8*** CI[- 74.4, -82.4] | | | -53.1*** CI[- 40.8, -63.0] | -59.3*** CI[- 49.5, -67.2] | -62.4*** CI[- 53.6, -69.6] | -26.1** CI[-9.6, -39.5] |

Table 5. The matrix of estimates of change (%) in the number of insect splats from the ZINB models for each country, with lower and upper 95% confident intervals. Significant results are shown by asterisks (* p < 0.05, ** p < 0.01, *** p < 0.001).

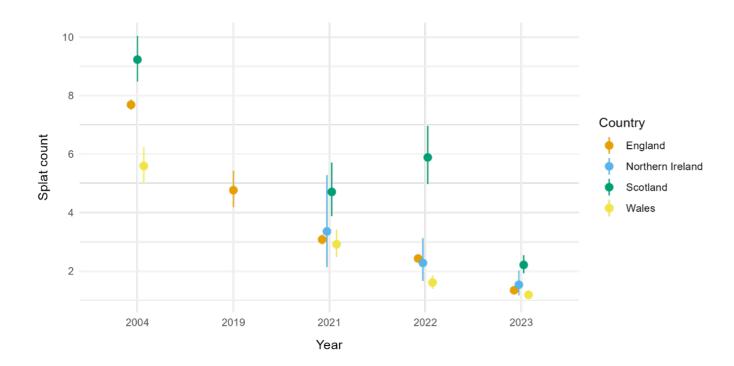


Figure 14. Predictions of splat count (corrected for distance) from the country ZINB models across year values.

Regional Results

England

The region in England with the highest number of journeys recorded via the Bugs Matter app was the South East, with 693 in 2021, 968 in 2022, and 1,144 in 2023, whilst London recorded the lowest number of journeys (Table 6, Figure 15, Appendix 30). The East Midlands saw the highest increase in journeys between 2022 and 2023, with an additional 1,602 miles recorded over 213 additional journeys. The East of England and the North West recorded fewer journeys in 2023 than in 2022.

London recorded the greatest decrease in the number of insect splats between 2004 and 2023 of 91.2%, followed by the South East of 86.5%, and the North West of 85.2%. The lowest reduction between 2004 and 2023 was in the East Midlands (74%).

Only the East Midlands recorded an increase in the number of insect splats between 2022 and 2023 (5.7%), but this difference was not statistically significant. There was also no statistically significant difference in the numbers of insect splats between 2022 and 2023 in the West Midlands and London (Table 7). Predicted splat counts are shown in Figure

| | 2021 | | 2 | 022 | 2023 | |
|-----------------------------|------------------|--------------------------------------|------------------|--------------------------------------|------------------|--------------------------------------|
| Region | Journey count | Total journey distance (miles) | Journey count | Total journey distance (miles) | Journey count | Total journey distance (miles) |
| East Midlands | 217 | 7,506 | 218 | 8,041 | 431 | 9,643 |
| East of England | 483 | 13,048 | 850 | 26,291 | 833 | 18,421 |
| London | 28 | 492 | 43 | 510 | 62 | 784 |
| North East | 23 | 1,061 | 82 | 2,300 | 105 | 2,712 |
| North West | 175 | 7,830 | 225 | 7,061 | 186 | 4,673 |
| South East | 693 | 19,078 | 968 | 28,262 | 1,144 | 27,423 |
| South West | 460 | 14,107 | 392 | 14,658 | 479 | 14,876 |
| West Midlands | 177 | 6,992 | 261 | 8,603 | 286 | 9,257 |
| Yorkshire and The Humber | 179 | 6,432 | 275 | 7,156 | 373 | 7,389 |

Table 6. Journey summary statistics for each region in England in the Bugs Matter survey years.

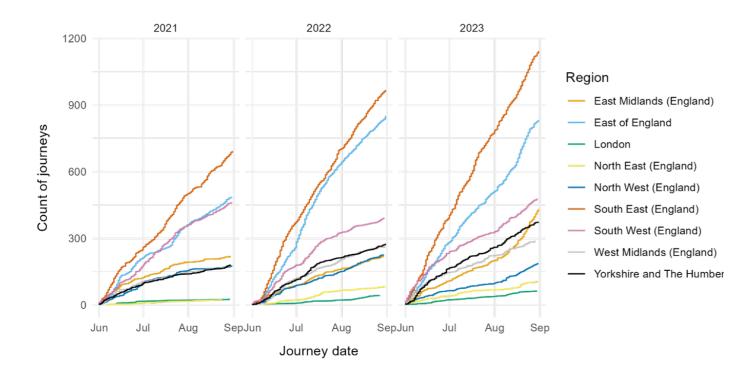


Figure 15. Cumulative count of journeys in each region in England in each Bugs Matter survey year.

| Estimates | Region | 2004-2021 | 2004-2022 | 2004-2023 | 2021-2022 | 2022-2023 |
|-----------|-----------------------------|-----------|-----------|-----------|-----------|-----------|
| Estimate | East Midlands (England) | 59.5 | 75.4 | 74 | 39.4 | -5.7 |
| CI 2.5% | East Midlands (England) | 66.4 | 80 | 78.1 | 52.7 | 15 |
| CI 97.5% | East Midlands (England) | 50.9 | 69.7 | 69.1 | 22.4 | -31.5 |
| p value | East Midlands (England) | <0.001 | <0.001 | <0.001 | <0.001 | 0.618 |
| Estimate | East of England | 56.5 | 63.3 | 82.1 | 15.8 | 51.3 |
| CI 2.5% | East of England | 62 | 67.2 | 84.1 | 27.4 | 57 |
| CI 97.5% | East of England | 50 | 59 | 80 | 2.3 | 44.9 |
| p value | East of England | <0.001 | <0.001 | <0.001 | 0.021 | <0.001 |
| Estimate | London | 34 | 85.9 | 91.2 | 78.6 | 38.1 |
| CI 2.5% | London | 74.1 | 95.3 | 96.4 | 92.9 | 74.7 |
| CI 97.5% | London | -72.5 | 57.9 | 78.9 | 37.5 | -52.7 |
| p value | London | 0.372 | <0.001 | <0.001 | 0.004 | 0.296 |
| Estimate | North East (England) | 54.4 | 57.8 | 82.3 | 7.5 | 58.1 |
| CI 2.5% | North East (England) | 74 | 70.3 | 87.1 | 48.7 | 71 |
| CI 97.5% | North East (England) | 18.1 | 39.7 | 75.5 | -63 | 39.4 |
| p value | North East (England) | 0.005 | <0.001 | <0.001 | 0.788 | <0.001 |
| Estimate | North West (England) | 51.2 | 71.2 | 85.2 | 41.1 | 48.7 |
| CI 2.5% | North West (England) | 60.3 | 77.3 | 88.2 | 55.1 | 60.4 |
| CI 97.5% | North West (England) | 39.7 | 63.5 | 81.4 | 22.7 | 33.5 |
| p value | North West (England) | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 |
| Estimate | South East (England) | 65.3 | 73.8 | 86.5 | 24.5 | 48.3 |
| CI 2.5% | South East (England) | 69.3 | 76.5 | 87.7 | 33.9 | 53.9 |
| CI 97.5% | South East (England) | 60.9 | 70.8 | 85.1 | 13.7 | 42.1 |
| p value | South East (England) | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 |
| Estimate | South West (England) | 62.6 | 65.2 | 84.5 | 6.9 | 55.5 |
| CI 2.5% | South West (England) | 67.7 | 69.9 | 86.4 | 22 | 62.2 |
| CI 97.5% | South West (England) | 56.7 | 59.8 | 82.4 | -11 | 47.6 |
| p value | South West (England) | <0.001 | <0.001 | <0.001 | 0.417 | <0.001 |
| Estimate | West Midlands (England) | 52.5 | 74.2 | 77.9 | 45.7 | 14.4 |
| CI 2.5% | West Midlands (England) | 61.3 | 78.9 | 81.4 | 58 | 31.5 |
| CI 97.5% | West Midlands (England) | 41.5 | 68.4 | 73.7 | 29.8 | -7.1 |
| p value | West Midlands (England) | <0.001 | <0.001 | <0.001 | <0.001 | 0.176 |
| Estimate | Yorkshire and The Humber | 68.7 | 66 | 81.4 | -8.9 | 45.5 |
| CI 2.5% | Yorkshire and The Humber | 75 | 72.5 | 84.6 | 16.9 | 56.4 |
| CI 97.5% | Yorkshire and The Humber | 60.7 | 57.8 | 77.6 | -42.7 | 31.8 |
| p value | Yorkshire and The Humber | <0.001 | <0.001 | <0.001 | 0.544 | <0.001 |

Table 7. Estimates of change (%) in the number of insect splats from the ZINB models for each region, with lower and upper 95% confident intervals and p values.

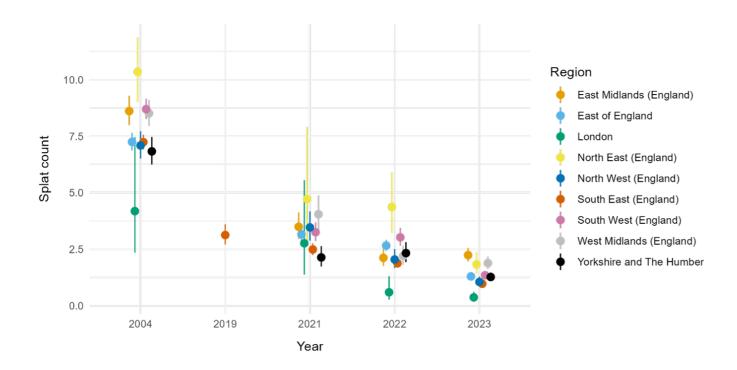


Figure 16. Predictions of splat count (corrected for distance) from the ZINB model for each region in England across year values.

County Results

England

The number of journeys recorded in each UK county via the Bugs Matter app are shown in Table 8. In 2023, the most journeys were recorded in Kent (385), followed by Norfolk (364), and then North Yorkshire (170). Over the lifetime of the Bugs Matter app, the most journeys have been recorded in the counties of Kent (1292), Essex (670) and Norfolk (579). A greater number of counties (14) recorded more than 100 journeys compared to previous years (2022: 9, 2021: 6), indicating a more widespread involvement in Bugs Matter.

Norfolk saw the highest increase in the number of journeys between 2022 and 2023 (198 more journeys in 2023 compared to 2022), followed by Northamptonshire (115 more journeys). Journeys are yet to be recorded in three counties (Clackmannan, Midlothian and Shetland). Whilst journeys of all distances are valuable, short journeys can help to build a better picture of insect population trends at the county scale, especially if they cover a variety of land cover types.

| County | 2004 | 2019 | 2021 | 2022 | 2023 | Total |
|--------------------|------|------|------|------|------|-------|
| Aberdeenshire | 65 | 0 | 6 | 39 | 14 | 59 |
| Angus | 15 | 0 | 0 | 0 | 16 | 16 |
| Argyll and Bute | 22 | 0 | 14 | 8 | 9 | 31 |
| Ayrshire and Arran | 31 | 0 | 7 | 4 | 10 | 21 |
| Banffshire | 2 | 0 | 0 | 7 | 1 | 8 |
| Bedfordshire | 177 | 0 | 11 | 35 | 32 | 78 |
| Berkshire | 324 | 0 | 19 | 33 | 57 | 109 |
| Berwickshire | 11 | 0 | 3 | 0 | 0 | 3 |
| Bristol | 1 | 0 | 7 | 5 | 4 | 16 |
| Buckinghamshire | 143 | 0 | 20 | 45 | 110 | 175 |
| Caithness | 10 | 0 | 1 | 1 | 2 | 4 |
| Cambridgeshire | 507 | 0 | 68 | 186 | 92 | 346 |
| Cheshire | 245 | 0 | 27 | 59 | 52 | 138 |
| City of Aberdeen | 6 | 0 | 0 | 3 | 8 | 11 |
| City of Dundee | 2 | 0 | 0 | 3 | 0 | 3 |
| City of Edinburgh | 34 | 0 | 0 | 3 | 9 | 12 |
| City of Glasgow | 5 | 0 | 10 | 16 | 8 | 34 |
| Clackmannan | 18 | 0 | 0 | 0 | 0 | 0 |
| Clwyd | 169 | 0 | 28 | 34 | 43 | 105 |
| Cornwall | 168 | 0 | 42 | 66 | 92 | 200 |
| Cumbria | 268 | 0 | 74 | 33 | 56 | 163 |
| Derbyshire | 188 | 0 | 47 | 73 | 72 | 192 |
| Devon | 532 | 0 | 99 | 72 | 165 | 336 |
| Dorset | 302 | 0 | 22 | 33 | 25 | 80 |
| Dumfries | 16 | 0 | 0 | 3 | 2 | 5 |
| Dunbartonshire | 26 | 0 | 4 | 3 | 4 | 11 |

| County | 2004 | 2019 | 2021 | 2022 | 2023 | Total |
|-------------------------------------|-------|------|------|------|------|-------|
| Durham | 120 | 0 | 7 | 47 | 47 | 101 |
| Dyfed | 150 | 0 | 38 | 31 | 41 | 110 |
| East Lothian | 33 | 0 | 5 | 2 | 7 | 14 |
| East Riding of Yorkshire | 162 | 0 | 11 | 35 | 42 | 88 |
| East Sussex | 171 | 1 | 36 | 36 | 90 | 162 |
| Essex | 565 | 0 | 236 | 275 | 159 | 670 |
| Fife | 43 | 0 | 8 | 4 | 12 | 24 |
| Gloucestershire | 409 | 0 | 155 | 68 | 58 | 281 |
| Greater London | 83 | 0 | 30 | 47 | 63 | 140 |
| Greater Manchester | 79 | 0 | 49 | 79 | 32 | 160 |
| Gwent | 111 | 0 | 170 | 348 | 60 | 578 |
| Gwynedd | 99 | 0 | 8 | 10 | 18 | 36 |
| Hampshire | 1,055 | 0 | 97 | 117 | 166 | 380 |
| Herefordshire | 71 | 0 | 28 | 36 | 30 | 94 |
| Hertfordshire | 388 | 0 | 37 | 73 | 73 | 183 |
| Inverness | 29 | 0 | 13 | 36 | 32 | 81 |
| Isle of Wight | 23 | 0 | 3 | 4 | 17 | 24 |
| Kent | 630 | 478 | 355 | 552 | 385 | 1,292 |
| Kincardineshire | 23 | 0 | 0 | 5 | 21 | 26 |
| Lanarkshire | 70 | 0 | 10 | 7 | 12 | 29 |
| Lancashire | 256 | 0 | 25 | 36 | 22 | 83 |
| Leicestershire | 264 | 0 | 67 | 54 | 103 | 224 |
| Lincolnshire | 269 | 0 | 27 | 59 | 39 | 125 |
| Merseyside | 46 | 0 | 7 | 17 | 26 | 50 |
| Mid Glamorgan | 26 | 0 | 6 | 13 | 37 | 56 |
| Midlothian | 4 | 0 | 0 | 0 | 0 | 0 |
| Moray | 17 | 0 | 0 | 5 | 6 | 11 |
| Norfolk | 534 | 0 | 49 | 166 | 364 | 579 |
| North Yorkshire | 484 | 0 | 72 | 104 | 170 | 346 |
| Northamptonshire | 289 | 0 | 58 | 23 | 138 | 219 |
| Northumberland | 138 | 0 | 13 | 33 | 32 | 78 |
| Nottinghamshire | 168 | 0 | 18 | 15 | 82 | 115 |
| Orkney | 4 | 0 | 0 | 0 | 4 | 4 |
| Oxfordshire | 414 | 0 | 111 | 95 | 114 | 320 |
| Perth and Kinross | 171 | 0 | 14 | 19 | 35 | 68 |
| Powys | 129 | 0 | 17 | 40 | 148 | 205 |
| Renfrewshire | 11 | 0 | 2 | 0 | 9 | 11 |
| Ross and Cromarty | 41 | 0 | 19 | 12 | 11 | 42 |
| Roxburgh, Ettrick and Lauderdale | 28 | 0 | 12 | 9 | 7 | 28 |

| County | 2004 | 2019 | 2021 | 2022 | 2023 | Total |
|-----------------------------------|------|------|------|------|------|-------|
| Rutland | 5 | 0 | 0 | 4 | 0 | 4 |
| Shetland | 1 | 0 | 0 | 0 | 0 | 0 |
| Shropshire | 205 | 0 | 23 | 66 | 44 | 133 |
| Somerset | 454 | 0 | 113 | 102 | 88 | 303 |
| South Glamorgan | 9 | 0 | 14 | 17 | 21 | 52 |
| South Yorkshire | 93 | 0 | 26 | 81 | 93 | 200 |
| Staffordshire | 267 | 0 | 41 | 72 | 79 | 192 |
| Stirling and Falkirk | 53 | 0 | 14 | 30 | 45 | 89 |
| Suffolk | 229 | 0 | 82 | 112 | 113 | 307 |
| Surrey | 525 | 0 | 40 | 66 | 85 | 191 |
| Sutherland | 12 | 0 | 9 | 6 | 0 | 15 |
| The Stewartry of Kirkcudbright | 8 | 0 | 1 | 1 | 2 | 4 |
| Tweeddale | 6 | 0 | 1 | 1 | 0 | 2 |
| Tyne & Wear | 28 | 0 | 0 | 0 | 23 | 23 |
| Warwickshire | 220 | 0 | 29 | 42 | 81 | 152 |
| West Glamorgan | 37 | 0 | 2 | 11 | 38 | 51 |
| West Lothian | 6 | 0 | 3 | 3 | 15 | 21 |
| West Midlands | 88 | 0 | 24 | 7 | 16 | 47 |
| West Sussex | 320 | 0 | 25 | 18 | 119 | 162 |
| West Yorkshire | 254 | 0 | 67 | 43 | 66 | 176 |
| Western Isles | 1 | 0 | 0 | 2 | 0 | 2 |
| Wigtown | 3 | 0 | 1 | 1 | 4 | 6 |
| Wiltshire | 253 | 0 | 26 | 54 | 52 | 132 |
| Worcestershire | 286 | 0 | 23 | 33 | 36 | 92 |

Table 8. The number of journeys in each county in the Bugs Matter survey years, and totals over the lifetime of the Bugs Matter app (2021-2023)

Participation in the Bugs Matter Citizen Science Survey

Sign-ups to the Bugs Matter app

A total of 5,281 citizen scientists signed up to the Bugs Matter app in 2021, of which 654 (12.4%) recorded one or more journeys that year. A further 1,885 citizen scientists signed up to the Bugs Matter app in 2022, of which 248 (13.2%) recorded one or more journeys in 2022. A further 1,260 citizen scientists signed up to the Bugs Matter app in 2023, of which 281 (22.3%) recorded one or more journeys in 2023. The much higher conversion rate seen in 2023 is likely due to the ease at which new users can participate as they no longer require a paper splatometer or need to provide address details.

Of the 5,281 citizen scientists that signed up to the Bugs Matter app in 2021, 303 participated in 2022 and 175 participated in 2023. Of the 1,885 citizen scientists that signed up to the Bugs Matter app in 2022, 105 participated in 2023 (Table 9). This means a total of 654 users participated in 2021, 551 users participated in 2022, and 561 users participated in 2023. The overall conversion rate, which is the proportion of users that signed up and completed one or more journeys across the lifetime of the Bugs Matter app, was 16.49%. The average number of journeys recorded per user was 9.48. In 2021 it was 12.16, in 2022 it was 15.55, and in 2023 it was 14.86. In England it was 9.45, in Scotland it was 6.61, in Northern Ireland it was 14.31 and in Wales it was 13.93.

The majority of citizen scientists signed up to the Bugs Matter app in the run up to the survey or during the survey season itself, with sign-up rates increasing after marketing campaigns. For example, a marked increase in sign-up rates occurred after Bugs Matter featured on BBC Springwatch in 2021 and 2022.

In 2021, sign-ups started in mid-May. In 2022 sign-ups started in early-May. In 2023, sign-ups primarily started in June. The sign-up rate reduced towards the end of the survey periods and very few citizen scientists signed up between September-April. The majority of citizen scientists are based in England (Figure 17).

| | Signed up in 2021 | Signed up in 2022 | Signed up in 2023 |
|--|-------------------|-------------------|-------------------|
| Number of new sign-ups | 5,281 | 1,885 | 1,260 |
| Number of participants in 2021 survey | 654 | NA | NA |
| Number of participants in 2022 survey | 303 | 248 | NA |
| Number of participants in 2023 survey | 175 | 105 | 281 |
| Conversion rate (proportion of users that signed up and did one or more journeys in the same year) | 12.40% | 13.20% | 22.30% |

Table 9. The number of sign-ups, participants and conversion rates for 2021, 2022 and 2023.

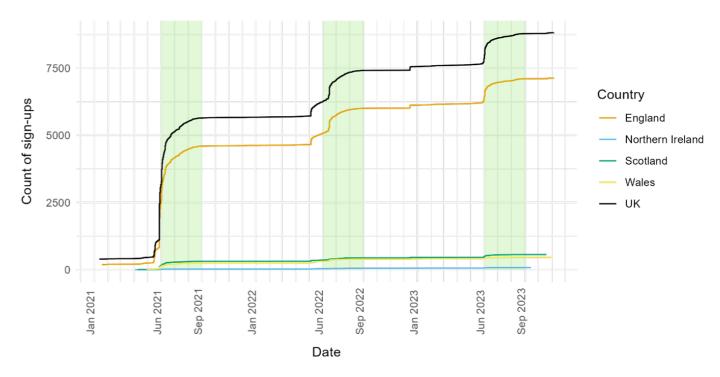


Figure 17. Cumulative count of sign-ups in each country over the lifetime of the Bugs Matter app.

Citizen scientists from all English regions have signed up to the Bugs Matter app. Most users are from the South East, East of England or the South West. A high number of sign-ups in the South East is largely a reflection of marketing efforts by Kent Wildlife Trust who administer the survey. Consistently, the region with the fewest sign-ups is the North East (Figure 18).

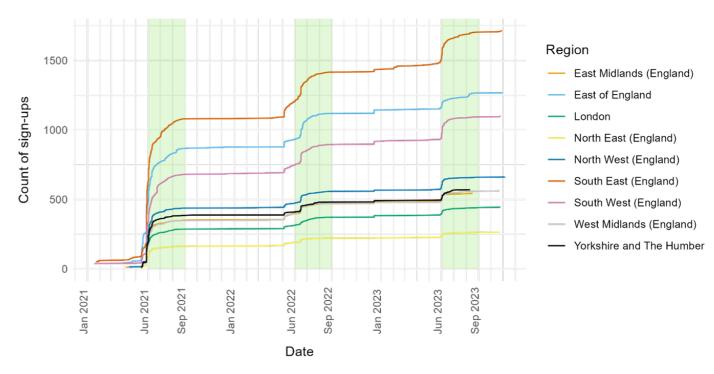


Figure 18. Cumulative count of sign-ups in each region in England over the lifetime of the Bugs Matter app.

Figure 19 shows a heat map of sign-ups by county over the lifetime of the Bugs Matter app. A large number of sign-ups have occurred in Kent (665) and Essex (576), followed by Greater London (445) and then Hampshire (296). It should be noted that the number of sign-ups is not a fair metric to compare between geographic regions with different population densities.

However, these results can help target marketing efforts to increase participation in regions and/or counties with the lowest numbers of sign-ups.

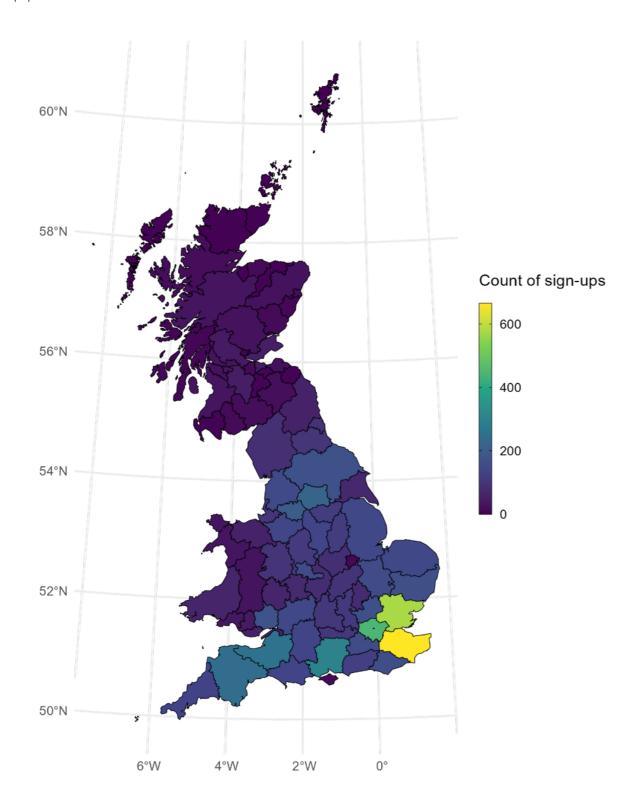


Figure 19. Heat map of total sign-ups for each county over the lifetime of the Bugs Matter app.

There was a range of time intervals between when a citizen scientist signed up to the Bugs Matter app and when they recorded their first journey (Figure 20).

Nonetheless, many citizen scientists recorded their first journey within 20 days of signing up to the app. A number of citizen scientists signed up to the app in 2021 but recorded their first journey in 2023.

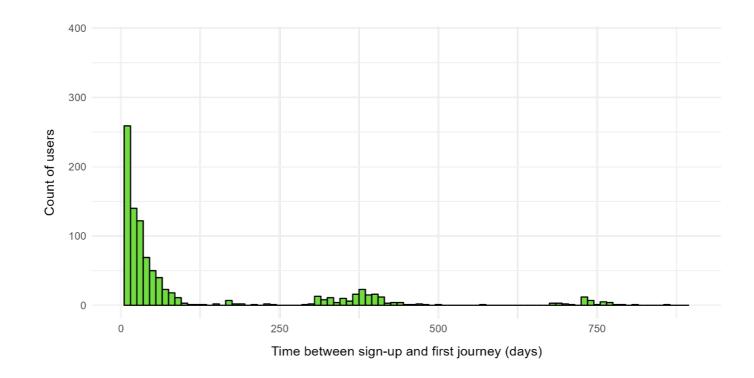


Figure 20. Histogram showing counts of users in bins of time between sign-up and recording a first journey.



Bugs Matter app development

Artificial Intelligence

Bugs Matter is currently working with artificial intelligence

insect splats from a photograph of a vehicle number plate.

professionals at Greenhouse AI to train and test an AI

algorithm that could automatically count the number of

The Bugs Matter app

The Bugs Matter app is available to download for free from the Apple App Store and Google Play. The app was built by Natural Apptitude and uses the Coreo data collection system. There are a number of planned upgrades for the Bugs Matter app. These include:

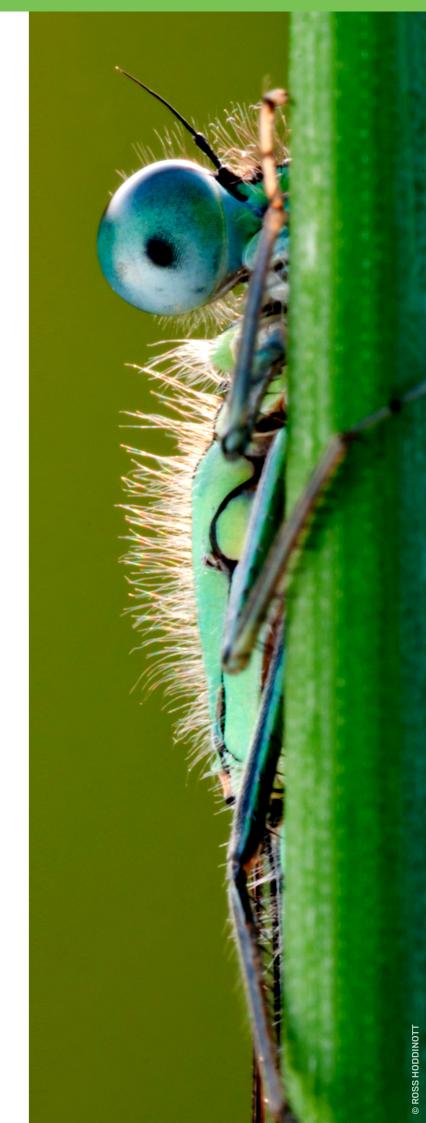
- · Account deletion functionality built into app.
- Push notifications to provide users with survey statistics and reminders to record journeys.
- App translation and launch overseas.

Synthesis

The Bugs Matter Citizen Science Survey takes place every summer and involves citizen scientists recording the number of insect splats on their vehicle number plates following a journey, providing a standardised and large-scale approach to monitor the abundance of flying insects over time. The survey ran in 2021, 2022 and 2023, and a comparative analysis with a 2004 baseline dataset shows a 77.6% reduction in the number of insect splats (43.1%/decade) in the UK by 2023, consistent with rates of insect abundance decline reported by others. Nonetheless, one should be cautious about inferring trends of insect abundance from these results until a longer time series of data is available.

Fewer citizen scientists signed up to the app in 2023 than in previous years, however participation was much higher. It is clear that the improvements to the app (e.g. discontinuation of paper splatometers) has increased participation, and it is promising to see that some citizen scientists are using the app to record a large number of journeys, which indicates the survey concept and useability of the app are effective to encourage long-term data collection by citizen scientists

Kent Wildlife Trust and Buglife administer the Bugs Matter citizen science survey and are extremely grateful to those who have signed up to the app and participated in the survey so far. Bugs Matter has the potential to provide an efficient, standardised and scalable approach to monitor trends in insect abundance locally, regionally, and globally, and the dedicated team behind the survey will work hard to realise its potential.



Support the survey

If you would like to support the Bugs Matter survey please visit:

Kent Wildlife Trust

kentwildlifetrust.org.uk/bugs-matter

Bug Life

buglife.org.uk/get-involved/surveys/bugs-matter/

If you would like to partner with Bugs Matter, please email corporate@kentwildlife.org.uk for further details.

You can also get in touch via info@bugsmatter.app if you would like to support the project through technological innovations, partnerships, or if you have feedback on the survey.



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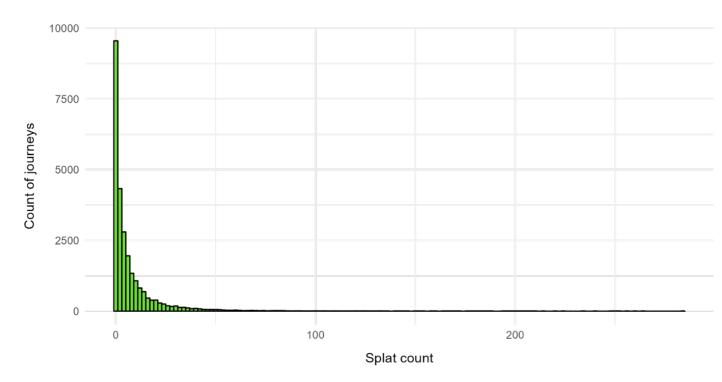
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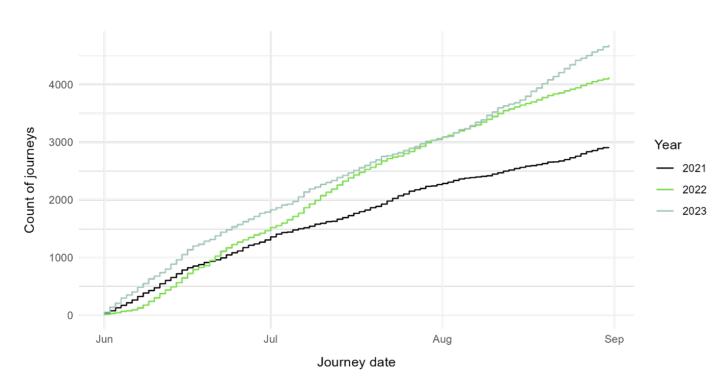
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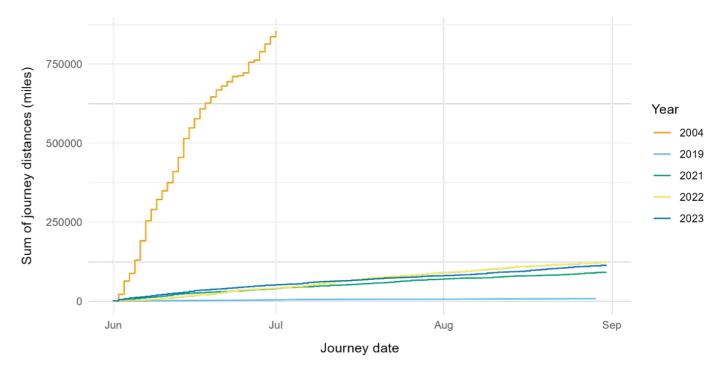
Appendices



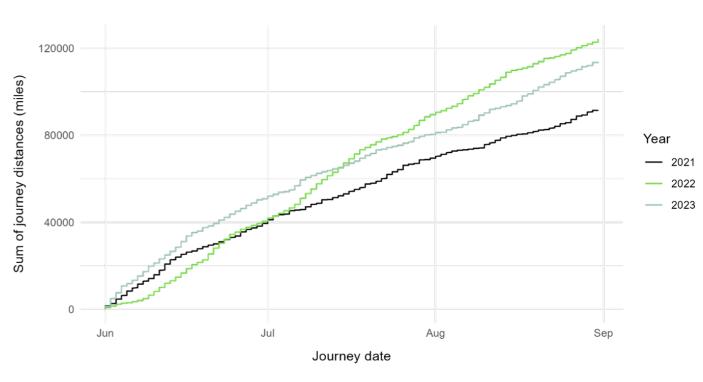
Appendix 1. Histogram of the splat count data from all years.



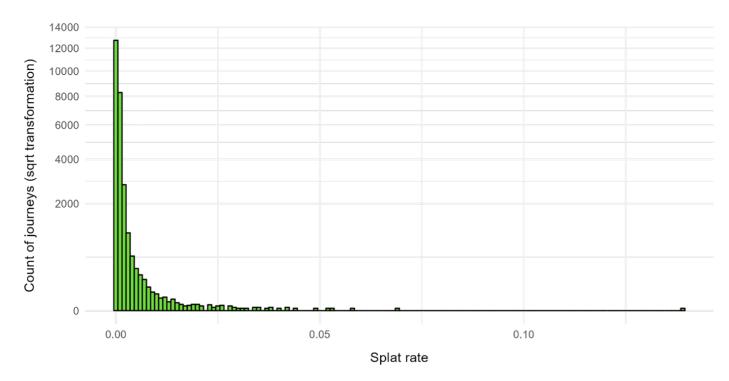
Appendix 2. Cumulative count of journeys in each Bugs Matter survey years.



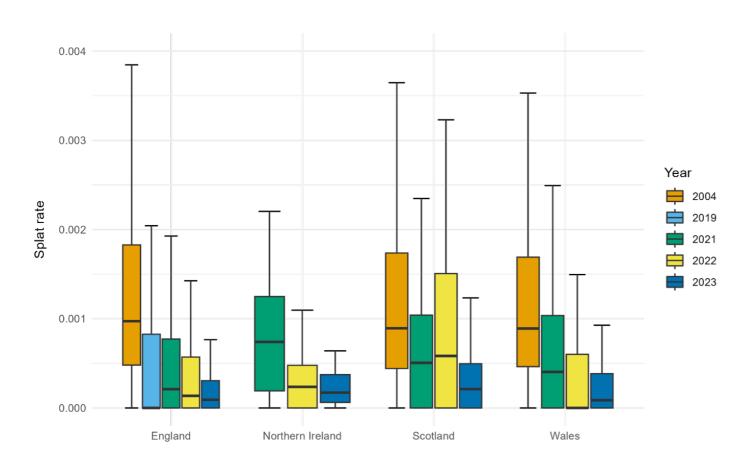
Appendix 3. Cumulative sum of journey distances in each survey year.



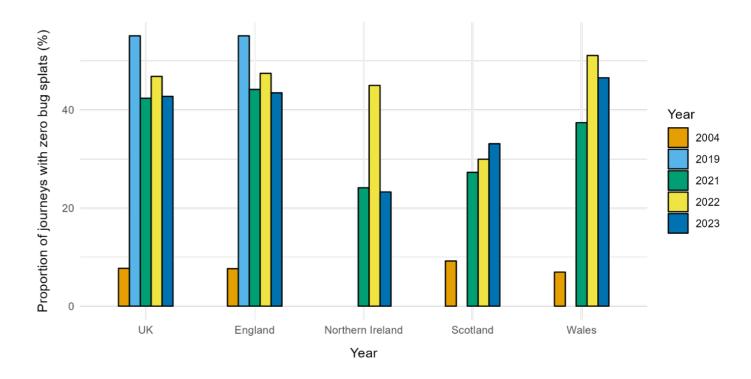
Appendix 4. Cumulative sum of journey distances in each Bugs Matter survey year.



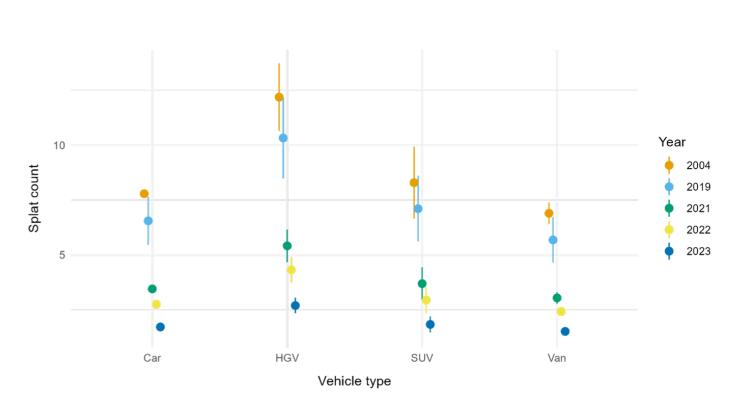
Appendix 5. Histogram of the splat rate (splats per cm per mile) data.



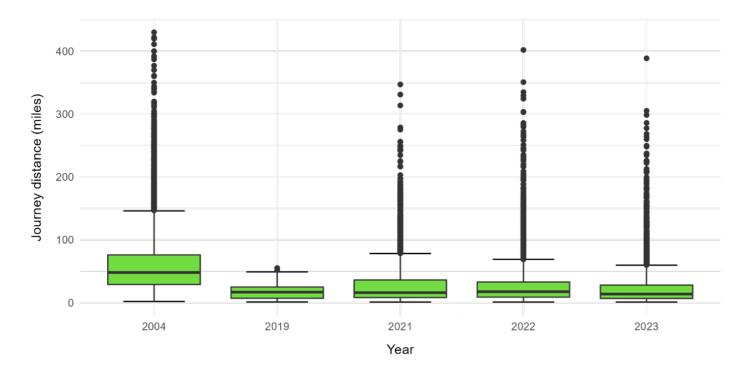
Appendix 6. Grouped boxplot showing the spread of the insect splat rate (splats per cm per mile) data by country. The boxes indicate the interquartile range (central 50% of the data) either side of the median splat rate, which is the horizontal line inside the box. The vertical lines extend out by 1.5 times the interquartile range.



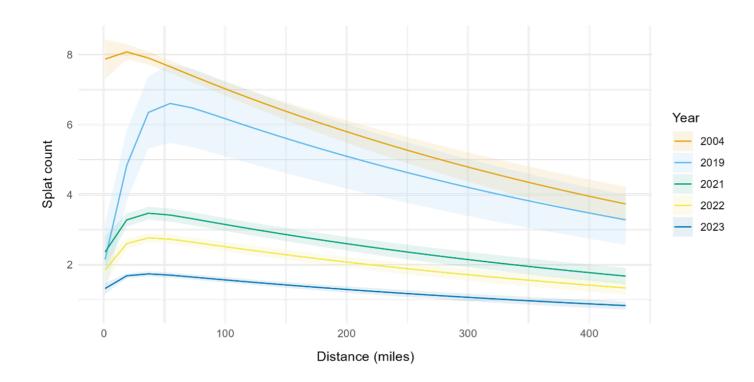
Appendix 7. Car plot showing the proportion of journeys with zero bug splats in each country across survey years.



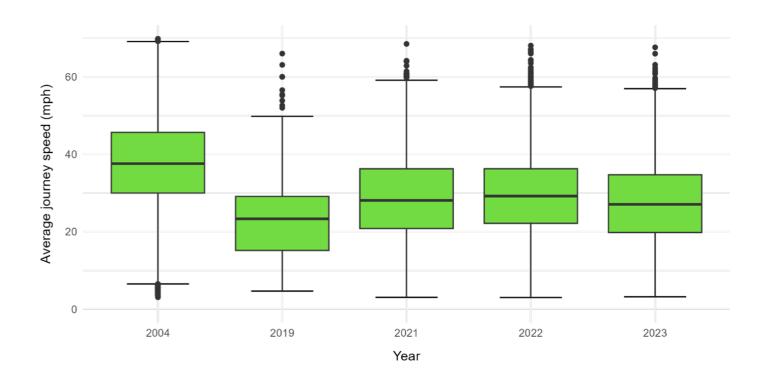
Appendix 8. Predictions of splat count (corrected for distance) by the ZINB model across vehicle type values.



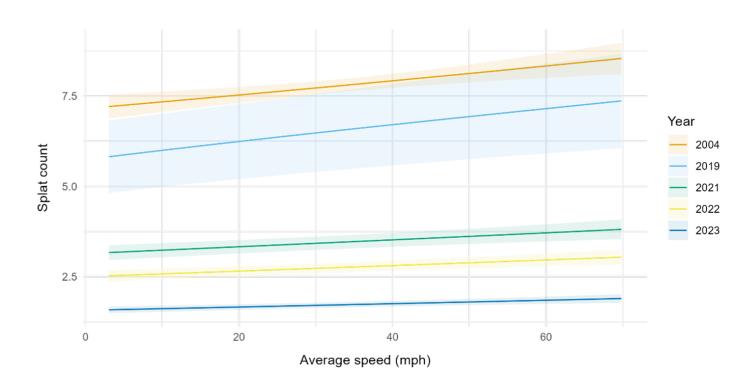
Appendix 9. Boxplot showing the spread of the journey distances. The boxes indicate the interquartile range (central 50% of the data) either side of the median journey distance which is shown by the horizontal line inside the box. The vertical lines extend out by 1.5 times the interquartile range.



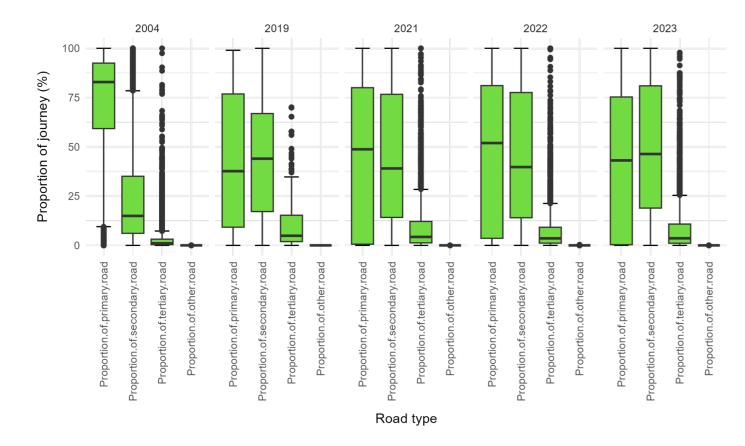
Appendix 10. Predictions of splat count (corrected for distance) by the ZINB model across distance and year values.



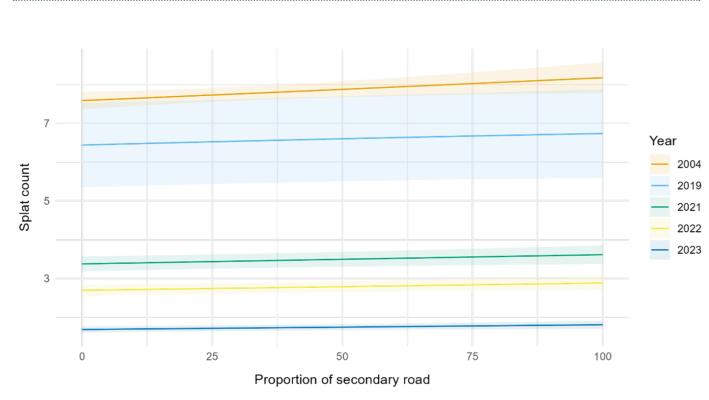
Appendix 11. Boxplot showing the spread of the average journey speed. The boxes indicate the interquartile range (central 50% of the data) either side of the median average journey speed which is shown by the horizontal line inside the box. The vertical lines extend out by 1.5 times the interquartile range.



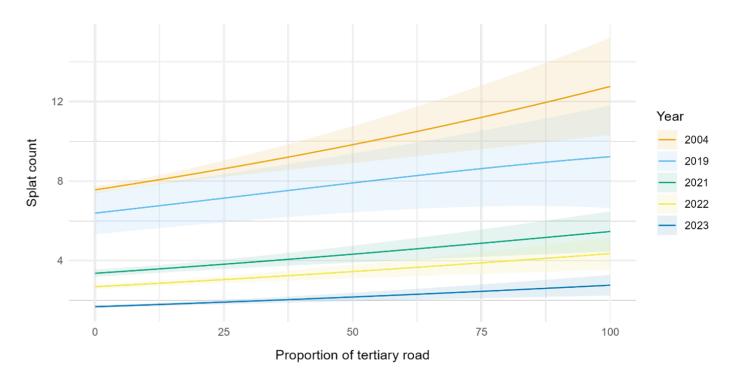
Appendix 12. Predictions of splat count (corrected for number plate area and journey distance) by the ZINB model across average speed and year values.



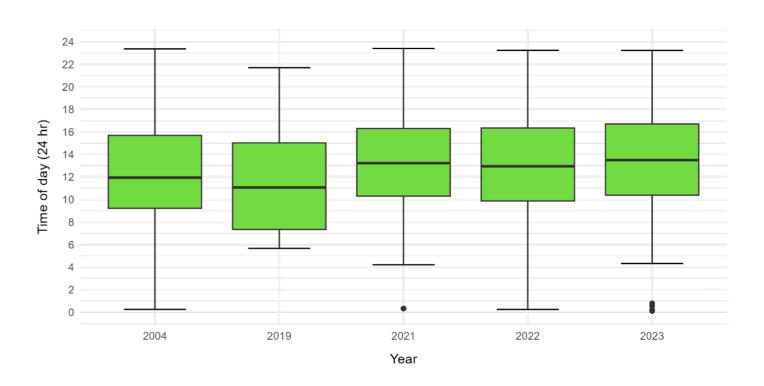
Appendix 13. Grouped boxplot showing the spread of the road type data (the proportions (%) of primary, secondary, tertiary or other roads along each journey). The boxes indicate the interquartile range (central 50% of the data) either side of the median proportion of journey, which is shown by the horizontal line inside the box. The vertical line extends out by 1.5 times the interquartile range.



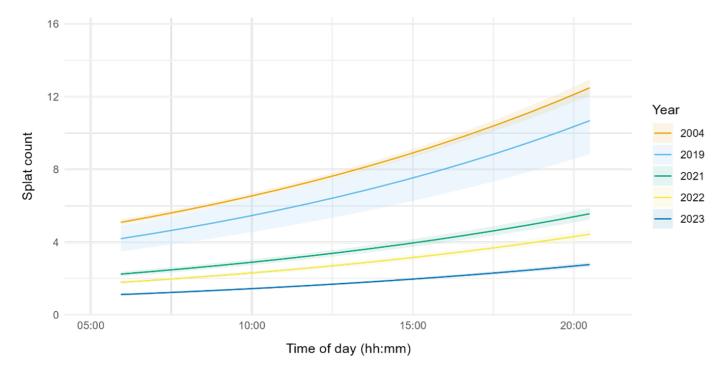
Appendix 14. Predictions of splat count (corrected for distance) by the ZINB model across proportion of secondary road and year values.



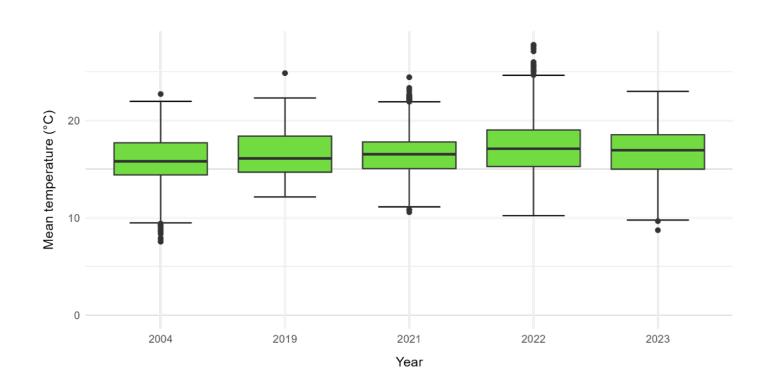
Appendix 15. Predictions of splat count (corrected for distance) by the ZINB model across proportion of tertiary road and year values.



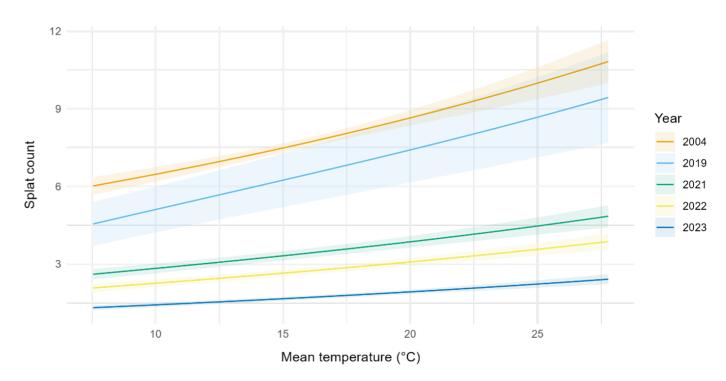
Appendix 16. Boxplot showing the spread of the time of day of journeys. The boxes indicate the interquartile range (central 50% of the data) either side of the median time of day of journeys, which is shown by the horizontal line inside the box. The vertical lines extend out by 1.5 times the interquartile range.



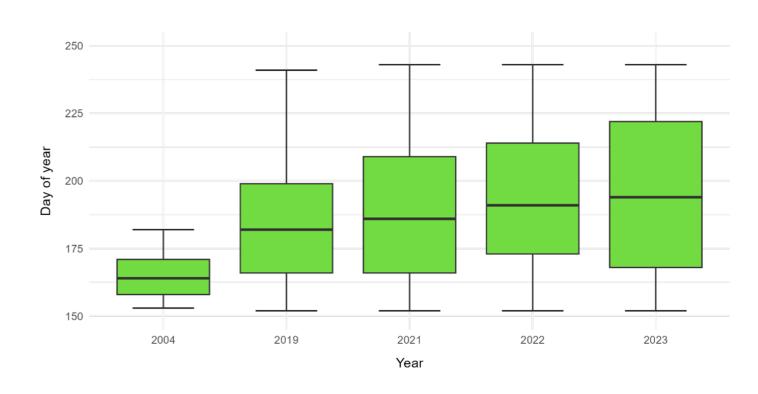
Appendix 17. Predictions of splat count (corrected for distance) by the ZINB model across time of day and year values.



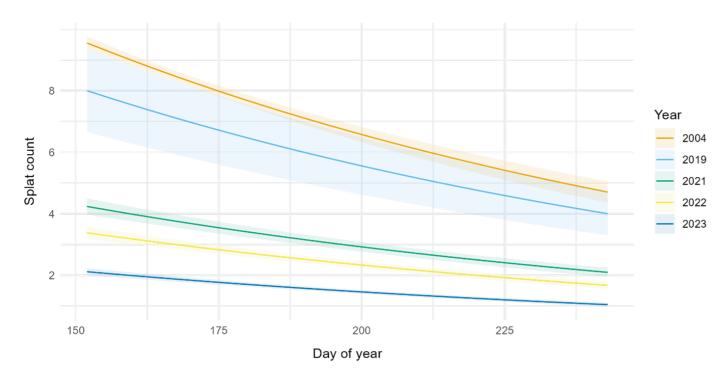
Appendix 18. Boxplot showing the spread of the mean temperature of the journeys. The boxes indicate the interquartile range (central 50% of the data) either side of the median mean temperature which is shown by the horizontal line inside the box. The vertical lines extend out by 1.5 times the interquartile range.



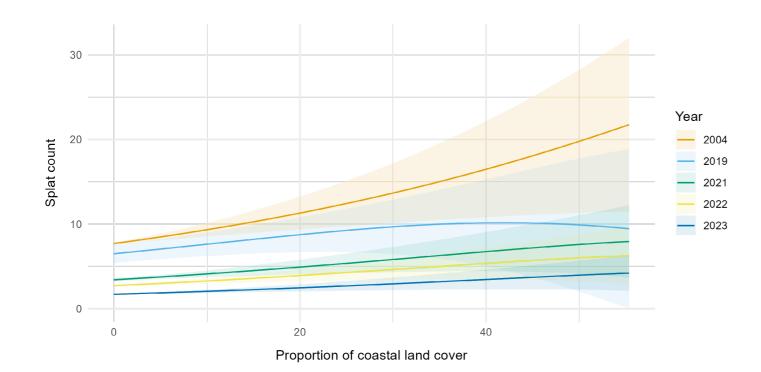
Appendix 19. Predictions of splat count (corrected for distance) by the ZINB model across mean temperature and year values.



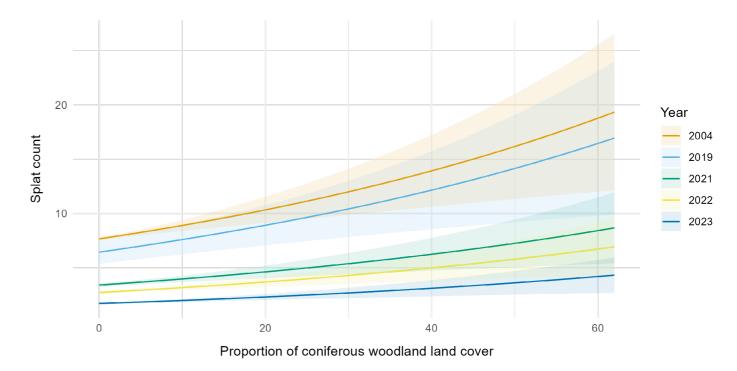
Appendix 20. Boxplot showing the spread of the day of year of journeys. The boxes indicate the interquartile range (central 50% of the data) either side of the median day of year of journeys, which is shown by the horizontal line inside the box. The vertical lines extend out by 1.5 times the interquartile range.



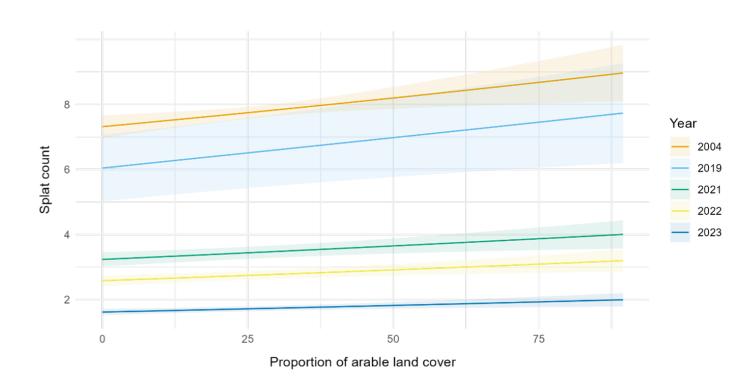
Appendix 21. Predictions of splat count (corrected for distance) by the ZINB model across calendar date and year values.



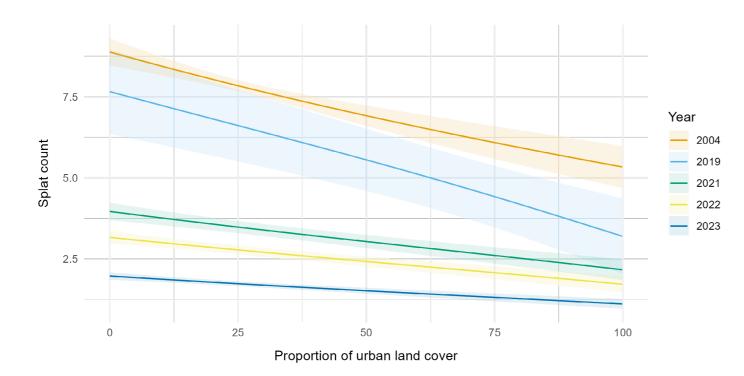
Appendix 22. Predictions of splat count (corrected for number plate area and journey distance) by the ZINB model across proportion of coastal land cover and year values.



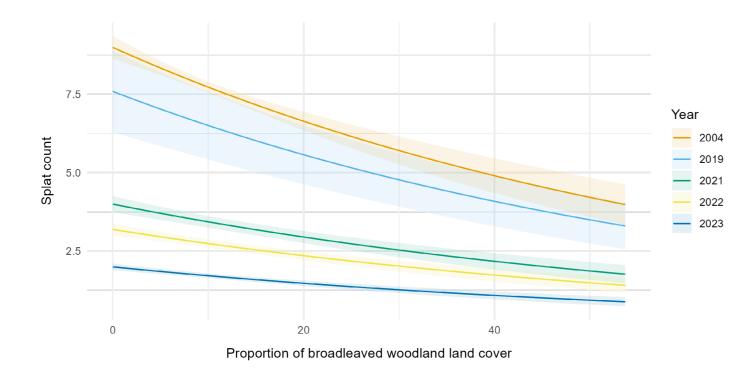
Appendix 23. Predictions of splat count (corrected for number plate area and journey distance) by the ZINB model across proportion of coniferous woodland land cover and year values.



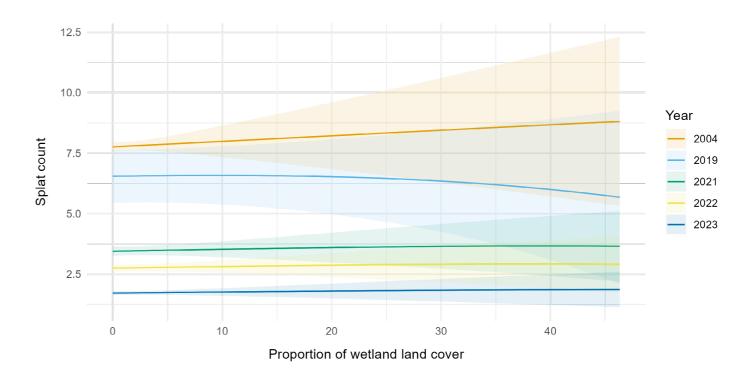
Appendix 24. Predictions of splat count (corrected for number plate area and journey distance) by the ZINB model across proportion of arable land cover and year values.



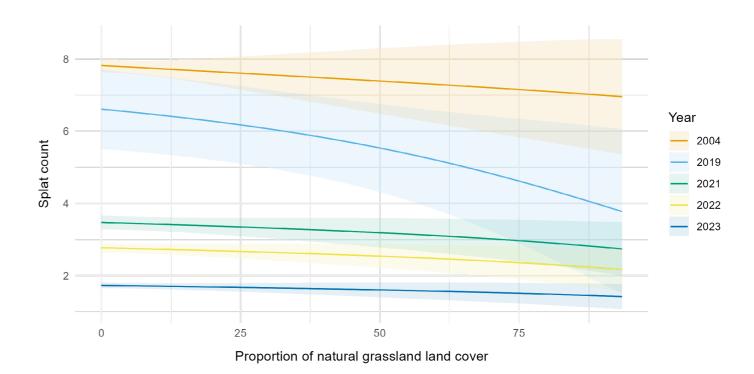
Appendix 25. Predictions of splat count (corrected for number plate area and journey distance) by the ZINB model across proportion of urban land cover and year values.



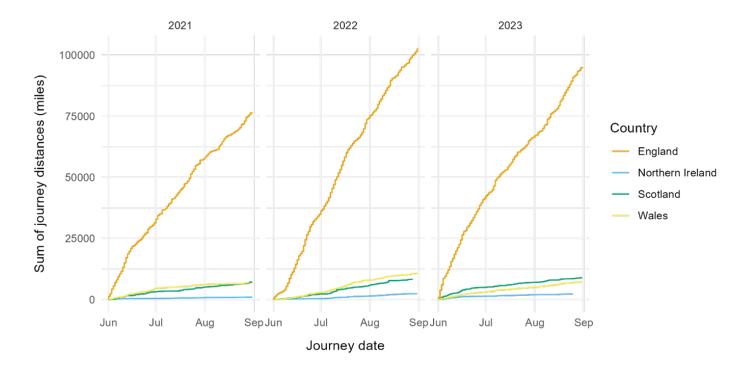
Appendix 26. Predictions of splat count (corrected for number plate area and journey distance) by the ZINB model across proportion of broadleaved woodland land cover and year values.



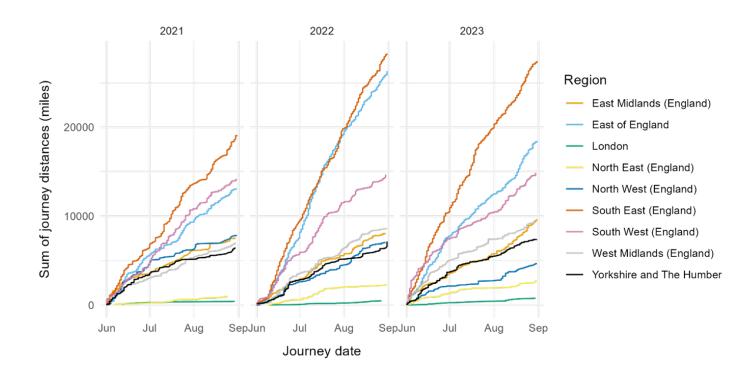
Appendix 27. Predictions of splat count (corrected for number plate area and journey distance) by the ZINB model across proportion of wetland land cover and year values.



Appendix 28. Predictions of splat count (corrected for number plate area and journey distance) by the ZINB model across proportion of natural grassland land cover and year values.



Appendix 29. Cumulative sum of journey distances in each country in each Bugs Matter survey year.



Appendix 30. Cumulative sum of journey distances in each region in England in each Bugs Matter survey year.