Bugs **Matter**

THE 2022 REPORT

The Bugs Matter Citizen Science Survey

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

Address for correspondence: info@bugsmatter.app

buglife

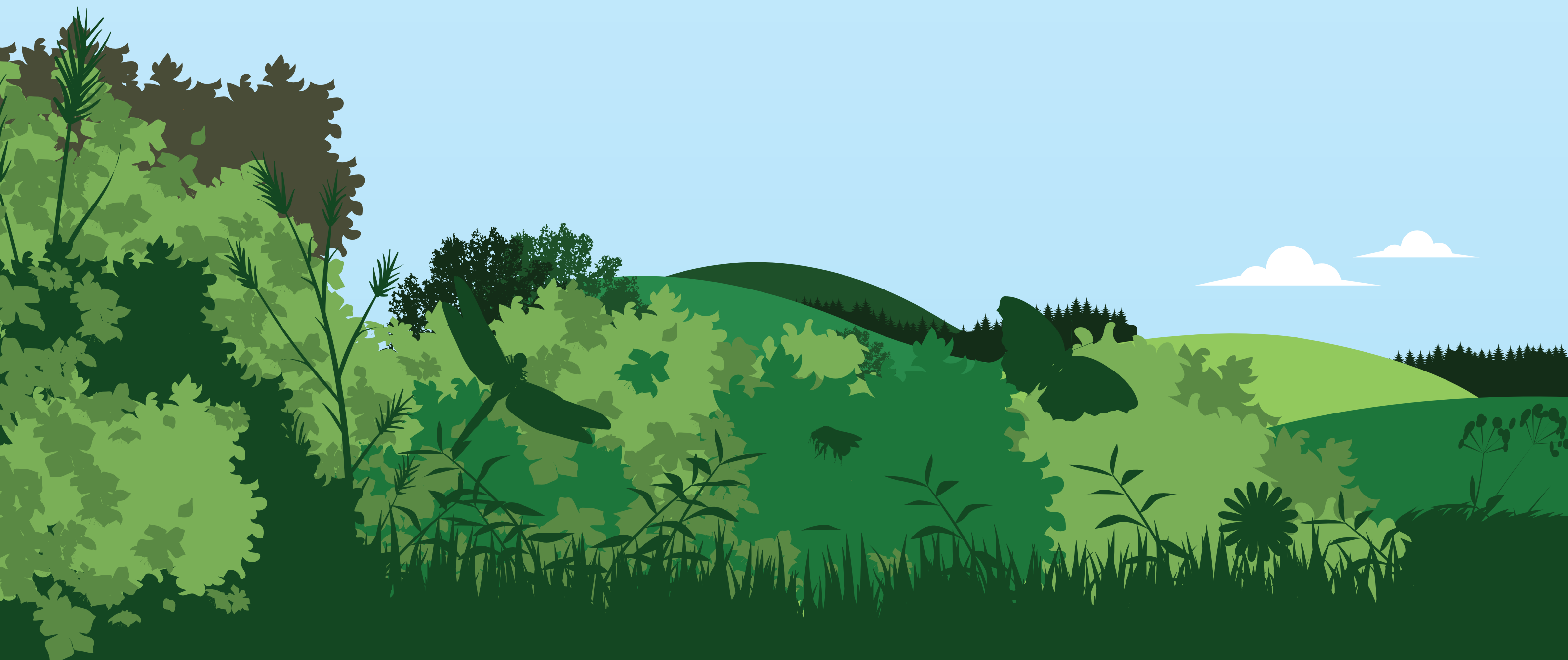
Kent wildlife Trust

Find more information about the Bugs Matter project here:
kentwildlifetrust.org.uk/bugs-matter

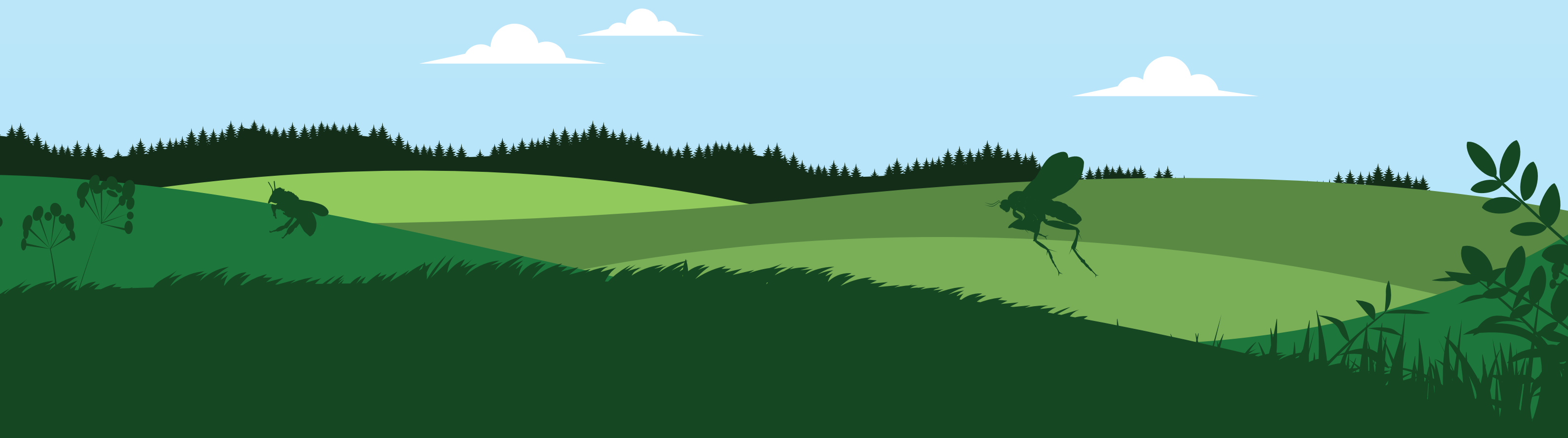
Authors and Contributers

KEY AUTHOR:
Dr Lawrence Ball Kent Wildlife Trust

CONTRIBUTORS:
Andrew Whitehouse Buglife
Evan Bowen-Jones Kent Wildlife Trust
Isabelle Rayner Kent Wildlife Trust
Matt Shardlow Buglife
Mollie Amor Kent Wildlife Trust
Nikki Banfield Buglife
Paul Hadaway Kent Wildlife Trust
Paul Hetherington Buglife
Paul Tinsley-Marshall Butterfly Conservation
Robbie Still Kent Wildlife Trust



Contents



© JAYBEE WWW.PHOCUS-ON.CO.UK.JPG

Summary

In recent years, scientists 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 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 = 519 journeys in Kent), 2021 (n = 3212 journeys nationwide) and 2022 (n = 4140 journeys nationwide) are compared with the results of a nationwide survey using this methodology led by the RSPB ('Big Bug Count') in 2004 (n = 14320 journeys).

Compared to 2004, the results show a decrease in the number of insect splats in the UK of 63.7%, 5.3% greater than in 2021 (58.4%).

Compared to 2004, the number of insect splats in England decreased by 68% by 2022, 7% greater than in 2021 (61%). Compared to 2004, the number of insect splats in Scotland decreased by 40% in 2022, 9% less than the decrease in 2021 (49%). In Wales, the number of insect splats recorded decreased by 75% in 2022, 20% greater than in 2021 (55%). In Northern Ireland, the number of insect splats recorded decreased by 46% between 2021 and 2022, although this result is based on a relatively small dataset.

These results are consistent with the declining trends in insect populations widely reported by others, and informs a growing requirement for conservation research, policy and practice targeted at invertebrates in the UK. However, these results are based on data with low temporal resolution and consequently we interpret this change between two points in time 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 long-term 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 data.

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 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, provide natural pest control services, and decompose organic matter and recycle nutrients into the soil. Without them, we could not grow onions, cabbages, broccoli, chillies, most tomatoes, coffee, cocoa, most fruits, sunflowers, and rapeseed, and demand for synthetic fibres would surge because bees pollinate cotton and flax. 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 200000 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.

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 abundance.

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 2022 report

This comprehensive report describes the Bugs Matter Citizen Science Survey in the UK as of December 2022. The methods and any changes to the methods are described. Data on the number of journeys, the circumstances and environmental conditions of the journeys, and the number of insects splats are presented. Finally, the results of a comparative analysis of the Bugs Matter survey data and pre-existing baseline data from 2004 are presented. The 2004 baseline data was collected as part of a national survey using the same sampling method led by the RSPB ('Big Bug Count'), and provides an opportunity to assess invertebrate abundance over an 18-year timeframe (Tinsley-Marshall *et al*., 2021a, 2021b). 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 and 2022, using the Bugs Matter mobile application (Figure 1).

To take part in the survey, citizen scientists sign up to the Bugs Matter app and receive a standardised sampling grid, termed a 'splatometer', in the post. Within the app, users add details about the vehicle used for sampling via an Application Programming Interface (API) number plate look-up service. Multiple vehicles can be added by a single user. This data 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 from previous journeys. 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, route, 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. Then, by holding up the 'splatometer' to the front number plate, they record the number of insect splats within the sampling boxes of the 'splatometer' on the number plate. 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, along with the journey distance, using vehicle odometer readings.

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

Collating explanatory variables

Time of day was calculated for each journey as the intermediate time between the journey start and end times. As 97% 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 was not included in the 2021 analysis. The 'sf' package (Pebesma, 2018) in R was used to work with the spatial data. The average speed of the journey was calculated by dividing the journey distance by the journey duration. The vehicle type, acquired via the API in 2021 and 2022, was classified into four categories: car, heavy goods vehicle (HGV), sports utility vehicle (SUV), and van. Two additional categories were included in the 2021 analysis (multi-purpose vehicle and sports car), which were merged with the car category as it was deemed that there was not enough information provided via the API to accurately include these classes. 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). 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).

Normalized difference vegetation index (NDVI) described 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. Maximum greenest pixel composites of normalized difference vegetation index (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. Artificially-surfaced areas such as roads and buildings show low NDVI values, whilst vegetated areas show as high values. NDVI does not differentiate agricultural land and natural habitats. The NDVI values were averaged within a 500 m buffer of each journey route to approximate the suitability of the habitat for insects surrounding each journey route. The NDVI values were rescaled to a -10-10 range to aid interpretation of the model coefficients.

Finally, the proportions of each journey that was conducted on '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

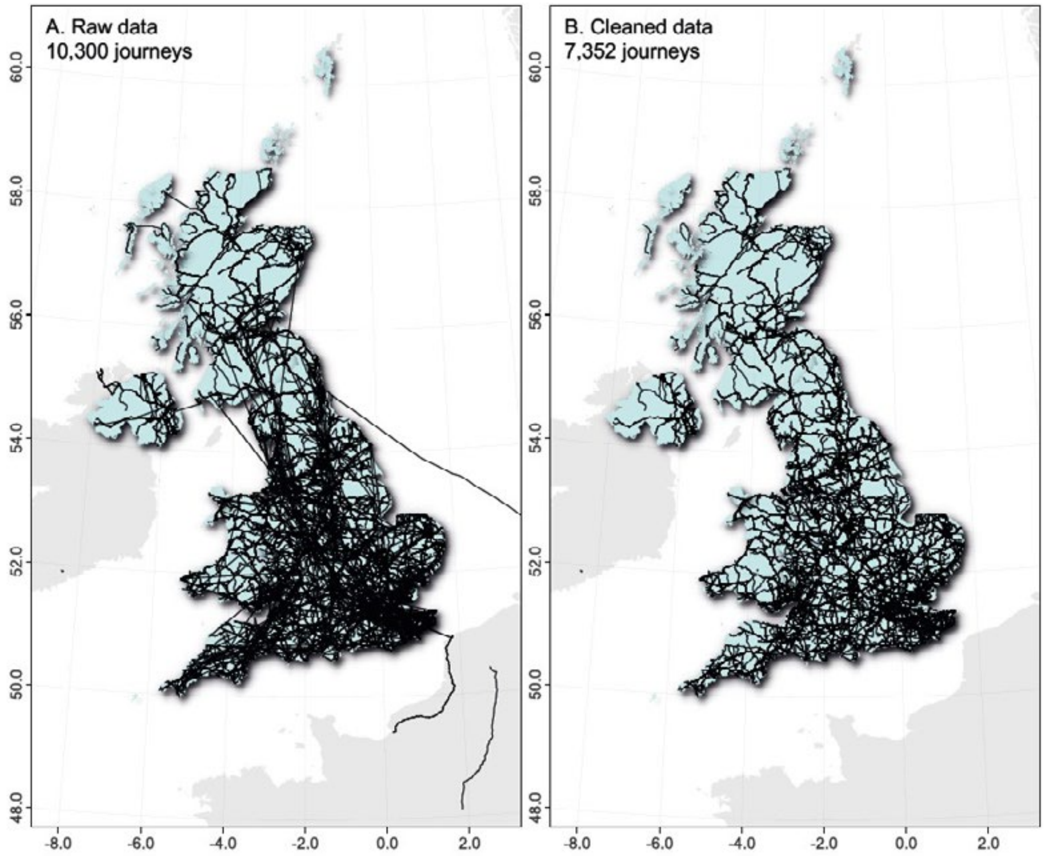


Figure 2. Map showing all journeys recorded in the Bugs Matter app over its lifetime,before (A) and after (B) data cleaning.

'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, as the proportions of each road type (primary, secondary, and tertiary) sum 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 (splat count).

All journeys were assigned to one country, region, or 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. 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 and 2022 (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 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 (in 2021, a 0.3 mile threshold was used). Similarly, journeys with durations less than 3 minutes were removed (in 2021 a 1 minute threshold was used). Journeys with an average speed of over 70 mph or under 3 mph (in 2021 thresholds of 1 mph and 80 mph were used) were assumed to result from inaccurate GPS tracking and were omitted. Only journeys that recorded less than 300 insect splats were retained (in 2021 a threshold of 500 insect splats was used), as journeys with more than 300 insect splats (or more than 50 per 'splatometer' window) 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.

After data cleaning, 22191 of 28724 journeys were retained (Table 1). It should be noted that changing the data cleaning process has caused changes in some of the trend estimates of insect abundance since the last report. For example, a number of spurious records with high insect splat counts from Scotland have been removed from the dataset, changing the estimated trend for Scotland.

	Journey count				Journey distance (miles)			
Data cleaning step	**2004**	**2019**	**2021**	**2022**	**2004**	**2019**	**2021**	**2022**
Raw journey count	17758	666	4811	5489	1120187	11521	211155	201286
Remove overseas/ferry journeys	17728	666	4803	5480	1117041	11521	210678	199360
Remove journeys from outside survey period	17725	600	4681	5442	1116835	10587	201367	198357
Remove journeys with GPS errors	17725	600	3917	4688	1116835	10587	146760	147516
Remove journeys with length/distance < 1 mile	17616	528	3793	4623	1110996	9213	146740	147494
Remove journeys with duration < 3 minutes	17448	521	3792	4623	1096969	9136	146734	147494
Remove journeys with average speed > 70 mph	17251	520	3790	4622	1076466	9125	146423	147420
Remove journeys with average speed < 3 mph	17205	519	3768	4601	1075625	9122	146195	147095
Remove journeys with splat count > 300	17193	519	3768	4601	1073950	9122	146195	147095
Remove journeys with rain	14320	519	3212	4140	859408	9122	112312	124402

Table 1. The total journey counts and journey distance after each data cleaning step. After data cleaning, 22191 of 28724 journeys were retained.

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 journey distance, expressed in a unit of 'splats per mile'. This metric makes the data comparable between journeys and is easily defined as the number of insects sampled on the number plate per mile. Differences in insect splat rate (splats per mile) 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, local NDVI, and road type, on splat count. 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 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 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 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 (Figures 11 and 12). 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 zero-inflated 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 $c = 15.324$, indicating overdispersion ($c = 0$ for equidispersion). Therefore, the ZINB model provided the best fit and was subsequently used for the main analysis.

Model	Log.likelihood	AIC	BIC	Likelihood.ratio.test.. DF.diff.
Poisson	-130261.6	260553.3	260673.1	191595.4 , -14
NB	-61603.9	123239.8	123367.6	15421.6 , -14
ZIP	-125591.2	251242.4	251482.1	41710.9 , -28
ZINB	-61537.4	123136.7	123384.4	4919.3 , -28

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

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, which means 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 and 2022 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 visualized effectively in a forest plot. Also presented in his report, are plots of adjusted predictions, corrected for journey distance, of splat count, in relation to the survey year and other independent variables. The marginaleffects package (Arel-Bundock, 2022) was used. To examine country-specific trends, the analysis was repeated using the data for each country separately, but 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.

Summary statistics

This section summarizes and describes the dataset.

National summary statistics

In 2004, 191,521 insects were sampled over 14,320 journeys comprising 859,408 miles. In 2019, 1,021 insects were sampled over 519 journeys comprising 9,122 miles.

In 2021, 9,957 insects were sampled over 3,212 journeys comprising 112,312 miles. In 2022, 8,599 insects were sampled over 4,140 journeys comprising 124,402 miles (Figures 3-6).

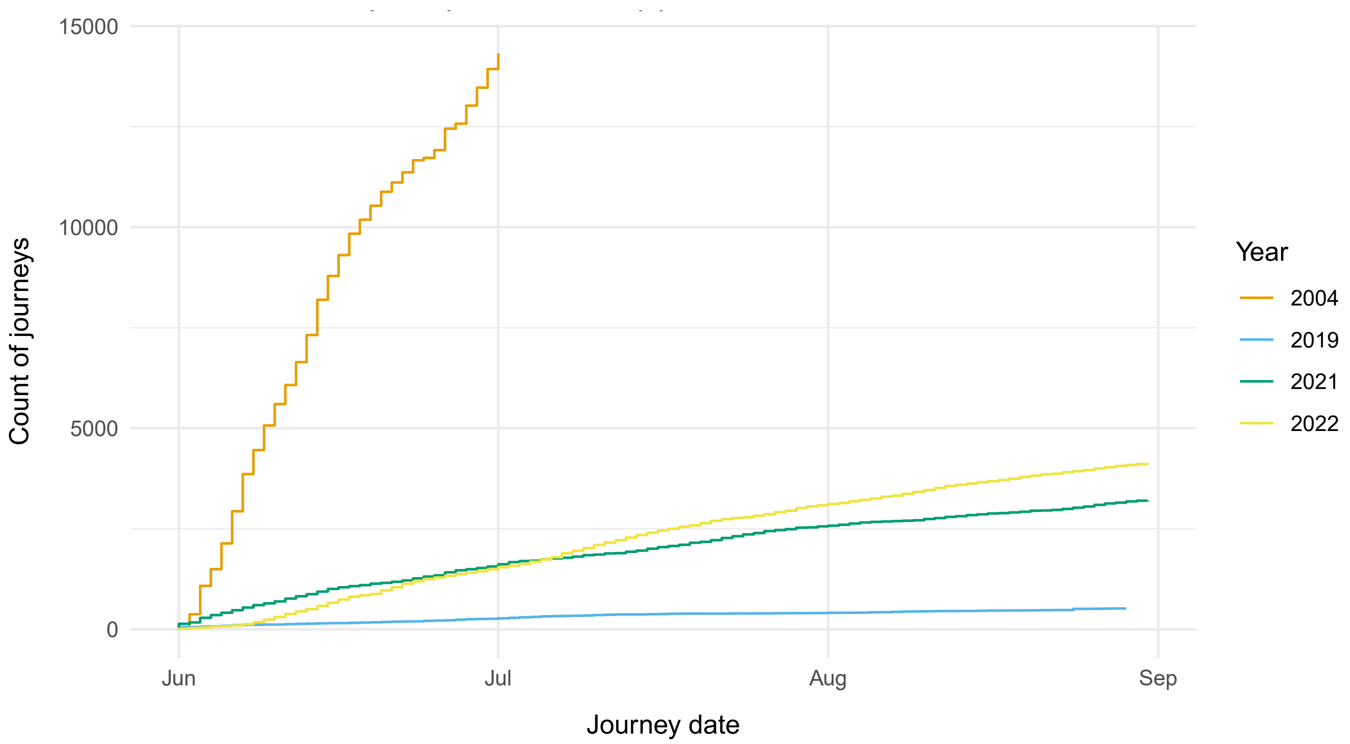


Figure 3. Cumulative count of journeys in each survey year

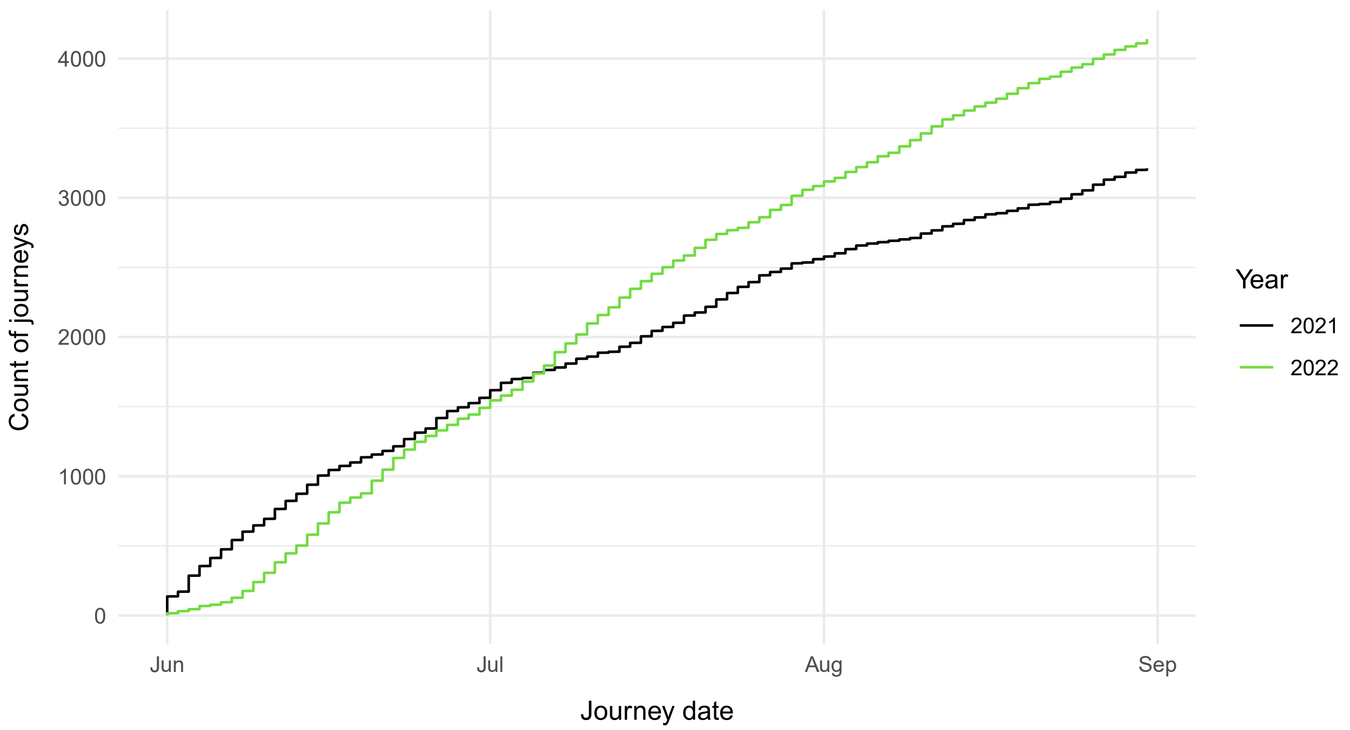


Figure 4. Cumulative count of journeys in each Bugs Matter survey year

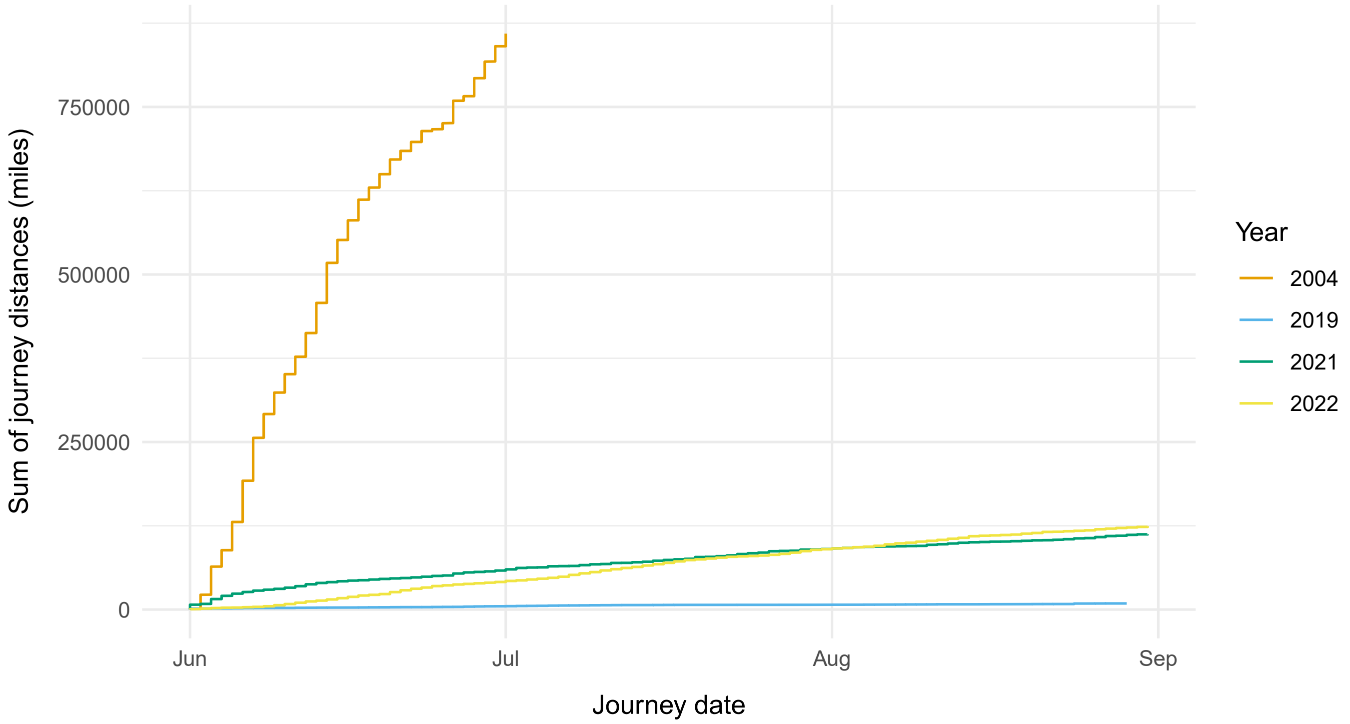


Figure 5. Cumulative sum of journey distances in each survey year

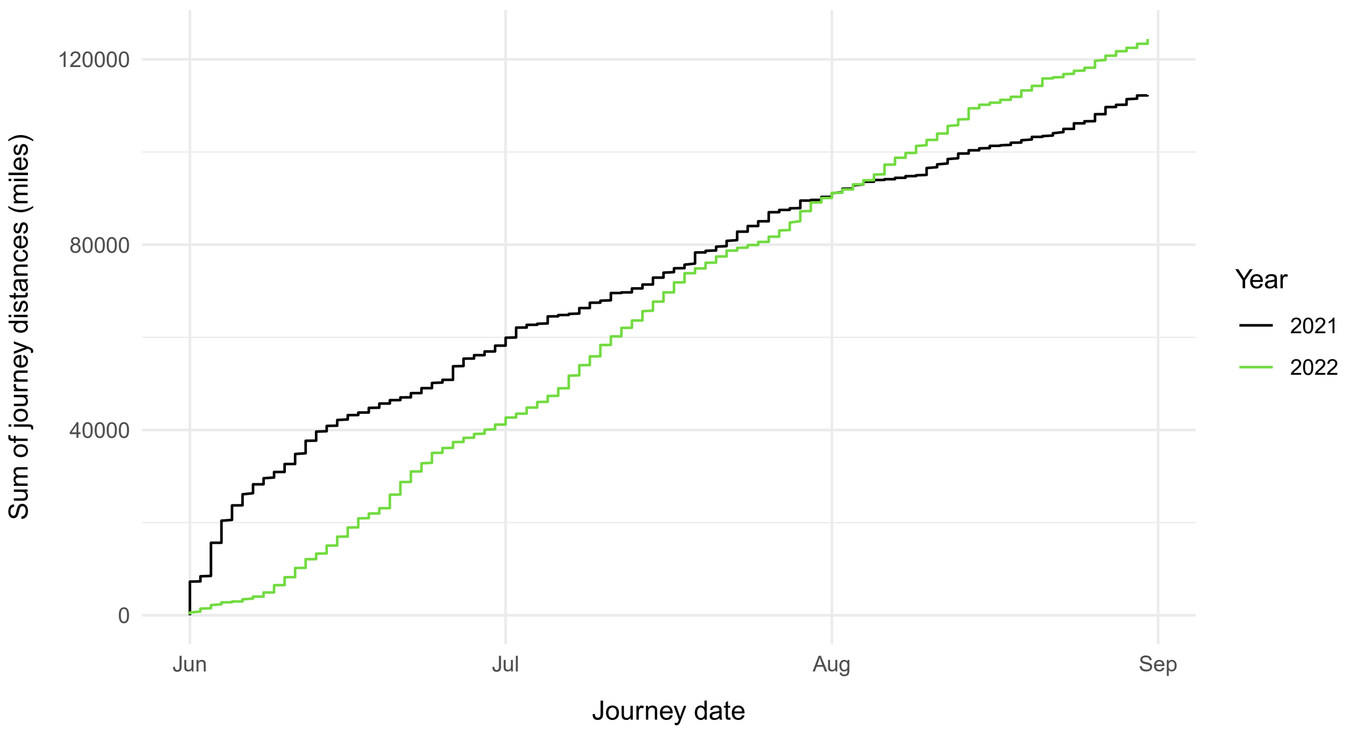


Figure 6. Cumulative sum of journey distances in each Bugs Matter survey year

Country summary statistics

The highest number of journeys recorded via the Bugs Matter app was in England, with 2706 journeys in 2021 and 3327 journeys in 2022. The second highest number of journeys was recorded in Wales, followed by Scotland, and finally Northern Ireland.

All countries recorded more journeys in 2022 than in 2021. On average, the longest journeys were in Scotland, whilst the shortest journeys were in Wales (Table 3, Figures 7-8).

	2021				2022			
Country	**Splat count**	**Journey count**	**Total journey distance (miles)**	**Mean journey distance (miles)**	**Splat count**	**Journey count**	**Total journey distance (miles)**	**Mean journey distance (miles)**
England	8131	2706	95838	35	6564	3327	102867	31
Northern Ireland	110	28	877	31	171	83	2636	32
Scotland	870	167	7247	43	1315	237	8182	35
Wales	846	310	8346	27	549	493	10717	22

Table 3. Journey summary statistics for each country in the Bugs Matter survey years.

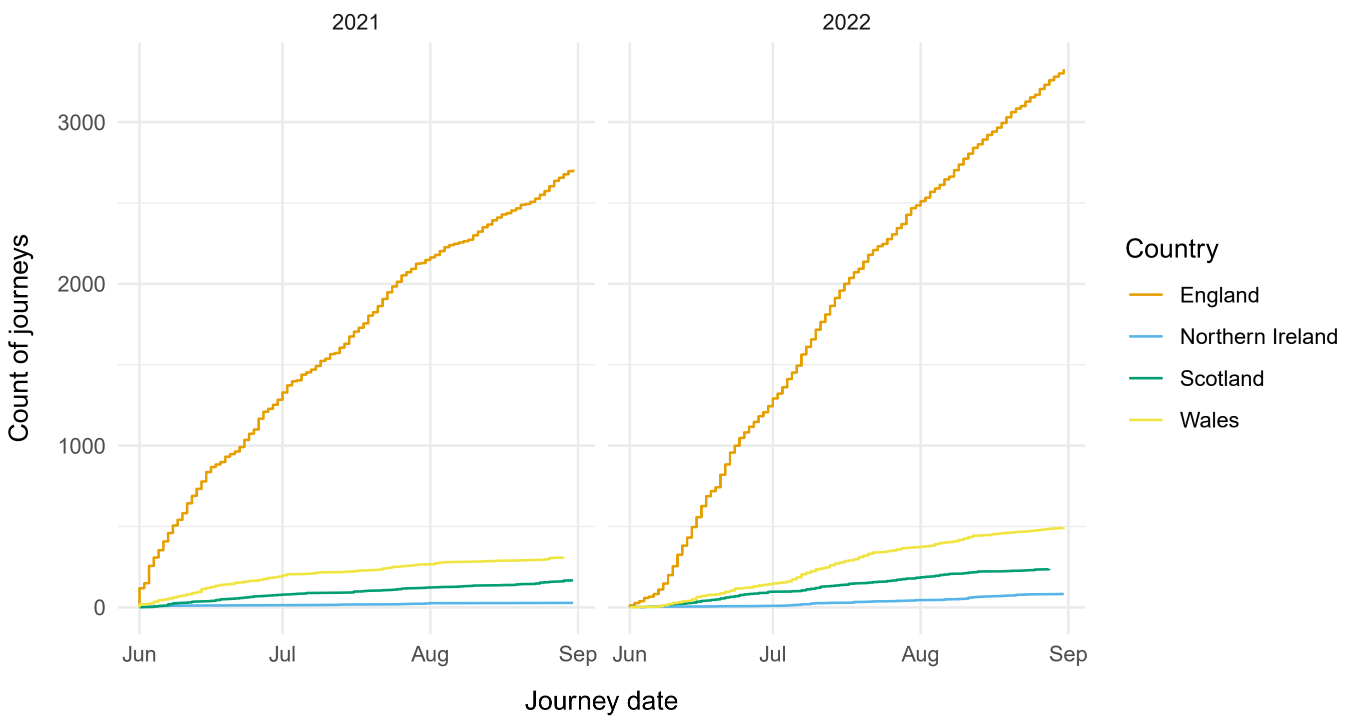


Figure 7. Cumulative count of journeys for each country in each Bugs Matter survey year

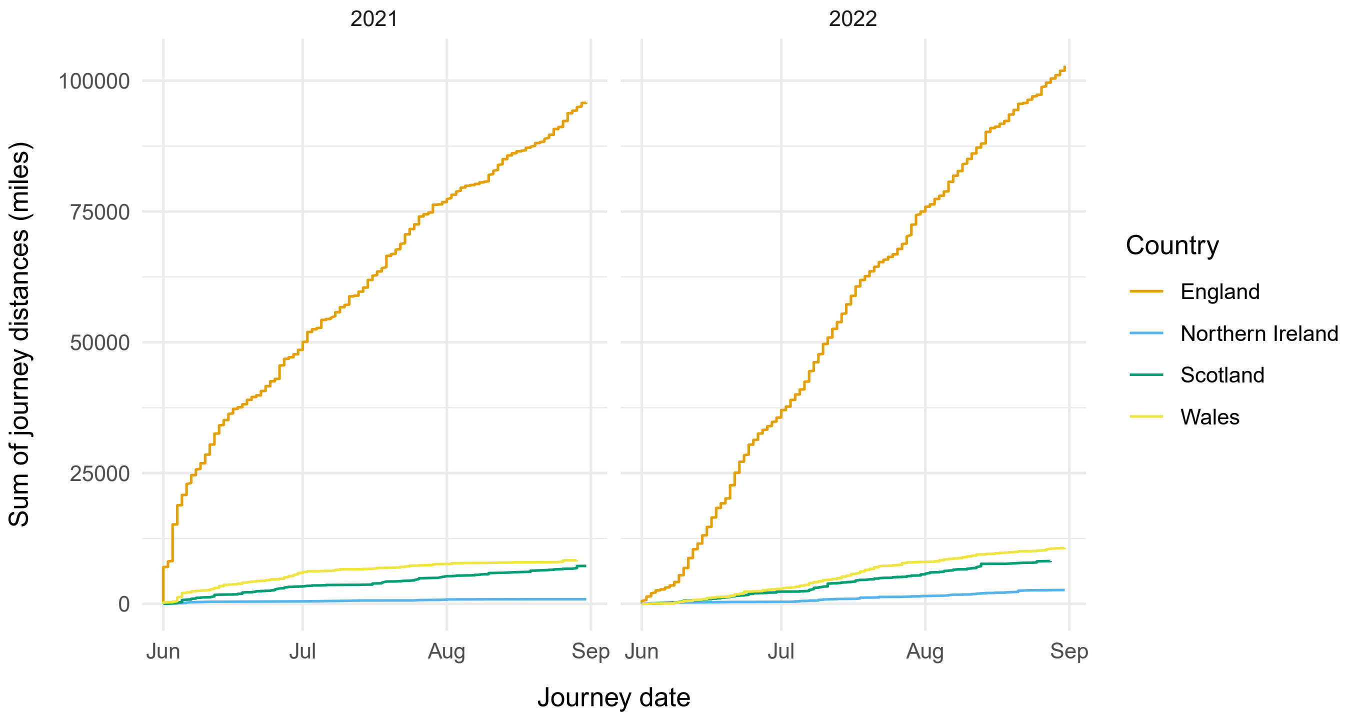


Figure 8. Cumulative sum of journey distances for each country in each Bugs Matter survey year

Regional summary statistics

The region in England with the highest number of journeys recorded via the Bugs Matter app was the South East, with 786 in 2021 and 973 in 2022, whilst London recorded the lowest number of journeys (Table 4, Figures 9-10).

The East of England saw the highest increase in journeys between 2021 and 2022, with an additional 10000 miles recorded over 300 journeys. The South West and the East Midlands were the only regions to record fewer journeys in 2022 than in 2021.

	2021			2022		
Region	**Splat count**	**Journey count**	**Total journey distance (miles)**	**Splat count**	**Journey count**	**Total journey distance (miles)**
East Midlands	714	247	9290	379	219	8086
East of England	1368	532	15175	1766	853	26289
London	95	28	492	27	43	510
North East	193	29	1541	281	85	2469
North West	881	193	8724	390	228	7162
South East	1789	786	25649	1630	973	28162
South West	1537	486	17775	1036	395	14996
West Midlands	936	198	8995	455	259	8589
Yorkshire and The Humber	618	207	8196	600	272	6604

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

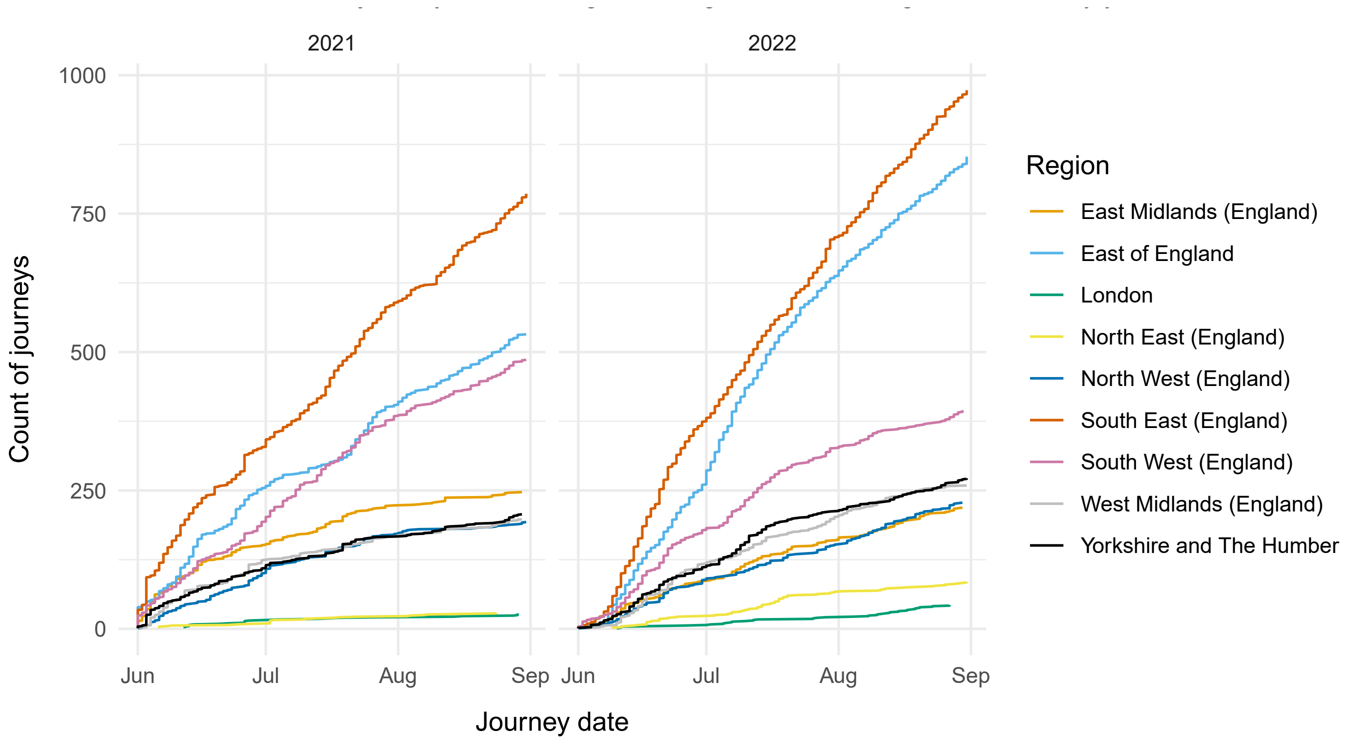


Figure 9. Cumulative count of journeys in each region in England in each Bugs Matter survey year

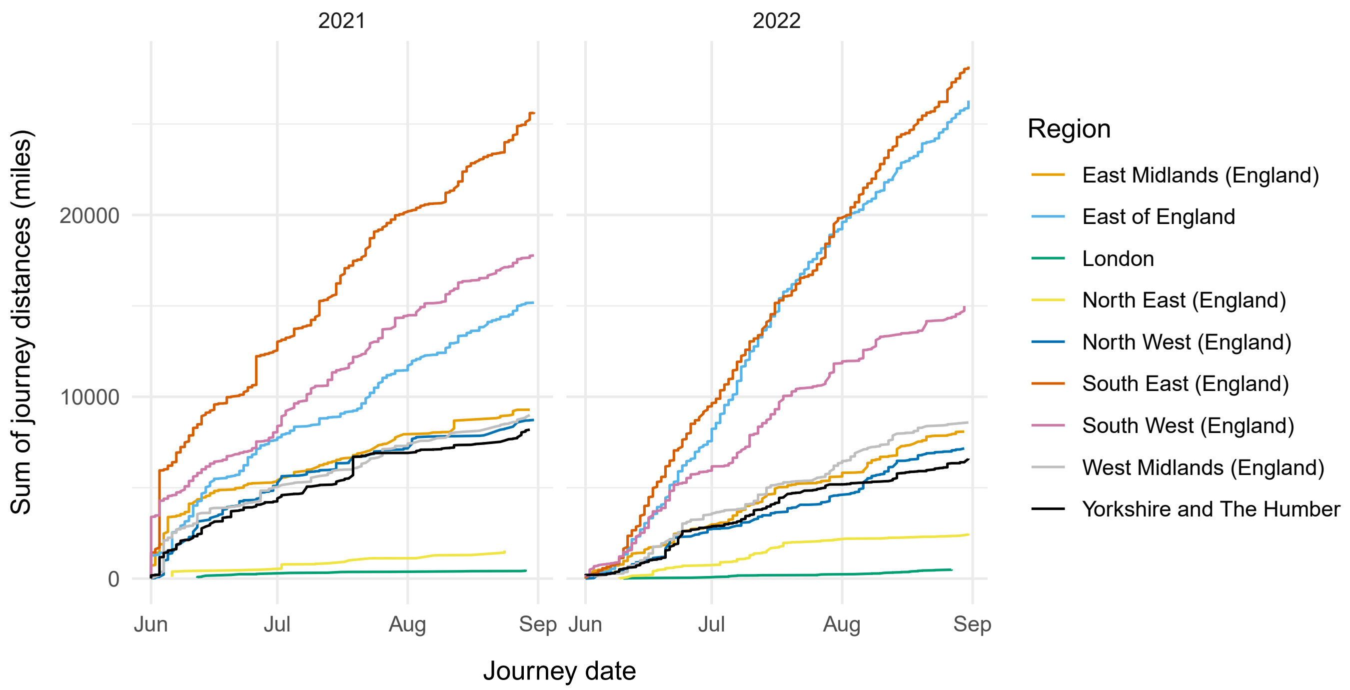


Figure 10. Cumulative sum of journey distances in each region in England in each Bugs Matter survey year

County summary statistics

The number of journeys recorded in each UK county via the Bugs Matter app are shown in Table 5. The most journeys were recorded in Kent (934), followed by Gwent (522), and then Essex (519). These were counties where Kent Wildlife trust had partnered with the local Wildlife Trusts to promote the survey, highlighting the effectiveness of these collaborations. Both Kent and Gwent saw the highest increases in the number of journeys between 2021 and 2022 (178 cumulatively), followed by Cambridgeshire (117). Journeys are yet to be recorded in six counties. 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-use types.

County	2021	2022	Total
Aberdeenshire	6	40	46
Angus	0	0	0
Argyll and Bute	14	8	22
Ayrshire and Arran	7	4	11
Banffshire	0	7	7
Bedfordshire	19	36	55
Berkshire	19	33	52
Berwickshire	3	0	3
Bristol	7	5	12
Buckinghamshire	20	45	65
Caithness	1	1	2
Cambridgeshire	69	186	255
Cheshire	27	59	86
City of Aberdeen	0	3	3
City of Dundee	0	3	3
City of Edinburgh	0	3	3
City of Glasgow	10	16	26
Clackmannan	0	0	0
Clwyd	32	34	66
Cornwall	44	64	108
Cumbria	91	33	124
Derbyshire	47	73	120
Devon	116	74	190
Dorset	22	33	55
Dumfries	0	3	3
Dunbartonshire	4	3	7
Durham	7	49	56
Dyfed	53	31	84
East Lothian	5	2	7
East Riding of Yorkshire	11	35	46
East Sussex	36	36	72
Essex	242	277	519
Fife	8	4	12
Gloucestershire	157	68	225
Greater London	30	47	77
Greater Manchester	49	80	129

County	2021	2022	Total
Gwent	172	350	522
Gwynedd	10	10	20
Hampshire	111	115	226
Herefordshire	28	36	64
Hertfordshire	45	73	118
Inverness	15	36	51
Isle of Wight	3	4	7
Kent	378	556	934
Kincardineshire	0	5	5
Lanarkshire	10	7	17
Lancashire	25	38	63
Leicestershire	73	55	128
Lincolnshire	50	59	109
Merseyside	8	17	25
Mid Glamorgan	6	13	19
Midlothian	0	0	0
Moray	0	5	5
Norfolk	75	166	241
North Yorkshire	76	101	177
Northamptonshire	65	23	88
Northumberland	19	34	53
Nottinghamshire	19	15	34
Orkney	0	0	0
Oxfordshire	158	95	253
Perth and Kinross	14	19	33
Powys	17	34	51
Renfrewshire	2	0	2
Ross and Cromarty	19	11	30
Roxburgh, Ettrick and Lauderdale	12	9	21
Rutland	0	4	4
Shetland	0	0	0
Shropshire	24	63	87
Somerset	113	104	217
South Glamorgan	14	17	31
South Yorkshire	27	81	108
Staffordshire	41	72	113
Stirling and Falkirk	14	30	44
Suffolk	83	112	195
Surrey	48	69	117
Sutherland	9	6	15
The Stewartry of Kirkcudbright	1	1	2
Tweeddale	1	1	2

County	2021	2022	Total
Tyne & Wear	0	0	0
Warwickshire	30	42	72
West Glamorgan	2	11	13
West Lothian	3	3	6
West Midlands	35	7	42
West Sussex	27	18	45
West Yorkshire	82	43	125
Western Isles	0	2	2
Wigtown	1	1	2
Wiltshire	31	55	86
Worcestershire	31	34	65

Table 5. The number of journeys in each county in the Bugs Matter survey years.

Splat counts

Across all years, 20.7% of journeys recorded zero insect splats (Figure 11). Zero insect splats were sampled in 7.7% of journeys in 2004, 51.3% of journeys in 2019, 39.9% of journeys in 2021, and 47% of journeys in 2022. For the Bugs Matter survey years, 43.9% of journeys recorded zero insect splats, 18.7% of journeys recorded one insect splat, 10.6% of journeys recorded two insect splats, and 7.2% of journeys recorded three insect splats, whilst 19.6% of journeys recorded four or more insect splats (Figure 12). England and Wales recorded the highest numbers of journeys with zero insect splats (Figure 13).

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 must be increased 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. The sensitivity of the sampling approach can be increased simply by increasing the sampling area of the number plate. For this reason, the Bugs Matter survey will discontinue the use of splatometers, and instead utilize the entire number plate as the sampling area, which is a standard size in the UK and approximately four times the size of the sampling area when using a splatometer. 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, 2021 and 2022 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.

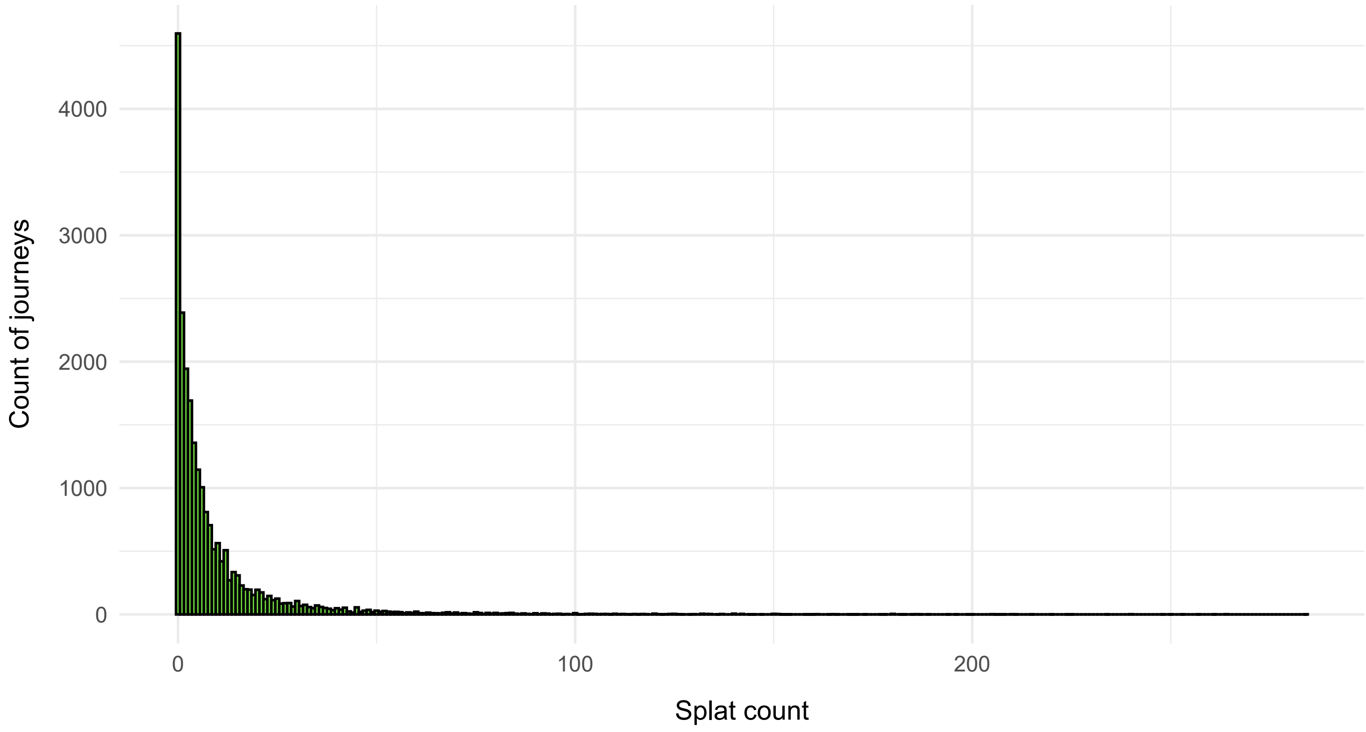


Figure 11. Histogram of the splat count data from all years

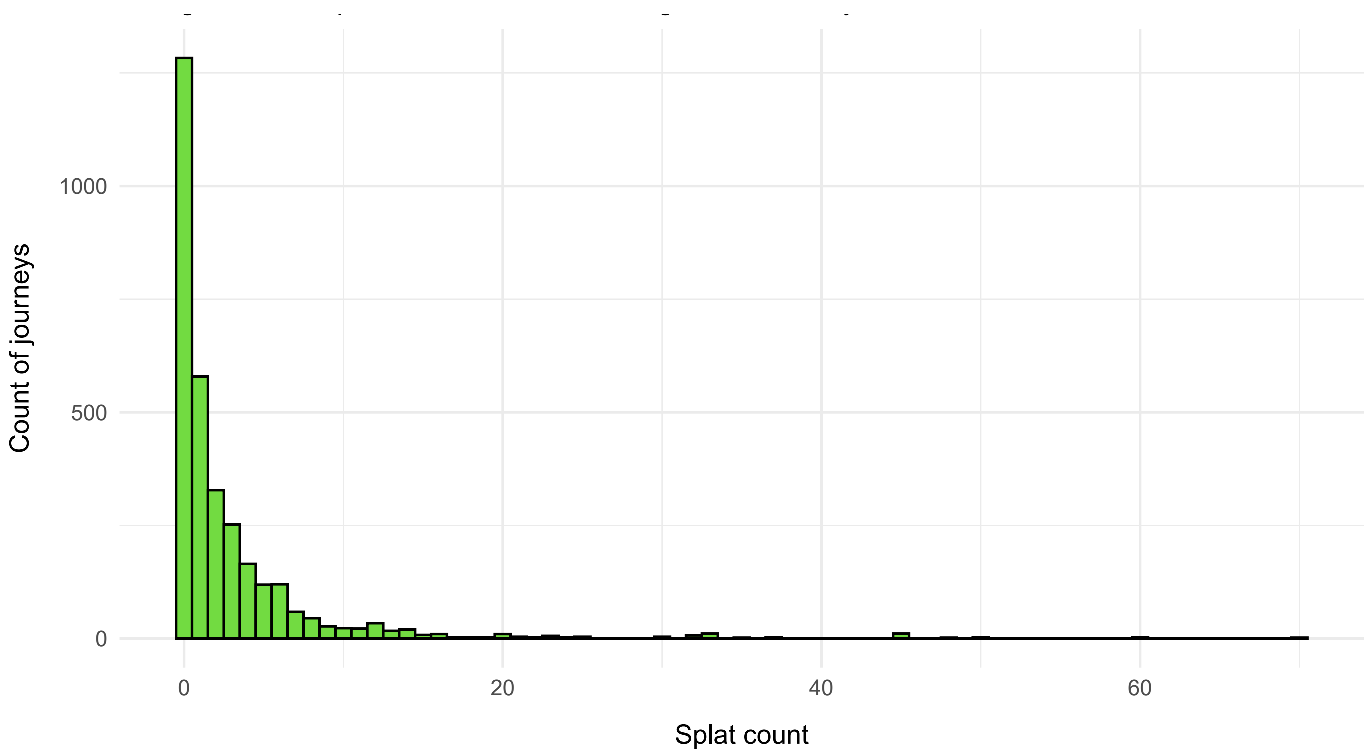


Figure 12. Histogram of the splat count data from the Bugs Matter survey in 2021–2022 from all years

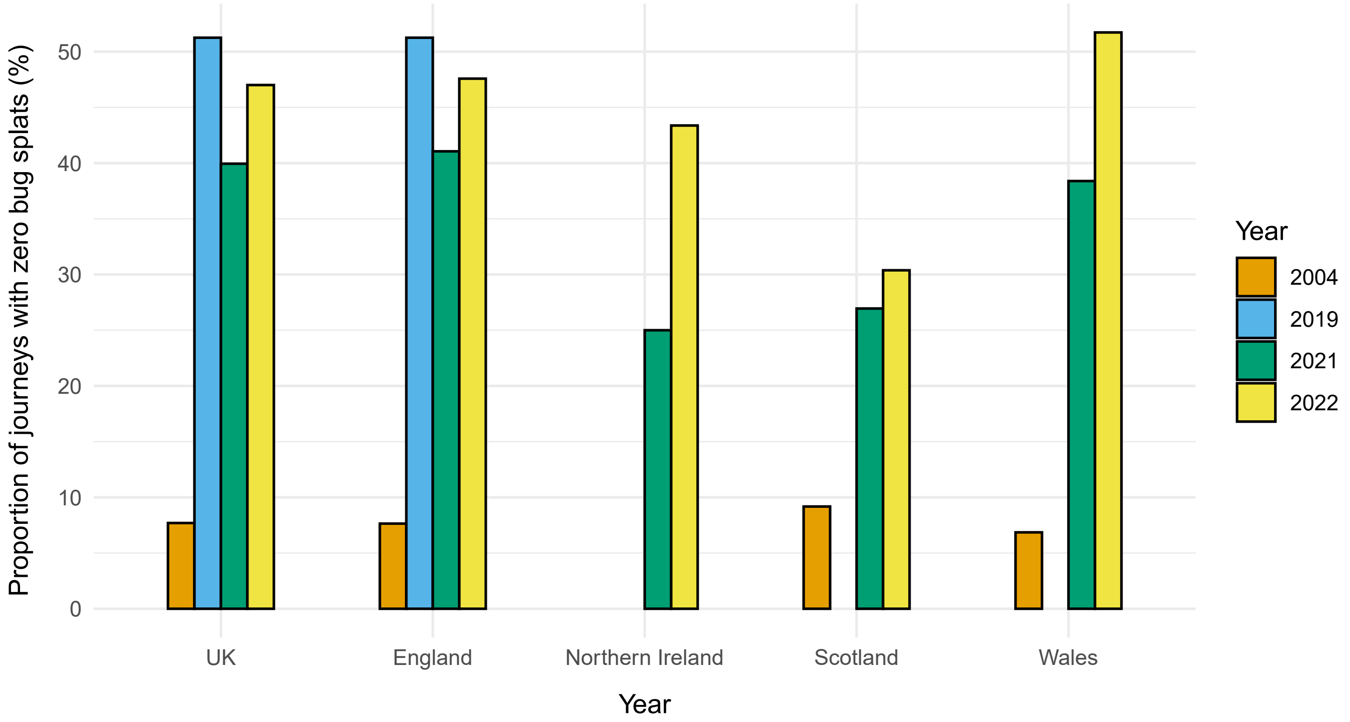
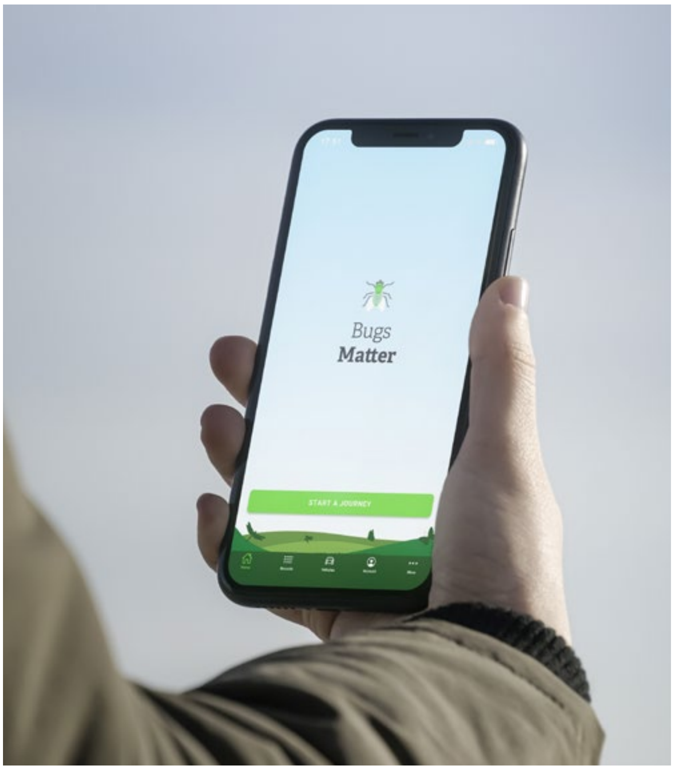


Figure 13. Bar plot showing the proportion of journeys with zero bug splats in each country across survey years

Splat rates

The average splat rate was 0.234 splats per mile in 2004, 0.108 splats per mile in 2019, 0.099 splats per mile in 2021, and 0.075 splats per mile in 2022 (Figure 14). One month into the 2022 survey season, variation in the mean splat rate greatly reduced, and by September, the mean splat rate was fairly representative of that of the entire dataset (Figure 14). 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. The overall spread of the insect splat rate data is shown in Figure 15, 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 16, and for each country in Figure 17. England, Northern Ireland and Wales all showed decreased mean splat rates from 2021 to 2022. In contrast, to the other countries, Scotland recorded a higher mean splat rate in 2022 than in 2021. Several heat maps show mean splat rates for each year by country (Figure 18), region (Figure 19), and county (Figure 20). 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.



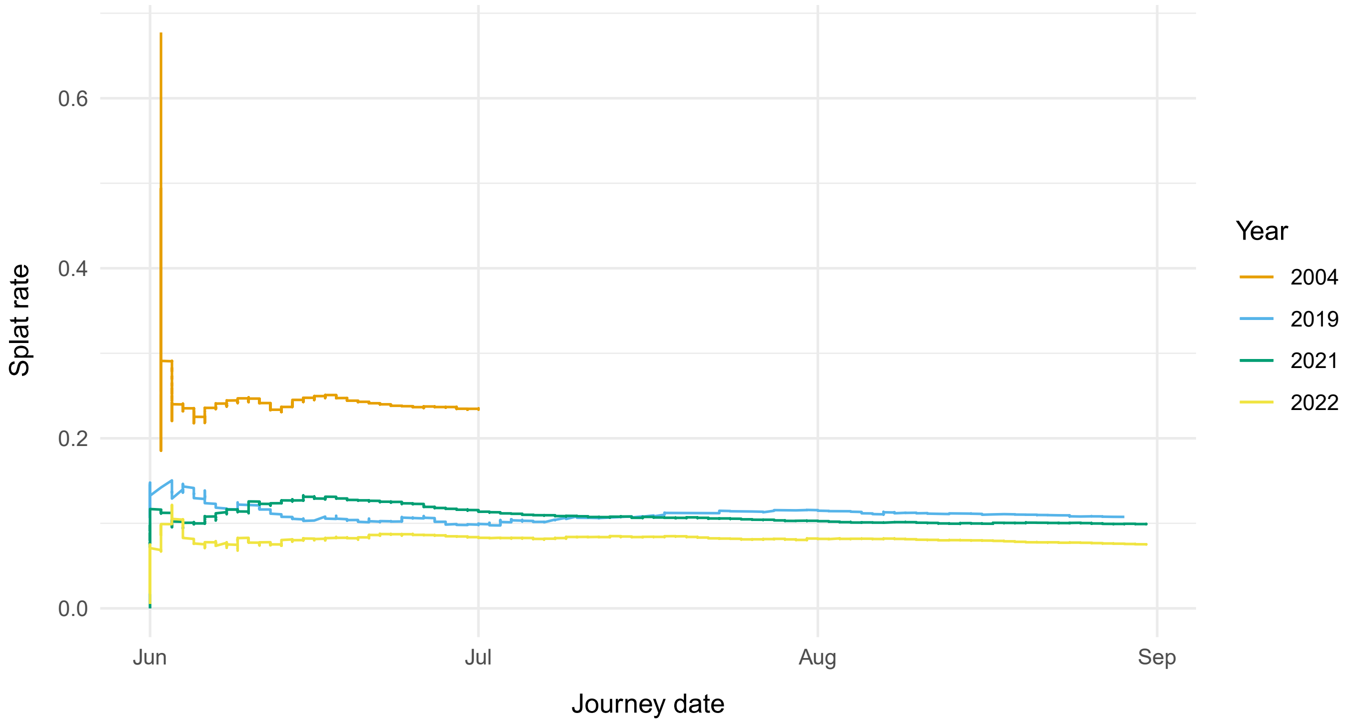


Figure 14. Cumulative mean of insect splat rate in each survey year

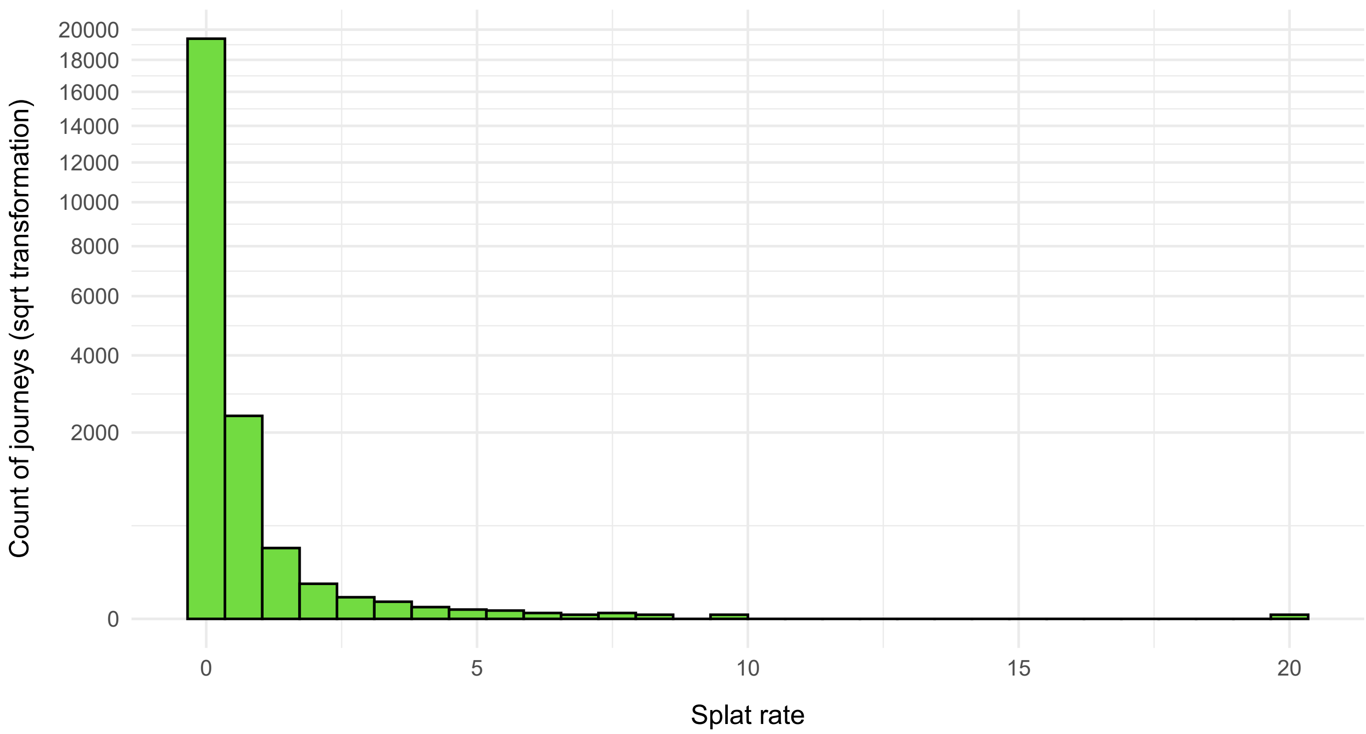


Figure 15. Histogram of the splat rate (splats per mile) data

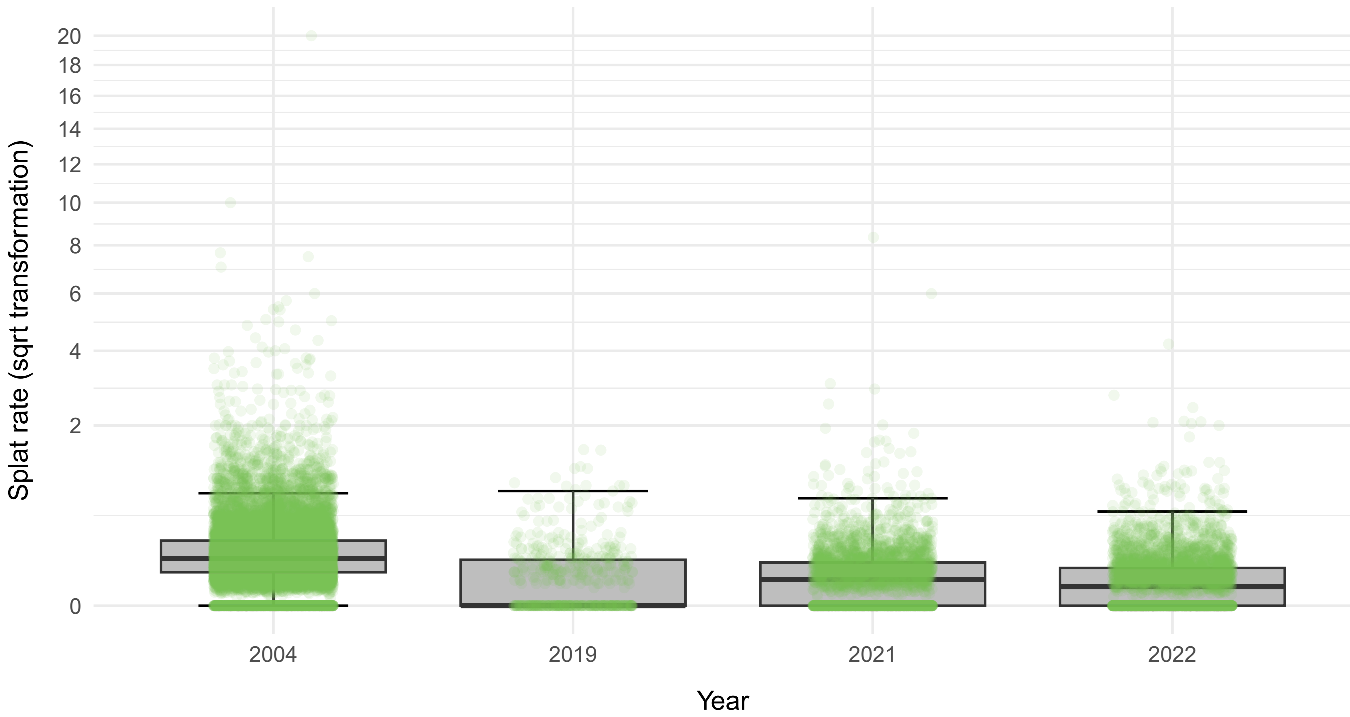


Figure 16. Boxplot with jittered data points showing the spread of the insect splat rate (splats per mile) data. The boxes indicate the interquartile range (central 50% of the data) either side of the median splat rate, which is shown by the horizontal line inside the box. The vertical lines extend out by 1.5 times the interquartile 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

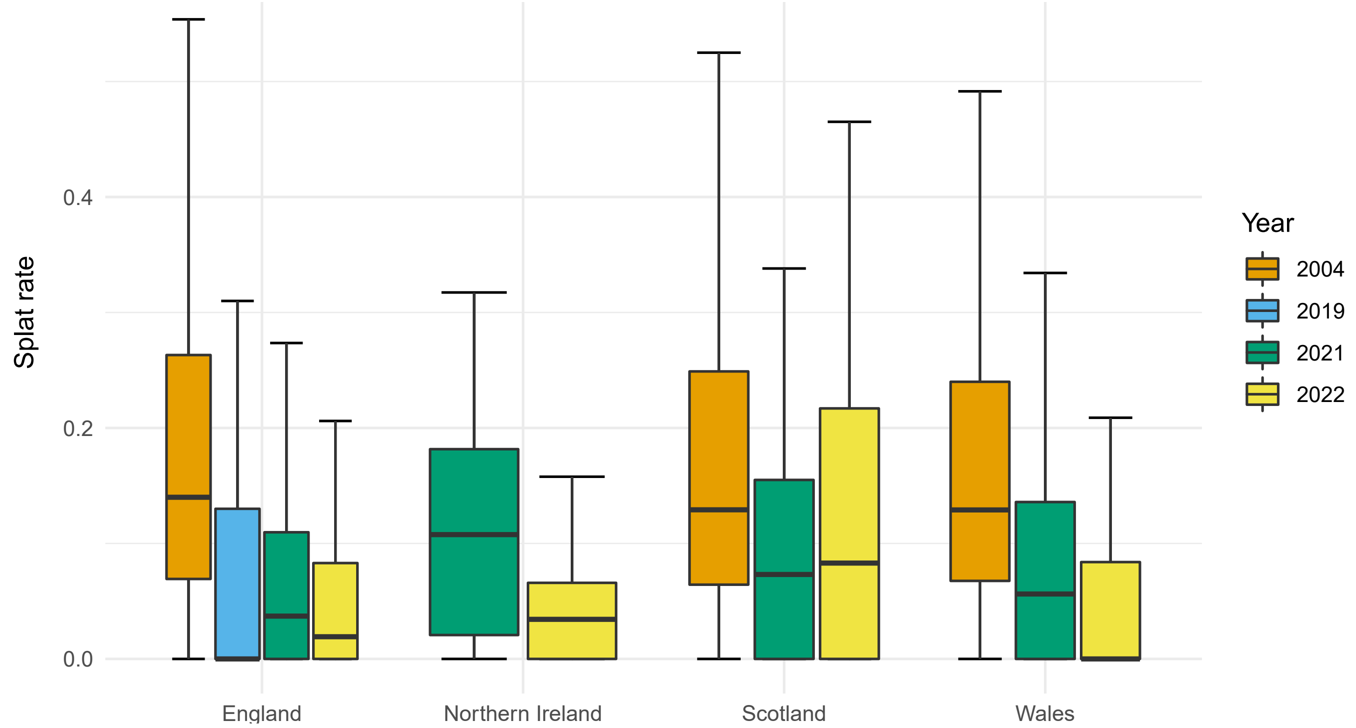


Figure 17. Grouped boxplot showing the spread of the insect splat rate (splats per mile) data by country. The boxes indicate the interquartile range (central 50% of the data) either side of the median splat rate, which is the horizontal line inside the box. The vertical lines extend out by 1.5 times the interquartile range

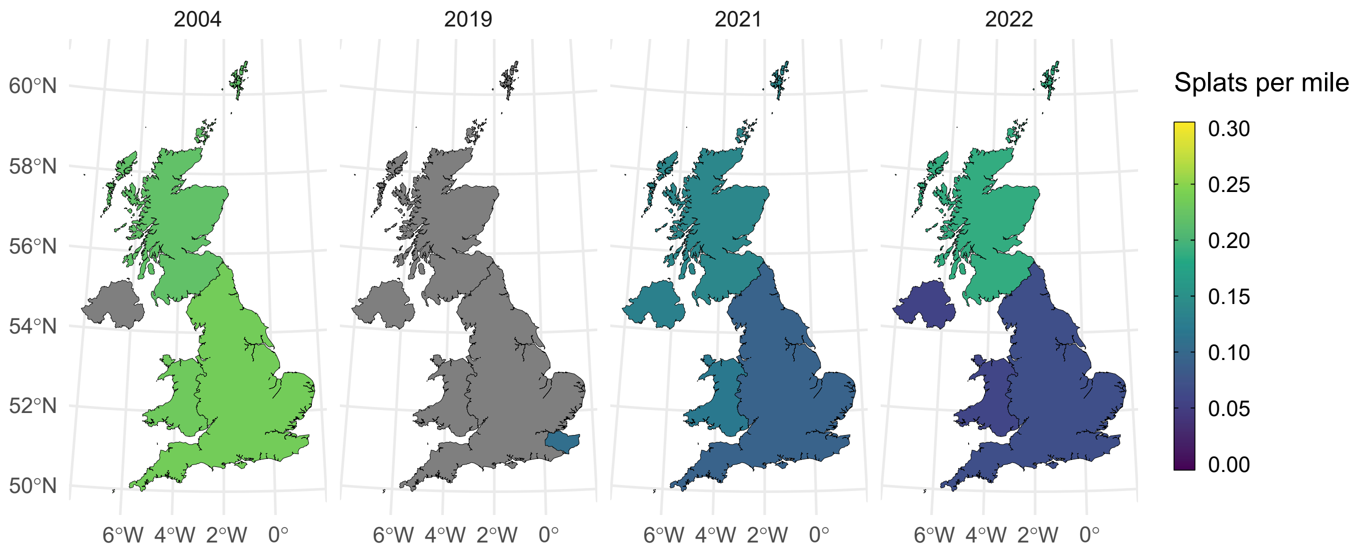


Figure 18. Heat map of mean splat rate for each country across survey years

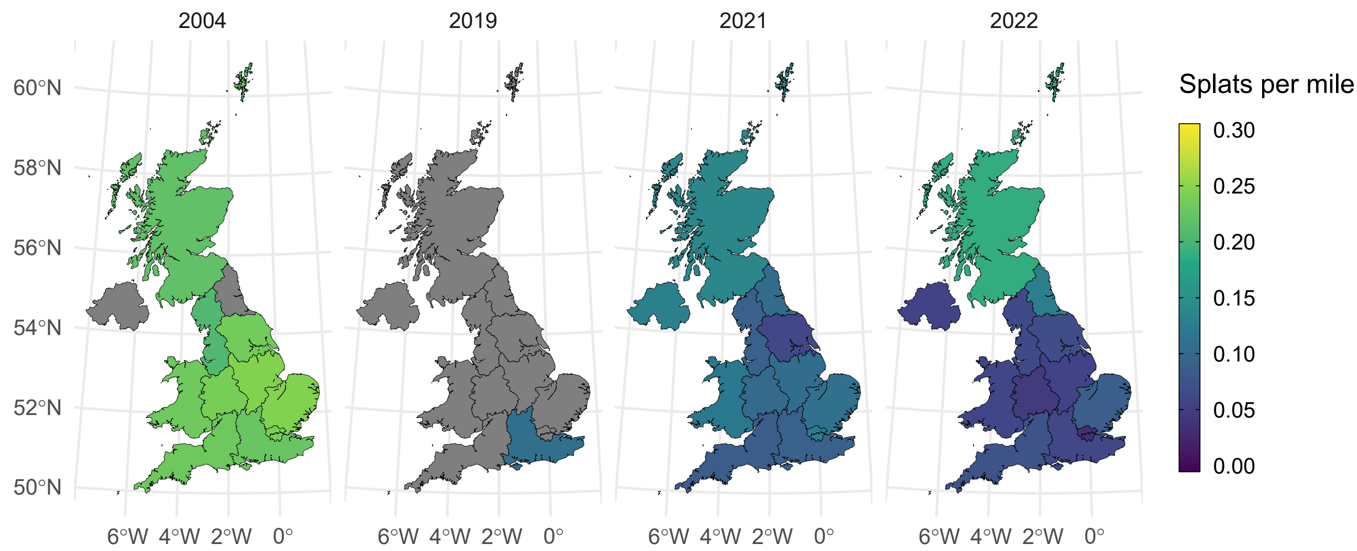


Figure 19. Heat map of mean splat rate for each region across survey years

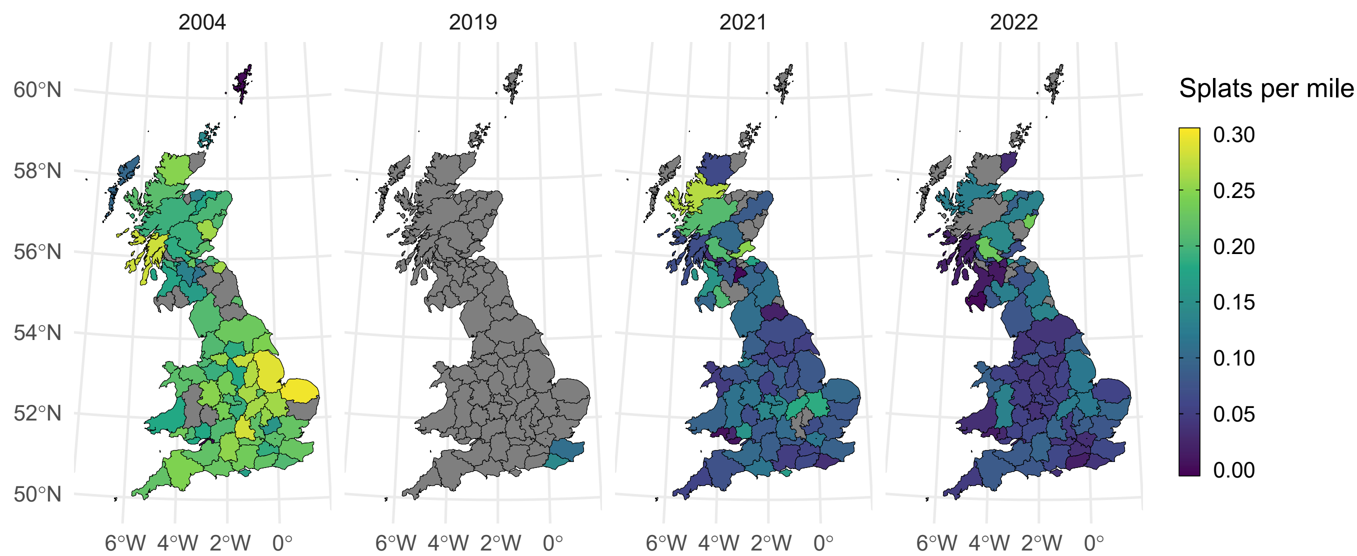


Figure 20. Heat map of mean splat rate for each county across survey years

Independent variables

The majority of journeys (94%) were undertaken in a car with the remainder being undertaken in HGVs, SUVs, or vans (Table 6).

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
Car	13370	318	3084	3999
HGV	256	66	2	0
SUV	31	135	16	9
Van	663	0	110	131

Table 6. The number of journeys undertaken in each vehicle type in each survey year.

The average journey distance in 2004 was 60 miles, in 2019 it was 17.6 miles, in 2021 it was 35 miles, and in 2022 it was 30 miles (Figure 21). Short journeys in 2019 would be expected due to the survey being focused on Kent. The mean average journey speed in 2004 was 37.4 mph, in 2019 it was 22.3 mph, in 2021 it was 29.5 mph, and in 2022 it was 29.7 mph (Figure 22).

The mean proportion of journeys conducted on primary roads was 63%. The mean proportion of journeys conducted on secondary roads was 31.9%. The mean proportion of journeys conducted on tertiary roads was 5.2%, and these proportions differed most notably between 2004 and the recent surveys in 2021 and 2022 (Figure 23).

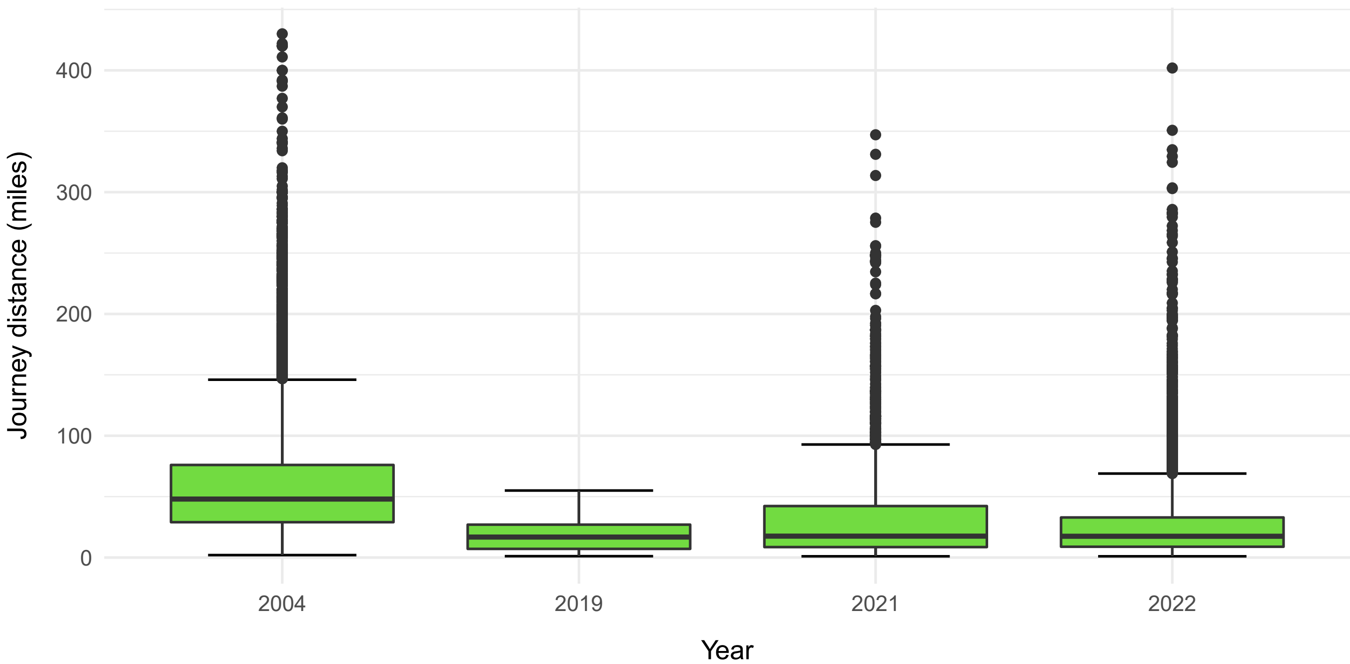


Figure 21. Boxplot showing the spread of the journey distances. The boxes indicate the interquartile range (central 50% of the data), either side of the median journey distance which is shown by the horizontal line inside the box. The vertical lines extend out by 1.5 times the interquartile range, outside of which is the outlying data shown as points.

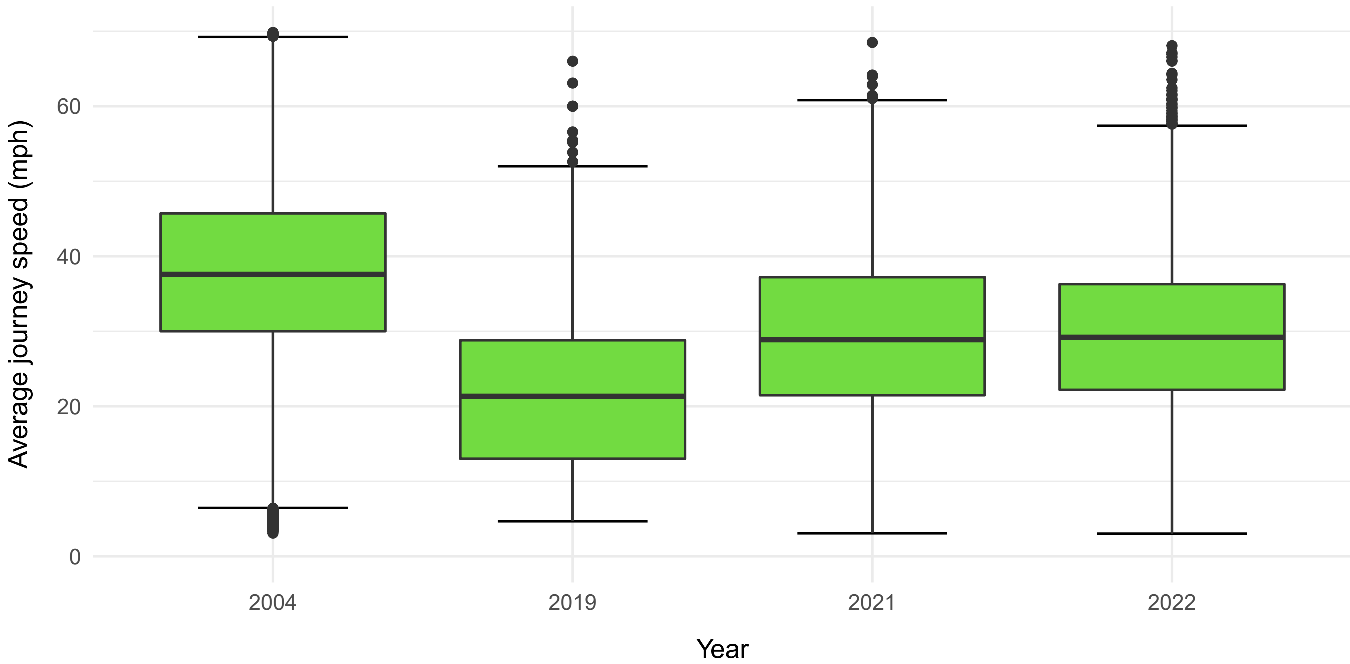


Figure 22. Boxplot showing the spread of the average journey speed. The boxes indicate the interquartile range (central 50% of the data), either side of the median average journey speed which is shown by the horizontal line inside the box. The vertical lines extend out by 1.5 times the interquartile range.

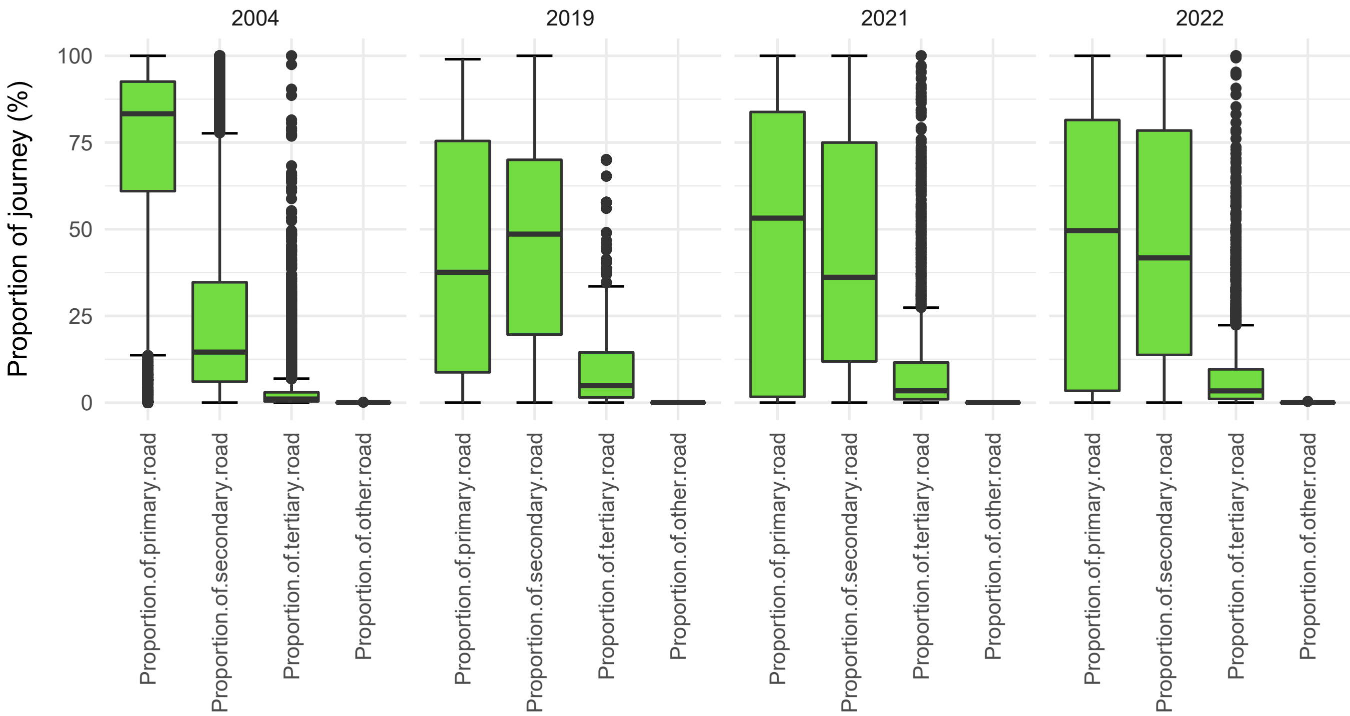


Figure 23. Boxplot showing the spread of the road type data. For every journey, we know what proportion of the journey (%) was driven on each of primary, secondary, tertiary or other roads. The boxes indicate the interquartile range (central 50% of the data), either side of the median proportion of journey which is shown by the horizontal line inside the box. The vertical lines extend out by 1.5 times the interquartile range.

The average time of day of journeys in 2004 was 13:45, in 2019 it was 12:45, in 2021 it was 13:36, and in 2022 it was 13:20 (Figure 24).

The average journey temperature in 2004 was 15.9°C, in 2019 it was 16.6°C, in 2021 it was 16.5°C, and in 2022 it was 17.3°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. (Figure 25).

The average NDVI surrounding journeys in 2004 was 5.293, in 2019 it was 5.846, in 2021 it was 5.726, and in 2022 it was 5.035 (Figure 26).

Lower NDVI values in 2022 are the result of the hot and dry summer, which led to desiccation of vegetation and lower chlorophyll levels in plant foliage. The average calendar date of journeys in 2004 was 165, in 2019 it was 185, in 2021 it was 188, and in 2022 it was 194 (Figures 3-6 and 24).

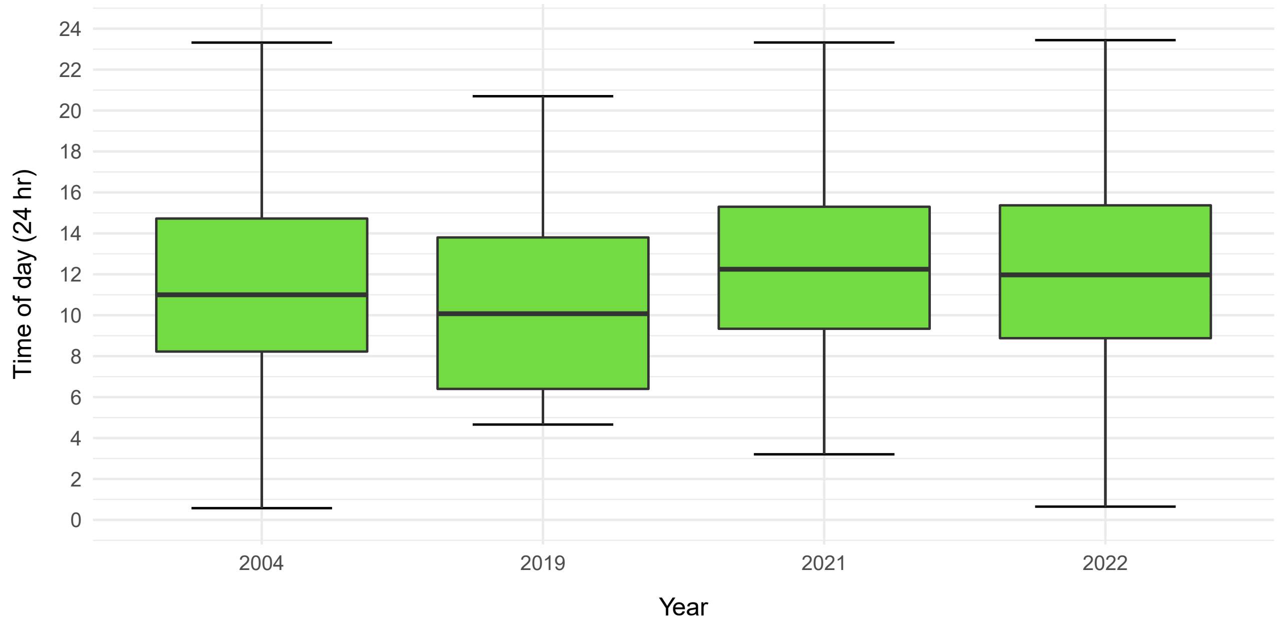


Figure 24. Boxplot showing the spread of the time of day of journeys. The boxes indicate the interquartile range (central 50% of the data), either side of the median time of day of journeys which is shown by the horizontal line inside the box. The vertical lines extend out by 1.5 times the interquartile range.

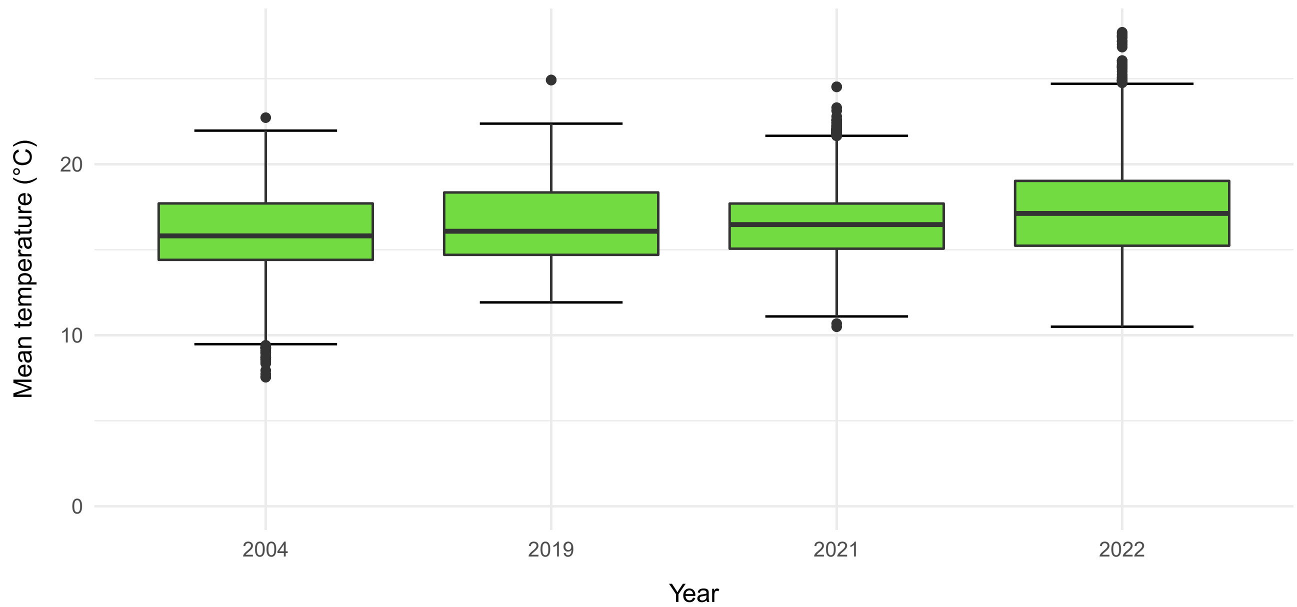


Figure 25. Boxplot showing the spread of the time of day of journeys. The boxes indicate the interquartile range (central 50% of the data), either side of the median time of day of journeys which is shown by the horizontal line inside the box. The vertical lines extend out by 1.5 times the interquartile range.

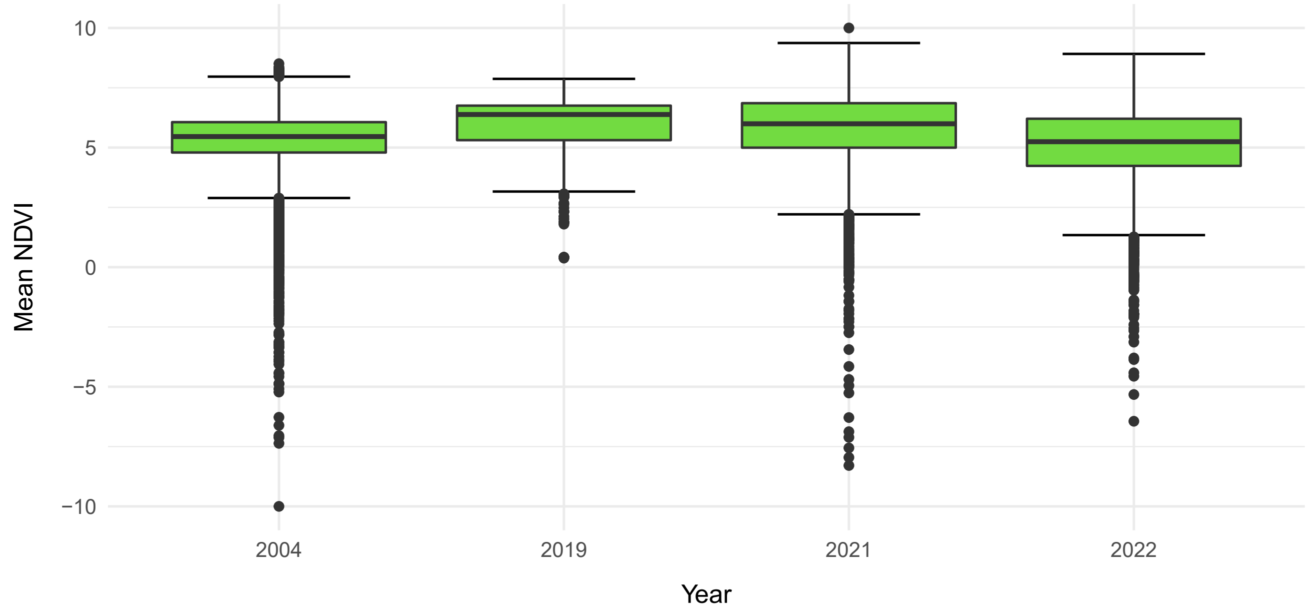


Figure 26. Boxplot showing the spread of the mean NDVI (vegetation greenness) surrounding journey routes (500 m buffer). The boxes indicate the interquartile range (central 50% of the data), either side of the median mean NDVI which is shown by the horizontal line inside the box. The vertical lines extend out by 1.5 times the interquartile range.

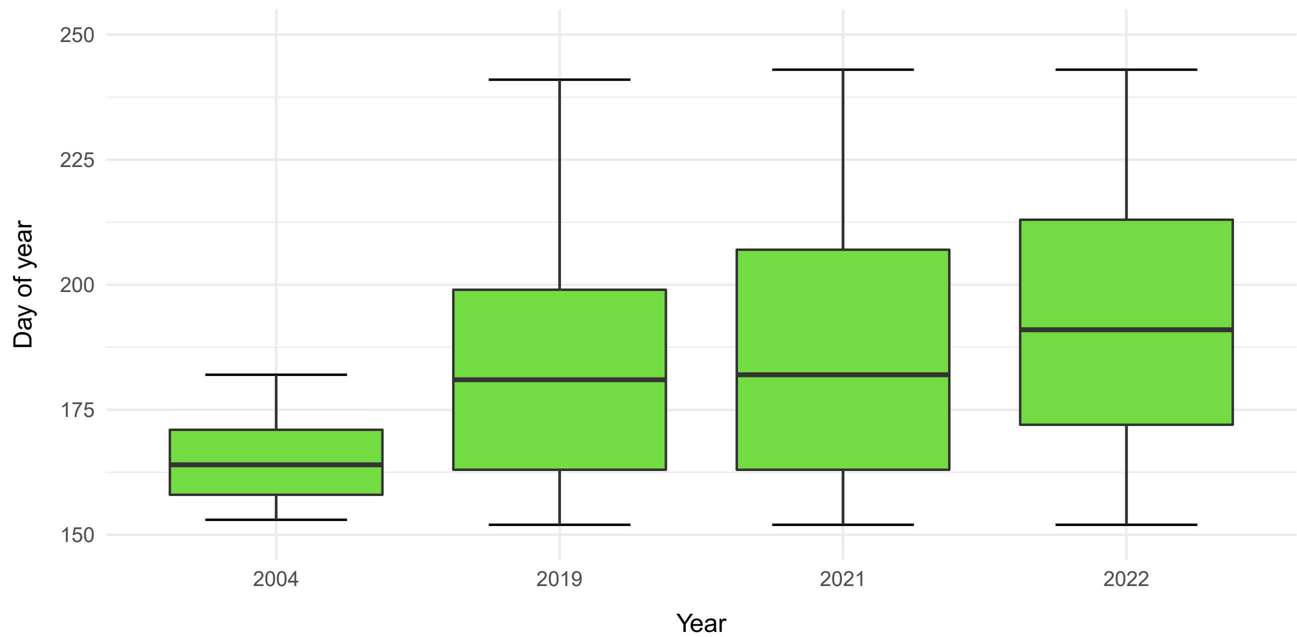


Figure 27. Boxplot showing the spread of the calendar date of journeys. The boxes indicate the interquartile range (central 50% of the data), either side of the median calendar date of journeys, which is shown by the horizontal line inside the box. The vertical lines extend out by 1.5 times the interquartile range.

Main results

The results of the statistical model which estimates how the number of insect splats changes over time, space and in response to a range of other factors.

Results of the zero-inflated negative binomial (ZINB) statistical modelling

The results of the ZINB model show a 22.1% (95% CI [7.2%, 34.6%]) reduction in the number of insect splats in the UK in 2019 (14.7%/ decade), a 58.4% (95% CI [55.7%, 61.0%]) reduction in 2021 (34.4%/ decade), and a 63.7% (95% CI [61.5%, 65.8%]) reduction in 2022 (35.4%/ decade), compared to 2004 (Figure 28).

A 12.6% (95% CI [5.9%, 18.9%]) reduction was observed between 2021 and 2022. The ZINB model found the differences were statictically significant ($p = < 0.001$). The estimate of change in the number of insect splats between 2004 and 2022 (a decrease of 63.7%) has a lower confidence interval of 61.5% and an upper confidence interval of 65.8%, 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 4919, and in a model with only year as a predictor it was 3201. This shows that the goodness of fit of the model increased substantially (53%) with the addition of the other independent variables. The VIF scores (max VIF = 2.29, mean VIF = 1.31) showed low collinearity between independent variables.

The purpose of the ZINB statistical model is to predict splat count while taking into account 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 mile). This is best practice, as we explicitly model the splat count as a function of journey distance, however it means our results are in a unit of 'splat counts (corrected for journey distance)' rather than the slightly more interpretable 'splat rate (splats per mile)'. The predictions of splat count are 7.4 in 2004, 5.2 in 2019, 3.2 in 2021, and 2.7 in 2022 (Figure 29). The wide confidence interval in 2019 is due to the small sample size from that year. Figures 30-38 show the ZINB model predictions of splat count corrected for journey distance, in relation to the survey year and the other independent variables.

It is important to note that the results reported here are based on data from only three points in time with a skewed temporal distribution, and consequently do not constitute a trend. With such a low temporal resolution, there is a risk of uncharacteristically high or low insect abundances during these sampling years which imply an apparent change in abundance but is 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 12.6% reduction in the number of insects splats in the UK between 2021 and 2022 is a concerning statistic. However, for the reasons outlined in the previous paragraph, 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, and road types), journeys tended to take place slightly later in the year in 2022. Moreover, the sample size may still be too small to ensure an even and accurate representation of bug populations across the UK for each year. Vegetation greenness was lower and temperatures were higher in 2022, with record-breaking 40+ °C recorded on several days. Assuming the journeys in each year provide similarly representative data, the observed 12.6% decrease between 2021 and 2022 could be the result of both a long-term background rate of decline and short-term reduced insect abundance as a result of the hot and dry conditions in 2022. Data from future years will help to clarify whether and for how long insect populations were affected by the extreme climate in the UK in 2022, 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, -35.4%/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, -38.0%/ decade and -46.0%/decade, and are slightly higher than the -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).

Image: Chalkhill blue butterfly

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 the measurements in statistical models. For instance, the inclusion of mean temperature, NDVI, time of day of the journey, and calendar date of the journey help control for inter-annual and spatial differences in temperature, spatial variation in vegetation 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. We can see this in our results 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 and helicopters.

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, the vehicle speed, the journey distance, and the types of roads driven, all create sampling bias, but by measuring these variables and including them in our models, we can control for these effects 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, land-use change and climate change could explain a further proportion of the unexplained variation in the data. Our model also lacks data on a number of other factors that influence insect abundance and activity, such as variation in habitat type and management, roadside verge management, disease and predation of insects, weather conditions including humidity or wind, and natural variation in insect lifecycles or flight periods.

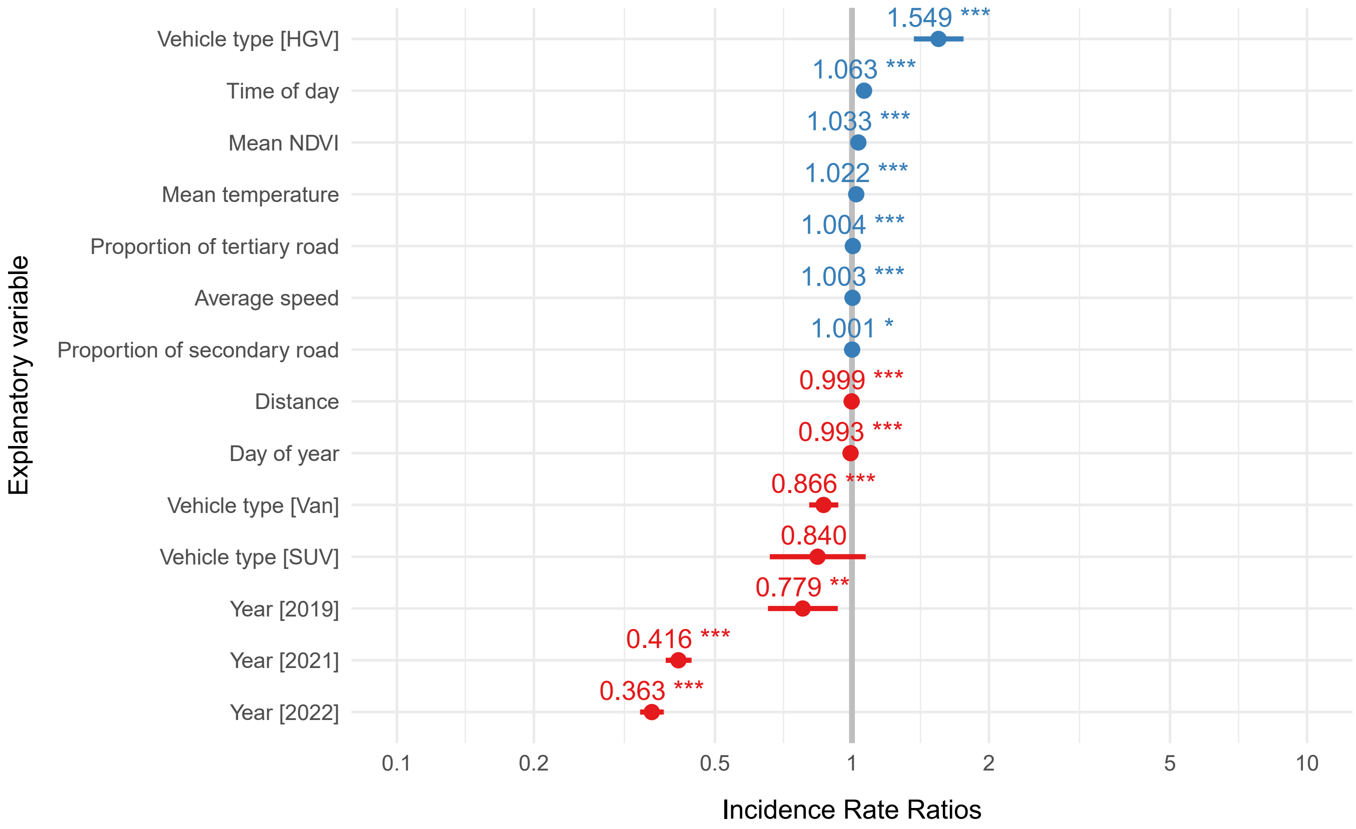


Figure 28. Forest plot of incidence rate ratios from the ZINB negative binomial model of Bugs Matter survey data of insects on car number plates in the UK, showing the quantity of change (a multiplier) in splat rate (splats per mile) given a one–unit change in the independent variable, while holding 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 29. Predictions of splat count (corrected for distance) by the ZINB model across year values.

Independent variables

The ZINB model results show that compared to conventional cars, splat count was 55% higher for HGVs and 13% lower for vans, but SUVs did not differ significantly from cars (Figure 30). 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.

Splat count increased steeply with journey distance, up to a distance of between 20-50 miles, where it started to decrease, by 0.1% with each mile of journey distance (Figure 31). This shows 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 odds of a zero-count journey occurring decreased by 6% with each one mile increase in journey distance. This shows that despite the splat count decreasing on longer journeys, there is a much greater chance that at least one insect will be sampled.

Splat count increased by 0.3% with each 1 mph increase in average journey speed (Figure 32). 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.

For each one percent increase in the proportion of journey route that was on secondary roads, splat rate increased by 0.1% (Figure 33). For each one percent increase in the proportion of journey route that was on secondary roads, splat rate increased by 0.4% (Figure 34). This tell us 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. This means that journeys that mostly follow secondary and tertiary roads, have high variation in the number of insects sampled. This may be related to high variation in insect abundance or activity along these roads, or it may be due to differing speeds at which vehicles travel along these road types.

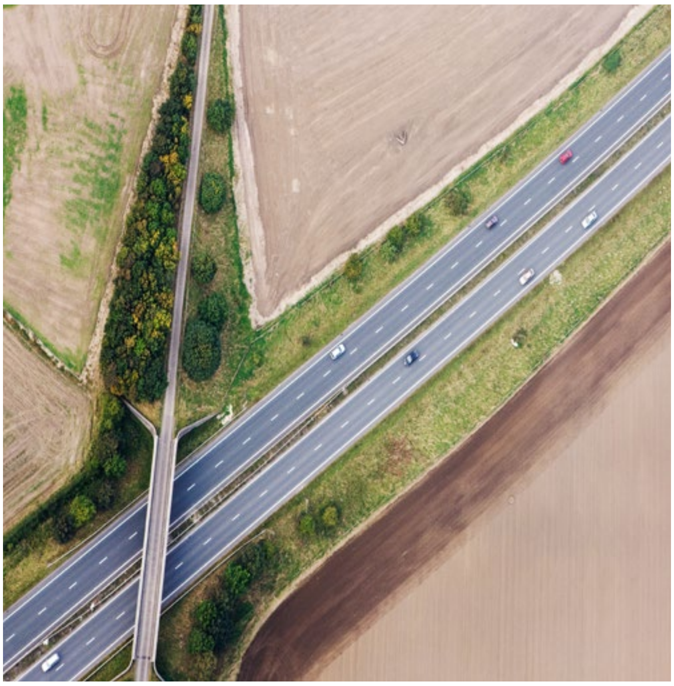


Image: Arial view of UK motorway

For instance, some tertiary roads may have a speed limit of 20 mph and some may have a speed limit of 60 mph.

On average, splat count increased by 6% with each hour of the day that passed (Figure 35). This could be due to the fact that insects are more active at higher ambient air temperatures which occur later in the day (Mellanby, 1939). Indeed, splat count increased by 2% with each one degree increase in mean daily temperature (Figure 36). Insects may also be attracted to the light emitted from vehicle headlights and road lighting leading to greater numbers of insects sampled from dusk.

Splat count increased by 3% with each one unit increase in NDVI (Figure 37). The results of the ZINB zero-inflated model showed that the odds of a zero-count journey occurring decreased by 30% with each one unit increase in NDVI. These results confirm that greater numbers of insects are sampled in more vegetated areas. However, NDVI does not distinguish between the greenness of crop fields and the greenness of naturally-vegetated habitats. Whilst our results likely reflect the broad scale differences in insect abundance between urban and rural areas due to the relative suitability of habitats, differences in insect abundance between agricultural land and natural habitat remains unknown. Calculating the areas of different habitat types surrounding journey routes will be one aim for the 2023 analysis. We would expect insect abundance to be low in most arable environments, due to pesticide use, the negative influence of crop monocultures on insect abundance, a lack of habitat attributes that provide nesting or overwintering habitats, and a lack of undisturbed habitat and habitat continuity due to intensive management for crops. Indeed 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).

Calculating the areas of different habitat types surrounding journey routes may also provide insights into how habitat fragmentation might be affecting the evolution of flying insects. When habitats become very 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 if successful so wings shrink, wing muscles atrophy, dispersal reduces (Davies and Saccheri, 2013) and, we assume, long-distance dispersal eventually stops. 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). While in South America, birds in primary forest, body size is reducing but wing size is increasing (Jirinec et al., 2021) indicating that dispersal or at least flight is still evolutionarily beneficial to birds in less fragmented habitats.

It may be that reductions in the occurrence of insects in traps, on windscreens, and on number plates is being caused, at least in part, by reduced activity, flight and dispersal of insects, which may be a response to combinations of climate change, habitat fragmentation and pesticide-contaminated landscapes that reduce the occurrence of genes associated with long distant flight. Of course, reduced activity of flying insects would itself be indicative of reduced pollination rates for 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 an extinction event, and may be associated with declines in insect abundance at a landscape scale.

Splat count decreased by 0.7% with each day that passed during the survey season (Figure 38), 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. It will be considered whether starting the survey season in April or May, rather than June, could provide a more complete picture of insect abundance, especially as many species have flight periods in spring.

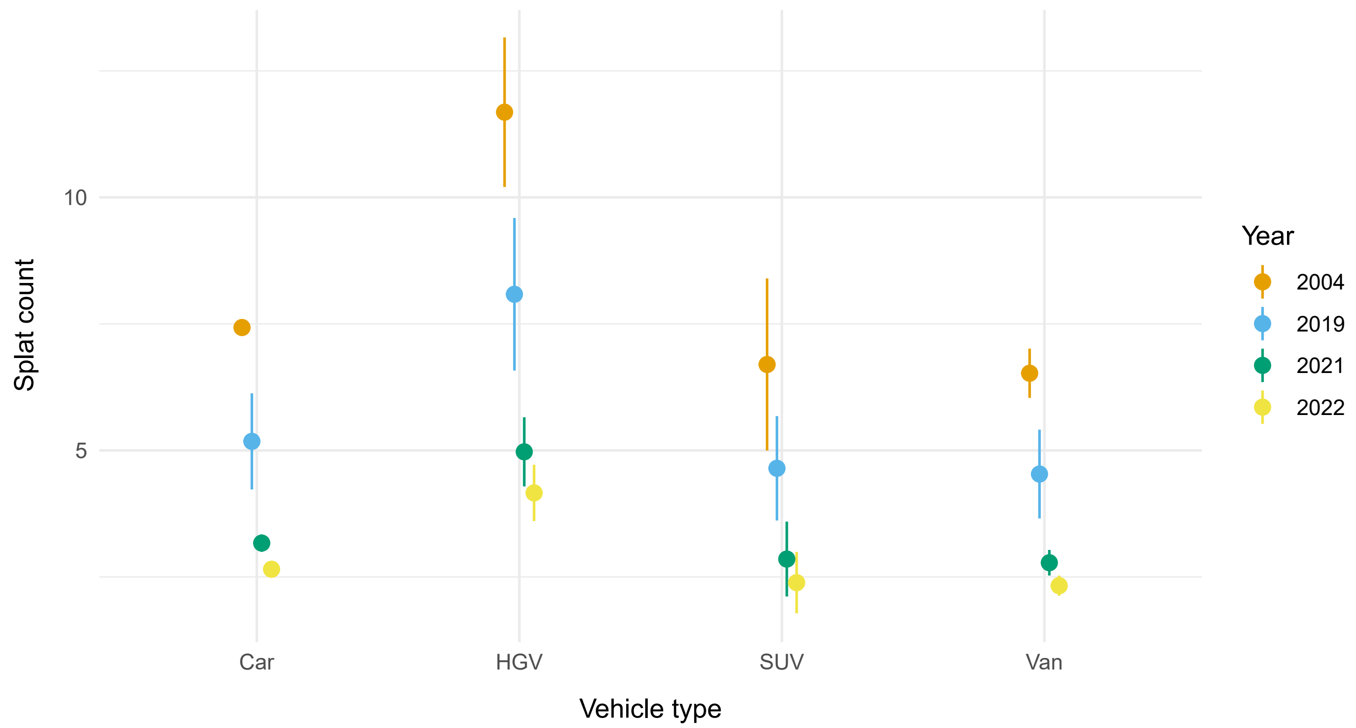


Figure 30. Predictions of splat count (corrected for distance) by the ZINB model across vehicle type values.

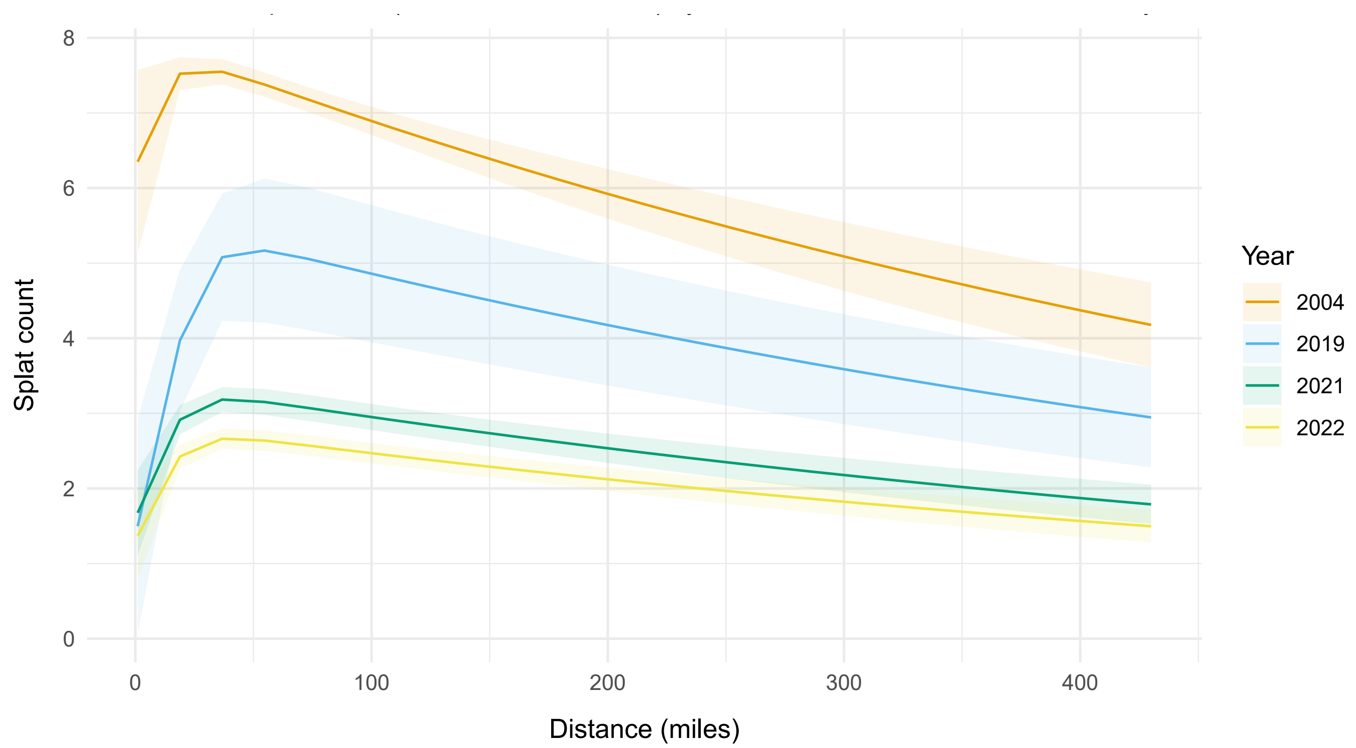


Figure 31. Predictions of splat count (corrected for distance) by the ZINB model across distance and year values.

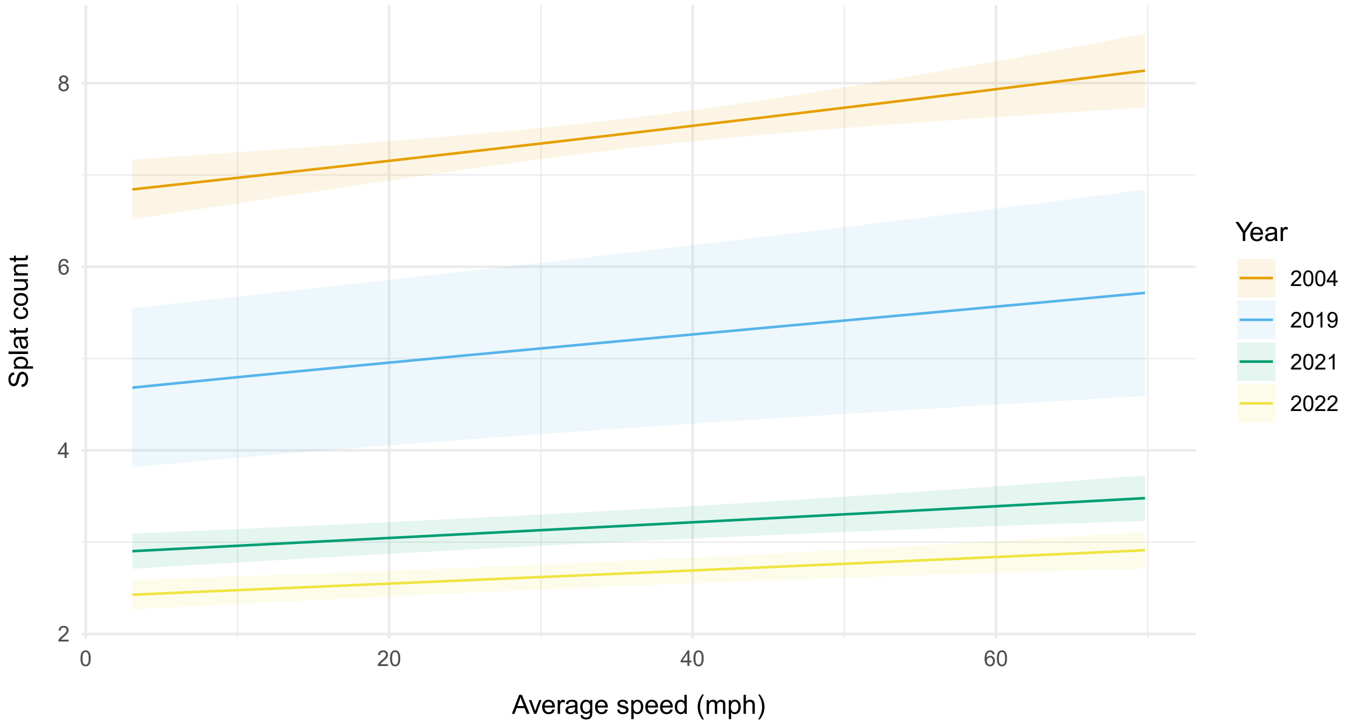


Figure 32. Predictions of splat count (corrected for distance) by the ZINB model across average speed and year values.

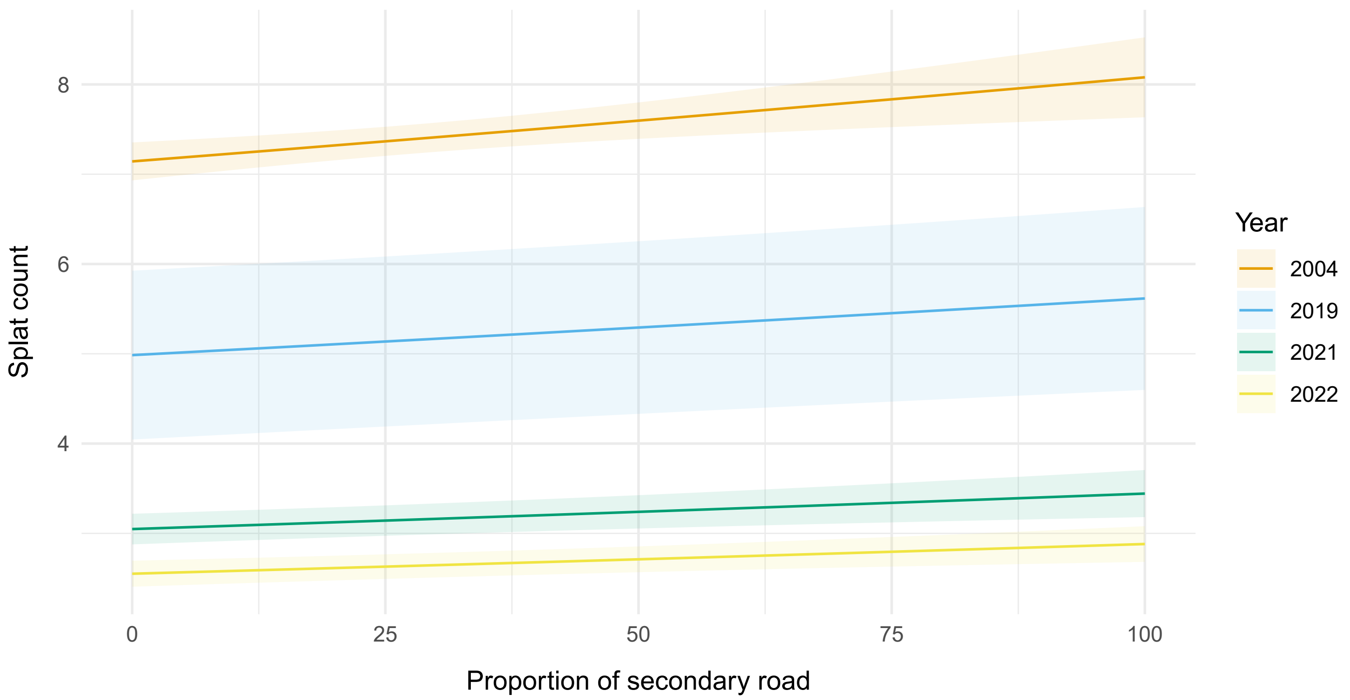


Figure 33. Predictions of splat count (corrected for distance) by the ZINB model across proportion of secondary road and year values.

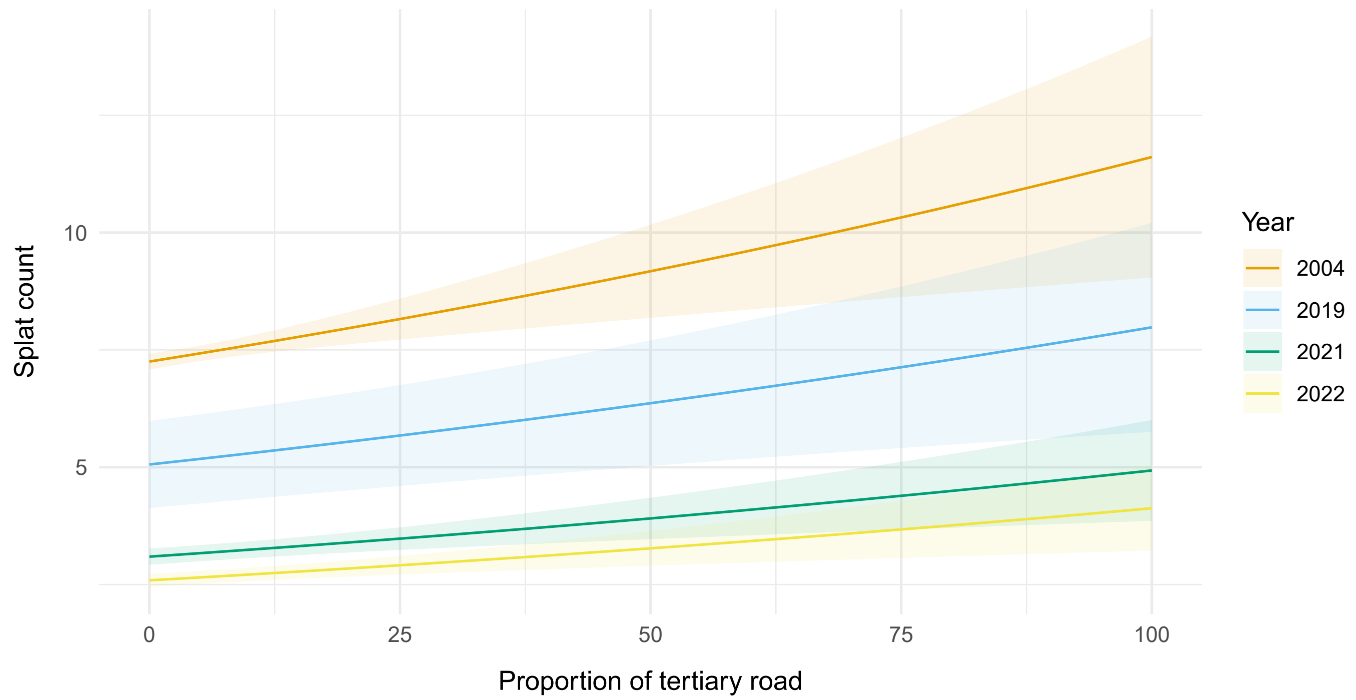


Figure 34. Predictions of splat count (corrected for distance) by the ZINB model across proportion of tertiary road and year values.

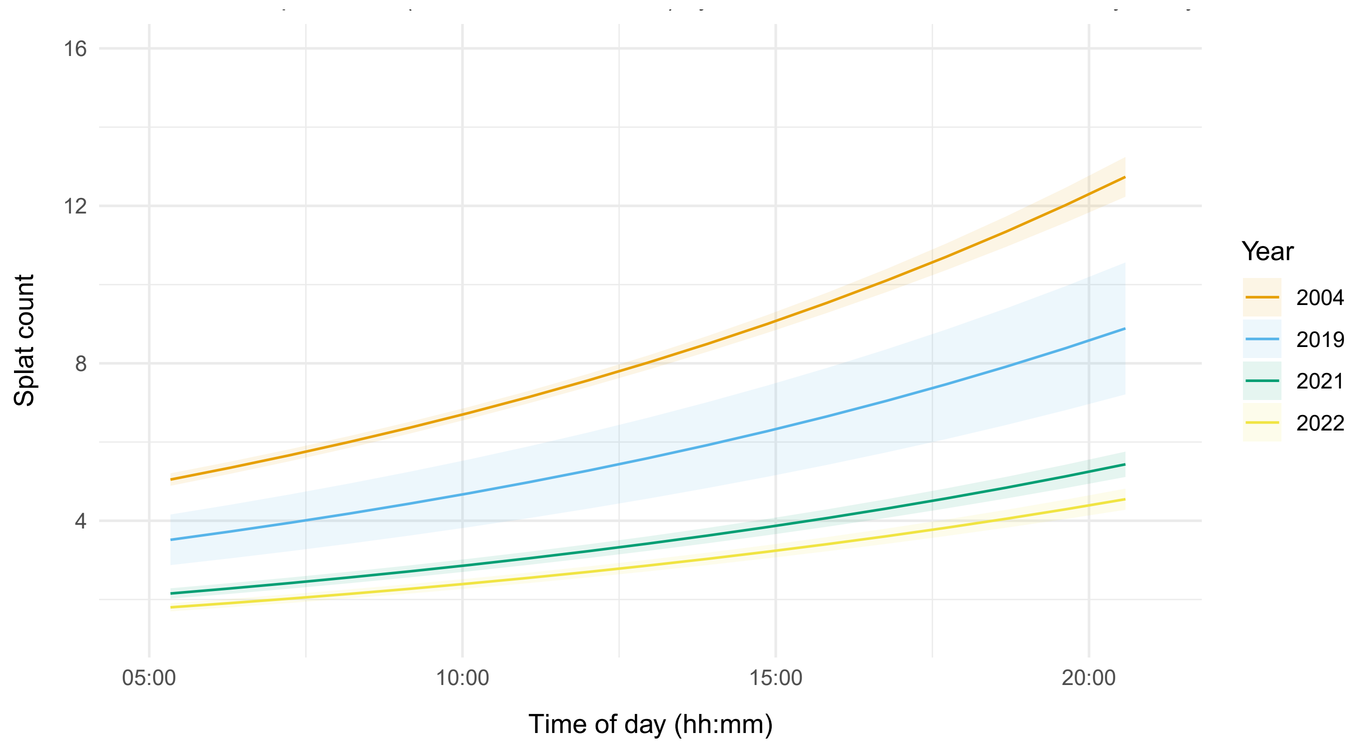


Figure 35. Predictions of splat count (corrected for distance) by the ZINB model across time of day and year values.

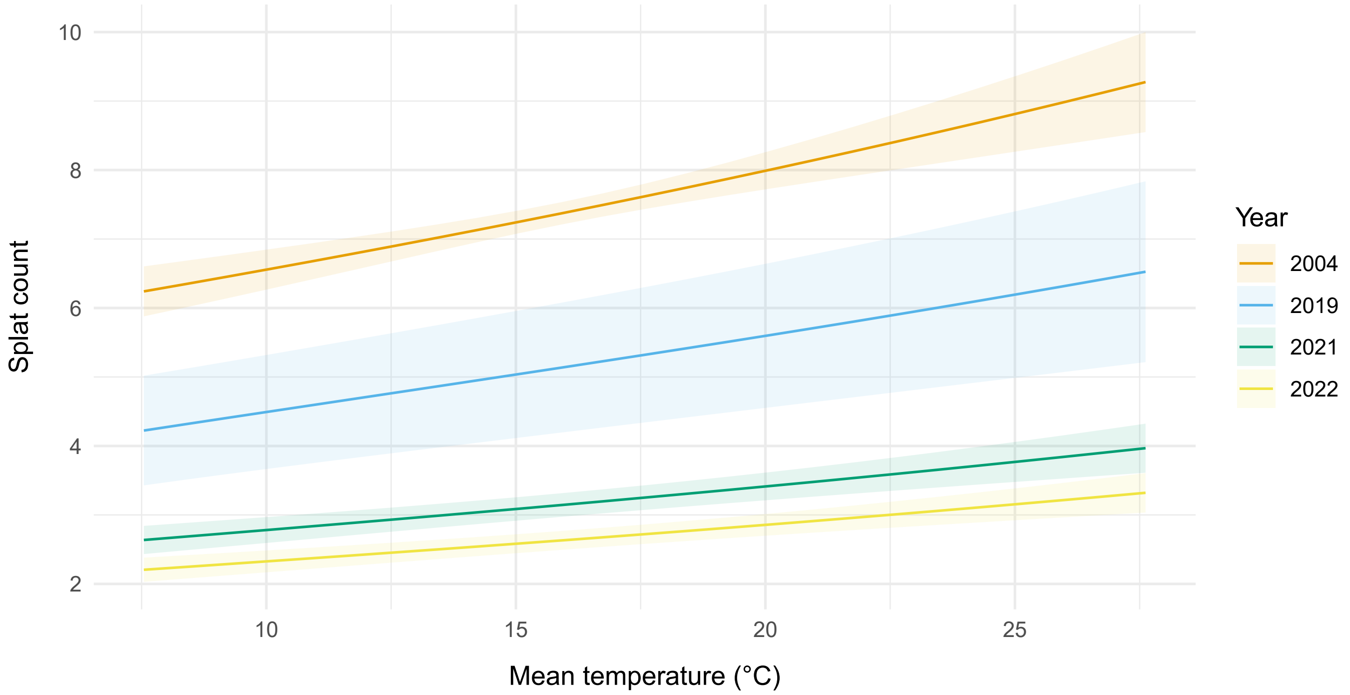


Figure 36. Predictions of splat count (corrected for distance) by the ZINB model across mean temperature and year values.

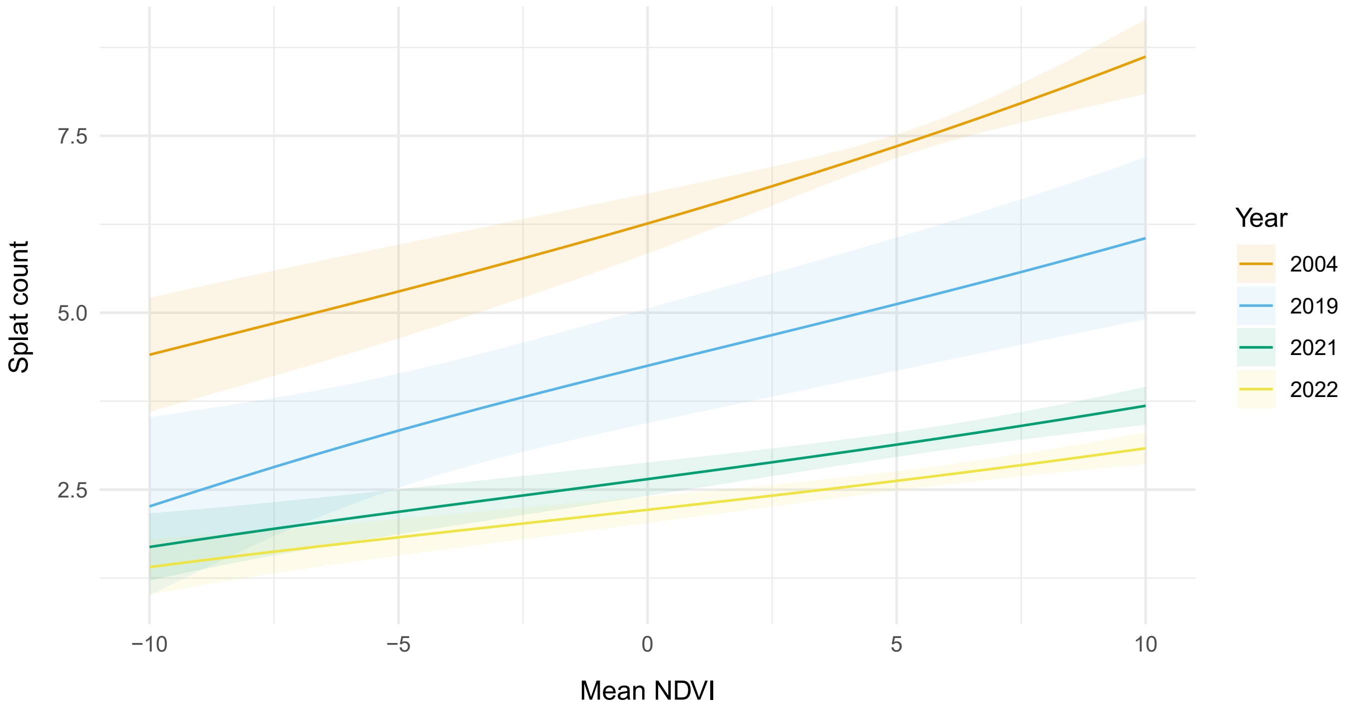


Figure 37. Predictions of splat count (corrected for distance) by the ZINB model across mean NDVI and year values.

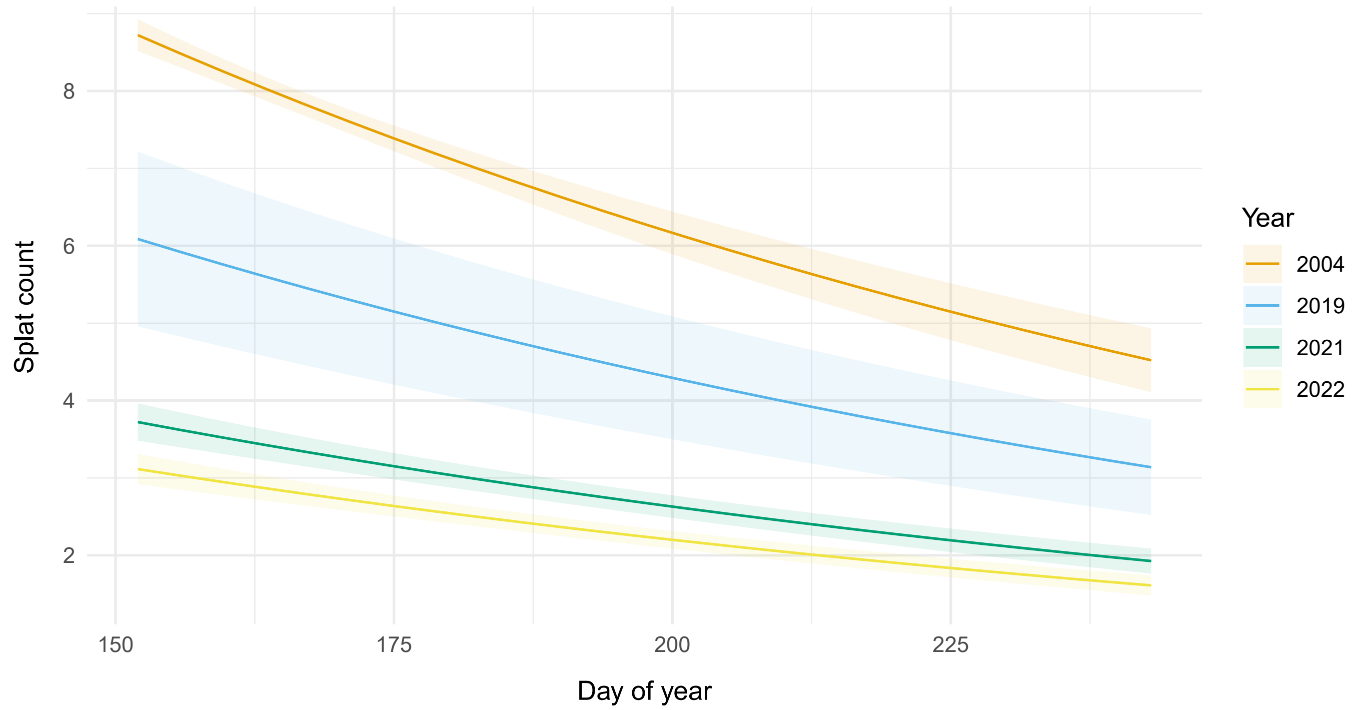


Figure 38. Predictions of splat count (corrected for distance) by the ZINB model across calendar date and year values.

Country analysis

In England, compared to 2004, the number of insect splats recorded on vehicle number plates decreased by 42.1% in 2019, 61.3% in 2021, and 67.5% in 2022. In Scotland, the number of insect splats decreased by 48.5% in 2021 but by 40.3% in 2022. In Wales, the number of insect splats decreased by 55.1% in 2021, and 74.8% in 2022. The number of insect splats decreased by 16.1% in England, 45.5% in Northern Ireland and 43.9% in Wales, between 2021 and 2022. Over the same period, the number of insect splats increased by 16% in Scotland, although this difference was not statistically significant (Table 7). Predicted splat counts are shown in Figure 39.

Latitudinal variation in insect declines has been described previously. 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, and the time period of the decline is much longer, yet a similar 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.

		2004	2019	2021
2019	England	-42.1*** CI [-33.8, -49.3]		
	Northern Ireland			
	Scotland			
	Wales			
2021	England	-61.3*** CI [-59.0, -63.4]	-33.2*** CI [-23.3, -41.8]	
	Northern Ireland			
	Scotland	-48.5*** CI [-35.2, -58.9]		
	Wales	-55.1*** CI [-45.9, -62.7]		
2022	England	-67.5*** CI [-65.6, -69.3]	-43.9*** CI [-35.7, -51.2]	-16.1*** CI [-10.2, -21.6]
	Northern Ireland			-45.5* CI [-11.3, -66.6]
	Scotland	-40.3*** CI [-26.1, -51.7]		+16 CI [-9.3, +48.1]
	Wales	-74.8*** CI [-69.3, -79.3]		-43.9*** CI [-31.2, -54.2]

Table 7. 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).

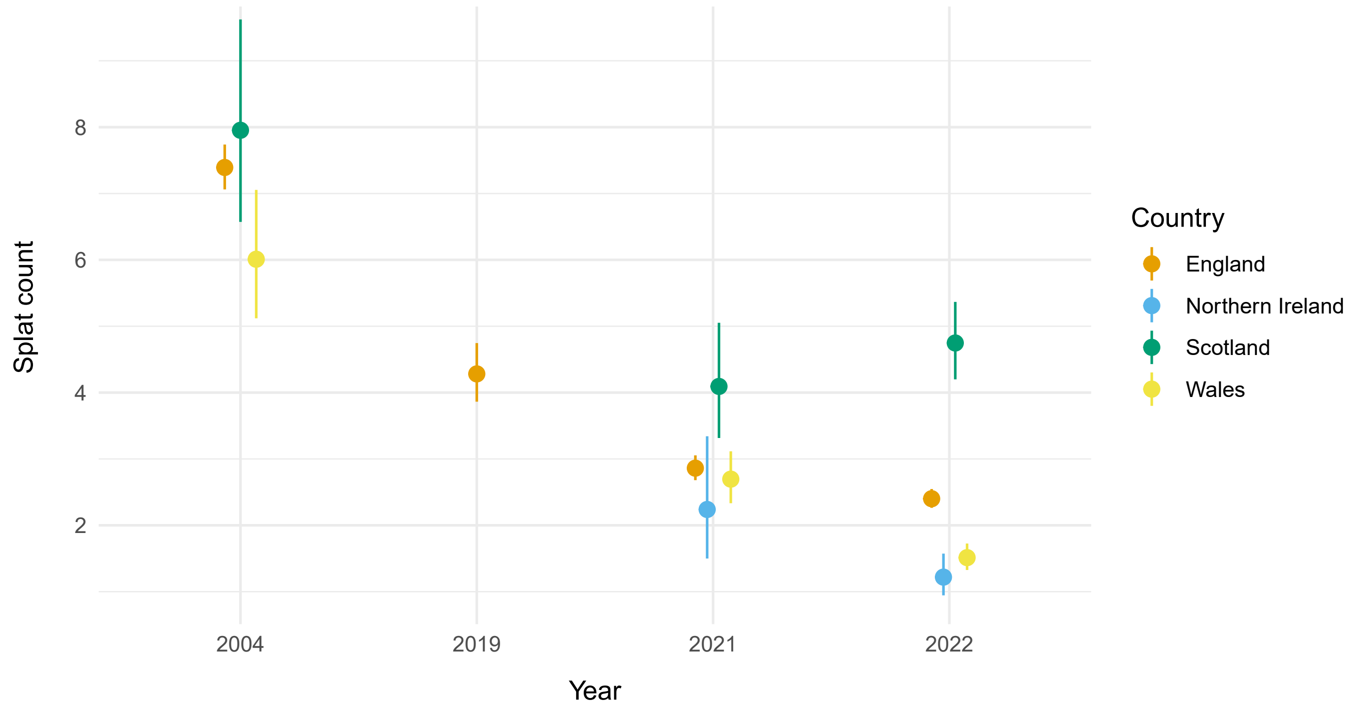


Figure 39. Predictions of splat count (corrected for distance) from the country ZINB models across year values.

Regional analysis: England

Yorkshire and the Humber recorded the greatest decrease in the number of insect splats between 2004 and 2021 of 69.6% whilst London recorded the greatest decrease in the number of insect splats between 2004 and 2022 of 82.4%. The lowest reduction between 2004 and 2021 was in London (39.5%), although there was not a statistically significant difference.

Only Yorkshire and the Humber recorded an increase in the number of insect splats between 2021 and 2022, but this difference was not statistically significant. Significant differences between these years tended to be in those regions with the greatest decreases in insect splat rate. (Table 8). The South West and the North East saw relatively little change in the number of insect splats between 2021 and 2022. Predicted splat counts are shown in Figure 40.

	2004-2021			2004-2022			2021-2022		
Region	**CI 2.5%**	**Estimate**	**CI 97.5%**	**CI 2.5%**	**Estimate**	**CI 97.5%**	**CI 2.5%**	**Estimate**	**CI 97.5%**
East Midlands	-61.4	-67.6***	-72.8	-70.9	-76.5***	-80.9	-7.9	-27.3**	-42.7
East of England	-49.9	-56.1***	-61.5	-57.2	-62.1***	-66.3	0	-13.5*	-25.3
London	62.5	-39.5	-76.8	-47.3	-82.4**	-94.3	-26.2	-70.9*	-88.8
North East	-16.9	-53.1**	-72.6	-32.2	-54.6***	-69.2	64.6	-3.2	-44.3
North West	-35.8	-47.7***	-57.3	-66.5	-74***	-79.7	-34.8	-50.2***	-62.1
South East	-63.6	-67.4***	-70.8	-69.1	-72.2***	-75.0	-3.2	-14.8*	-24.9
South West	-59.7	-65.1***	-69.8	-59.8	-65.2***	-69.9	-16	-0.3	18.4
West Midlands	-37.3	-48.3***	-57.2	-64.5	-71.3***	-76.8	-28.8	-44.5***	-56.7
Yorkshire and The Humber	-62.4	-69.6***	-75.3	-54	-62.9***	-70.1	56.6	21.8	-5.4

Table 8. Estimates of change (%) in the number of insect splats from the ZINB models for each region, with lower and upper 95% confident intervals. Significant results are shown by asterisks (* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$).

Statistical analysis

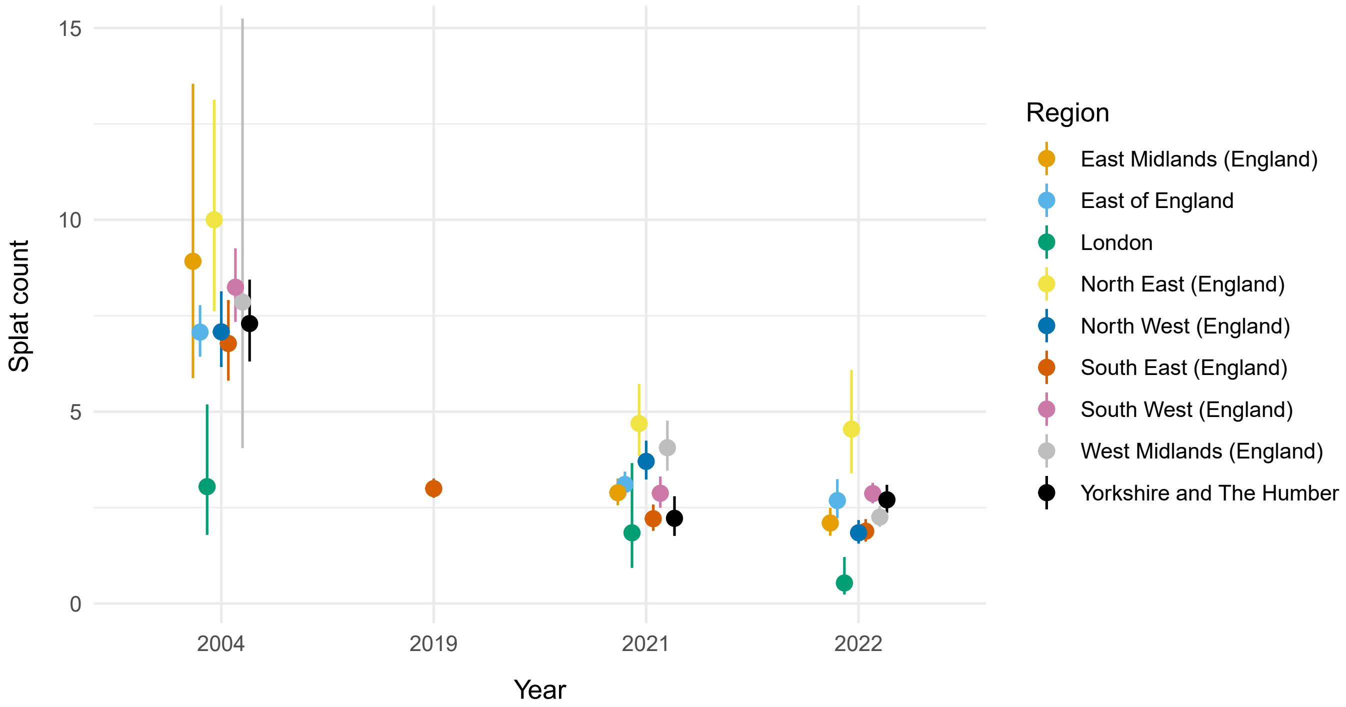


Figure 40. Predictions of splat count (corrected for distance) from the ZINB model for each region in England across year values.

Participation in the Bugs Matter Citizen Science Survey

Sign-ups to the Bugs Matter app

A total of 5252 citizen scientists signed up to the Bugs Matter app in 2021, of which 716 (13.6%) recorded one or more journeys that year. A further 1703 citizen scientists signed up to the Bugs Matter app in 2022, of which 247 (14.5%) recorded one or more journeys in 2022. Of the 5252 citizen scientists that signed up to the Bugs Matter app in 2021, 302 recorded one or more journeys in 2022 (Table 9). This means a total of 716 users participated in 2021 whilst 549 users participated in 2022. 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 14.37%. The average number of journeys recorded per user was 8.21. In 2021 it was 9.85 whilst in 2022 it was 11.07. In England it was 8.05, in Scotland it was 5.42, in Northern Ireland it was 9.43 and in Wales it was 10.94.

Fewer citizen scientists signed up to the app in 2022 than in 2021 and participation was lower, however more journeys were recorded in 2022. This demonstrates that a dedicated group of citizen scientists are using the app to record many journeys, which is promising, and indicates the survey concept and useability of the app are effective to encourage long-term data collection by citizen scientists.

	Signed up in 2021	Signed up in 2022
Number of new sign-ups	5252	1703
Number of participants in 2021 survey	716	NA
Number of participants in 2022 survey	302	247
Conversion rate (proportion of users that signed up and did one or more journeys in the same year)	13.6%	14.5%

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

The majority of citizen scientists signed up to the Bugs Matter app in the runup to the survey or during the survey 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, sign-ups started in mid-May whereas sign-ups started in early-May in 2022.

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 41).

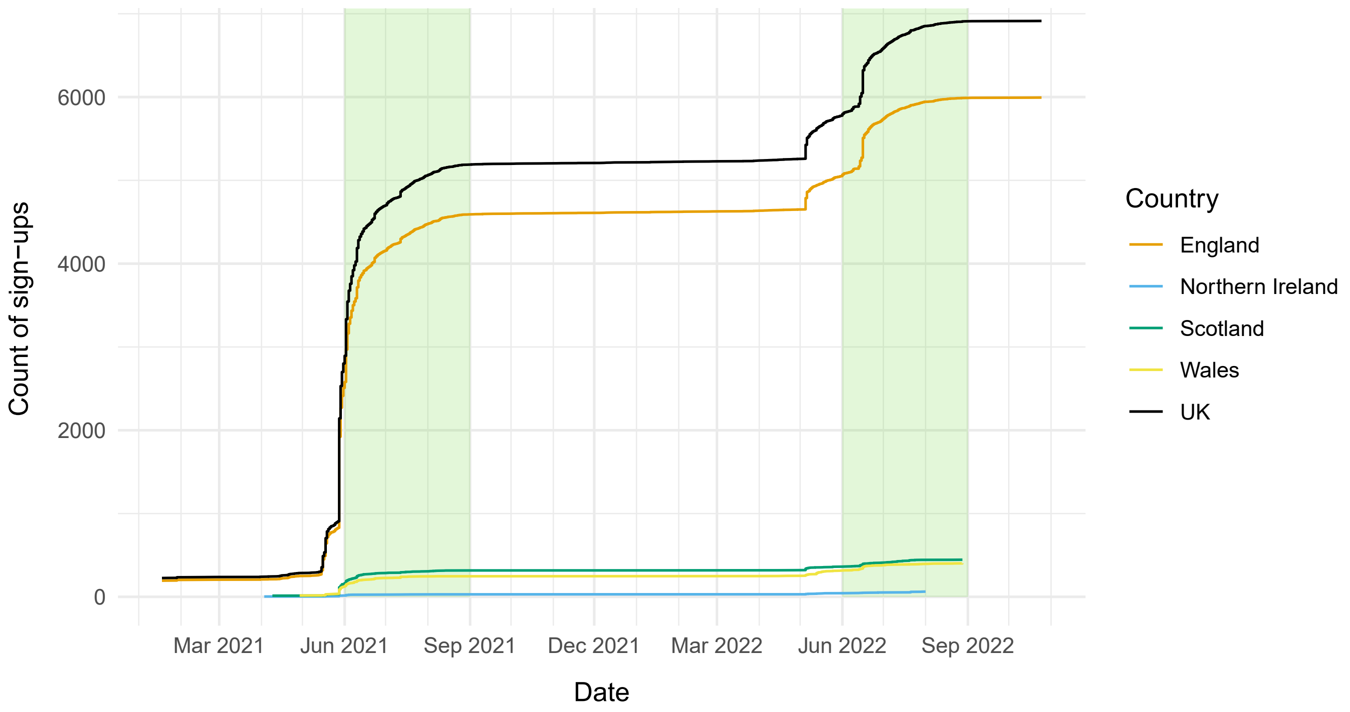


Figure 41. Cumulative count of sign–ups in each country over the lifetime of the Bugs Matter app

Citizen scientists from all English regions signed up to the Bugs Matter app. The most sign-ups were in the South East, followed by the East of England, then 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. The region with the fewest sign-ups was the North East (Figure 42).

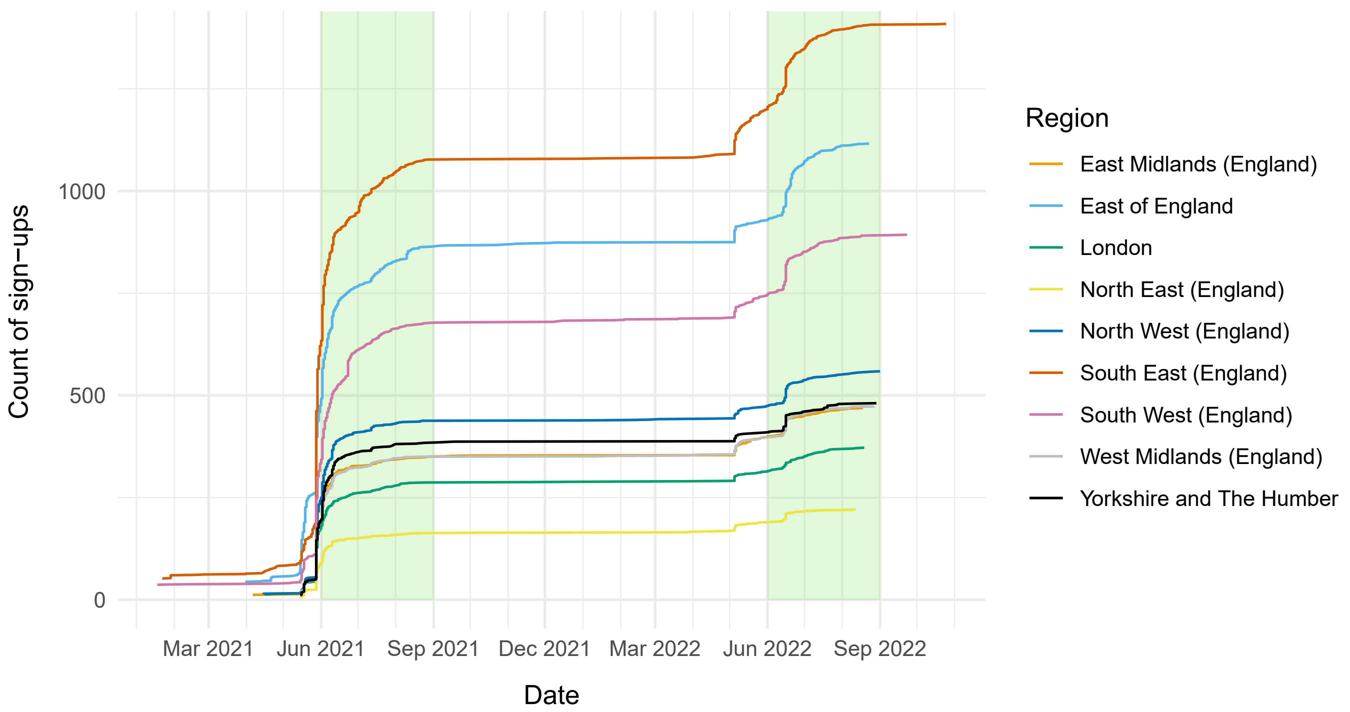


Figure 42. Cumulative count of sign-ups in each region in England over the lifetime of the Bugs Matter app

Figure 43 shows a heat map of sign-ups by county. A large number of sign-ups were in Kent and Essex, followed by London and then Hampshire (Figure 43). Besides Gwent, who is an active partner in the Bugs Matter survey, Wales had relatively few sign-ups. 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.

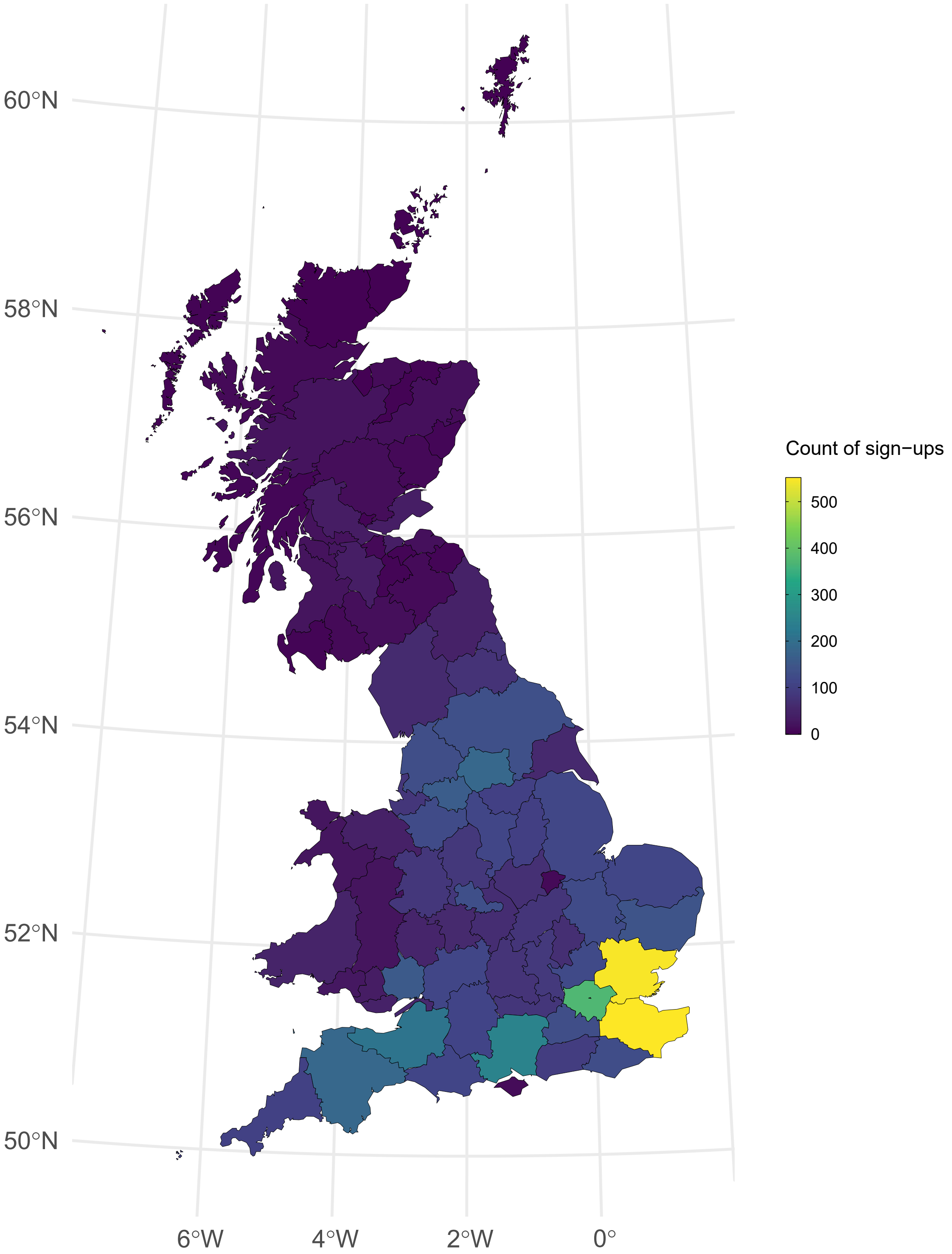


Figure 43. Heat map of total sign–ups for each county over the lifetime of the Bugs Matter app

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 44). Nonetheless, many citizen scientists recorded their first journey within 20 days of signing up to the app, and of course very few recorded journeys after 100 days because the survey runs for approximately 90 days (June-August). It is surprising to see a substantial number of citizen scientists signed up to the app in 2021 but recorded their first journey in 2022.

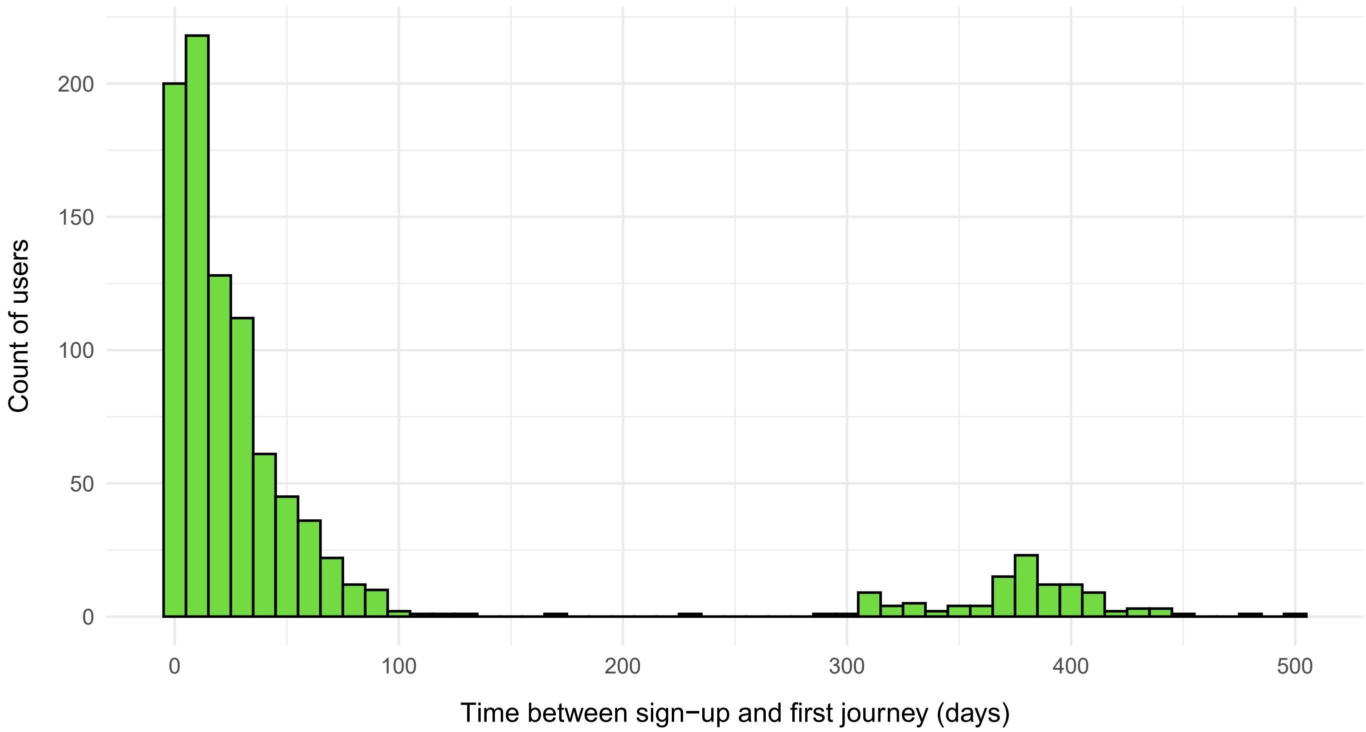


Figure 44. Histogram showing counts of users in bins of time between sign−up and recording a first journey


©STUART CROFTS

Bugs Matter app development

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 Aptitude and uses the Coreo data collection system. There are a number of planned upgrades for the Bugs Matter app prior to the 2023 survey season. These include:

- Resolution of sign-up issues for existing users of Coreo-based mobile applications.
- Discontinuation of splatometers, removing reference to splatometers from the app and app stores, and subsequently, removal of requirement for address details.
- Addition of a virtual template (or virtual splatometer) to the camera screen to help users locate their entire number plate in the photograph.
- Introduction of a limited number of push notifications to remind users to record journeys and inform users of survey progress.
- Provision of further information on how vehicle specification data is important for the analysis of trends in insect abundance.
- Provision of an option to add dimensions for custom or non-UK number plates.
- Provision of a checkbox option if there are too many insect splats on the number plate to count.

Artificial Intelligence

Bugs Matter is currently working with artificial intelligence professionals at Greenhouse AI to train and test an AI algorithm that could automatically count the number of insect splats from a photograph of a vehicle number plate.

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 and 2022, and **a comparative analysis with a 2004 baseline dataset, shows a 63.7% reduction in the number of insect splats (35.4%/decade) by 2022,** 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 2022 than in 2021 and participation was lower, however more journeys were recorded in 2022. It is clear that improvements are required to maximise sign-ups and participation, however, it is promising to see that citizen scientists are using the app to record many 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/

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.

References

Arel-Bundock V. (2022) marginaleffects: Marginal Effects, Marginal Means, Predictions, and Contrasts. R package version 0.8.0. https://CRAN.R-project.org/package=marginaleffects

Bowden J.J., Eskildsen A., Hansen R.R., Olsen K., Kurle C.M. and Høye T.T. (2015) High-Arctic butterflies become smaller with rising temperatures. Biology Letters 11(10), 1–4. doi: 10.1098/rsbl.2015.0574

Brereton T.M., Botham, M.S., Middlebrook, I., Randle, Z., Noble D., Harris, S., Dennis, E.B., Robinson A., Peck. K. and Roy, D.B. (2020) United Kingdom Butterfly Monitoring Scheme report for 2019. UK Centre for Ecology & Hydrology, Butterfly Conservation, British Trust for Ornithology and Joint Nature Conservation Committee. url: https://ukbms.org/sites/default/files/UKBMS%20 Butterfly%20Annual%20Report%202019%20Low%20res.pdf

Cameron A.C. and Trivedi P.K. (1990) Regression-based tests for overdispersion in the Poisson model. Journal of econometrics, 46(3), 347-364. doi: 10.1016/0304-4076(90)90014-K

Chapman R.F., Simpson S.J., and Douglas A.E. (2013) The Insects: Structure and Function. Cambridge University Press.

Coelho R., Infante P. and Santos M.N. (2020) Comparing GLM, GLMM, and GEE modelling approaches for catch rates of bycatch species: A case study of blue shark fisheries in the South Atlantic. Fish Oceanography. 29, 169–184. doi: 10.1111/fog.12462

Cornes R.G., van der Schrier E.J.M. van den Besselaar, and Jones P.D. (2018) An Ensemble Version of the E-OBS Temperature and Precipitation Datasets, Journal of Geophysical Research: Atmospheres, 123, 9391-9409. doi: 10.1029/2017JD028200

Davies W.J. and Saccheri I.J. (2013) Maintenance of body-size variation and host range in the orange-tip butterfly: evidence for a trade-off between adult life-history traits. Ecological Entomology 38, 49–60. doi: 10.1111/j.1365-2311.2012.01402.x

Dempster J.P. (1991) Fragmentation, isolation and mobility of insect populations. In The conservation of insects and their habitats (ed. N. M. Collins & J. A. Thomas), pp. 143-154. London: Academic Press.

Dempster J.P., King M.L. and Lakhani K.H. (1976) The status of the swallowtail butterfly in Britain. Ecological Entomology 1(2), 71–84. doi: 10.1111/j.1365-2311.1976.tb01207.x

Didan K. (2015) MOD13Q1 MODIS/Terra Vegetation Indices 16-Day L3 Global 250m SIN Grid V006. NASA EOSDIS Land Processes DAAC. doi: 10.5067/MODIS/MOD13Q1.006

Dorman M. (2022) mapsapi: 'sf'-Compatible Interface to 'Google Maps' APIs. R package version 0.5.3. https://CRAN.R-project.org/package=mapsapi

Fenberg P.B., Self A., Stewart J.R., Wilson R.J. and Brooks S.J. (2016) Exploring the universal ecological responses to climate change in a univoltine butterfly. Journal of Animal Ecology, 85(3), 739–748. doi: 10.1111/1365-2656.12492

Fox R., Dennis E.B., Harrower C.A., Blumgart D., Bell J.R., Cook P., Davis A.M., Evans-Hill L.J., Haynes F., Hill D., Isaac N.J.B., Parsons M.S., Pocock M.J.O., Prescott T., Randle Z., Shortall C.R., Tordoff G.M., Tuson D. and Bourn N.A.D. (2021) The State of Britain's Larger Moths 2021. Butterfly Conservation, Rothamsted Research and UK Centre for Ecology & Hydrology, Wareham, Dorset, UK. url: https://butterfly-conservation.org/sites/default/files/2021-03/StateofMothsReport2021.pdf

Fox R., Parsons M.S., Chapman J.W., Woiwood I.P. Warren M.S. and Brooks D.R. (2013) The state of Britain's larger moths 2013. Butterfly Conservation & Rothamsted Research Wareham, Dorset. url: https://butterfly-conservation.org/sites/default/files/1state-of-britains-larger-moths-2013-report.pdf

Gorelick N., Hancher M., Dixon M., Ilyushchenko S., Thau D., and Moore R. (2017) Google Earth Engine: Planetary-scale geospatial analysis for everyone. Remote Sensing of Environment. doi: 10.1016/j.rse.2017.06.031

Goulson D. (2019) Insect declines and why they matter. A report commissioned by the South West Wildlife Trusts. url: https://www.kentwildlifetrust.org.uk/sites/default/files/2020-01/Actions%20for%20Insects%20-%20Insect%20declines%20and%20why%20they%20matter.pdf

Hallmann C.A., Sorg M., Jongejans E., Siepel H., Hofland N., Schwan H., Stenmans W., Müller A., Sumser H., Hörren T., Goulson D. and de Kroon H. (2017) More than 75% decline over 27 years in total flying insect biomass in protected areas. PLoS ONE 12(10), e0185809. doi: 10.1371/journal.pone.0185809

Hill J.K., Thomas C.D. and Lewis O.T. (1999) Flight morphology in fragmented populations of a rare British butterfly, Hesperia comma. Biological Conservation, 87, 277-283. doi: 10.1016/S0006-3207(98)00091-3

Jirinec V., Burner R.C., Amaral B.R., Bierregaard Jr R.O., Fernández-Arellano G., Hernández-Palma A., Johnson E.I., Lovejoy T.E., Powell L.L., Rutt C.L. and Wolfe J.D. (2021) Morphological consequences of climate change for resident birds in intact Amazonian rainforest. Science advances, 7(46). doi: 10.1126/sciadv.abk1743

Jourdan J., Baranov V., Wagner R., Plath M., and Haase P. (2019) Elevated temperatures translate into reduced dispersal abilities in a natural population of an aquatic insect. Journal of Animal Ecology, 88(10), 1498-1509. doi: 10.1111/1365-2656.13054

Macadam C.R, Whitehouse A.T. and Shardlow M. (2020) No Insectinction - how to solve the insect declines crisis. Buglife - The Invertebrate Conservation Trust, Peterborough. url: https://cdn.buglife.org.uk/2020/05/NoInsectinction2020.pdf

Mellanby K. (1939) Low temperature and insect activity. Proceedings of the Royal Society of London. Series B-Biological Sciences, 127(849), 473-487. Doi: 10.1098/rspb.1939.0035

Møller A.P. (2019) Parallel declines in abundance of insects and insectivorous birds in Denmark over 22 years. Ecology and Evolution, 9(11), 6581–6587. doi: 10.1002/ece3.5236

Møller A.P. (2021) Citizen Science for Quantification of Insect Abundance on Windshields of Cars Across Two Continents. Frontiers in Ecology and Evolution, 541. doi: 10.3389/fevo.2021.657178

Møller A.P. (2021a) Abundance of insects and aerial insectivorous birds in relation to pesticide and fertilizer use. Avian Research, (12)43, doi: 10.1186/s40657-021-00278-1

Newson P. and Krumm J. (2009) "Hidden Markov map matching through noise and sparseness." Proceedings of the 17th ACM SIGSPATIAL International Conference on Advances in Geographic Information Systems. ACM.

Outhwaite C.L., McCann P. and Newbold T. (2022) Agriculture and climate change are reshaping insect biodiversity worldwide. Nature. doi: 10.1038/s41586-022-04644-x

Pebesma E. (2018) "Simple Features for R: Standardized Support for Spatial Vector Data." The R Journal, 10(1), 439–446. doi: 10.32614/RJ-2018-009,

Polidori C., Gutiérrez Cánovas C., Sánchez E., Tormos J., Castro L., and Sánchez Fernández, D. (2019) Climate change driven body size shrinking in a social wasp. Ecological Entomology, 45(1), 130-141. doi: 10.1111/een.12781

R Development Core Team (2022) R: A Language and Environment for Statistical Computing. Vienna, Austria.

Sánchez-Bayo F., and Wyckhuys K.A.G. (2019) Worldwide decline of the entomofauna: A review of its drivers. Biological Conservation, 232(January), 8–27. doi: 10.1016/j.biocon.2019.01.020

Sokal R.R. and Rohlf F.J. (1995) Biometry: the principles and practice of statistics in Biological Research. W. H. Freeman; 3rd Edition

Taylor L.R. (1986) Synoptic Dynamics, Migration and the Rothamsted Insect Survey: Presidential Address to the British Ecological Society, December 1984. Journal of Animal Ecology, 55(1), 1–38. https://doi.org/10.2307/4690

Thomas C.D., Jones T.H. and Hartley S.E. (2019) "Insectageddon": A call for more robust data and rigorous analyses. Global Change Biology, 25(6), 1891–1892. doi: 10.1111/gcb.14608

Tinsley-Marshall P., Skilbeck A. and Riggs A. (2021a) Bugs Matter citizen science survey demonstrates temporal difference in invertebrate abundance in Kent and South East England. Kent Wildlife Trust, Maidstone doi: 10.13140/RG.2.2.15903.89768

Tinsley-Marshall P.J., Riggs A., Skilbeck A., Ball L. and Still R. (2021b) Nature's Sure Connected: A practical framework and guidance for evidencing landscape-scale outcomes of landscape-scale conservation. Kent Wildlife Trust. doi: 10.13140/RG.2.2.10556.77447

Van Dam A. (2022) Wait, why are there so few dead bugs on my windshield these days? Washington Post. Published 21st October 2022. Available from: https://www.washingtonpost.com/business/2022/10/21/dead-bugs-on-windshields/

van der Sluijs J.P. (2020) Insect decline, an emerging global environmental risk. Current Opinion in Environmental Sustainability, 46, 39–42. doi: 10.1016/j.cosust.2020.08.012

Vasiliev D. and Greenwood S. (2021) The role of climate change in pollinator decline across the Northern Hemisphere is underestimated. Science of The Total Environment 775(145778). doi: 10.1016/j.scitotenv.2021.145788

Venables W.N. and Ripley B.D. (2002) Modern Applied Statistics with S. Fourth Edition. Springer, New York. ISBN 0-387-95457-0

Wikipedia (2022) Windshield phenomenon [Online]. [Accessed 22nd November 2022]. Available from: https://en.wikipedia.org/wiki/Windshield_phenomenon

Wilson R.J., Brooks S.J. and Fenberg P.B. (2019) The influence of ecological and life history factors on ectothermic temperature–size responses: analysis of three Lycaenidae butterflies (Lepidoptera). Ecology and Evolution, 9(18), 10305–10316. doi: 10.1002/ece3.5550

Wu C.H., Holloway J.D., Hill J.K., Thomas C.D., Chen I., and Ho C.K. (2019) Reduced body sizes in climate-impacted Borneo moth assemblages are primarily explained by range shifts. Nature communications, 10(1), 1-7. doi: 10.1038/s41467-019-12655-y

Yau K.K., Wang K., and Lee A.H. (2003) Zero inflated negative binomial mixed regression modeling of over dispersed count data with extra zeros. Biometrical Journal: journal of mathematical methods in biosciences, 45(4), 437-452. doi: 10.1002/bimj.200390024

Zeileis A. Kleiber C., and Jackman S. (2008) Regression Models for Count Data in R. Journal of Statistical Software 27(8). url: http://www.jstatsoft.org/v27/i08/.