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The recording behaviour of field-based citizen scientists and its impact on biodiversity trend analysis

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SUMMARY

Opportunistic species sightings submitted by citizen science volunteers are a valuable source of species data for trends analysis, as used in biodiversity indicators. However, projects collecting these data give people flexibility where and when to make records, and the recording behaviour of participants varies between individuals. Here we tested the effect of recorder behaviour on outputs of the analysis of temporal biodiversity trends. Using a large (c. 3 million records), 20 year unstructured citizen science dataset of butterfly records in Great Britain, we manipulated recorder behaviour by constructing biased 50% subsamples of the dataset by preferentially including different types of recorders (based on high and low values of four metrics independently describing the temporal, spatial and taxonomic attributes of recorder behaviour). We found that, in general, the three outputs (namely: occupancy trend, precision of the trend, and the estimate of occupancy) showed relatively little deviation from random expectation across most of the different types of recorder behaviour. Occupancy trends showed least deviation, while estimates of occupancy itself showed greatest deviation from the random expectation. Regarding the recorder behaviours, the outputs were most sensitive to variation in 'recorder potential', which describes the difference between 'thorough' and 'incidental' recorders. Importantly, by demonstrating the robustness of occupancy trends to differences in recorder behaviour, this study provides support for the appropriate use of occupancy trend modelling for unstructured citizen science. However, we did not consider change in recorder behaviour over time, so further research is required to assess the impact of this on trend modelling. This study highlights the value of developing solutions to further increase the robustness of biodiversity trend analysis. These solutions should include both analytical developments and enhancements in project design to engage participants.

1. Introduction

In the face of the global biodiversity crisis, understanding changes in biodiversity is important to help us address the threats to biodiversity (Dirzo et al., 2014). This needs to be supported by accurate information on biodiversity trends (Kühl et al., 2020). In particular, there is recent concern about invertebrate declines, but our ability to address the causes of decline is hampered by the lack of information we have for many species in many parts of the world (Eisenhauer et al., 2019; Montgomery et al., 2020).

For many species, records from volunteers, through citizen science, are a valuable source of data to assess changes in biodiversity (Rapacciuolo et al., 2021). For some groups of species there are structured monitoring schemes that provide excellent information on abundance trends, but such high quality data is limited to a few popular species groups in a few well-recorded regions or countries (Pilotto et al., 2020; Proença et al., 2017). In contrast, the amount of opportunistically-collected species records is dramatically increasing, as evidenced through the increasingly popularity of species recording platforms, such as iNaturalist or, in the UK, iRecord (Amano et al., 2016; Oliver et al.,

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2021). The fact that these data are 'unstructured' means that organisers do not specify sampling protocols or control the data collection process, resulting in an uneven distribution of records in space and time (Boakes et al., 2016; Isaac and Pocock, 2015). Occupancy modelling is one valuable approach to make use of these data and estimate trends in site occupancy, while taking account of imperfect detection, i.e. the fact that species could be present but not reported (Altwegg and Nichols, 2019; Guillera-Arroita, 2017; Isaac et al., 2014). This approach is increasingly widely used to create trends for large numbers of species at national and continental scales (Baker et al., 2019; Outhwaite et al., 2020; Powney et al., 2019; Soroye et al., 2020; Termaat et al., 2019; van Strien et al., 2016).

In addition to variation in the distribution of biodiversity records in space and time, there is also variation amongst recorders in their patterns of recording (August et al., 2020; Boakes et al., 2016), as also in online citizen science (Ponciano and Brasileiro, 2014; Rallapalli et al., 2015). In the past, trend analysis has been shown to be reasonably robust to simple measures of variation of information content across recording visits, i.e. the species list length per visit (van Strien et al., 2010), but it has also been shown that accounting for observer identity leads to improvements in the performance of spatial distribution models (Johnston et al., 2018). It is therefore possible that heterogeneity of recorder behaviour has the potential to influence occupancy model outputs, but its impact is currently not known.

Variation in patterns of field-based citizen science recording can be described by each individual's spatial, temporal and taxonomic pattern of recording (August et al., 2020). Classifying recorders into groups, based on their positions on these axes, provides a way to explore the impact of recorder behaviour on the performance of occupancy models.

Here we tested the impact of manipulating recorder behaviour on the outputs from occupancy modelling by undertaking occupancy analysis on subsets of the unstructured citizen science dataset of UK butterflies. Subsets were created either by randomly sampling records or by selecting data submitted by recorders with different types of recording behaviour. These biased subsets would have differed in their patterns of recording (including sample size per species and spatial coverage), leading to potential differences in estimates of occupancy trend, precision of this trend and estimates of mean occupancy. We used UK butterflies as an exemplar for this work because they are well-recorded and studied (Fox et al., 2023) and the patterns of recording by individuals are well-characterised (August et al. 2020).

2. Methods

We ran occupancy models for eight species of butterfly from subsamples of an existing dataset of records of butterflies from Great Britain. The dataset was the Butterflies of the New Millennium (BNM), with records submitted by volunteers and collated by Butterfly Conservation (Asher et al., 2001) and we used BNM records for a 20 year period (1995–2014), which was a phase of intensive sampling (Lobo et al., 2021).

First, we cleaned the recorder names in the dataset, then we subsampled the dataset according to the different recorder behaviours and different dataset sizes, and finally we ran occupancy models to assess the impact of recorder behaviour and dataset size on the model outputs.

2.1. Previous work to characterise recorder behaviour

Previously, August et al. (2020) used metrics of recorder behaviour to describe 5,268 users of the iRecord Butterflies mobile phone app, which is a multi-species citizen science project focussed on butterflies in the UK. They found that the users can be described by their position along four axes of recording behaviour: recording intensity, spatial extent, recording potential and rarity recording (Table 1). Individuals in that dataset were unambiguously identified with a unique code, but the dataset was only of four years' duration, so was not suitable for the study of temporal trends.

Table 1
Description of the four metrics used to describe recorder behaviour in August et al. (2020). We have given names and narrative descriptions of the type of recorder exhibiting high or low values for each metric for ease of interpretation, but these names are not intended to imply that recorders differ in the importance of their contributions. 'Dabblers', with records from 10 days or fewer, were not included in analysis.

Metric from August et al. (2020)	High values	Low values
Recording intensity	**Frequent recorders:** record frequently, regularly and with low periodicity (i.e. short gaps between records)	**Occasional recorders:** record infrequently and irregularly
Spatial extent	**Roaming recorders:** record over many, widely-distributed locations	**Patch recorders:** record locally and their records are more aggregated
Recording potential*	**Thorough recorders:** have recorded a large proportion of species, record fewer single species lists on a site visit and record more rare species than average	**Incidental recorders:** record fewer species, fewer rare species and have more visits of only a single species
Rarity recording*	**Twitchers:** tend to preferentially record rarer species, and have a greater propensity to record single species lists, i.e. those people who specifically go looking for rare species and only report the rarer species that they see	**All-rounders:** no bias towards rare species and more likely to record lists of multiple species

*Recording potential and rarity recording were orthogonal axes taken from a principal components analysis by August et al. (2020), and both were required to best characterise taxonomic coverage by recorders.

2.2. Standardising recorder names in the database

We summarised the dataset by visits; a visit was defined as a list of one or more butterfly species recorded on a single date in a 1 km × 1 km grid square by a single recorder. The BNM dataset is a well-curated dataset, but the recorder names came from many different data sources and are identified by names written as free text, rather than by unique identifiers (as in August et al., 2020).

In the original dataset there were 8,874,402 species records, representing 3,484,565 visits, with 91,890 unique text strings for the recorder name. Dealing with the complexity of name formats is difficult: it includes challenges such as using full names or initials, hypocorisms (i.e. informal versions of personal names) with different initial letters (such as Elizabeth/Liz and Robert/Bob), and the inclusion or not of middle initials. It would be impossible to perfectly link names to unique individuals in such a large, heterogeneous dataset. We used a simple approach to attempt to standardise the name formats (described in Appendix S1) and we removed records from those that were not associated with an individual (e.g. '…group' or '…society' or '…and…'). This process resulted in 3,437,755 species records, representing 1,413,135 visits, and 56,657 unique text strings for recorder name. Overall, our approach will probably tend to over-estimate the number of recorders and under-estimate their recording contribution (because, we expect that it is more frequent for one recorder to have multiple aliases than multiple recorders to have the same alias). This simplification does not interfere with the primary aims of our research, which is to explore the impact of variation in recorder behaviour in the results of the modelling. Henceforth, each unique text string is called a 'recorder'.

2.3. Metrics of recorder behaviour

We used the recorderMetrics package (August et al., 2020) to score each recorder according to four metrics relating to their recording behaviour. Each of the four metrics represents a different recorder behaviour and the correlations between axes are low (August et al., 2020) (Table 1).

It is not possible to determine these scores for recorders with low recording activity (10 days or fewer with records), so we omitted such recorders from the construction of data subsamples. This resulted in the exclusion of 45,958 recorders, although the remaining 18.9% of recorders (>10 days of activity) accounted for the vast majority (91.6%) of species records. The final, cleaned dataset for analysis therefore comprised 3,147,865 species records, representing 1,290,683 visits, and 10,699 unique text strings for recorder name.

2.4. *Constructing subsets of the dataset*

Our aim was to assess how different recording behaviours influence the model outputs. We therefore needed to manipulate the dataset by constructing subsets of the full dataset that were biased for each of these recording behaviours. We did this by selecting recorders (without replacement) from the final dataset, until we achieved datasets with a predetermined number of records.

In order to construct these biased subsets we had to select recorders for inclusion in a way that was biased according to their value of one of the four recorder metrics. Simply selecting the recorders at the top or bottom of the recorder metrics would have created unrealistic datasets. Instead the biased subsets were constructed probabilistically: the list of recorders were ranked by their value for each metric and we took a weighted random sample so that each successive decile of recorders were twice as likely to be selected as the previous decile. For example, the 90th percentile recorder for a specific metric was twice as likely to be selected compared to the 80th percentile recorder, which in turn was twice as likely to be selected compared to the 70th percentile recorder. Recorders were added to the data subset in this biased way until we reached 50% of the total number of records in the full dataset (about 1.6 million records). We also repeated this analysis for thresholds of 80% and 20% of the records (about 2.5 and 0.6 million records, respectively) and found broadly similar results (Appendix S3). This was done separately for high-to-low and low-to-high values of each of the four recorder behaviour metrics, so by doing this, we obtained eight biased datasets that we used for analysis of species trends (Fig. 1). The ideal would have been to run the occupancy trend models with hundreds of different subsets for each type of bias in recorder behaviour, but due to the major computational demands of running these models, we constructed each biased dataset once.

One of the challenges with making a fair assessment of the impact of biases in recorder behaviour is that the full dataset does not provide the ‘truth’ for the values of the outputs. Indeed, the full dataset is likely to be biased itself, especially in its spatial coverage (Boyd et al., 2021; Isaac and Pocock, 2015), and certain subsets of the data may actually be more representative than the full dataset (Boyd et al., 2022). However, we do not have an independent assessment of the true species trends. Comparing the outputs from the final, cleaned dataset with the 50% biased subsets is not a fair test because reducing the amount of data is likely to affect the precision of estimates. We therefore compared the 50% biased subsets with 50% random subsets. This enabled us to assess the sensitivity of the outputs to changes in the recording behaviour of volunteers. For the 50% random subsets we selected recorders (without replacement) at random until we obtained a dataset with 50% the number of records compared to the final dataset for analysis. This was done four times to estimate variation due to random subsampling (Fig. 1).

2.5. *Running occupancy trend analysis*

For the full dataset and each of the data subsets, we ran Bayesian occupancy models (Outhwaite et al., 2018, 2020) to estimate the annual occupancy for eight focal species of butterfly. Occupancy models are used with presence/absence datasets to account for imperfect detection: the data are used to estimate detection rate and, taking this into account, the true rate of presence in the sampled sites (the ‘occupancy’) is estimated (Altwegg and Nichols, 2019; Guillera-Arroita, 2017). The specific form of occupancy model that we used included a smoothing term across years to reduce stochastic variability in occupancy due to data variation (Outhwaite et al., 2018).

The models were run for each of eight species of butterfly in turn (Table 2). These butterfly species were selected because they were

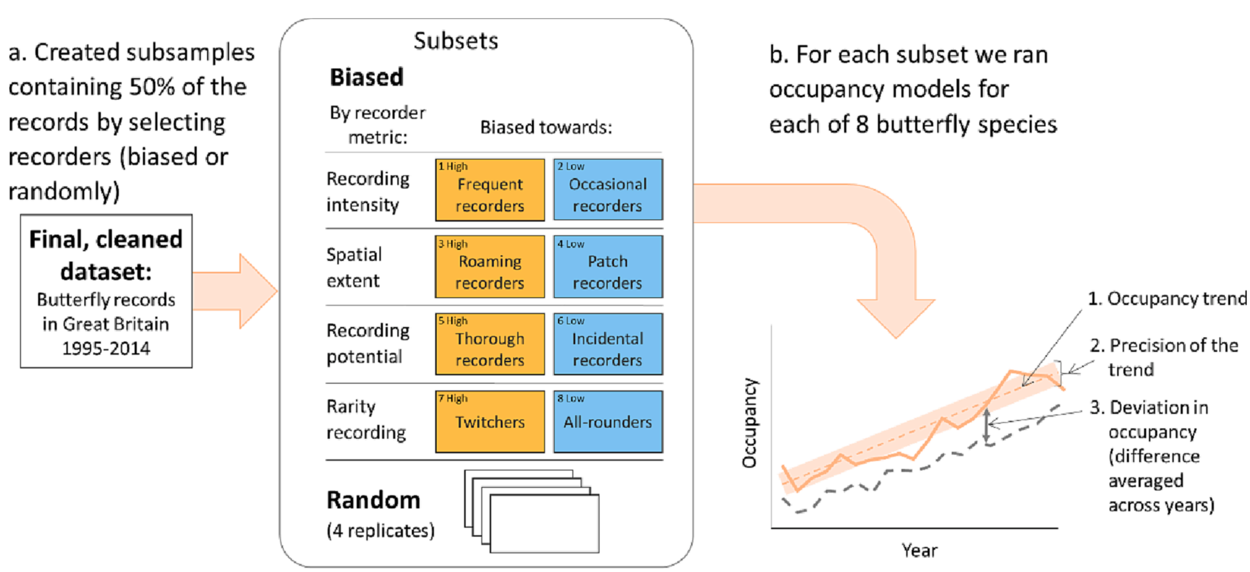

Fig. 1. The process of this research showing the construction of subsets of the full, cleaned dataset and the three metrics obtained from each output. In the graph the dashed black line is the control (annual estimates of occupancy from the random or full datasets, depending on the question) and the orange line shows a single set of posteriors from the Bayesian occupancy model (solid line), a linear trend of occupancy (dotted line) and the variance of slopes from across the posteriors. As well as 50% subsets, we ran this process for 80% and 20% subsets. The final, cleaned dataset excluded records that were not associated with an individual (e.g. attributed to a ‘group’ or ‘society’) and excluded records from those recording on 10 days or fewer. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 2
The eight species of butterfly in this analysis, ordered by mean annual occupancy. The occupancy, trend and variance of the trend were obtained from 1000 posterior samples of the outputs from Bayesian occupancy analysis of the full dataset.

Species	English vernacular name	Specialism*	Mean annual occupancy of visited squares**	Trend in occupancy (linear slope)**	Variance of the trend**
Aglais io	Peacock	Wider countryside	0.951	0.876×10^{-2}	5.706×10^{-4}
Aphantopus hyperantus	Ringlet	Wider countryside	0.804	1.133×10^{-2}	5.690×10^{-4}
Pararge aegeria	Speckled Wood	Wider countryside	0.732	1.910×10^{-2}	4.042×10^{-4}
Coenonympha pamphilus	Small Heath	Wider countryside	0.275	-0.550×10^{-2}	3.855×10^{-4}
Erynnis tages	Dingy Skipper	Habitat specialist	0.100	0.241×10^{-2}	2.166×10^{-4}
Boloria selene	Small Pearl-bordered Fritillary	Habitat specialist	0.058	$0.034 \text{x} 10^{-2}$	1.494×10^{-4}
Polyommatus coridon	Chalk Hill Blue	Habitat specialist	0.034	0.030×10^{-2}	1.342×10^{-4}
Euphydryas aurinia	Marsh Fritillary	Habitat specialist	0.016	0.026×10^{-2}	0.573×10^{-4}

* According to Brereton et al. (2015).
** This dataset refers to 20 years of butterfly records (1995–2014) in which a visit refers to a unique combination of recorder name, date and 1 × 1 km grid cell, and we removed records that were not associated with an individual, and those from individuals who had records on ten dates or fewer (see Sections 2.2 and 2.3). The results are from occupancy analysis of this dataset.

relatively easy to identify, varied substantially in their occupancy (from common and widespread species to rare and restricted species), their specialism (from habitat specialists to wider countryside species (Brereton et al., 2015)) and their trends. Each data subset provided information on the visits for which that species of butterfly was reported (a 'presence') or was not reported (a non-detection, i.e. an inferred 'absence').

2.6. Summarising the results of the biased subsamples compared to the control

The Bayesian occupancy model was run with 20,000 iterations and a burn-in of 10,000 (as per Outhwaite et al., 2019) and provided 1000 posterior samples of the estimated annual occupancy for each species from each data subset. From these data we could estimate three outputs (Fig. 1). Firstly, we estimated the trend in occupancy, which was defined as the slope of a linear trend across years. This was calculated for each of the 1000 samples and averaged across samples. Secondly, we estimated the precision of the trend, which we defined as the variance across the 1000 samples. Thirdly, we estimated the deviation in occupancy. We calculated this by taking the difference between the occupancy estimate for one posterior sample and the full dataset for each year in turn. We averaged this difference across years, and then averaged this across all 1000 posterior samples. Even though occupancy varied substantially across species and years (from 0.016 to 0.951), we found that the absolute difference (sample – full model) was a better metric across species than relative difference (sample / full model).

Z-scores were used to compare the outputs of the analysis of biased subsamples to the outputs from random subsamples. Z-scores are calculated as the observed value minus the mean of the control sample, divided by the standard deviation of the control sample. For the three outputs (trend, precision of the trend and deviance in occupancy), the observed value (average slope, variance of slope and average difference in occupancy, respectively) from the biased subsample was compared to the mean and standard deviation of the four random subsamples. Z-scores were calculated separately for each species and for each type of bias (high and low, for each of the four recorder metrics). When the absolute value of the z-score exceeded 1.96, then it was regarded as a significant deviation from a normally distributed set of expected values. To assess the overall impact of each of the four recorder behaviours on each of the three output metrics, the 'mean absolute error' was calculated from z-scores for high and low biased subsamples averaged across all species.

We explored how changes in the patterns of recording (including sample size per species and spatial coverage) could have affected the model outputs. Firstly, we tested for a relationship between the number of records per species and the precision of the trend (relative to the control). Secondly, we tested for differences in the spatial coverage across habitats. The Land Cover Map has information on the habitat coverage of every 1 km square in the UK (Rowland et al. 2017) and from this we calculated the proportional area of nine habitat types (according to Border et al. 2019) across the 1 km squares in each biased subsample. These were compared to the random subsamples, and to the total for the whole of the UK.

3. Results

3.1. The creation of subsamples

It was important to confirm that our method of constructing the biased subsamples only impacted the recorder metric of interest. Visualising the distribution of recorders according to the value of each metric shows that manipulating the inclusion of individuals according to the four recorder metrics did result in observed differences in that metric between the biased and random subsamples (shown by differences in the curves on the plots on the diagonal in Fig. 2). In contrast, there was no substantial variation in the distribution of recorder metrics that were not manipulated (shown by the high degree of congruence of the curves in plots that are not on the diagonal in Fig. 2). Therefore our results demonstrated our ability to create datasets that were biased by one type of recorder behaviour independent of the others.

3.2. The effect of variation in recorder behaviour

To assess the effect of manipulating recorder behaviour compared to the observed data, we compared the results of the biased subsamples to the random subsamples. We found that despite differences in occupancy and trend for the eight butterfly species, there was no systematic effect across butterflies (Appendix S2) and so here we report the results aggregated across all eight species (Fig. 3).

Considering the effect of the biased subsamples on the trends in occupancy, we found no consistent effect of recorder behaviour on the estimates of the slope (i.e. the median across species of the z-score was within the range −1.96 to + 1.96; Fig. 3a). This indicates that trends obtained from occupancy models are robust to differences in the patterns of recording behaviour between datasets. The precision of the trend was affected by recording potential and spatial extent (Fig. 3b), whereas the occupancy itself was affected by recording potential and

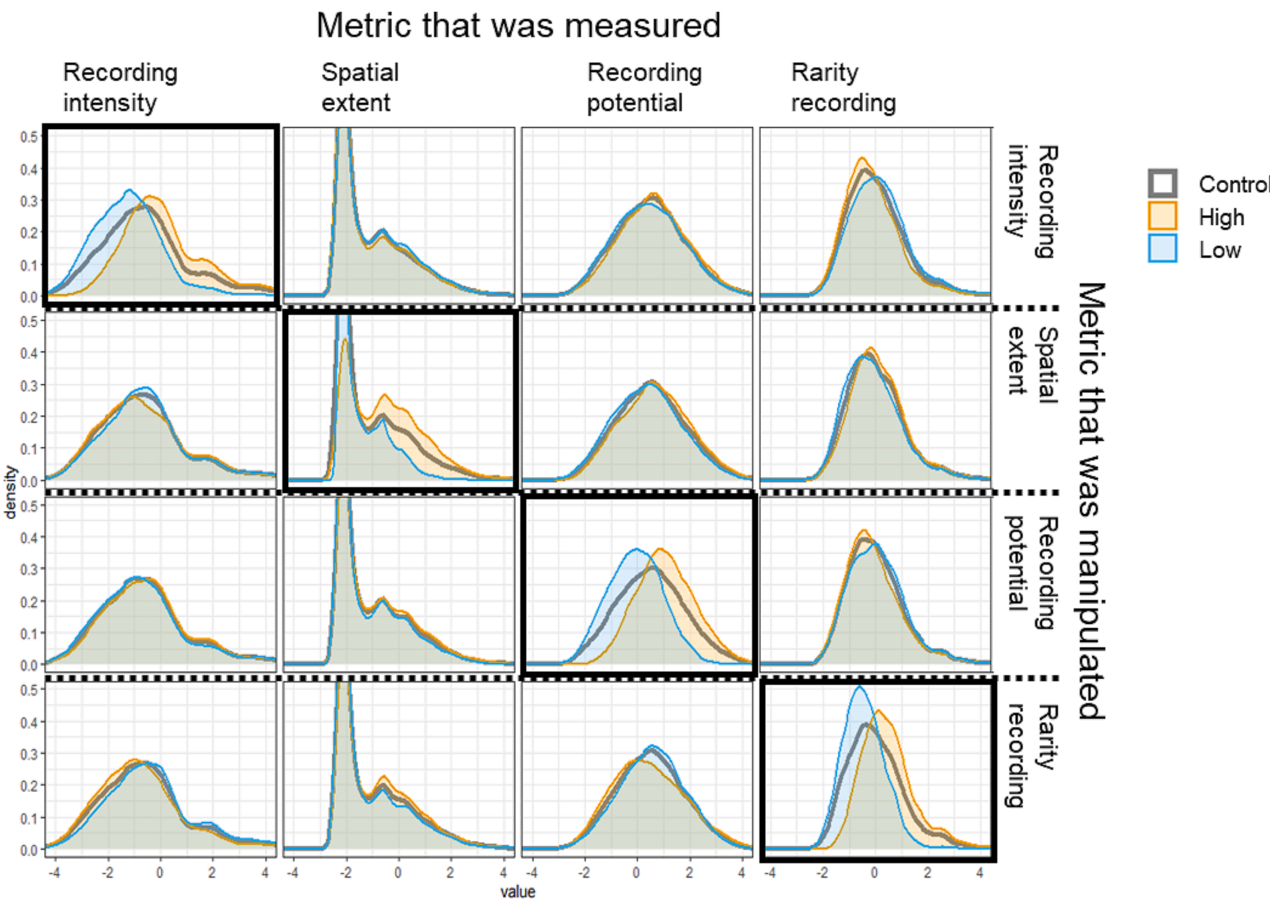

Fig. 2. The distribution of recorder metrics for the recorders included in the biased 50% subsample datasets. Each plot shows three datasets: the control (removing 50% of records randomly) and the two biased datasets (removing 50% of records but biased towards high or low values of each recorder metric). Each row shows results for one manipulated dataset. The plots on the diagonal (highlighted with a thick border) show the measured impact of manipulating that metric.

rarity recording (Fig. 3c). Across all three metrics, recording potential had the greatest impact on the results, and recording intensity had the least (Fig. 3d).

The precision of the slope was assessed by its variance (i.e. high variance is low precision; Fig. 3b). It was not sensitive to manipulations of two metrics of recorder behaviour (recording intensity and rarity recording), but it was sensitive to the other two metrics. Specifically, the variance was greater than expected (compared to the random subsamples, i.e. the z-score was larger) when manipulating the dataset for high values of spatial extent and for both high and low values of recording potential. This showed that, surprisingly, the trend estimates have high variation when there are more records from 'thorough' recorders (i.e. high recording potential: naturalists who record a high proportion of the species present and are more likely to make records of multiple species per visit) compared to incidental recorders. The trends are also less precise when there are more data from patch recorders (low spatial extent) compared to roaming recorders. Both of these results seems counterintuitive, because both 'thorough recorders' and 'patch recorders' would generally be expected to provide informative records, yet increasing their relative contribution leads to lower precision.

The occupancy estimates were also affected when manipulating recording potential and rarity recording. The effect was greatest for recording potential, as shown by the fact that the z-scores comparing the biased to the control subsamples lay outside of the range −1.96 to + 1.96 for almost all species. The effect of this can be clearly seen in the species that exhibit the greatest effects (Fig. 4), in which the occupancy estimates are shifted up or down the y-axis, even though the slope itself is fairly consistent between control and biased subsamples.

These effects, comparing biased to random subsets of the data were consistent across different sized subsets of the data (Fig. S3.1 in Appendix S3). Although not the primary focus of our study, these results also allowed us to examine the effect of the size of the randomly-selected datasets on the outputs. We found that as the random subsets got smaller then, compared to the full dataset, the trends were estimated higher for the rarer butterflies, the trend variance greatly increased, and differences in occupancy increased, although the direction of this last effect varied by species (Fig. S3.2 in Appendix S3).

The number of records for each species varied across the random and biased subsamples, but we found no consistent evidence that the number of records for a species affected the precision of the trend (Appendix S4). When considering the distribution of records according to habitat (Appendix S5), we found that, as expected, habitats were not sampled representatively: built-up areas and broad-leaved woodland were substantially over-represented in the random subsamples compared to the whole of the UK, and moorland, heath and bog and semi-natural grassland were substantially under-represented. Biasing the data subsamples by different types of recording behaviour had some effect on relative habitat coverage (Fig. 5; Appendix S5 for details). Differences in the habitat coverage could be one explanation how different types of recorder behaviour influence the model outputs.

4. Discussion

There is an increasing use of opportunistically-collected citizen science data for modelling biodiversity trends and, concurrent with this, is a growth in modelling approaches to deal with the challenge of imperfect detection in non-standardised sampling (Bird et al., 2014; Isaac et al., 2014; Rapacciuolo et al., 2021). Bringing greater standardisation

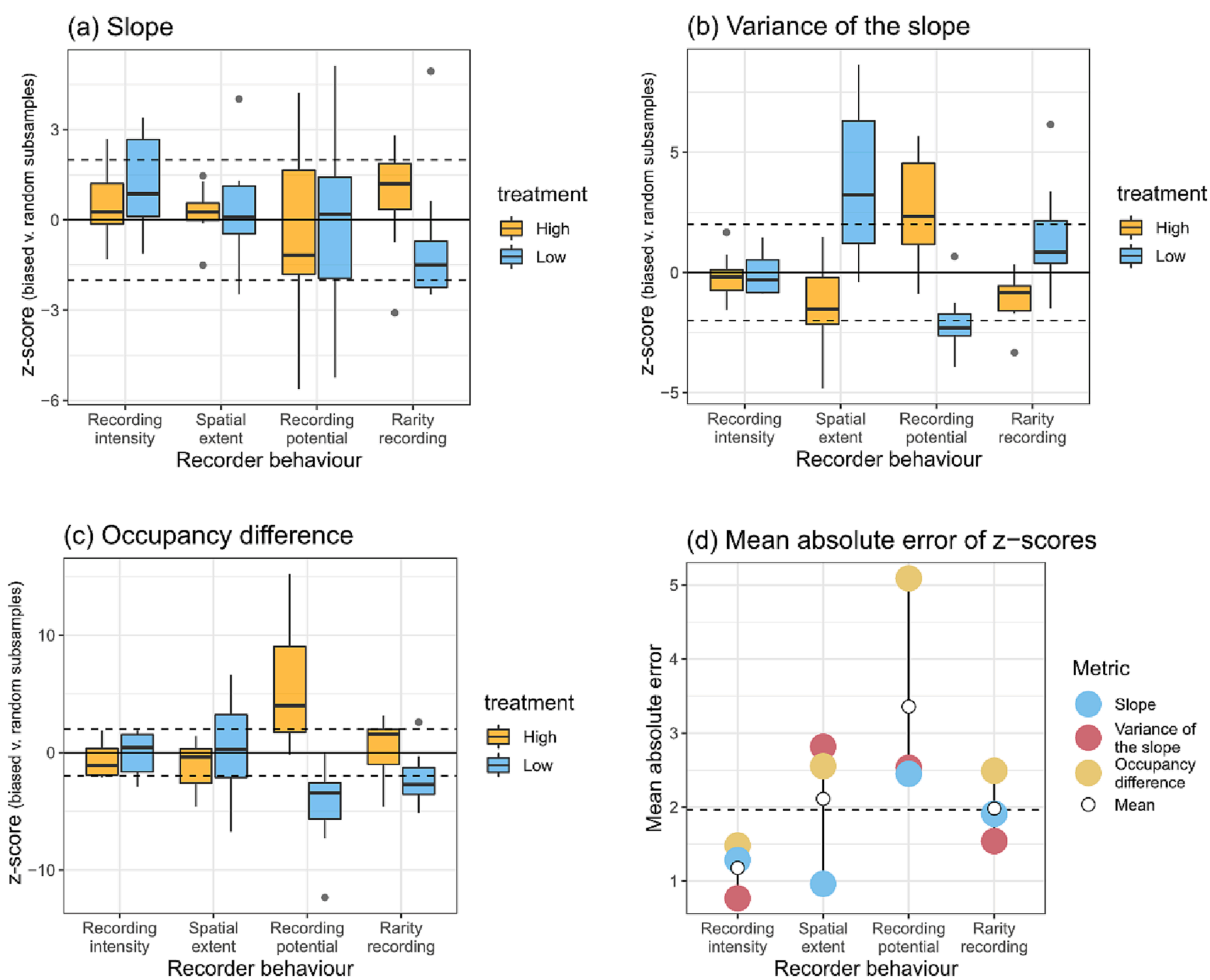

Fig. 3. The effect of taking biased subsamples, according to high and low values of four types of recorder behaviour on the estimates of (a) the slope, (b) the variance of the estimate of the slope (i.e. inverse of precision) and (c) the difference in occupancy compared to the full dataset, and (d) the comparison of the mean absolute error of the z-score for the three metrics. The boxplots show the z-scores of the biased subsamples, based on comparison with four replicates of the same-sized random subsamples for the eight species of butterfly. Here we show the results for 50% subsamples, although the results are similar for 80% and 20% subsamples. We show the results for all species combined because there was no consistent effect across species (see Appendix S3). Horizontal dotted lines represent a significance value of 0.05 for the comparisons of each biased subsample to the control subsample.

in sampling, e.g. through semi-structured citizen science will help this (Kelling et al., 2019), but it will not fully address issues of spatial unevenness in datasets. There are differences in recording behaviour between individuals (August et al., 2020; Boakes et al., 2016), so it is important to understand the impact of these differences on analysis (Johnston et al., 2022). Here, we undertook simulations to help to address this question. Variation in recorder behaviour has been characterised for some unstructured citizen science datasets (August et al., 2020; Boakes et al., 2016) and our simulations assessed the effect of different types of recording behaviour on the results of trend analysis using occupancy modelling (Guillera-Arroita, 2017; Isaac et al., 2014). Overall, we found that three output metrics from occupancy models (i.e. trend, precision of trend and estimate of occupancy) are not substantially affected by most aspects of recorder behaviour, although there are some important caveats to this, as explored below.

4.1. Effects of recorder behaviour on the occupancy model results

Firstly, we considered impacts on the trend in occupancy because reporting often focuses on biodiversity trends to assess the 'state of nature', quantify the impact of drivers of change, and evaluate interventions (Hayhow et al., 2019; Outhwaite et al., 2020). Secondly, we considered the precision of the trend estimates. This is important because greater precision (when models are correctly specified) provides greater confidence in evaluating the statistical significance of trends and so detect change as early as possible. Thirdly, we considered the estimate of occupancy itself (averaged across years) because this provides an estimate of species' distribution size, which is valuable for some assessments, such as Red List reporting (Cardoso et al., 2011).

Across the eight species we modelled, which varied in their trend and rarity, the occupancy trend was robust to differences in recorder behaviour (Fig. 3a). This suggests that the reported trends for biodiversity taxa in Britain would not have been affected by any systematic variation in recording behaviour across datasets for the taxonomic groups (Outhwaite et al., 2020). However, the precision of the trend and the estimate of occupancy could have been affected if recorder behaviour differed across datasets (Fig. 3b and c).

When considering the type of recording behaviour that has greatest impact, our results showed that the models were most robust to differences in recording intensity (the frequency and regularity of records per participant; Fig. 3d). Therefore, when accounting for the total size of the dataset (the number of records), the intensity of recording by individuals

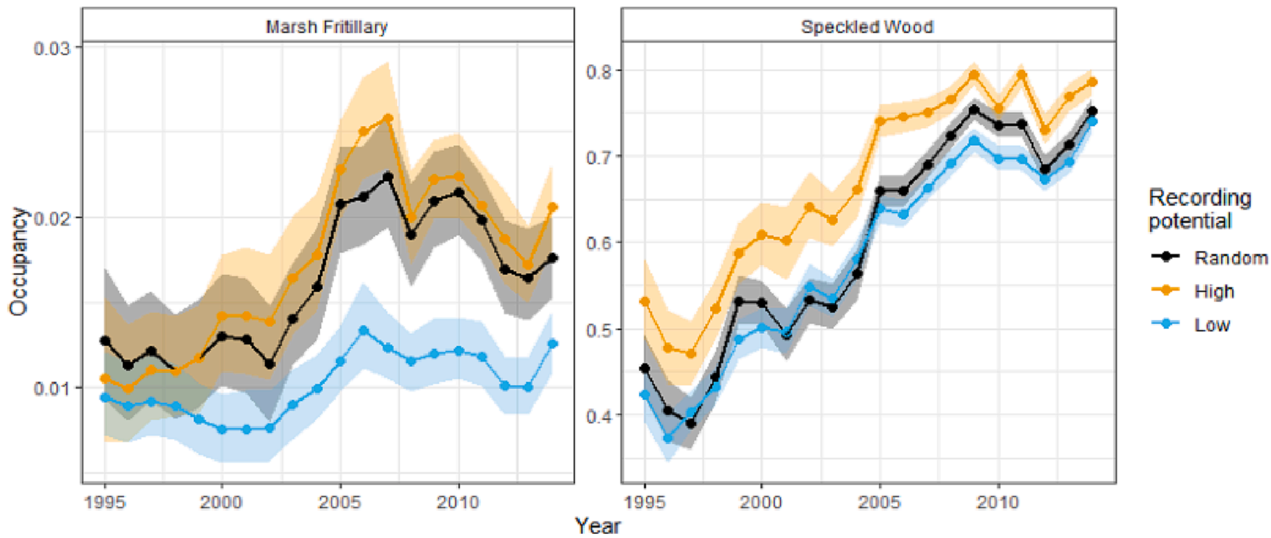

Fig. 4. Example trends for two species of butterfly showing the effect of bias of recorder type (high and low recording potential) on estimates of occupancy. Marsh Fritillary (*Euphydryas aurinia*) and Speckled Wood (*Pararge aegeria*) had particularly extreme effects of the subsamples that were manipulated to be biased for low and high values of recording potential, respectively. The coloured areas show the 95% confidence intervals of the posteriors from the Bayesian occupancy analysis. Note the difference in the scale on the y-axis: Marsh Fritillary is a rare species (occupancy = 0.5–2.5% of sampled grid squares), whereas Speckled Wood is much more common (occupancy = 37–80% of sampled grid squares).

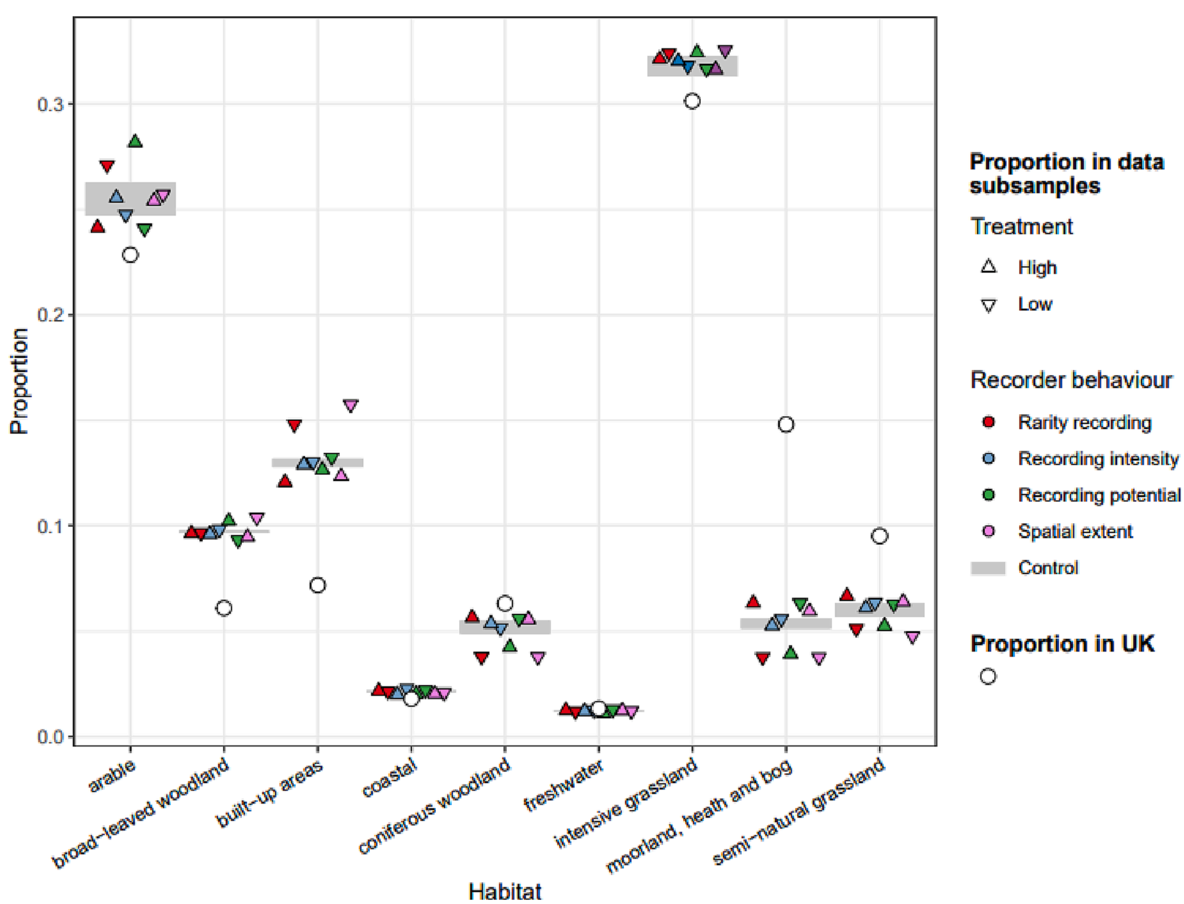

Fig. 5. The proportion of habitats in the whole of the UK (white circle), the four random subsamples (grey rectangle indicating the full range), and the biased subsamples indicated by recorder behaviour (four different colours, with symbols indicating subsamples that were biasing high or low). This shows that, as expected, the citizen science recording is not representative across habitat types (grey bars compared to white circles) and that biasing across to different types of recorder behaviour creates differences from the random subsamples (coloured triangles compared to grey bars).

(the number of records and the gap between periods of recording) does not affect the estimates of occupancy, trend in occupancy, or its precision. In contrast, the other three aspects of recording behaviour do affect different aspects of the outputs. In particular, the overall outputs were most sensitive to recording potential (Fig. 3d).

The precision of the trend estimate was sensitive to two aspects of recorder behaviour. Although greater precision in trend estimates seems positive, certain subsets of the data could lead to occupancy trend estimates that were erroneously precise, e.g. due to model misspecification or lack of representativeness of the dataset. When considering the outputs of occupancy trend modelling, the results are with respect to the subset of sites that have been sampled, which may not be representative of the region of interest (Boyd et al., 2021). Our results suggest that this could be particularly problematic when there are biases towards the types of recorders that we termed 'thorough recorders' (i.e. with high recording potential) or 'patch recorders' (i.e. with low spatial extent of recording).

4.2. The potential reasons why recorder behaviour affects biodiversity trend analysis

Since we found that some types of recorder behaviour impacts on the occupancy model outputs, this raises the question: what were the underlying causes for these effects? We expect that the effects are due to a combination of both the range of sites included in the dataset and the information content per site (e.g. number of revisits and the detectability per species). When manipulating the data according to different aspects of recorder behaviour, there were differences in the habitat coverage of sites (in our case, 1 km squares; Fig. 5), hence biasing the sample of sites over which occupancy and its trend is estimated. For example, participants with higher rarity recording behaviour might lead to the inclusion of more nature reserves in the dataset, which could cause model estimates to be less representative of the whole region. There is a balance for project organisers in encouraging participants to visit more grid squares (thus potentially provide greater spatial representativeness for the estimate of occupancy), which comes at the cost of fewer revisits (thus potentially providing poorer estimates of detection probability). The overall effect on the precision of the trend is difficult to predict *a priori* and so should be a focus for future research.

4.3. Limitations of this study and opportunities to develop solutions

In the current study, we focussed on a well-recorded taxon, and our data subsample (50% of the total, including all species of butterfly) was 1.6 million records over the 20 year period, i.e. an average of 80,000 species records per year and c. 10–15,000 site visits per year. This is far more than is available for most taxa and in almost all other parts of the world. We note that, although there were some significant effects of recorder behaviour on two of the output metrics, the differences were quite modest compared to the expected values. It will be important to test our results further with smaller datasets in which biases in outputs due to recorder behaviour might be more pronounced, but we expect that the overall pattern of our results will be similar.

A practical challenge for this study was the lack of standardised, unique versions of people's names. This problem has only recently been addressed in other areas, such as authors of academic papers (Haak et al., 2012). Further work could improve our approach of standardising people's names, and the increased use of online portals (with a unique identifier associated with each unique registration) will reduce this problem, but harmonising unique identifiers across datasets and across platforms will remain a challenge (Johnston et al., 2022). Johnston et al. (2018) indicated the value of including individual recorder identify when modelling citizen science data, so developing pipelines to retrospectively improve standardisation of recorder identities would be valuable.

One of the other major limitations of this study is the fact that the true values of the parameters of interest (trend, precision of trend or occupancy) were not known. The full dataset was subject to spatial and temporal biases itself (Fig. 5), in common with all unstructured recording (Geldmann et al., 2016; Pernat et al., 2021; Petersen et al., 2021). Therefore, here, we only report on differences from random subsamples of the dataset. In particular, because the occupancy is estimated from the set of sampled sites, if those sampled sites are not representative of the species or range of interest, then the estimated trend in occupancy may not represent the true value (Boyd et al., 2022). Modelling simulated datasets (as per Isaac et al., 2014) would be required to understand the impact of this, although it is challenging to set up realistic, but tractable, simulation studies with variation in species, site suitability and recorders.

In this study we manipulated the overall dataset, however many aspects of recording vary over time (Knape et al., 2022), so it is possible that the metrics of recording behaviour could also change over time. This could be due to the inclusion of different types of recorder, e.g. selective recruitment towards beginners or experienced recorders will change the average recording behaviour of participants. It could also be because the motivation of participants will change over time (Rotman et al., 2014) or the recording environment changes, e.g. because technology facilitates people making more records more frequently (Pocock et al., 2017). Indicators of these changes can be seen in the pattern of species composition of records, e.g. with more records of commoner, conspicuous species than in the past (Ball et al., 2021). Indeed, such a shift in recording behaviour can actually be elicited by the project organisers, e.g. the dramatic shift in eBird towards people reporting 'complete lists' rather than 'incidental' records was due to communication and technological facilitation (Sullivan et al., 2014). In our study, the estimate of occupancy was the output that was the most sensitive to recorder behaviour. Therefore if recording behaviour changed over time, then it would effect trend estimates (Fig. 6). Currently the variation in recorder behaviour over time is not well known, and so there is a need to better describe and understand these changes in long-term recording projects, and to assess their impact on biodiversity trend analysis.

Describing the potential impacts of changing recording behaviour is valuable, but it is more fruitful to propose solutions to these issues. One approach could be to enhance the analytical models to take account of potential bias: by using models that are demonstrably robust to potential sources of bias in the dataset (as identified in the current study, see also van Strien et al. (2010)); by weighting sites appropriately to increase the representativeness of the dataset (Johnston et al., 2020); or by explicitly modelling recorders in the analysis (Johnston et al., 2018). A second approach would be to influence recorder behaviour directly. These citizen science data come from people's engagement with nature, and so will be influenced by many different individual factors, including the opportunity and motivation to record (Soga et al., 2021). Engagement with recorders could support beneficial forms of recorder behaviour to reduce biases in the dataset (Callaghan et al., 2019). Depending on the question of interest this could include recording previously unvisited sites, or prioritising the revisiting of sites. Creating feedback loops for recorders to be more engaged with the impact of their recording, and encouraging behaviour change that would benefit the data, is a promising area of innovation which will benefit from advances in technology and data science.

4.4. Conclusions

Overall, our results suggest that species' trend estimates from occupancy modelling are largely robust to heterogeneity in recorder behaviour. This is an encouraging result, supporting the value of using occupancy modelling with unstructured citizen science for biodiversity monitoring. There are some systematic biases when manipulating the dataset according to some aspects of recorder behaviour and although the impact on the outputs was modest, this could become more

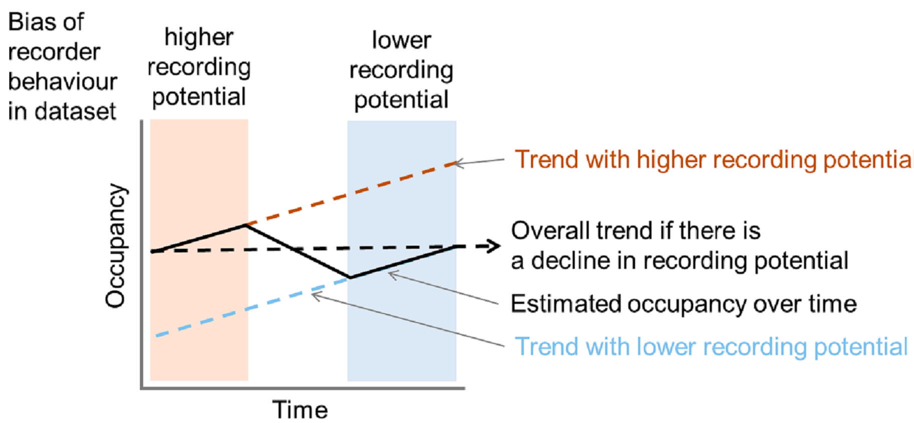

Fig. 6. Hypothetical illustration of how changes in recording behaviour could affect the estimated trend in occupancy due to biases in the estimates of occupancy over time. Specifically this shows a shift from higher to lower recording potential (from thorough recorders to incidental recorders, such as could be facilitated by technology making it easier for more people to take part in recording).

important if patterns of the recording behaviour of project participants changed over time. In particular, the influence of recorder behaviour on the inclusion of sites in the dataset, and the impact of differing site inclusion on overall estimates of occupancy requires further investigation, especially through simulations when the true values of occupancy and trend can be known.

CRediT authorship contribution statement

Michael J.O. Pocock: Conceptualization, Methodology, Visualization, Writing – original draft, Funding acquisition. **Mark Logie:** Methodology, Formal analysis. **Nick J.B. Isaac:** Writing – review & editing, Funding acquisition. **Richard Fox:** Resources, Writing – review & editing. **Tom August:** Conceptualization, Methodology, Formal analysis, Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ecolind.2023.110276.

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