

# 1 **Integrating structured and unstructured citizen science data** 2 **to improve wildlife population monitoring**

3 Philipp H. Boersch-Supan<sup>1,2\*</sup> & Robert A. Robinson<sup>1</sup>

4 <sup>1</sup> British Trust for Ornithology, Thetford, United Kingdom

5 <sup>2</sup> Department of Geography and Emerging Pathogens Institute, University of Florida, Gainesville, FL, United States

6 \* Corresponding author: [pboesu@gmail.com](mailto:pboesu@gmail.com)

## 7 **Abstract**

8 Accurate and robust population trend assessments are key to successful biodiversity  
9 conservation. Citizen science surveys have provided good evidence of biodiversity declines  
10 whilst engaging people with them. Citizen scientists are also collecting opportunistic biodiversity  
11 records at unprecedented scales, vastly outnumbering records gathered through structured  
12 surveys. Opportunistic records exhibit spatio-temporal biases and heterogeneity in observer  
13 effort and skill, but their quantity offers a rich source of information. Data integration, the  
14 combination of multiple information sources in a common analytical framework, can potentially  
15 improve inferences about populations compared to analysing either in isolation. We combine  
16 count data from a structured citizen science survey and detection-nondetection data from an  
17 opportunistic citizen science programme. Population trends were modelled using dynamic N-  
18 mixture models to integrate both data sources. We applied this approach to two different  
19 inferential challenges arising from sparse data: (i) the estimation of population trends for an area  
20 smaller than a structured survey stratum, and (ii) the estimation of national population trends for  
21 a rare but widespread species. In both cases, data integration yielded population trajectories  
22 similar to those estimated from structured survey data alone but had higher precision when the  
23 density of opportunistic records was high. In some cases this allowed inferences about  
24 population trends where indices derived from single data sources were too uncertain to assess  
25 change. However, there were differences in the trend magnitude between the integrated and the  
26 standard survey model.

27 We show that data integration of large-scale structured and unstructured data is feasible and  
28 offers potential to improve national and regional wildlife trend estimates, although a need to  
29 independently validate trends remains. Smaller gains are achieved in areas where uptake of  
30 opportunistic recording is low. The integration of opportunistic records from volunteer-selected  
31 locations alone may therefore not adequately address monitoring gaps for management and  
32 policy applications. To achieve the latter, scheme organisers should consider providing  
33 incentives for achieving representative coverage of target areas in both structured and  
34 unstructured recording schemes.

35 **Keywords:** biodiversity monitoring; breeding bird survey; Citizen science; population trend;  
36 data integration;

## 37 **1 Introduction**

38 The ability to accurately and robustly quantify species' population trajectories is key to  
39 successful biodiversity conservation. Monitoring of changes in a species' population size or  
40 range is essential to assess threat status; to act as an early-warning signal of population declines;  
41 for conservation resource prioritization; and to assess the efficacy of environmental policies  
42 (Lawton 1993; Johnston *et al.* 2015). Yet, most wildlife populations cannot be completely  
43 enumerated, or even robustly surveyed, because resources for monitoring are finite. Large  
44 geographic biases exist in monitoring effort even for well sampled taxa like birds (Meyer *et al.*  
45 2015, 2016; Amano, Lamming & Sutherland 2016). This affects our knowledge of species  
46 distributions, as well as our understanding of the processes underlying population dynamics  
47 because potential drivers, such as climate or land-use change, can differ between surveyed and  
48 unsurveyed regions (Pearce-Higgins *et al.* 2015).

49 National scale biodiversity monitoring schemes such as those that make up the Pan-European  
50 Common Bird Monitoring Scheme (van Strien, Pannekoek & Gibbons 2001; Birdlife  
51 International 2004) or the European Butterfly Monitoring Scheme (van Swaay *et al.* 2008, 2019)  
52 are designed to provide coverage of a broad range of common species, allowing the derivation of  
53 indicators of the state of nature while making the most of finite resources (Burns *et al.* 2018;  
54 Hayhow *et al.* 2019). Such high-level efforts have become closely intertwined with high-level  
55 (i.e. national and supra-national) conservation legislation and policy. However, the  
56 implementation of conservation policy on a legislative and executive level is increasingly  
57 devolved within nations. For example, in the UK conservation is now devolved to sub-national  
58 governments (NUTS 1 level) and their executive agencies, resulting in legislation and  
59 implementation approaches, including e.g. red list assessments, that are specific to England,

60 Scotland, Wales, and Northern Ireland (Bainbridge 2014; Kirsop-Taylor 2019); similarly, in  
61 Germany federal conservation legislation provides an overarching legal framework but delegates  
62 implementation to the states, and the executive agencies implementing state laws may be  
63 devolved further to government regions (NUTS 2 level) or districts (NUTS 3 level) (Rose-  
64 Ackerman 1994). There is also a shift from treating conservation and management as  
65 jurisdictional issues towards more holistic approaches focussed on the maintenance of healthy  
66 ecosystems and ecosystem services at the appropriate spatial scales (Kirsop-Taylor 2019). Apart  
67 from individually designated large protected areas (e.g. national parks, protected landscapes),  
68 such approaches are promoted e.g. through the European Landscape Convention and within  
69 programmes of the EU common agricultural policy (Lomba *et al.* 2014). Again, the  
70 implementation varies among signatory states. Within the UK such natural subdivisions are  
71 reflected, for example, in the National Character Areas in England (Natural England 2014) or the  
72 Area Statements in Wales (Welsh Government 2017), both of which are based on a combination  
73 of landscape features, bio- and geodiversity, and socio-economic activity. The plethora of spatial  
74 units that arise from jurisdictional devolution and landscape-centric approaches, creates an  
75 increasing desire to repurpose data from national biodiversity monitoring schemes to provide  
76 information at smaller spatial scales, not addressed by national trends and indicators.

77 Many national biodiversity monitoring schemes are based on long-term structured surveys,  
78 which use predetermined monitoring sites and standardized survey methods. Structured surveys  
79 provide robust estimates of population trends but require large and long-term commitments by  
80 institutions – and where conducted as citizen science schemes, volunteers – and can be  
81 challenging to organize and coordinate (Schmeller *et al.* 2009). Instead, projects which rely on  
82 opportunistic records by interested members of the public may be a more effective means to

83 increase the spatio-temporal coverage of distribution and abundance data (Dickinson,  
84 Zuckerberg & Bonter 2010; Isaac & Pocock 2015). Although such projects may have primary  
85 goals other than monitoring, e.g. raising awareness about focal taxa or facilitating personal  
86 record keeping for naturalists, there is increasing interest in using such schemes to fill knowledge  
87 gaps in regions that are poorly or not at all covered by structured surveys, and as a basis to obtain  
88 indices of population trajectories that meaningfully capture true wildlife population trends (Kéry  
89 *et al.* 2010; Isaac *et al.* 2014; Horns, Adler & Şekercioğlu 2018). Trend modelling based on such  
90 data is challenging because of known biases in site selection, visit timing, survey effort, and/or  
91 surveyor skill (Isaac & Pocock 2015; Johnston *et al.* 2018, 2020). Thus, there is usually a trade-  
92 off between collecting a small amount of higher ‘quality’ data conforming to a defined common  
93 structure or a larger amount of relatively heterogeneous (i.e. lower ‘quality’) data (Gardiner *et al.*  
94 2012; Bayraktarov *et al.* 2018).

95 The consequences of this trade-off are a topic of active research (Aceves-Bueno *et al.* 2017;  
96 Bayraktarov *et al.* 2018; Kelling *et al.* 2018; Specht & Lewandowski 2018; Boersch-Supan,  
97 Trask & Baillie 2019; Johnston *et al.* 2020; Robinson *et al.* 2020), and there is a growing set of  
98 modelling approaches to address the challenges of unstructured datasets using auxiliary  
99 structured biodiversity data and/or observation models that account for preferential sampling,  
100 usually at the cost of increased model complexity and computational demands (van Strien, van  
101 Swaay & Termaat 2013; Fithian *et al.* 2015; Robinson, Ruiz-Gutierrez & Fink 2018; Isaac *et al.*  
102 2019; Johnston *et al.* 2019, 2020).

103 Other recent work has investigated whether relatively simple models are sufficient to extract  
104 population trend information from less structured data (Roberts, Donald & Green 2007; Roy *et*  
105 *al.* 2012; Walker & Taylor 2017; Boersch-Supan *et al.* 2019). These simpler approaches

106 generally rely on the assumption that the information gain from a larger quantity of records  
107 outpaces potential biases from opportunistic sampling.

108 However, integrating these two data sources may help overcome some of these issues, by  
109 combining the structure of survey data with the improved coverage of less structured schemes.  
110 This has the potential to improve the precision of model parameters and the resulting inferences  
111 (Fithian *et al.* 2015; Isaac *et al.* 2019), perhaps especially for species that are poorly covered by  
112 structured monitoring programmes, as well as offering a route to gain a more mechanistic  
113 understanding of the drivers of those population dynamics.

114 In the UK, biological recording by volunteers provides information on the occurrence or  
115 abundance of over 10000 taxa, although records are sparse for the vast majority of taxa (Roy *et*  
116 *al.* 2014; Hayhow *et al.* 2019; Outhwaite *et al.* 2020). As part of these efforts, comprehensive  
117 structured bird monitoring is undertaken through the Breeding Bird Survey (BBS; Figure 1)  
118 which provides population trends for about 120 common and widespread bird species  
119 (Greenwood *et al.* 1995; Freeman *et al.* 2007; Harris *et al.* 2018), but knowledge gaps remain for  
120 rare and cryptic species (approximately 220 species are regular breeders (Robinson 2010)).

121 Opportunistic citizen science recording schemes such as BirdTrack (Figure 1;  
122 [www.birdtrack.net](http://www.birdtrack.net); Baillie *et al.* (2006); Newson *et al.* (2016)) provide greater coverage in space  
123 and time, but lack the structured protocols and formal sampling design. A recent comparison of  
124 these two datasets showed that national-scale annual reporting rate trends in BirdTrack were  
125 broadly consistent with BBS abundance trends for common species, and those exhibiting marked  
126 population changes (Boersch-Supan *et al.* 2019). However, the magnitude of reporting rate–  
127 abundance relationships were inconsistent across species, and agreement in trends for rarer

128 species could not be ascertained, in part because of high uncertainty about population change in  
129 trends from either dataset.

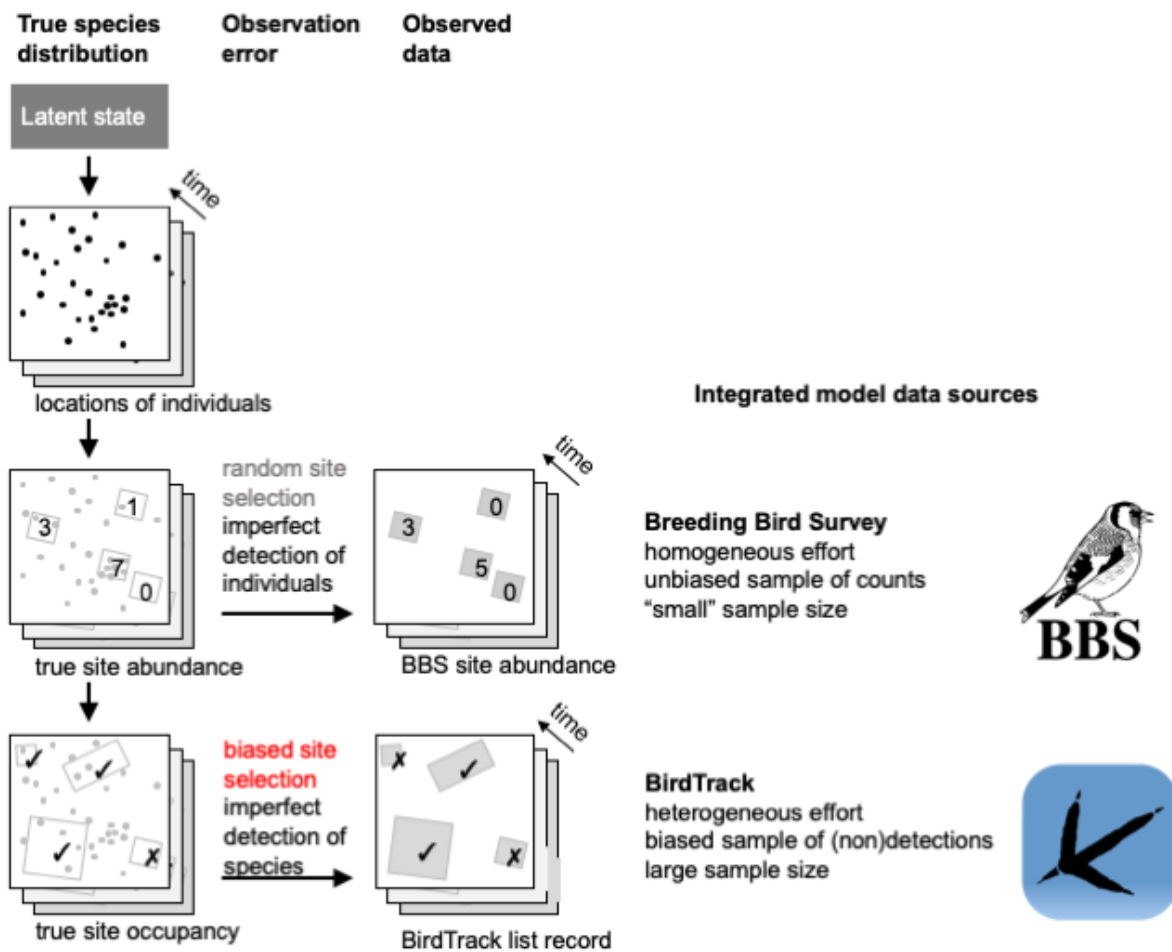
130 In this study, we leverage the spatio-temporal overlap of two citizen science schemes to  
131 investigate the utility of joint analyses of structured and opportunistic datasets to derive  
132 population trends for uncommon breeding birds at regional and local scales. This has the  
133 potential to address a gap in currently available monitoring products with high relevance for  
134 landscape management. In particular we evaluate integrated trend models for two different  
135 inferential challenges: (i) the estimation of population trends for areas smaller than a BBS  
136 stratum to improve small-area inferences about population trends for local managers and  
137 decision makers, and (ii) the estimation of national population trends for a rare but widespread  
138 species to assess the utility of data integration when a species is not widespread enough to fulfil  
139 minimum sample size criteria for the structured survey model.

## 140 **2 Materials and Methods**

### 141 **2.1 Data sources**

142 We employed structured survey data from the Breeding Bird Survey (BBS) (Gregory, Baillie &  
143 Bashford 2000; Harris *et al.* 2018), which follows a rigorous protocol in which skilled volunteers  
144 count all birds heard or seen in three distance bands along two 1km transects within a 1km<sup>2</sup> site  
145 on two annual morning visits during the breeding season. The two visits are not designed a priori  
146 as replicates, but rather ensure coverage of both early breeding residents and later breeding  
147 migrants. The early visit takes place April to mid May, and is followed by a late visit in mid May  
148 to June. BBS provides a spatial coverage which is extremely high for a national monitoring  
149 scheme (1.10-1.65% of the UK territory for the study period (Harris *et al.* 2018)), and sampling

150 is largely unbiased with respect to habitat types (with the exception of mountainous areas)  
 151 (Martay *et al.* 2018). The survey follows a stratified random design which aligns coverage with  
 152 variable volunteer availability. Coverage within strata ranges from 0.1% to 9%. This allows an  
 153 unbiased assessment of UK-wide and national trends for many common species, but the survey  
 154 was not designed to allow for inferences at sub-stratum level, or to provide reliable coverage of  
 155 rare species.



156  
 157 Figure 1: BBS surveys and BirdTrack lists are both observations of the true spatio-temporal distribution of birds.  
 158 Observations from each scheme differ in their information quality and quantity. BBS counts are collected with  
 159 known effort and spatially unbiased, but comparably sparse. BirdTrack lists are more numerous, but come from non-  
 160 random locations and effort is heterogeneous. Figure adapted from Isaac *et al.* (2019).



161 Structured data were supplemented with records from BirdTrack (Newson *et al.* 2016), which is  
162 also a citizen science dataset, but with less stringent observation requirements and a wider range  
163 of participants than the BBS: last year 2766 volunteers contributed to BBS whereas 6869  
164 individuals submitted at least one BirdTrack list. BirdTrack participants contribute lists of  
165 species they have detected during a self-selected time interval spent at a self-selected location.  
166 Compared to the BBS there are about three times as many locations (i.e. 1km British National  
167 Grid squares) in the UK that have at least one BirdTrack record during the breeding season in  
168 recent years (Figure S1). However, the relative density of records for both schemes follows a  
169 similar large-scale pattern: Coverage is higher near urban centres and lower in less populated and  
170 more mountainous areas (Boersch-Supan *et al.* 2019; Darvill *et al.* 2020). On smaller spatial  
171 scales the site-selection biases in BirdTrack are complex. Broadly speaking, sites fall into two  
172 clusters: sites that are convenient to access, e.g. in the vicinity of participants' homes, and more  
173 distant sites that offer more diverse bird assemblages (Johnston *et al.* 2020).

174 We only considered timed complete BirdTrack lists, i.e. lists for which birdwatchers recorded a  
175 start and end time and reported that they had listed all detected species. To match the spatial  
176 grain and temporal extent of the BBS data we only used lists with a location precision of 1km  
177 collected from 01 April to 30 June of each year. The resulting dataset constitutes detection/non-  
178 detection data with biases associated with self-selection of sites and visit timings. Finally, we  
179 filtered available data to retain only locations which had lists in three or more years, and within a  
180 year we randomly sub-sampled lists from locations that had more than 25 visits.

## 181 **2.2 Modelling approach**

182 We used a state-space modelling approach to integrate data from BBS surveys and BirdTrack  
183 lists [Isaac *et al.* (2019); Supplementary Materials]. The model assumes an underlying biological



184 process describing species-specific abundances  $N_{j,t}$  at a site  $j$  in every year  $t$ , and their changes  
185 from year to year as a result of individuals that survive and remain at each site, and those that are  
186 gained to a site by recruitment or immigration. Following Zipkin *et al.* (2017) we link this  
187 process model to the count and detection-nondetection data with a separate observation model  
188 for each data source: a dynamic N-mixture model for the count data and a dynamic occupancy  
189 model for the detection-nondetection data (Figure S2).

190 Model parameters were estimated in a Bayesian framework using JAGS via the jagsUI package  
191 in R (Plummer 2003; Kellner 2018; R Core Team 2018). Markov-chain Monte Carlo (MCMC)  
192 estimation was run on four parallel chains until the Gelman-Rubin convergence diagnostic  $\hat{R}$   
193 indicated convergence, usually after 10,000-50,000 iterations.

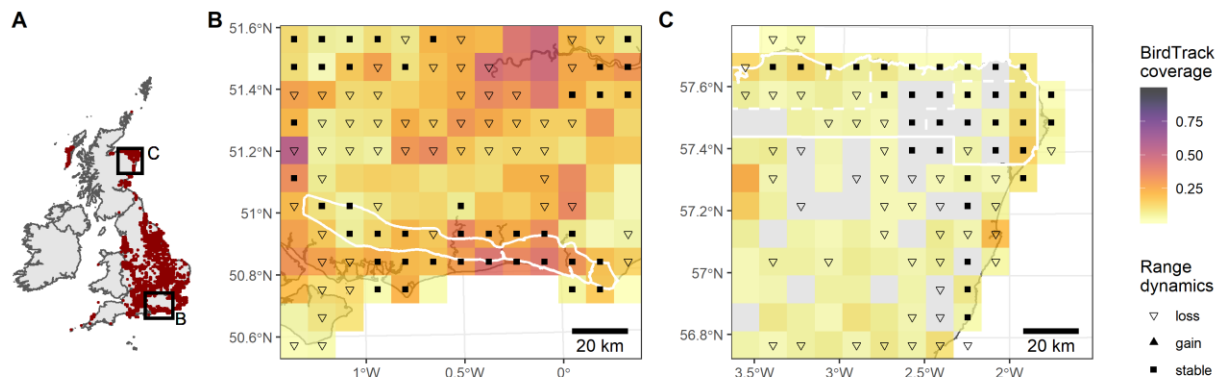
194 We stratified the modelled sites based on prior information on site occupancy pre-dating the BBS  
195 and BirdTrack data from the 1988-1991 Bird Atlas (Gibbons, Reid & Chapman 1993). Sites that  
196 fell into occupied tetrads (2km x 2km squares) in the Atlas were assigned a positively-biased  
197 normal prior truncated at zero for the initial abundance  $N_+(5,10)$ , and sites that fell into  
198 unoccupied or unsurveyed tetrads were assigned a zero-biased normal prior, truncated at zero,  
199 i.e. a half-normal prior  $N_+(0,10)$ .

200 Population trajectories from integrated models were compared to relative abundance indices  
201 derived from BBS data alone using the standard BBS trend model, a survey weighted count  
202 model with fixed additive site and year effects (Freeman *et al.* 2007) (Supplementary Methods)  
203 and occupancy indices derived from dynamic occupancy models using BirdTrack data alone  
204 which closely mirrored the structure of the integrated model (Kéry *et al.* 2010).

## 205 3 Case studies

### 206 3.1 Improving small-area trends

207 The motivation for this case study was to assess the utility of data integration to draw inferences  
208 about population trends areas smaller than a BBS stratum. We chose the Corn Bunting *Miliaria*  
209 *calandra* as the focal species (Figure 2), a lowland farmland bird whose dramatic decline in  
210 range and abundance in the UK has made it a red listed species of conservation concern (Eaton *et*  
211 *al.* 2015) and the target of management interventions (Perkins *et al.* 2011). We fitted integrated  
212 models for two areas to contrast different levels of recording coverage: the South Downs  
213 National Character Area of southern England which has an expanse of c. 1,000km<sup>2</sup> (Figure  
214 S3), and a similar sized area largely dominated by arable farmland in North East Scotland  
215 (Figure S4). The South Downs are close to major conurbations and are well covered by  
216 BirdTrack records from recreational birdwatchers; recording in North East Scotland occurs at  
217 much lower rates (Figure 2).



218

219 Figure 2: A: The range of Corn Bunting in Great Britain and Ireland 2007-2011. B: The South Downs NCA (white  
220 outline) is well covered by BirdTrack observations. C: Farmland in the NE of Scotland is poorly covered by  
221 BirdTrack observations. Coloured squares indicate BirdTrack list density. Grey squares lack BirdTrack lists.  
222 Symbols indicate Corn Bunting status based on the 2007-2011 Bird Atlas. White outlines show the spatial domain of  
223 the integrated models.

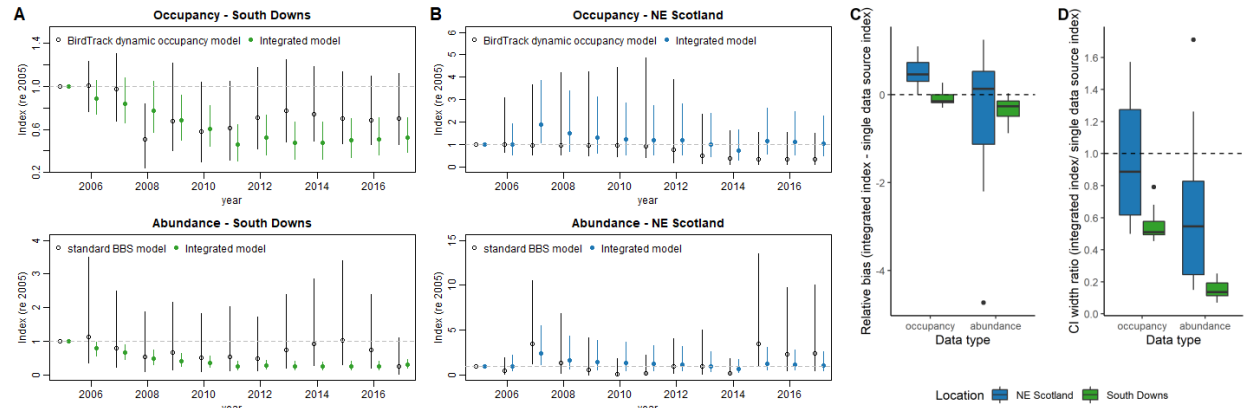
### 224 **3.1.1 Species-specific model details**

225 Survival and colonisation rates were separately estimated within each stratum (occupied,  
226 unoccupied, unsurveyed) as a yearly random effect, using an informative Beta prior (mean 0.58,  
227 variance 0.24) based on a mark-recapture estimate of survival probability (Luebcke 1977).

### 228 **3.1.2 Results**

229 Single data source trend models and the integrated trend could be derived for the South Downs  
230 NCA. Because of the lower density of records in both schemes in north east Scotland, some or  
231 all trend models failed to fit for the two areas with the highest density of BirdTrack lists that  
232 were of equal size to the South Downs NCA. Model fitting was successful when using records  
233 from an area spanning Elgin to Peterhead, approximately three times the size of the South Downs  
234 NCA (Figure 2, Figure S4).

235 For both areas the trend estimates from the joint model did not differ substantially from  
236 occupancy changes derived from BirdTrack or abundance changes derived from BBS alone,  
237 respectively. All models for the South Downs NCA showed a range and abundance decline  
238 between 2005 and 2011 followed by a period of relative stability (Figure 3A), and the models for  
239 North East Scotland yielded highly uncertain abundance and occupancy trends, neither of which  
240 provided statistically significant evidence of change since 2005 (Figure 3B).



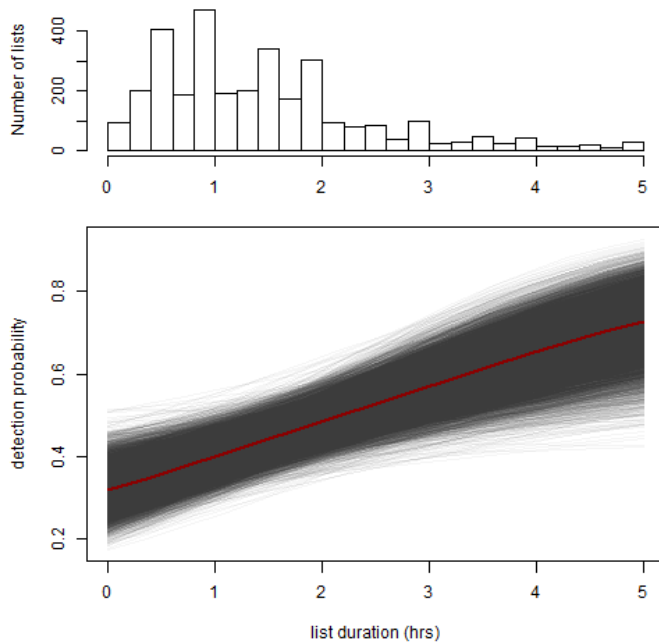
241

242 Figure 3: Occupancy and abundance trend estimates for Corn Bunting in the South Downs (A, green) and  
243 NE Scotland (B, blue) based on single data sources (BBS *or* BirdTrack; open symbols) and the integrated model (BBS  
244 *and* BirdTrack; solid symbols). Error bars show posterior 95% credible intervals. Boxplots aggregate relative bias  
245 (C) and precision (D) of annual index values comparing the integrated and single data source models.

246 The integrated trend was negatively biased compared to both reference trends at both locations,  
247 although point estimates for yearly index values from the integrated model were within the  
248 credible intervals of each reference trend. In the South Downs credible intervals for the  
249 integrated occupancy trend were about 50% as wide as those of the BirdTrack occupancy trend  
250 model, and integrated abundance trend credible intervals were even narrower at about 20% of  
251 those of the BBS trend (Figure 3C,D). The integrated model predicts a significant decline of  
252 Corn Bunting range and abundance in the study area between 2005 and 2011. In contrast, models  
253 based on either dataset alone do not allow inferences about population change given the large  
254 uncertainty about annual index values. In Scotland inferential gains from data integration were  
255 much more modest. The nominal precision of the integrated model results was on par with the  
256 BirdTrack occupancy trend, and the credible intervals of the integrated abundance trend were  
257 about half as wide as those for the BBS standard model (Figure 3C,D).

258 Aside from the inferences about range and abundance changes the integrated model also  
259 provides estimates of detection parameters such as the influence of time spent recording on the  
260 probability of detecting a given species (Figure 4). This is a crucial feature to assess the

261 properties of unstructured observations, as observation protocols for these data are less stringent  
262 leading to substantial heterogeneity in observer effort.



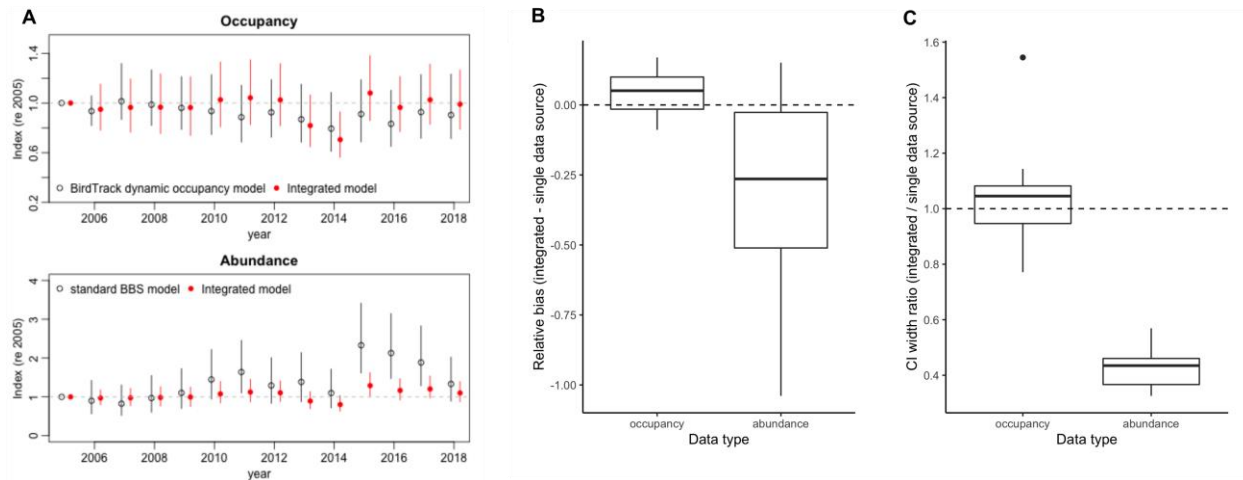
263  
264 Figure 4: Detection probability of Corn Bunting in the South Downs increases with recording duration. Top:  
265 Distribution of BirdTrack list durations (in hours). Bottom: Estimated effect of list duration on the probability of  
266 detecting at least one individual. Red line shows median, grey lines show realisations from the detection model  
267 posterior.

### 268 **3.2 A rare but widespread species**

269 The second case study assessed the utility of data integration to draw inferences about population  
270 trends for a species that is not widespread enough to fulfil the minimum sample size criterion for  
271 standard BBS reporting at the country level. We chose the Pied Flycatcher *Ficedula hypoleuca* in  
272 Wales as the focal species (Figure S5). It is a migratory woodland bird with a distribution  
273 restricted to upland deciduous woods in parts of western and northern Britain. It is red listed,  
274 both in Wales and UK wide, due to its breeding population decline over the last 25 years (Eaton  
275 *et al.* 2015; Johnstone & Bladwell 2016).

276 **3.2.1 Results**

277 In the relative comparison the occupancy change estimates from the joint model did not differ  
278 substantially from occupancy changes derived from BirdTrack alone (Figure 5).



279  
280 Figure 5: A: Occupancy and abundance trend estimates for Pied Flycatcher in Wales based on single data sources  
281 (BBS or BirdTrack; open symbols) and the integrated model (BBS and BirdTrack; red solid symbols). Error bars  
282 show posterior 95% credible intervals. B,C: Relative bias and precision of annual index values comparing the  
283 integrated and single data source models..

284 The integrated abundance trend was more precise with credible intervals about 40% the width of  
285 those of the BBS trend, however, the integrated trend was negatively biased compared to the  
286 BBS trend (Figure 5 B,C). This bias was strong enough in recent years to result in diverging  
287 inferences between the two models. The BBS model indicates that the Welsh Pied Flycatcher  
288 population is growing, with significant gains in 2011 and 2015-2017 compared to the reference  
289 year 2005. Population fluctuations indicated by the integrated trend model followed a similar  
290 pattern of gains and losses but with overall smaller magnitudes of change, resulting in a  
291 prediction of a stable population with no statistically significant gains or losses in any year since  
292 2005 (Figure 5 A). Despite their discrepancy both of these findings are more optimistic than  
293 trends observed for other humid-zone migrants in England (Morrison *et al.* 2013).

## 294 **4 Discussion**

295 Integrated models of BBS and BirdTrack data provided realistic estimates of the regional  
296 population trajectories of both bird species. In all cases the integrated trends had higher nominal  
297 precision for the abundance trajectory compared to models based on structured count data alone.  
298 Integrated occupancy trends were at least as precise as, or more precise than occupancy trends  
299 based on unstructured detection-nondetection data alone. Bias in the trends for both species was  
300 harder to assess. Population trajectories followed similar shapes, but overall effect sizes differed  
301 between models. Further work is required to validate integrated trend models against existing  
302 independent survey data, and to develop cross-validation strategies for evaluating integrated  
303 models in the absence of independent reference data. The availability of independent reference  
304 data is limited to a small number of species and regions (e.g. Stevens, Murn & Hennessey  
305 (2019), Stevens, Murn & Hennessey (2020)). In part this is due to the relative recent  
306 development of BirdTrack, which means that, as yet, temporal overlap with several established  
307 national surveys for rare bird species (e.g. Cirl Bunting (Stanbury *et al.* 2010), Dotterel (Hayhow  
308 *et al.* 2015), Hen Harrier (Wotton *et al.* 2018)) is insufficient for formal comparisons - a situation  
309 that should improve in the future.

310 Although the BBS collects detectability data using distance sampling, this information is  
311 currently not included in the calculation of routine BBS trends, as the effects of heterogeneous  
312 detection on trend estimates are deemed small (Newson *et al.* 2013). However, this assumption is  
313 less likely to hold for rare species. The integrated model therefore attempted to capture  
314 observation uncertainty in structured data using an N-mixture model. Although this type of  
315 observation model has been shown to be robust under certain field conditions (Bötsch, Jenni &  
316 Kéry 2019), N-mixture models are known to be sensitive to violations of their assumptions,



317 including the closure assumption (i.e. that there is no change in occupancy between survey visits)  
318 (Barker *et al.* 2018). Given the two BBS visits are not designed as replicates this assumption  
319 only holds for species with relatively unchanged detectability within the survey window. Using  
320 the distance sampling data to model detectability in the BBS data would be preferable (Farr,  
321 Green & Zipkin 2020), however, the corresponding observation model is computationally much  
322 more demanding than the N-mixture model. Computational effort for the estimation of  
323 integrated model parameters was high with the larger case study requiring model fitting times in  
324 the order of 5-24 hours on dedicated scientific computing hardware with Intel Xeon E5  
325 processors and ample memory. This makes model development and checking slow and may limit  
326 the roll-out of this model type for routine reporting across many species and regions.

327 The expected gains from data integration will vary both depending on the target species and  
328 target area. Target areas are an important consideration because sampling coverage for both  
329 structured and unstructured data are not evenly distributed (Figure 6). The modelling approach  
330 used for the Corn Bunting case study performed well in the South Downs because this area has  
331 good BBS coverage and exceptional BirdTrack coverage. In North East Scotland low coverage  
332 from BBS and very low coverage from BirdTrack made it impossible to fit some or all trend  
333 models for an area equivalent to the South Downs NCA (c. 1,000 km<sup>2</sup>). Model fitting did  
334 succeed when increasing the spatial domain to about 3,000km<sup>2</sup>, but even then gains in  
335 precision from the integrated approach were modest. In fact, for much of Scotland the target  
336 species range does not overlap with the distribution of opportunistic sampling effort (Figure 2),  
337 making it impossible to gain information from opportunistic observations e.g. about the efficacy  
338 of agri-environment schemes and indicating the lower limit at which such data might inform  
339 policy.

340 Similarly, the modelling strategy used here would likely not provide gains for country-level  
341 trends in Northern Ireland at the current level of BirdTrack coverage (Figure S1). Integration of  
342 opportunistic records is thus not a silver bullet for closing gaps in biodiversity monitoring on  
343 sub-national scales. At current levels of recording in the UK precision gains in bird trends from  
344 data integration can be expected at most NUTS 1 units (e.g. countries, statistical regions of  
345 England), densely settled NUTS 2 units (e.g. counties) or similarly sized landscape units such as  
346 NCAs, but likely only few NUTS 3 units (e.g. unitary authorities, districts, council areas).

347 In summary, we demonstrate that integration of structured and unstructured biodiversity records  
348 is in principle feasible for trend reporting at national and sub-national scale. Given the growing  
349 popularity of recreational biodiversity recording, opportunistic records are available in many  
350 countries which also maintain structured survey schemes, making our approach transferable  
351 beyond the UK and to non-avian taxa. However our findings also highlight that addressing  
352 monitoring gaps at these scales can not be solved with statistical models alone, but requires a  
353 careful consideration of the most promising survey approaches: In densely populated areas  
354 existing opportunistic citizen science schemes may provide a relatively easy solution to fill  
355 information gaps, but elsewhere information gains require steering the observation efforts in both  
356 opportunistic (see e.g. Callaghan *et al.* (2019b), Callaghan *et al.* (2019a)) and structured  
357 schemes, as is done e.g. for the BBS by targeted efforts to increase observer coverage of  
358 mountainous survey strata (Darvill *et al.* 2020). Birds are disproportionately well covered by both  
359 structured and unstructured schemes within the UK and globally (Amano *et al.* 2016; Sorte &  
360 Somveille 2020). Given the generally lower coverage of non-avian taxa by structured surveys,  
361 the potential for relative information gain from opportunistic schemes is expected to be much  
362 larger. At the same time, our findings imply that scheme design considerations are likely even

363 more important for these taxa to ensure that spatially biased and/or heterogenous coverage from  
364 opportunistic observations at national and sub-national scales does not affect the representativity  
365 of derived trends.

## 366 **5 Author contributions**

367 PHBS and RAR conceived the study; PHBS led data analysis and writing with input from RAR.  
368 Both contributed critically to the manuscript and gave final approval for publication.

## 369 **6 Data availability statement**

370 The BTO is committed to making data and information readily available. Data underlying this  
371 study are available by making a direct request to [datarequests@bto.org](mailto:datarequests@bto.org), or through our website  
372 <https://www.bto.org/our-science/data/data-request-system>.

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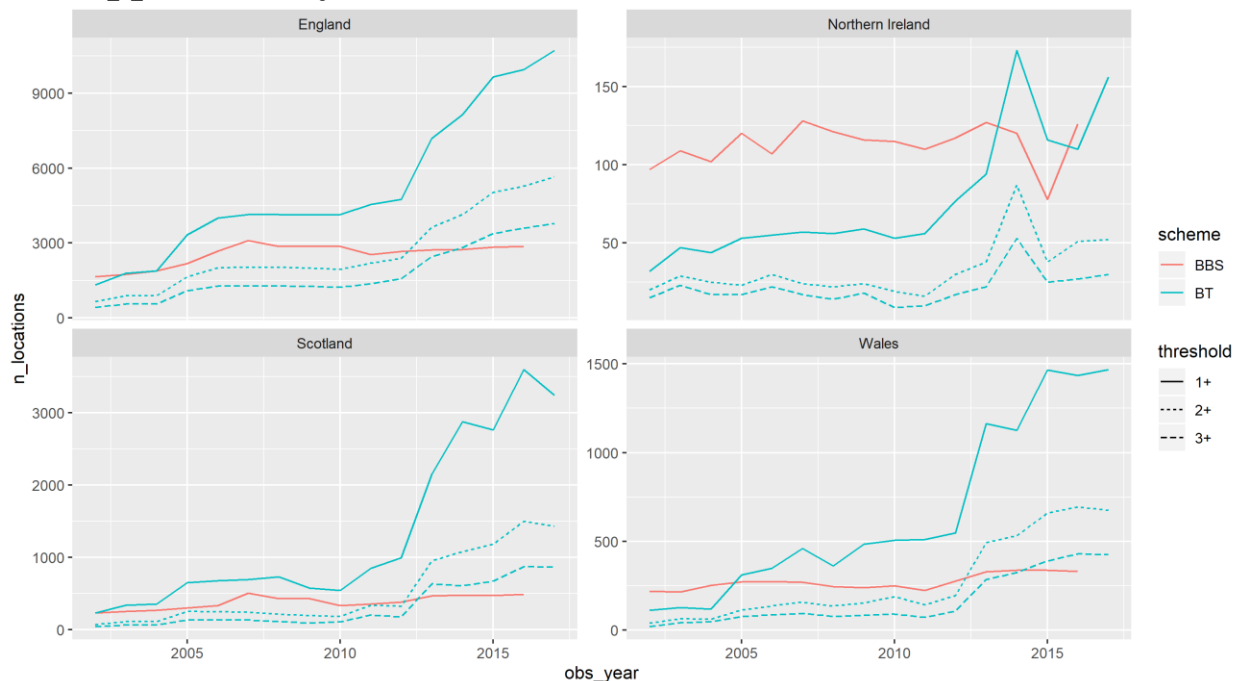
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## 575 9 Supplementary Materials

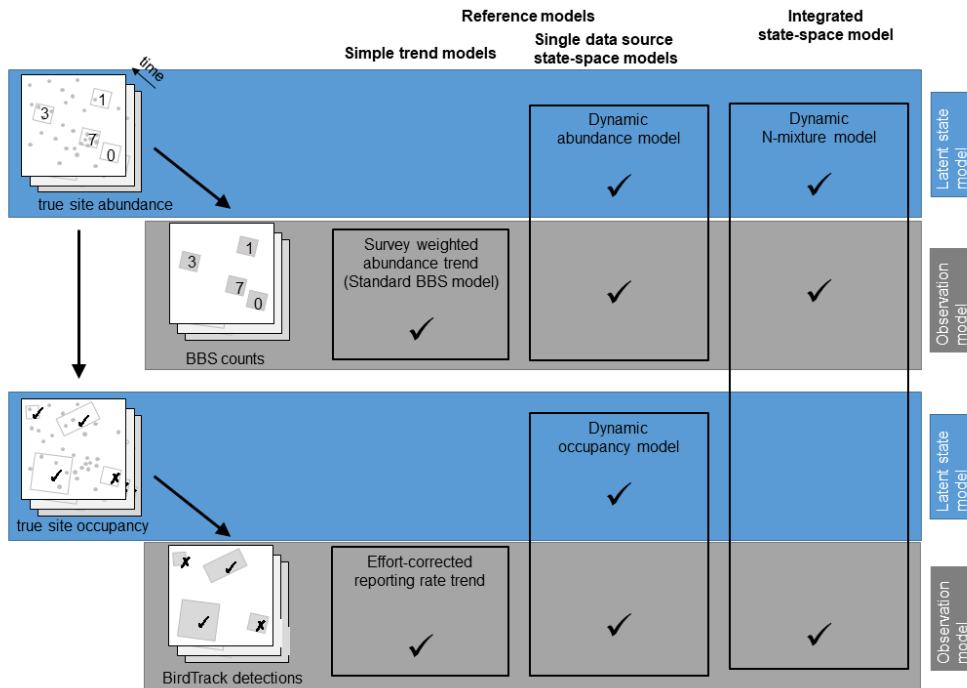


576

577 Figure S1: Opportunistic sampling coverage (measured here as annual locations with lists, solid blue line) has  
578 greatly increased since the inception of the BirdTrack scheme and now exceeds the number of BBS plots (solid red  
579 line) in all four countries. Revisits of locations by BirdTrack participants are relatively rare, however, with only  
580 about half of the sites having lists in two or more years (dotted blue line), and even fewer in three or more years  
581 (dashed blue line).

## 582 9.1 Integrated Model details

583 We used a state-space modelling approach which models the latent biological processes of  
 584 population persistence and growth and links them to the observed data using an observation  
 585 model that accounts for imperfect detection to integrate data from BBS surveys and BirdTrack  
 586 lists (Figure S2: ). This integrated model is compared to trends derived from each of the two data  
 587 sources separately. For the structured BBS data we use the statistical model that is used in the  
 588 official reporting of this survey (Freeman *et al.* 2007) as a reference model.  
 589 This is a simple trend model in that it relies on the randomised nature of the survey and does not  
 590 explicitly model the observation process. For the unstructured BirdTrack data the reference  
 591 model we use is a dynamic occupancy model which explicitly models the observation process  
 592 (van Strien *et al.* 2013). This class of models has been shown to be reasonably robust for  
 593 opportunistic biological records (Kéry *et al.* 2010; van Strien *et al.* 2013), unlike simpler trend  
 594 models (Boersch-Supan *et al.* 2019).



595



596 Figure S2: An overview of the modelling approaches used in his study. Reference models cover a single dataset at a  
597 time and serve as a comparison with the integrated model. There are two types of reference models, simple  
598 regression models of the observations and hierarchical models that explicitly separate the biological state process  
599 (i.e. the latent population dynamics) from the observation process. Data integration relies on this conceptual  
600 separation and link the two different data sources via a common process model.

### 601 **9.1.1 Biological process model**

602 The state process for this model assumes there is a population abundance  $N_{j,t}$  at a site  $j$  in every  
603 time step  $t$ , which is imperfectly observed.  $N_{j,t}$  changes between successive timesteps as a result  
604 of individuals that survive and remain at each site  $S_{j,t}$ , and those that are gained to a site by  
605 recruitment or immigration  $G_{j,t}$ . These sub-processes are expressed as

$$S_{j,t} \sim \text{Bin}(N_{j,t-1}, \omega)$$

$$G_{j,t} \sim \text{Pois}(\gamma)$$

606 where  $\omega$  is the apparent annual survival probability of individuals, and  $\gamma$  is the expected number  
607 of individuals that are gained at site  $j$  by recruitment or immigration between  $t - 1$  and  $t$ .

608 For every time step  $t > 1$  the total population abundance at site  $j$  is

$$N_{j,t} = S_{j,t} + G_{j,t}$$

609 For the first year ( $t = 1$ ), the state process is initialized by modelling abundance at each site  
610 according to a Poisson distribution with an expected count  $\lambda$

$$N_{j,1} \sim \text{Pois}(\lambda)$$

611 From the state model we can further derive the colonisation probability  $\phi_{j,t}$  of an unoccupied  
612 site as

$$\phi_{j,t} = 1 - e^{-\gamma}$$

613 as well as the extinction probability  $\epsilon_{j,t}$  as

$$\epsilon_{j,t} = (1 - \omega)^{N_{j,t}} \cdot e^{-\gamma}$$

### 614 **9.1.2 Observation model**

615 The true population abundance  $N_{j,t}$  in the survey area was linked to the data according to two  
616 sampling processes, counts of individuals in the case of BBS data and detection of at least one  
617 individual or non-detection in the case of BirdTrack lists. In both cases repeat visits to a site  
618 between April and the end of June were treated as replicates, implying the assumption of a  
619 closed population over this period, which we deemed reasonable for the species covered.

620 We assumed detection was imperfect for both sampling approaches, i.e. for count data the  
621 number of individuals encountered during a survey visit  $n_{j,t,k} \leq N_{j,t}$  and similarly, an occurrence  
622 record  $y_{j,t,k}$  could be a nondetection if none of the  $N_{j,t}$  individuals was seen or heard during a  
623 site visit. We modelled the count data as arising from a binomial process

$$n_{j,t,k} \sim \text{Bin}(N_{j,t}, p)$$

624 with an individual detection probability  $p$ . Detection-nondetection data were modelled as arising  
625 from a Bernoulli trial

$$y_{j,t,k} \sim \text{Bern}(1 - (1 - p_{occ})^{N_{j,t}})$$

626 with a separate detection probability  $p_{occ}$ , to take into account potential differences in survey  
627 methodology and/or observer skill between BBS and BirdTrack records.

## 628 **9.2 Reference Trends**

### 629 **9.2.1 BBS abundance trends**

630 Abundance models for BBS data followed the Poisson GLM approach employed in the official  
631 BBS trend production (Freeman *et al.* 2007), which models the mean local count  $\lambda_{it}$  at site  $i$  and  
632 year  $t$  based on the observed maximum counts  $y_{obs,it}$  across the two survey visits as a function  
633 of fixed additive site and year effects  $\beta_i$  and  $\beta_t$ , respectively.

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

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

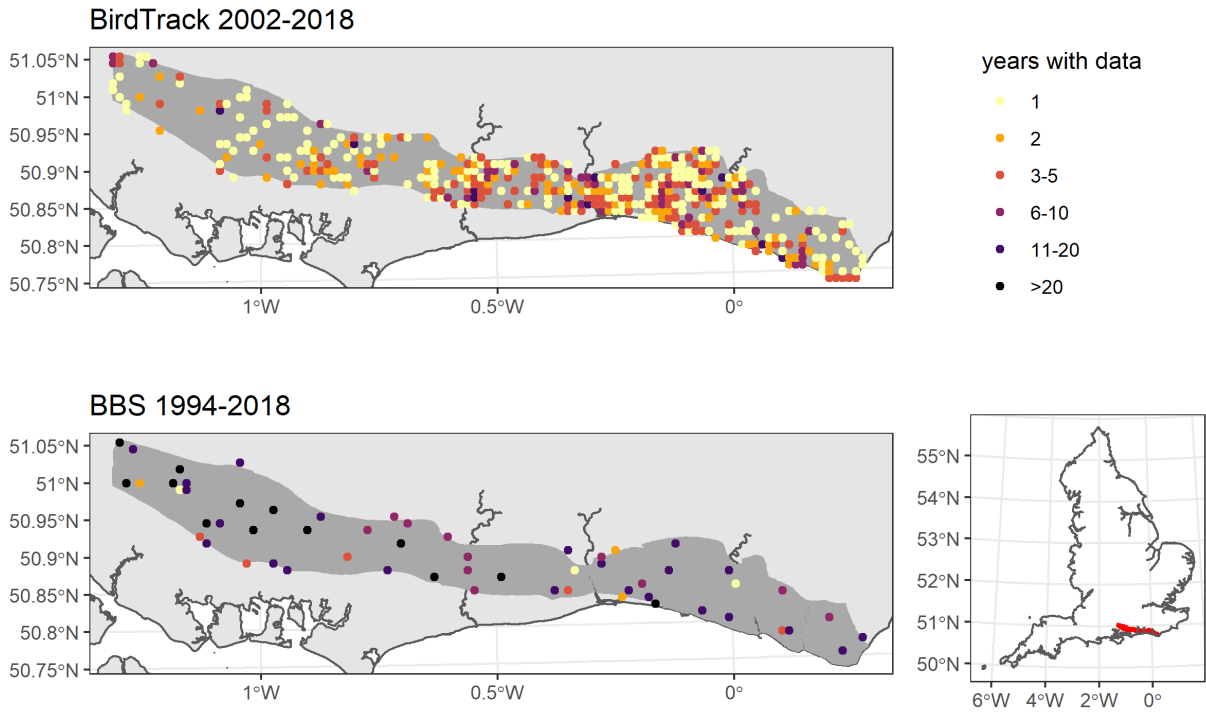
634 Abundance indices are derived from the conditional year effects  $\beta_t$ . For BBS data we further  
635 used sampling weights – equal to the inverse inclusion probability of a site within a stratum for a  
636 given year – to account for uneven monitoring coverage among BBS survey strata.

637 Parameter inference was conducted in a Bayesian framework using a weighted likelihood  
638 approach as implemented in the *brms* package (Bürkner 2018), rather than following the  
639 bootstrapping approach of Freeman *et al.* (2007).

### 640 **9.2.2 BirdTrack Dynamic Occupancy models**

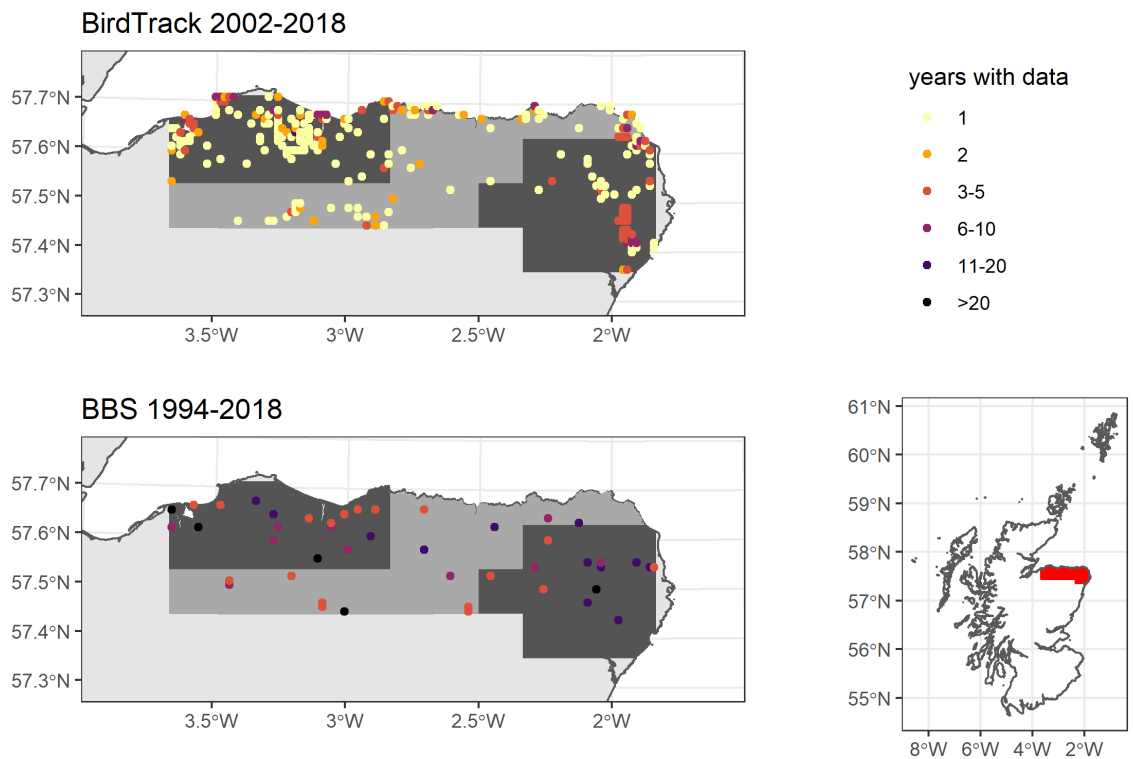
641 Occupancy trends from BirdTrack data were modelled using a dynamic site occupancy model  
642 (Kéry *et al.* 2010; van Strien *et al.* 2013) which closely mirrored the structure of the integrated  
643 model. The latent state  $N_{j,t}$  becomes a binary indicator of occupancy in these models, and initial  
644 occupancy  $N_{j,1}$  and the immigration/recruitment process  $G_{j,t}$  were modelled as a Bernoulli  
645 processes.

646 **9.3 Data details**



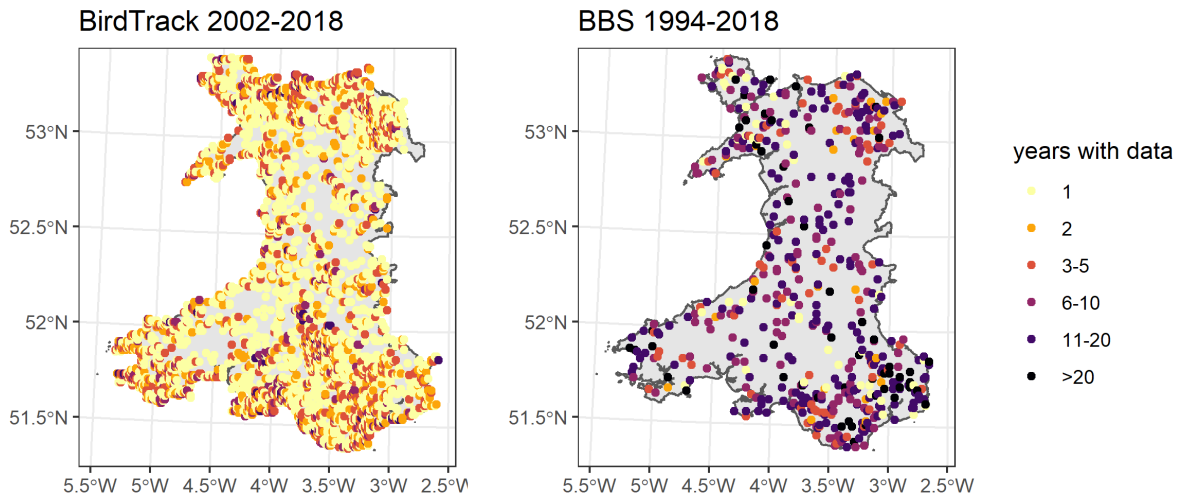
647

648 Figure S3: The study area for the South Downs Corn Bunting case study and locations of BBS surveys and complete  
649 BirdTrack lists.



650

651 Figure S4: The study area for the Scottish Corn Bunting case study and locations of BBS surveys and complete  
652 BirdTrack lists. Both dark shaded areas are approximately the same size as the South Downs NCA (Fig. S3), but  
653 data were too sparse in both to fit the integrated and/or references models. Model fitting succeeded when using  
654 records from the dark and medium grey shaded areas.



655  
656 Figure S5: Top: The study area for the Pied Flycatcher case study and locations of BBS surveys (n=519) and  
657 locations of complete BirdTrack lists (n=1034). Bottom: Time-series of the number of locations with BBS surveys  
658 and complete BirdTrack lists (solid) and locations with positive detections of the target species (dashed).

## 659 9.4 Model code examples

### 660 9.4.1 BBS survey weighted trend models

```
661 #BBS survey trend using maximum likelihood estimation with survey weights  
662 library(survey)  
663 bbs_design <- svydesign(ids = ~1, weights = ~weight, data = bbs_counts)  
664 bbs_trend <- svyglm(count ~ year_factor + square, design = bbs_design,  
665 family=poisson)  
666  
667 #BBS survey trend using Bayesian weighted Likelihood approach  
668 library(brms)  
669 bbs_trend_brms <- brm(count|weights(weight, scale = TRUE) ~ year_factor +  
670 square - 1, data = bbs_pf_counts, family = poisson)
```

### 671 9.4.2 BirdTrack dynamic occupancy model JAGS code

```
672 model{  
673   #Priors  
674   lambda ~ dnorm(0,0.2)T(0,) # initial abundance -half normal prior  
675   p ~ dbeta(2, 2) # detection # use beta prior centred on 0.5 since
```

```
676 we know detectability is ok
677
678     omega_intercept ~ dnorm(0,0.1)# survival intercept
679     gamma_intercept ~ dnorm(0,0.1)# colonisation intercept
680     tau <- 1/pow(sigma, 2)
681     sigma ~ dt(0, pow(2.5,-2), 1)T(0,)#half-cauchy prior following
682 https://arxiv.org/pdf/0901.4011.pdf
683     tau_gamma <- 1/pow(sigma_gamma, 2)
684     sigma_gamma ~ dt(0, pow(2.5,-2), 1)T(0,)#half-cauchy prior following
685 https://arxiv.org/pdf/0901.4011.pdf
686
687     for(t in 2:nYears){
688         logit(omega[t-1]) <- omega_intercept + omega_raneff[t-1]
689         omega_raneff[t-1] ~ dnorm(0, tau)
690         log(gamma[t-1]) <- gamma_intercept + gamma_raneff[t-1]
691         gamma_raneff[t-1] ~ dnorm(0, tau_gamma)
692     }
693
694
695     #Likelihood - Biological process model
696     for(i in 1:nSites) {
697         #First year of sampling
698         N[i,1] ~ dpois(lambda)
699
700         #All other years of sampling
701         for(t in 2:nYears) {
702             S[i,t-1] ~ dbin(omega[t-1], N[i,t-1])
703             G[i,t-1] ~ dpois(gamma[t-1])
704             N[i,t] <- S[i,t-1] + G[i,t-1]
705         }
706     }
707
708     #Detection process model for count data
709     for (i in 1:nCount) {
710         for (j in 1:nReps) {
711             for (t in 1:nYears) {
712                 y2[i,t,j] ~ dbin(p, N[i,t])
713             }
714         }
715     }
716     #derived quantities (track N total w/o using up memory for the entire N
717     array)
718     for (i in 1:nYears){
719         N.total[i] <- sum(N[,i])
720     }
721 }
```

### 721 **9.4.3 Joint model JAGS code for corn bunting case study**

```
722 #joint model with observation covariates for corn bunting
723 model {
```

```
724 #Priors
725 lambda[1] ~ dnorm(0,0.1)T(0,) # initial mean abundance for sites without
726 Atlas presences
727 lambda[2] ~ dnorm(5,0.1)T(0,) # initial mean abundance for sites with Atlas
728 presences
729 lambda[3] ~ dnorm(0,0.1)T(0,) # initial mean abundance for sites not
730 surveyed for 1990 Atlas
731 #gamma ~ dunif(0,10) # gains
732 for(j in 1:3){#set different baseline vital rates for different atlas
733 categories
734 mu_omega[j] ~ dbeta(57.4,41.2)# survival intercept using informative prior
735 derived from Luebcke 1977
736 gamma_intercept[j] ~ dnorm(0,0.1)# colonisation intercept
737 }
738 p ~ dunif(0,1) # detection probability prior
739 p.occ_intercept ~ dnorm(0,0.1)# intercept
740 p.occ_beta_time ~ dnorm(0,0.1)# coefficient on list duration
741 p.occ_beta_yday[1] ~ dnorm(0,0.1)# coefficient on list duration
742 p.occ_beta_yday[2] ~ dnorm(0,0.1)# coefficient on list duration^2
743
744 tau <- 1/pow(sigma, 2)
745 sigma ~ dt(0, pow(2.5,-2), 1)T(0,)#half-cauchy prior following
746 https://arxiv.org/pdf/0901.4011.pdf
747 tau_gamma <- 1/pow(sigma_gamma, 2)
748 sigma_gamma ~ dt(0, pow(2.5,-2), 1)T(0,)#half-cauchy prior following
749 https://arxiv.org/pdf/0901.4011.pdf
750
751
752 for(t in 2:nYears){
753 for(j in 1:3){#site classes
754 omega[j,t-1] ~ dnorm(mu_omega[j], tau)T(0,1)
755 gamma[j,t-1] <- gamma_intercept[j] + gamma_raneff[j,t-1]
756 gamma_raneff[j,t-1] ~ dnorm(0, tau_gamma)
757 }
758 }
759
760
761 #Likelihood - Biological process model
762 for(i in 1:nSites) {
763 #First year of sampling
764 N[i,1] ~ dpois(lambda[SitePrior[i]])
765 #All other years of sampling
766 for(t in 2:nYears) {
767 S[i,t-1] ~ dbin(omega[SitePrior[i],t-1], N[i,t-1])
768 G[i,t-1] ~ dpois(exp(gamma[SitePrior[i],t-1]))
769 N[i,t] <- S[i,t-1] + G[i,t-1]
770 }
771 }
772
```

```
773
774   #Detection process model for sites with detection/nondetection data *only*
775   #dense array formulation, i.e. imputing NAs
776   # for (i in 1:nSites){ # loop over state array to determine site-specific
777 Bernoulli parameters. This could be made more efficient by not calculating
778 this for all sites
779   #   for (t in 1:nYears){
780   #     p.site[i,t] <- 1-pow( (1-p.occ[i,t]),N[i,t] )
781   #   }
782   # }
783   #loop over observations
784   for (j in 1:nOccObs) {
785     OccObs[j] ~ dbern(1-pow((1-p.occ[j]),N[OccSite[j],OccYear[j]]))
786     logit(p.occ[j]) <- p.occ_intercept + p.occ_beta_time*OccDuration[j] +
787 p.occ_beta_yday[1]*OccYday[j] + p.occ_beta_yday[2]*(OccYday[j]*OccYday[j])
788   }
789
790   #Detection process model for sites with count data *only*
791   #looping over observations
792   for (j in 1:nCountObs) {
793     CountObs[j] ~ dbin(p, N[CountSite[j],CountYear[j]])
794   }
795
796
797   #derived quantities (so it's possible to track N total without using up
798 memory for the entire N array)
799   for (i in 1:nYears){
800     N.total[i] <- sum(N[,i])
801     N.occupied[i] <- sum(N[,i]>0)
802     mean_occ[i] <- mean(N[,i]>0)
803   }
804
805 }
```