2   # Robustness of simple avian population trend models for
3   # semi-structured citizen science data is species-dependent

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9   Abstract

10   Accurate and robust population monitoring is essential to effective biodiversity conservation.
11   Citizen scientists are collecting opportunistic biodiversity records on unprecedented temporal
12   and spatial scales, vastly outnumbering the records achievable from structured surveys.
13   Opportunistic records may exhibit spatio-temporal biases and/or large heterogeneity in observer
14   effort and skill, but the quantity-quality trade-offs between surveys and less structured schemes
15   remain poorly understood.

16   Recent work has advocated the use of simple trend models for opportunistic biodiversity records.
17   We examine the robustness of population trends of common United Kingdom birds derived from
18   two citizen-science schemes; BirdTrack, an opportunistic recording scheme, and the structured
19   Breeding Bird Survey (BBS). We derived reporting rate trends from BirdTrack lists using simple
20   statistical models which accounted for list-level effort covariates but not for preferential
21   sampling, and compared them to abundance and occurrence trends derived from BBS survey
22   data.

23   For 90 out of 141 species, interannual changes in reporting rates were positively correlated with
24   trends from structured surveys. Correlations were higher for widespread species and those
25   exhibiting marked population change. We found less agreement among trends for rarer species
26   and those with small or uncertain population trajectories. The magnitude of long-term changes in
27   reporting rates was generally smaller than the magnitude of occupancy or abundance changes,
28   but this relationship exhibited wide scatter, complicating the interpretability of reporting rate
29   trends. Our findings suggest that simple statistical models for estimating population trends from
30   opportunistic complete lists are robust only for widespread and common species, even in a
31   scheme with many observers and extensive coverage.

32   **Keywords:** Avian ecology; biodiversity monitoring; breeding bird survey; Citizen science;
33   population trend; list-length analysis

34   1   Introduction

35   The ability to accurately and robustly quantify species' population size trajectories over time is
36   key to successful biodiversity conservation. Monitoring of changes in a species' population size
37   is essential to assess threat status; to act as an early-warning signal to detect population declines;
38   for conservation resource prioritization; and to assess the efficacy of current environmental
39   policies (Lawton 1993; Johnston *et al.* 2015; IUCN 2016). Yet, most animal and plant
40   populations cannot be censused (i.e. completely enumerated), or even robustly surveyed, given
41   the limited resources available for population monitoring. Even for birds, which are one of the
42   best monitored taxonomic groups globally, large geographic biases exist in monitoring effort
43   (Meyer *et al.* 2015, 2016; Amano, Lamming & Sutherland 2016). This affects not only our
44   knowledge of species distributions, but also of the processes determining biodiversity change,
45   since the factors driving population dynamics, such as climate change effects, are likely to differ
46   between surveyed and unsurveyed regions (Pearce-Higgins *et al.* 2015).

47   Long-term structured surveys, which use randomly selected sites and survey methods that are
48   standardized over time and space, can provide robust population trends for many common
49   species. However, such structured surveys require large and long-term commitments by
50   volunteers and can be costly to organize and coordinate (Schmeller *et al.* 2009). Instead, citizen
51   science projects which rely on the opportunistic collection of biodiversity records by interested
52   members of the public may be a cost-effective means to greatly increase the spatial and temporal
53   scale of distribution and abundance data (Dickinson, Zuckerberg & Bonter 2010; Isaac & Pocock
54   2015). Even though such projects may have a primary goal other than population monitoring,
55   e.g. raising awareness about focal taxa or to facilitate personal record keeping for amateur
56   naturalists, there is an increasing interest in using such schemes to fill in knowledge gaps in
57   regions that are poorly or not at all covered by structured surveys, and as a basis to obtain indices
58   of population trajectories that meaningfully capture the true population trends of species (Kery *et*
59   *al.* 2010; Isaac *et al.* 2014; Horns, Adler & Şekercioğlu 2018). Trend modelling based on such
60   data is challenging because of known biases in site selection, visit timing, survey effort, and/or
61   surveyor skill (Isaac & Pocock 2015; Johnston *et al.* 2018, 2019). Thus there is usually a trade-
62   off between collecting a large amount of relatively heterogeneous (i.e. lower 'quality') data or a
63   smaller amount of higher 'quality' data conforming to a defined common structure.

64   The consequences of this quantity versus quality trade-off are still poorly understood (Aceves-
65   Bueno *et al.* 2017; Bayraktarov *et al.* 2018; Kelling *et al.* 2018; Specht & Lewandowski 2018).
66   There is a growing set of modelling approaches to address the challenges of unstructured data
67   sets using auxiliary structured biodiversity data and/or observation models that account for
68   preferential sampling, but these come at the cost of increased model complexity and
69   computational demands (Pagel *et al.* 2014; Fithian *et al.* 2015; Robinson, Ruiz-Gutierrez & Fink
70   2018; Johnston *et al.* 2019). Other recent work has investigated whether relatively simple models
71   are sufficient to extract population trend information from less structured data (Roberts, Donald
72   & Green 2007; Snäll *et al.* 2011; Kamp *et al.* 2016; Walker & Taylor 2017; Horns *et al.* 2018).
73   These simpler approaches generally rely on the assumption that the information gain from a
74   larger quantity of records outpaces potential biases from opportunistic sampling. They also make
75   two further assumptions, namely that reporting rates are a good proxy of site occupancy, and that
76   population abundance and site occupancy are positively correlated for each species. However,
77   reporting rate – site occupancy relationships may be influenced by, for example, species

78   detectability (Johnston *et al.* 2014). Further, while there is a large body of literature providing
79   empirical evidence that - in general - abundance-occupancy relationships are positive
80   (e.g. Gaston *et al.* 2000; Webb, Noble & Freckleton 2007; Webb, Freckleton & Gaston 2012),
81   there can be high interspecific variability in the exact nature of intraspecific abundance-
82   occupancy relationships (Webb *et al.* 2007). Ultimately, violations of these assumptions could
83   result in unreliable population trend estimates, potentially leading to incorrect species status
84   assessments. To develop robust biodiversity monitoring schemes, it is therefore essential that the
85   consequences of such assumptions are fully understood.

86   Few opportunities exist for the direct comparisons between opportunistic biodiversity data
87   against a robust benchmark, especially on large spatial and temporal scales, and across many
88   species. We here leverage the spatial and temporal overlap of two national citizen science
89   schemes to investigate the utility of semi-structured species lists to derive robust population
90   trends for common breeding birds across the United Kingdom. We use data from "BirdTrack"
91   (www.birdtrack.net), an opportunistic bird recording scheme (Baillie *et al.* 2006; Newson *et al.*
92   2016), and the "Breeding Bird Survey" (BBS), one of the most rigorous structured breeding bird
93   monitoring schemes globally (Gregory, Baillie & Bashford 2000). We then test the extent to
94   which assumptions made by relatively simple modelling approaches with regard to occurrence-
95   abundance relationships, and reporting rate-occurrence and reporting rate-abundance
96   relationships hold when applied to individual species within a national avifauna. Further, we
97   assess whether the strength of relationships between trends derived from different survey and
98   data types could be predicted from species characteristics.

99   2   Materials and Methods

100   2.1   Data sources

101   We estimated three different annual population indices – relative abundance, relative occurrence,
102   and birdwatcher reporting rate – for 141 of the commonest species of breeding birds in the
103   United Kingdom covering the period from 2005 to 2017.

104   The structured dataset employed in this analysis came from the Breeding Bird Survey (BBS),
105   which is a partnership project of the British Trust for Ornithology (BTO), the Joint Nature
106   Conservation Committee, and the Royal Society for the Protection of Birds (RSPB) (Gregory *et*
107   *al.* 2000; Harris *et al.* 2017). The BBS follows a strict sampling protocol in which skilled
108   volunteer surveyors count all birds heard or seen along two 1 km of transect lines, 500 m apart
109   from each other and within a 1 km^2 site on two annual visits during the breeding season. Sites are
110   randomly selected following a stratified random design which accounts for variable volunteer
111   availability across the survey area. Survey coverage of the BBS is high (1.10-1.65% of the UK
112   territory for the study period (Harris *et al.* 2017)), and largely unbiased with respect to habitat
113   types (with the exception of mountainous areas; Fig. S3), making it one of the most rigorous
114   avian monitoring schemes globally. As the BBS data serve as a reference in this study we
115   focussed on a set of 141 species (c. 60% of UK breeding species; Table S2) for which there was
116   a reasonable expectation that the BBS approach can deliver a meaningful estimate of breeding
117   population trend, e.g. by excluding species with large wintering or non-breeding populations
118   such as fieldfare *Turdus pilaris* and gulls (Harris *et al.* 2017).

119 The less structured dataset for the analysis was from BirdTrack, which is also a citizen science
120 dataset, but with less stringent survey requirements and a wider range of participants than the
121 BBS. BirdTrack participants contribute lists of species they have detected during a self-selected
122 time interval spent at a self-selected location. We only considered complete lists, i.e. lists for
123 which birdwatchers reported having listed all detected species, and furthermore only used lists
124 with a location precision of 1km collected from 01 April to 30 June of each year to match the
125 spatial grain and temporal extent of the BBS. The resulting dataset therefore constitutes
126 detection/non-detection data with potential biases associated with self-selection of sites and visit
127 timings. The BirdTrack data are similar to the eBird dataset used in Walker & Taylor (2017) and
128 Horns *et al.* (2018), who also restricted their analyses to complete lists from self-selected
129 locations with list-level effort covariates, but more structured than presence-only data used in
130 other studies, e.g. the analyses based on the Swedish Artportalen (Snäll *et al.* 2011) or the Danish
131 DOFbasen (Kamp *et al.* 2016), which did not allow for a distinction of complete lists and
132 incidental records and for which no effort covariates were available. Compared to the BBS there
133 are many more locations in the United Kingdom that have BirdTrack records, however, on a
134 national scale the relative density of records for either scheme follows a similar pattern with
135 fewer records in less populated and more mountainous areas such as the Scottish Highlands (Fig.
136 S3).

137 For both datasets, sites where a target species had never been observed in the considered
138 timespan were excluded from the analysis. This reflects the standard BBS analytical approach
139 (Freeman *et al.* 2007; Harris *et al.* 2017) and means that derived trends reflect measures of local
140 mean abundance and occupancy (sensu Wilson 2011).

141 Previous comparisons of trend models for opportunistic data against those fitted to structured
142 schemes have been criticised for not comparing like with like, for example by comparing year-
143 round occurrence data with breeding-season abundance data, or by including non-breeding
144 species in comparisons based on breeding bird survey data (Fogarty, Wohlfeil & Fleishman
145 2018). We aimed to address this concern by ensuring that the comparison between the two data
146 sources was based on the same annual sampling period (April-June) and excluded species that
147 were poorly covered by the structured surveys, and furthermore by propagating the uncertainty in
148 all trend estimates into the comparative analyses.

149 2.2 Trend models

150 2.2.1 BBS abundance trends

151 Abundance models for BBS data followed the Poisson GLM approach employed in the official
152 BBS trend production (Freeman *et al.* 2007), which models the mean local count λ_{it} at site i and
153 year t based on the observed maximum counts $y_{obs,it}$ across the two survey visits as a function
154 of fixed additive site and year effects β_i and β_t, respectively.

$$y_{obs,it} \sim \text{Poisson}(\lambda_{it})$$

$$log(\lambda_{it}) = \beta_i + \beta_t.$$

155 We further used sampling weights – equal to the inverse inclusion probability of a site within a
156 stratum for a given year – to account for uneven monitoring coverage among BBS survey strata.

157 Confidence intervals were calculated using design-based estimators as implemented in the
158 `svyglm` function from the R package `survey` (Lumley 2004), rather than following the
159 bootstrapping approach of Freeman *et al.* (2007).

2.2.2 BBS Occurrence Trends

161 Models of occurrence p_{it} for BBS data were based on truncating the count data to ≤ 1 and using
162 a binomial GLM.

$$y_{obs,it} \sim \text{Bernoulli}(p_{it})$$

163 The model structure and estimation otherwise mirrored the BBS abundance model described
164 above with year and site effects

$$logit(p_{it}) = \beta_i + \beta_t,$$

165 and the use of sampling weights and design-based estimators.

2.2.3 BirdTrack Reporting Rate Trends

167 Trends from BirdTrack data were based on the reporting probability model of Horns *et al.*
168 (2018). The presence or absence of a species y_{itk} on a list k at site i in year t was modelled as
169 the outcome of a Bernoulli trial

$$y_{itk} \sim \text{Bernoulli}(p_{it})$$

170 Because of the large number of sites with BirdTrack lists (c. 22,000) we used a random site
171 effect γ_i, but retained the categorical fixed year effect β_t of the BBS models. We further used list
172 duration, list length (number of species), and visit date (and its square to account for non-
173 linearity) as continuous predictors to control for heterogeneity in observation effort and observer
174 skill.

$$logit(p_{it}) = \gamma_i + \beta_t + \beta_{duration} + \beta_{length} + \beta_{date} + \beta_{date^2}$$

175 Models were fitted using the R package `glmmTMB` (Brooks *et al.* 2017). As BirdTrack has no
176 formal sampling design we did not use sampling weights to correct for variation in geographical
177 coverage, mirroring the modelling approach of Horns *et al.* (2018).

2.3 Calculation of relative change and associated confidence intervals

180 For all of the above models, year coefficient estimates were back-transformed to the response
181 scale using the appropriate inverse link function, the percentage change relative to the defined
182 index year 2005 was calculated. Confidence intervals (95%) for the relative change indices were
183 approximated by simulation following Krinsky & Robb (1986);Krinsky & Robb (1990). Briefly,
184 1000 sets of year coefficients were drawn from a multivariate normal distribution parameterized
185 with means $\hat{\beta}_t$ and the variance-covariance matrix of the corresponding model, followed by
186 calculating the percent change index for each set as above and taking the 2.5th and 97.5th
187 quantiles of the simulated indices.

2.4 Calculation of correlation coefficients among modelled trends

Similarly, pairwise correlations between estimated year coefficients from each of the three trend models and their associated confidence intervals were approximated for each species by simulation. That is, sets of year coefficients were drawn from a multivariate normal distribution parameterized with means $\hat{\beta}_t$ and the variance-covariance matrix of each model, followed by calculating Pearson's product-moment correlation coefficient r between sets of year coefficients from two models on the link scale.

2.5 Interspecific trend analysis

To determine whether the strength of intraspecific relationships among trends could be predicted using a species' characteristics, we used a multivariate generalized additive model (Wood 2017). Species characteristics assessed in the model included 'commonness', estimated from the average number of BBS sites in which a species was detected; the population trajectory of a species, based on the long-term (i.e. 12-year) BBS abundance trend; the species expected spatial distribution during breeding; and its detectability or recording probability. A species spatial distribution during breeding was assigned depending on the extent of its associations with conspecifics during nesting, as either semi-colonial, solitary or 'mixed' (i.e. mixed strategy; can nest either solitarily or semi-colonially). The species' body mass was used as a proxy for detectability (Johnston *et al.* 2014). Trait data on body mass and association during nesting were obtained from Storchová & Hořák (2018).

We modelled Fisher transformed correlation coefficients $z = \operatorname{arctanh}(r)$ (Fisher 1915) from all three sets of trend comparisons simultaneously by using factor-smooth interactions for continuous predictors, and regular interactions for categorical predictors (Supplementary Table 1.1). The model used an identity link function and normally distributed errors. Responses z were weighted by the inverse of their standard error to propagate the uncertainty contained in the correlation coefficient estimate. Model parameters were estimated using `mgcv` (Wood 2017).

The magnitude of long-term trends in reporting rates was compared to abundance and occurrence trends using weighted least squares regression. The relative trend direction in BirdTrack reporting rates, BBS abundance and BBS occurrence models were also compared. We followed the definitions of sensitivity and specificity employed by Horns *et al.* (2018), but accounted for uncertainty in the trend estimates, i.e. true positives were defined as trends that are significantly positive in both the structured survey and reporting rate models; false positives if the structured model reported a significant decrease or no trend, but the reporting rate model suggested a significant increase; false negatives if the structured data suggested an increase or non-significant trend, but the reporting rates suggested a significant decrease; and true negatives where both data sources suggested a significant decrease.

3 Results

3.1 Relative trend magnitude

Across all investigated species, and using structured survey data, long-term occurrence trends were similar to abundance trends although there was wide scatter around the regression line (Fig.

227   1a; regression estimates and 95% CIs: intercept=3.89 (-7.71, 15.49); slope=1.06 (0.9, 1.21);
228   R^2=0.56). However, for 29 very common species – those detected on more than 1500 (45%) BBS
229   sites – occurrence trends were much weaker (essentially zero) than abundance trends (Fig. 1b).

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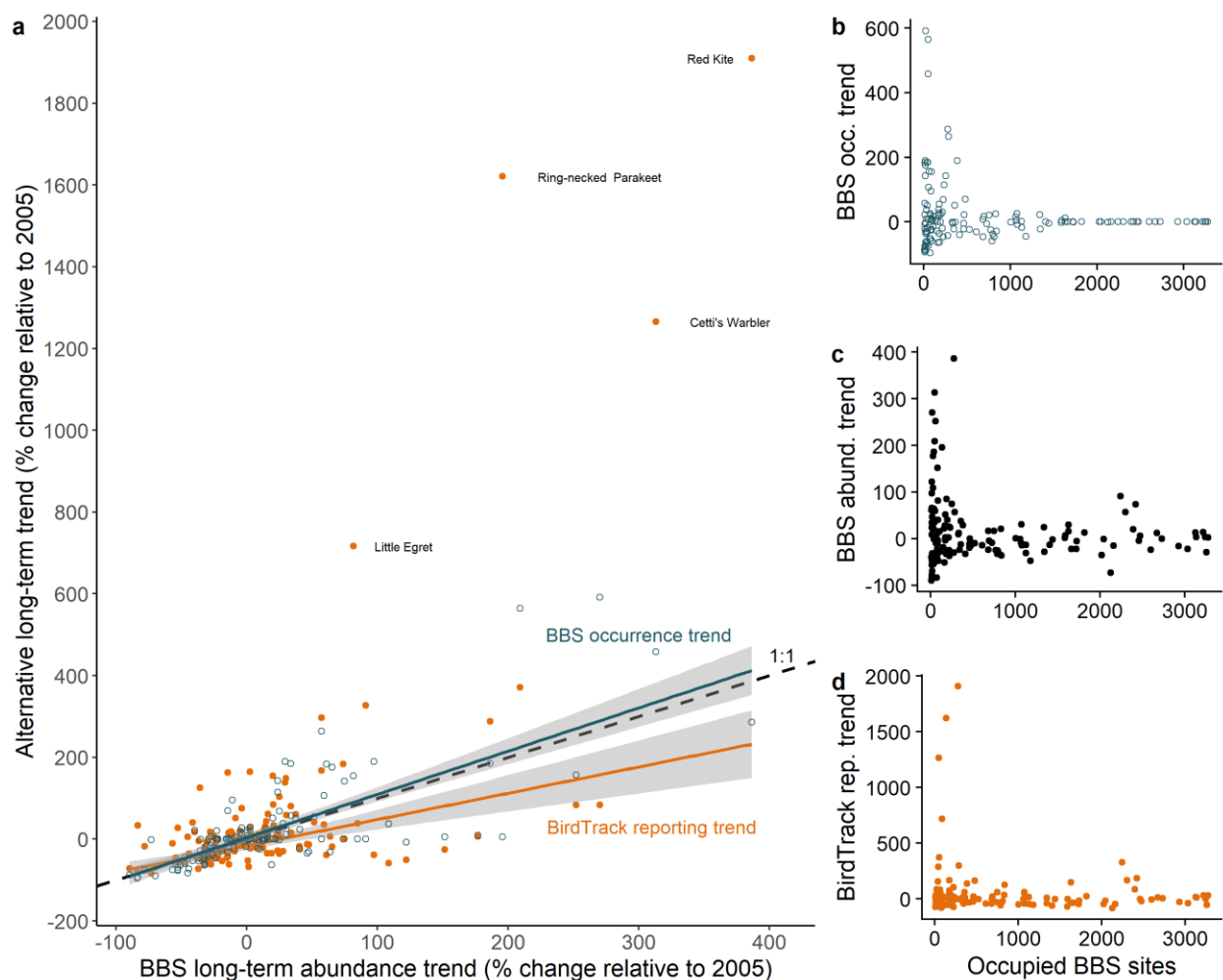
Figure 1: (a) Across all species, occurrence trends (open symbols, solid green line) and abundance trends based on
structured survey data (BBS) exhibited similar magnitudes. Reporting rate trends (solid symbols, solid orange line)
based on BirdTrack lists were generally attenuated compared to BBS trends. Each point represents a 12-year trend
estimate for a single species relative to 2005. Notable outliers are annotated, dashed line represents the 1:1 line,
i.e. where both occurrence trends and reporting rate trends, respectively, produce the exact same increases/decreases
as abundance trends within the 12 years of data. (b-d) For very widespread species (> 1500 BBS sites) a saturation
effect was apparent, with occurrence trends tending to zero (b). Reporting rate trends for these species did not
exhibit this effect (d). Note that Y-axis ranges differ in panels b-d.

239   Long-term BirdTrack reporting rate trends were negatively biased, and overall showed a smaller
240   magnitude of change relative to trends based on structured survey data, although with a few
241   marked outliers. The magnitude of reporting rate-trends was on average about two thirds of the
242   corresponding abundance trend (Fig 1a; intercept=-16.33 (-25.91, -6.74); slope=0.64 (0.43,
243   0.85); R^2=0.21). A similar bias and a slightly stronger attenuation was apparent when comparing
244   long-term reporting rate trends to occurrence trends (Fig. S1; intercept=-19.14 (-29.1, -9.19);
245   slope=0.47 (0.27, 0.67); R^2=0.13). For both comparisons, trends for Little Egret *Egretta garzetta*,
246   Cetti's Warbler *Cettia cetti*, Red kite *Milvus milvus*, and Ring-necked Parakeet *Psittacula*

7

247 *krameri* showed much larger reporting rate increases than abundance or occurrence trends (Figs.
248 1a, S1).

3.2 Relative trend direction

250 For the reporting rate-abundance comparison, false positives (i.e. significant decrease/no trend
251 from abundance/occurrence model estimates but significant increase from reporting rate model
252 estimates) occurred for 22 species, four of which had significant trends with opposite signs
253 (Common Tern *Sterna hirundo*, Tree Pipit *Anthus trivialis*, Tufted Duck *Aythya fuligula*, and
254 Willow Warbler *Phylloscopus trochilus*, Fig. 2a). False negatives (i.e. increase/ non-significant
255 trend in abundance/occurrence model estimates but significant decrease from reporting rate
256 model) occurred for 26 species, of which also four had significant opposing signs (Coal Tit
257 *Periparus ater*, Feral Pigeon *Columba livia*, Peregrine Falcon *Falco peregrinus*, and Sandwich
258 Tern *Thalasseus sandvicensis*, Fig. 2a). For the reporting rate-occurrence comparison (Fig. 2b),
259 false positives occurred for 19 species, of which three had significant trends of opposite signs
260 (Feral Pigeon, Peregrine Falcon, and Sandwich Tern), and 30 false positives, of which just a
261 single one had a significant trend of opposite sign (Common Eider *Somateria mollissima*).

262 The sensitivity for the long-term trend was 0.46 for the reporting rate-abundance comparison
263 (Fig. 2a), 0.45 for the reporting rate-occurrence comparison (Fig. 2b) and 0.77 for the
264 abundance-occurrence comparison (Fig. 2c). The corresponding specificities were 0.61 (Fig. 2a),
265 0.62 (Fig. 2b), and 0.82 (Fig. 2c), respectively.

a — abundance trend

reporting rate trend	-	n.s.	+
-	35	22	4
n.s.	6	23	7
+	4	18	22

b — occurrence trend

reporting rate trend	-	n.s.	+
-	31	29	1
n.s.	5	26	5
+	3	16	25

c — abundance trend

occurrence trend	-	n.s.	+
-	32	7	0
n.s.	13	49	9
+	0	7	24

266

267 **Figure 2:** Classification matrices enumerating the species for which significant positive (+), negative (-), or non-
268 significant trends (n.s.) were estimated, respectively, for each trend model comparison.

3.3 Interspecific patterns of correlation between alternative trend indices

271 Abundance and occurrence trajectories based on structured survey data were significantly
272 positively correlated for 106 out of 141 species ($\overline{\rho} = 0.59$, $IQR(\rho) = 0.39$, Fig. 3a). Correlations
273 were weaker overall when comparing reporting rate trends from BirdTrack lists to either BBS
274 trend (Fig. 3b,c), with 90 significant intraspecific correlations between reporting rate and
275 abundance ($\overline{\rho} = 0.44$, , $IQR(\rho) = 0.61$, Fig. 3b), and with 90 significant intraspecific
276 correlations between reporting rate and occurrence ($\overline{\rho} = 0.46$, , $IQR(\rho) = 0.55$, Fig. 3c).
277 Significant negative correlations were found for three species (Common Tern, Canada Goose

278   *Branta canadensis*, and Feral Pigeon) between reporting rate and abundance trends, and for two
279   species (Tufted Duck and Feral Pigeon) between reporting rate and occurrence trends.

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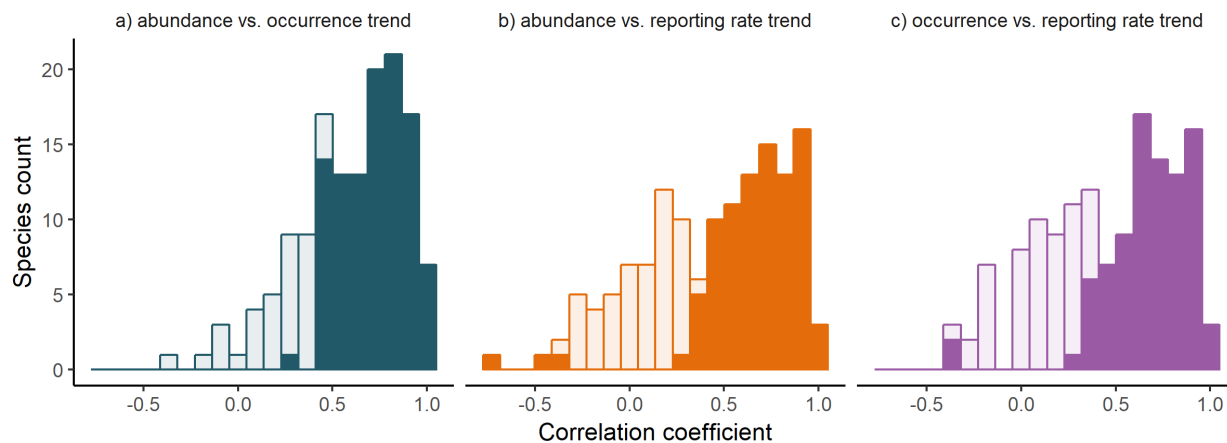
Figure 3: Estimated correlation coefficients for comparisons of intraspecific trends among trend model types. Solid
bars indicate correlation coefficient estimates that did not include zero in their associated 95% confidence interval.

283   All three pairwise comparisons showed similar patterns with respect to the investigated
284   covariates: Correlations increased for solitary and mixed strategy (i.e. those nesting either
285   solitarily or semi-colonially) breeders (Table S1), increased with absolute trend strength (Fig. 4
286   a), and commonness (Fig. 4 b). Site-occurrence, as determined from BBS data showed a
287   saturation effect for species detected on about 1500 or more sites, which equates to about >50%
288   of surveyed sites). This effect was less pronounced when comparing reporting rate trends to
289   occurrence trends, and absent when comparing reporting rate trends to abundance trends (Fig. 4
290   b). At intermediate levels of commonness reporting rate trends were marginally more closely
291   correlated with occurrence trends, than with abundance trends. There was a similar negative
292   correlation of body mass for all three comparisons (Fig. 4 c). While the effects of breeding
293   association were generally positive compared to the reference level of colonial breeders, this was
294   significant only for the correlations among reporting rate and occurrence trends in the case of
295   solitary and mixed strategy breeders (Fig. 4 d).
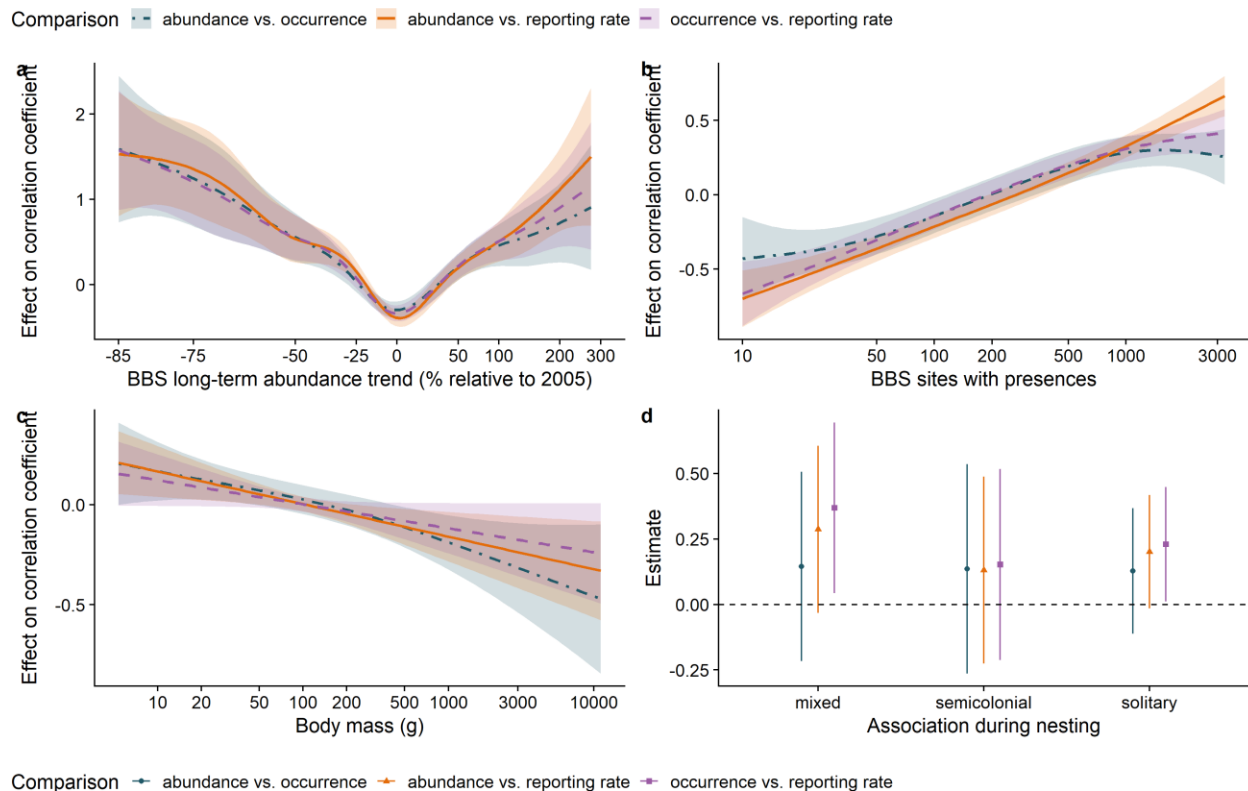
Figure 4: Estimated smooth relationships between the z-transformed correlation coefficient for intraspecific population trends and abundance trend magnitude (a), and commonness (as measured by the number of BBS sites with positive detections for a given species; b) showed similar patterns among all three types of trend models. Agreement among trends was highest for strongly trending and widespread species. The correlation between abundance and occurrence trends saturated for very common species (b). Correlations increased somewhat with decreasing body size (c) and for solitary or mixed-strategy breeders (d).

4 Discussion

Intraspecific abundance and occurrence trajectories based on structured survey data were generally positively correlated, with significant positive correlations found for about 75% of investigated species. This is consistent with previous analyses (Webb *et al.* 2007). However, occurrence trends did show a saturation effect for the 29 most common species, which generally exhibit some degree of abundance fluctuations, but essentially no range changes. This was especially apparent when trends were converted to an index of relative change - a scaling that is routinely applied to abundance indices (e.g. Harris *et al.* 2017), in particular when these are used as the basis for multi-species indicators (Massimino *et al.* 2015; Strien *et al.* 2016).

Our study also shows significant agreement between BirdTrack reporting rate trends and BBS-derived trends for over 60% of investigated species. It further shows that, for common species, reporting rate trends appear to resemble abundance fluctuations more closely than occurrence fluctuations. The absence of a saturation effect in reporting rate changes (in contrast to that found in the comparison of occurrence and abundance trends) may indicate that detections - and thus reporting rates - by BirdTrack participants are considerably lower for than those by BBS

318 volunteers. This is not surprising given that the BirdTrack participant base likely reflects a
319 broader range of birding experience, and that most BirdTrack lists are of shorter duration than a
320 full BBS survey. It does however raise questions about the precise interpretation of indices that
321 are derived from species list reporting rates.

322 Several prior studies (Kamp *et al.* 2016; Walker & Taylor 2017; Horns *et al.* 2018) have made
323 the implicit assumption that reporting rate trends resemble occurrence trends, rather than
324 abundance trends, for which we here find no convincing support. In a way, the finding that
325 reporting rate trends correspond more closely to abundance trends may be a positive one, given
326 that within-site abundance provides a more meaningful criterion for conservation prioritisation
327 than site occupancy (Johnston *et al.* 2015). However, we still find a substantial amount of
328 residual scatter in the reporting rate-abundance trend relationship, which indicates that the
329 reporting rate trend models applied here may not provide abundance proxies of sufficient
330 reliability for conservation planning (Oppel *et al.* 2012).

331 Fogarty *et al.* (2018) raised several important issues about previous comparative analyses by
332 Horns *et al.* (2018) that used structured survey data from the North American Breeding Bird
333 Survey and opportunistically collected data from eBird (Sullivan *et al.* 2009). Our study
334 addressed these issues and found significant agreement between reporting rate and abundance
335 trends, in concordance with Horns *et al.* (2018). However, overall our results paint a less
336 optimistic picture of the applicability and robustness of simple statistical trend models for the
337 derivation of population trends from opportunistic complete lists. In particular, there is little
338 evidence from our results that simple models, that is, models accounting for list characteristics
339 only, but not preferential sampling, provide a silver bullet for rare and poorly monitored species.
340 Instead the best predictors for a high correlation between reporting rate trends and abundance
341 trends were species commonness and magnitude of the abundance trend - characteristics that
342 may be poorly known in the absence of robust auxiliary data.

343 The finding that widespreadness and commonness predict agreement among trends from the
344 different datasets may also reflect fundamental properties of both survey schemes. Randomized
345 designed surveys with rigorous recording protocols exist precisely to deliver abundance (or
346 occurrence) measures that are unbiased - in space, in time, in species coverage - but the limited
347 availability and/or cost of skilled observers and consequently limited spatial coverage mean this
348 unbiasedness comes at the expense of relatively lower precision when rare species are
349 considered. Opportunistic recording schemes on the other hand, may be created with primary
350 objectives other than unbiased population assessments, e.g. as part of public awareness and
351 education schemes or to aid personal record keeping for wildlife enthusiasts. Recording for
352 personal record keeping in particular often puts a premium on maximising species diversity, and
353 hence additional effort is expended by recorders to visit sites harbouring rare species (Booth *et*
354 *al.* 2011), whereas schemes with a broad outreach focus are likely to exhibit preferential
355 recording biases towards abundant and conspicuous species (Boakes *et al.* 2016). Widespread
356 and common species are well covered in the latter type of opportunistic recording, and at the
357 same time recording coverage for these species is likely to be less affected by the former type of
358 rarity- or diversity-driven site selection. Lower agreement among trend estimates from the
359 different data sources considered in this study may therefore be expected for locally constrained
360 and/or rare species by the same token.

361   Reporting rate trends also showed a strongly attenuated magnitude, but this relationship
362   exhibited wide scatter, highlighting potential difficulties in the interpretation of reporting rate-
363   based indices. Many current conservation assessments (Eaton *et al.* 2015; IUCN 2016) rely on
364   thresholds relating to relative abundance and/or range changes. The differences we found in the
365   magnitude of trends based on different model types are therefore concerning as they influence
366   the ranking of species in conservation prioritisation (see Fig. S2). Abundance (absolute or
367   relative) or occupancy measures also form the basis of multi-species indicators, which play an
368   important role in the policy processes surrounding conservation actions at national and supra-
369   national levels (Massimino *et al.* 2015; Burns *et al.* 2018; Mace *et al.* 2018). As there are non-
370   random patterns in the strength of agreement between the different indices (namely based on
371   species commonness and trajectory strength), our results suggest that aggregating indices based
372   on different trend currencies (i.e. abundance, occurrence, reporting rates), as is e.g. the case in
373   Strien *et al.* (2016), may further exacerbate known problems of multispecies indicators
374   (Buckland & Johnston 2017). Interestingly, while reporting rate trends were generally attenuated
375   compared to BBS trends, there were four notable outliers (Little Egret, Cetti's Warbler, Red
376   Kite, and Ring-necked Parakeet; Fig. 1a) which showed markedly larger reporting rate increases
377   than BBS trends. All four species are relatively recent (re-)colonizers of the study area and are
378   expanding in range and abundance (Balmer *et al.* 2013; Harris *et al.* 2017). This finding indicates
379   that even complete lists (as opposed to opportunistic presence-only records), may still be biased
380   towards novel observations.

381   Our results show that an opportunistic citizen science scheme with substantial participation and
382   geographical coverage can provide a means of tracking a proxy of species abundance, at least for
383   common or strongly trending species. However, it does not provide a silver bullet for avian
384   population trend estimation based on simple models. Ultimately, characterising this trade-off
385   between more and less structured schemes as a comparison - or even a dichotomy - in the first
386   place is an approach that can only go so far. Data quality issues are not restricted to opportunistic
387   citizen science data sets, e.g. observer effects are also known from structured surveys (Sauer,
388   Peterjohn & Link 1994; Jiguet 2009; Eglington *et al.* 2010; Farmer *et al.* 2014). Ignoring known
389   features (e.g. preferential sampling) of any dataset conflicts with developing best practice
390   recommendations for large scale citizen science datasets (Johnston *et al.* 2019); and rather than
391   focussing on the strengths or shortcomings of individual datasets, we should aim to combine as
392   much of the available data in joint models that explicitly take account of the observation process
393   for any included dataset, and that ideally have (relative) population abundance as the target of
394   inference. This can be challenging (Oppel *et al.* 2012), but such joint models are quickly
395   maturing and their implementations are becoming more accessible (Pagel *et al.* 2014; Fithian *et*
396   *al.* 2015; Miller *et al.* 2019; Isaac *et al.*). This provides opportunities to leverage the structure of
397   robust survey schemes with the expanded coverage of opportunistic schemes. This is especially
398   important when considering the vast majority of taxa. Birds are not only disproportionately well
399   covered by structured survey schemes (Proença *et al.* 2017) and other strands of biodiversity
400   research (Clark & May 2002), but also receive disproportionate attention from the wider public
401   in opportunistic citizen science schemes (Amano *et al.* 2016). In contrast, most non-avian groups
402   of organisms are poorly surveyed, and data integration approaches leveraging both the depth of
403   structured and the breadth of unstructured data may be the only way to gain insight into
404   population status and trends.

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588 Supplementary Materials for

Robustness of simple avian population trend models for semi-structured citizen science data is species-dependent

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616 **Table S1   GAM summary table**

617 **Summary table of the generalized additive model comparing correlation coefficients among the**
618 **three different trend model types.**

	Estimate	Std. Error	t-value	p-value
A. parametric coefficients	Estimate	Std. Error	t-value	p-value
(Intercept)	0.7532	0.1155	6.5194	< 0.0001
comparisonBBS_abund_BT	-0.2641	0.1333	-1.9816	0.0483
comparisonBBS_occ_BT	-0.2717	0.1334	-2.0365	0.0424
comparisonBBS_abund_BBS_occ:association_during_nestingmixed	0.1449	0.1845	0.7853	0.4328
comparisonBBS_abund_BT:association_during_nestingmixed	0.2869	0.1630	1.7595	0.0794
comparisonBBS_occ_BT:association_during_nestingmixed	0.3691	0.1662	2.2206	0.0270
comparisonBBS_abund_BBS_occ:association_during_nestingsolitary	0.1278	0.1223	1.0450	0.2967
comparisonBBS_abund_BT:association_during_nestingsolitary	0.2010	0.1104	1.8211	0.0694
comparisonBBS_occ_BT:association_during_nestingsolitary	0.2295	0.1114	2.0591	0.0402
comparisonBBS_abund_BBS_occ:association_during_nestingsemicolonial	0.1360	0.2040	0.6666	0.5055
comparisonBBS_abund_BT:association_during_nestingsemicolonial	0.1311	0.1819	0.7209	0.4714
comparisonBBS_occ_BT:association_during_nestingsemicolonial	0.1525	0.1863	0.8186	0.4136
B. smooth terms	edf	Ref.df	F-value	p-value
s(log10chg20062016M):comparisonBBS_abund_BBS_occ	5.7603	6.8856	10.7406	< 0.0001
s(log10chg20062016M):comparisonBBS_abund_BT	6.8127	7.8704	15.6729	< 0.0001
s(log10chg20062016M):comparisonBBS_occ_BT	6.2824	7.3875	14.4649	< 0.0001
s(log10nsqus12):comparisonBBS_abund_BBS_occ	2.8831	3.5502	12.2792	< 0.0001
s(log10nsqus12):comparisonBBS_abund_BT	1.7518	2.1580	59.4252	< 0.0001
s(log10nsqus12):comparisonBBS_occ_BT	2.1563	2.6614	30.6174	< 0.0001
s(log10(weight_u_mean)):comparisonBBS_abund_BBS_occ	1.5135	1.8644	5.1597	0.0168
s(log10(weight_u_mean)):comparisonBBS_abund_BT	1.0012	1.0023	7.1184	0.0080
s(log10(weight_u_mean)):comparisonBBS_occ_BT	1.0000	1.0001	3.7334	0.0541
s(family)	29.5084	43.0000	2.8254	< 0.0001

619

620 ## Table S2   Included species and their long term trends
621 **Long term trends for the species included in the analysis. Trends significantly different from 0 at**
622 **p<0.05 are presented in bold print.**

Common name	BBS sites[a]	BBS abundance trend (%)	BBS occurrence trend (%)	reporting rate trend (%)
Barn Owl	74	15.11	25.49	**43.09**
Black Grouse	22	**270.33**	**591.91**	83.8
Blackbird	3244	**3.08**	0	2.28
Blackcap	2303	**57.39**	**0.1**	**167.88**
Blue Tit	3034	**-22**	0	**-40.19**
Bullfinch	832	**20.73**	**24.12**	**33.61**
Buzzard	1632	**30.19**	**11.72**	**148.21**
Canada Goose	692	-4.9	16.52	**20.25**
Carrion Crow	3139	3.31	0	**11.62**
Cetti's Warbler	49	**313.24**	**457.99**	**1265.98**
Chaffinch	3259	**-29.13**	**0**	**-53.01**
Chiffchaff	2243	**91.14**	**0.07**	**326.5**
Coal Tit	1127	**-13.66**	1.51	**15.55**
Collared Dove	1724	**-22.46**	**-0.26**	**-46.47**
Common Sandpiper	84	-10.91	95.46	**13.61**
Common Tern	86	**151.57**	5.28	**-25.91**
Coot	347	**-23.97**	**-22.15**	**-44.58**
Cormorant	331	9.19	-1.39	**11.73**
Corn Bunting	152	-18.85	-28.37	**-53.94**
Crossbill (Common)	77	-22.95	20.74	1.46
Cuckoo	683	**-24.07**	**-47.13**	**-42.09**
Curlew	610	**-14.46**	**-32.02**	**-43.48**
Dipper	80	**-36.6**	-53.35	-4.54
Dunlin	30	19.18	-62.66	**-35.04**
Dunnock	2730	-0.17	0	2.89
Egyptian Goose	42	**186.47**	**184.73**	**287.53**
Eider	15	23.88	142.85	**-29.03**
Feral Pigeon	839	**-35.68**	**-29.03**	**126.04**
Gadwall	61	**252.17**	**156.78**	**83.66**
Garden Warbler	526	-9.86	**-23.92**	-2.69
Goldcrest	1071	-8.6	4.16	**51.82**
Golden Plover	77	10.32	-25.01	-19.67
Goldfinch	2423	**73.8**	**0.12**	**183.5**
Goosander	53	59.28	106.24	**35.99**
Goshawk	14	34.04	57.47	15.53
Grasshopper Warbler	108	16	16.16	11.67
Great Crested Grebe	88	40.28	-23.47	**-17.48**
Great Spotted Woodpecker	1591	7.11	**3.71**	-3.99
Great Tit	2932	**-15.53**	0	**-28.63**
Green Woodpecker	1080	**-14.53**	**-8.31**	**-41.67**
Greenfinch	2126	**-73.07**	**-1.34**	**-83.49**

Greenshank	14	8.32	-22.11	3.93
Grey Heron	811	**-32.12**	**-46.39**	**-19.99**
Grey Partridge	226	**-36.96**	**-46.58**	**-72.66**
Grey Wagtail	275	**-29.82**	**-42.66**	-3.96
Greylag Goose	385	29.3	**189.39**	**138.57**
Hen Harrier	18	65.32	175.5	-19.09
Hobby	57	9.43	8.35	-9.74
Hooded Crow	159	22.11	-0.29	4.95
House Martin	1130	**-30.56**	**-16.92**	**-45.96**
House Sparrow	2044	-1.17	0	**-15.77**
Jackdaw	2395	**20.39**	**0.01**	84.95
Jay	1061	-0.62	**15.75**	-2.08
Kestrel	795	**-25.87**	**-38.18**	**-40.15**
Kingfisher	67	-9.81	-9.33	2.63
Lapwing	788	**-32.42**	**-59.86**	**-56.71**
Lesser Spotted Woodpecker	20	**-69.83**	**-89.69**	**-69.27**
Lesser Whitethroat	359	**37.67**	**50.51**	**60.07**
Linnet	1443	-2.2	**-5.13**	-2.66
Little Egret	88	**81.62**	**154.9**	**716.72**
Little Grebe	89	-3.61	11.59	**-12.14**
Little Owl	92	**-47.16**	**-59.98**	**-56.29**
Little Ringed Plover	13	61.04	183.34	**-38.5**
Long-tailed Tit	1341	**24.63**	**22.18**	**7.59**
Magpie	2460	**-4.72**	0	-1.9
Mallard	1728	-5.41	**-1.51**	**-16.61**
Mandarin Duck	52	**209.23**	**564.71**	**370.92**
Marsh Harrier	40	20.19	51.14	**154.81**
Marsh Tit	165	**-50.67**	**-64.03**	**-52.4**
Meadow Pipit	1005	0.94	**-1.01**	**-52.16**
Merlin	25	-33.24	-36.3	**-53.09**
Mistle Thrush	1343	**-28.17**	**-22.02**	**-41.07**
Moorhen	772	**-24.3**	**-24.84**	**-36.79**
Mute Swan	334	12.41	-4.27	**-20.17**
Nightingale	37	**-54.13**	**-61.14**	**-45.49**
Nuthatch	752	**16.33**	**20.64**	**61.11**
Oystercatcher	463	-11.94	-4.46	**18.63**
Peregrine	69	**-41.4**	**-53.15**	**40.76**
Pheasant	2478	5.82	0	**-19.85**
Pied Flycatcher	39	-0.7	-18.43	-12.03
Pied Wagtail	1587	1.56	-2.38	**-67.27**
Pochard	22	46.3	-34.75	-12.61
Quail	10	**-89.63**	**-87.49**	**-71.74**
Raven	481	-14.56	**70.03**	**163.08**
Red-breasted Merganser	14	122.29	-7.86	**-50.22**
Red-legged Partridge	728	-9.1	-6.19	**-29.6**
Red-throated Diver	11	-39.74	21.52	17.12

Red Grouse	192	**84.9**	0.8	38.29
Red Kite	279	**386.49**	**286.36**	**1909.57**
Redpoll (Lesser)	224	25.02	**68.33**	**103.84**
Redshank	101	-27.16	6.88	**-61.69**
Redstart	235	**23.76**	**114.65**	13.95
Redwing	14	-78.15	-75.62	-17.71
Reed Bunting	685	**16.25**	7.57	-0.84
Reed Warbler	174	2.55	19.98	**165.1**
Ring-necked Parakeet	135	**195.72**	**5.2**	**1621.27**
Ring Ouzel	44	33.78	184.56	**80.22**
Ringed Plover	31	108.8	37.6	**-58.25**
Robin	3127	**13.31**	**0**	15.94
Rock Pipit	22	**-52.57**	-74.61	27.65
Rook	1663	**-22.01**	-0.3	**-35.58**
Sand Martin	176	51.54	54.93	**41.52**
Sandwich Tern	14	**-83.36**	**-93.47**	33.57
Sedge Warbler	361	-12.3	-0.88	**12.42**
Shag	16	-44.98	**-82.58**	5.59
Shelduck	180	**-30.52**	-36.46	-7.85
Short-eared Owl	23	25	-1.79	**-36.11**
Shoveler	20	47.52	-30.41	**-13.89**
Siskin	287	**57.35**	**263.97**	**296.95**
Skylark	2160	**-15**	**0**	**-45.86**
Snipe	214	2.93	29.37	**-22.27**
Song Thrush	2674	**12.25**	**0.01**	**11.07**
Sparrowhawk	413	**-32.16**	**-41.01**	**-32.81**
Spotted Flycatcher	183	**-32.42**	**-63.59**	**-30.14**
Starling	2023	**-35.31**	**-0.13**	**-48.54**
Stock Dove	1075	**30.46**	**25.39**	**58.23**
Stonechat	217	**-25**	-20.02	5.92
Swallow	2600	**-23.36**	0	**-8.12**
Swift	1180	**-47.19**	**-44.96**	**-55.08**
Tawny Owl	109	-27.86	-15.39	17.47
Teal	42	63.83	-31.22	6.72
Tree Pipit	173	**27.78**	38.76	**-29.48**
Tree Sparrow	252	**74.91**	**141.73**	0.12
Treecreeper	465	0.31	21.29	-7
Tufted Duck	198	**40.68**	23.13	**-24.78**
Turtle Dove	76	**-83.49**	**-96.19**	**-81.24**
Twite	19	**-52.48**	-76.9	**-56.85**
Wheatear	459	**-19.45**	-22.57	**-24.63**
Whimbrel	33	**177**	9.62	6.04
Whinchat	81	**-31.35**	-26.97	**-26.22**
Whitethroat	1820	**13.3**	0.14	**21.69**
Wigeon	15	97.33	189.88	**-38.72**
Willow Tit	39	**-52.76**	**-68.48**	**-55.47**

Willow Warbler	1632	**15.54**	0.17	**-34.7**
Wood Warbler	53	**-44.3**	**-72.93**	**-35.91**
Woodcock	15	-56.72	**-74.62**	-11.06
Woodlark	22	-32.04	**-62.85**	**-33.35**
Woodpigeon	3276	2.64	**0**	**28.76**
Wren	3222	**14.14**	**0**	**30.69**
Yellow Wagtail	175	-3.71	27.47	**75.52**
Yellowhammer	1407	**-13.42**	**-0.37**	**-61.38**

623

624 **Figure S1 - Abundance-occurrence correlations**
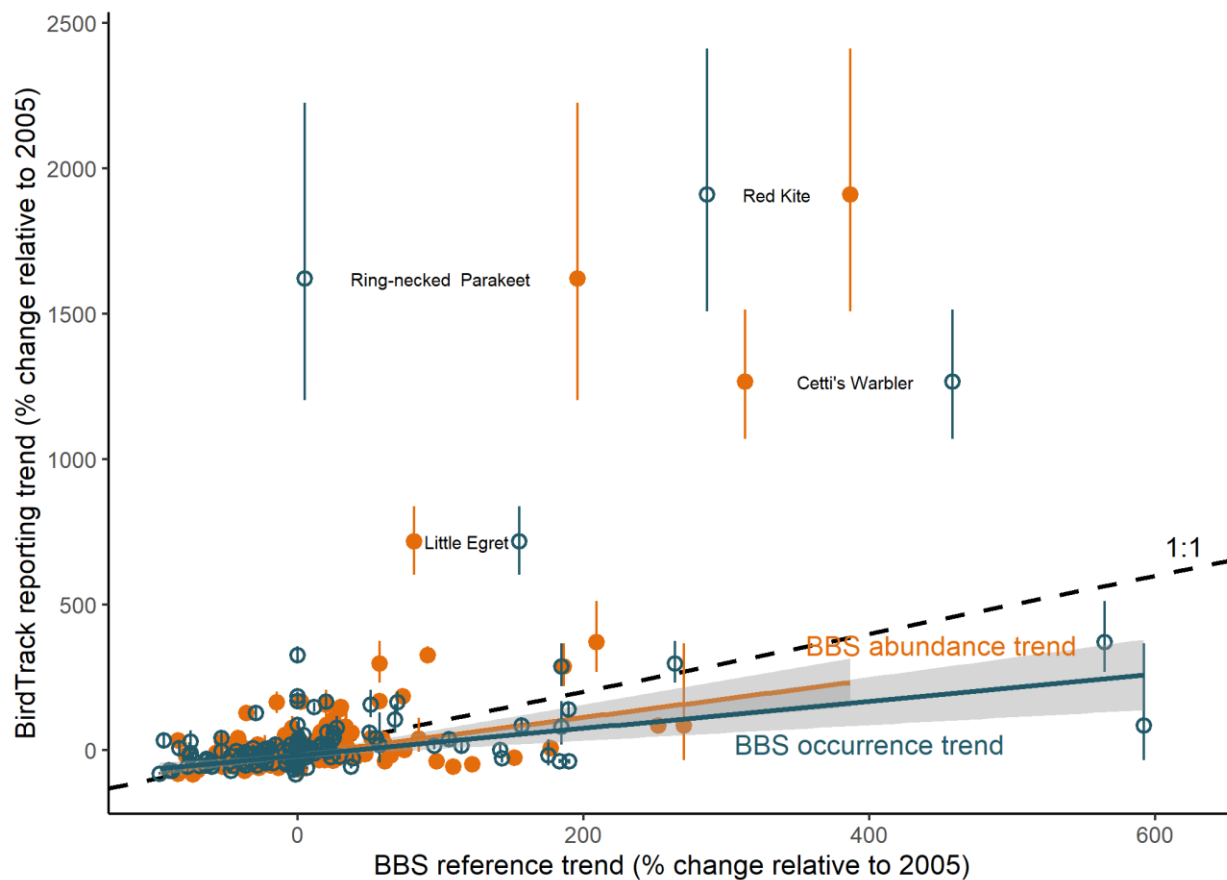
625

626 **Figure S1:** Long-term (12year) reporting rate trends from BirdTrack lists were generally attenuated compared to
627 abundance (solid orange symbols and line) and occurrence (green open symbols and line) trends from BBS data.
628 Notable outliers are annotated, dashed line represents the 1:1 line. Error bars and shading represent 95%
629 confindence intervals.

630

631 **Figure S2 - Rank correlations of trend ordered species**
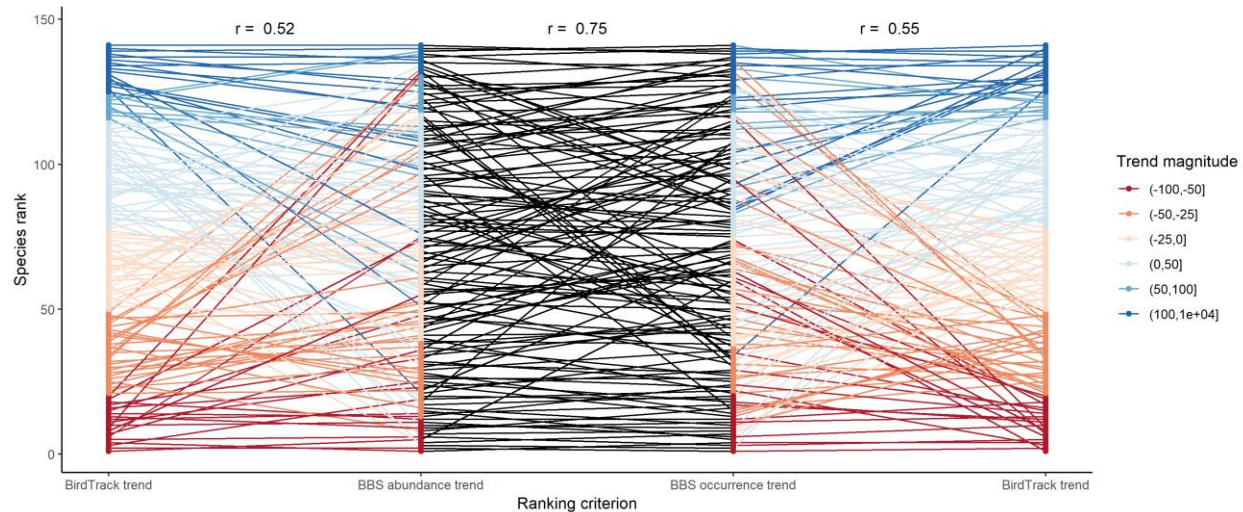
632

633 **Figure S2:** Species ranked by index trend strength from the strongest decline to the strongest increase based on each
634 of the three trend models. Lines connect species between models. Spearman rank correlations of the species ordering
635 among the three models are given at the top of the plot.

636

637 ## Figure S3 - Spatial distribution of records

638
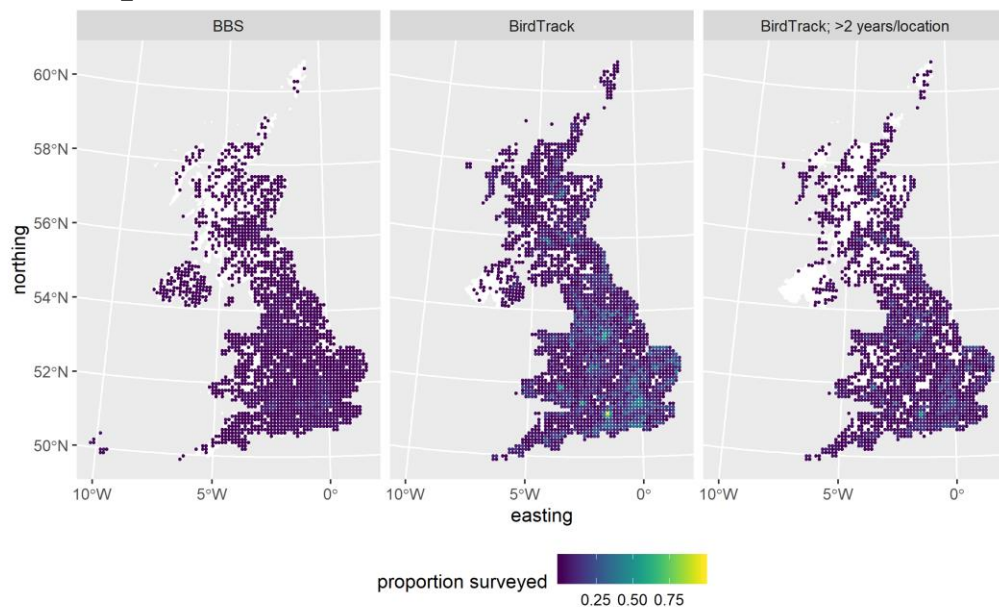
Figure S3: Spatial distributions of bird records used in this study. Maps show 10km x 10km cells of the British National Grid with at least one record. The colour scale represents the proportion of 1km x 1km cells with records within each of the 10km x 10km cells. Left: BBS survey locations are randomized in space following a stratified design that takes regional volunteer availability into account. As a result there is a relatively even density of records across the UK. Centre: BirdTrack has a much higher overall density of records across the UK, with the exception of Northern Ireland. Notable "hotspots" with near complete spatial coverage exist in urban centres. Right: When including only sites with more than two years of data the overall distribution of BirdTrack locations follows a similar pattern as the BBS with lower record densities in the Scottish Highlands and other upland areas.

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