

1 **An analysis of trends, uncertainty and species selection shows contrasting**
2 **trends of widespread forest and farmland birds in Europe**

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16 **Key words:**

17 Multi-species Index, statistical uncertainty, species selection, forest, farmland, Wild Bird Index

18

19 **Abstract**

20 1. Composite, multispecies biodiversity indices are increasingly used to report against international
21 and national environmental commitments and targets, the Wild Bird Index being a prominent
22 example in Europe, but methods to assess trends, error and species selection for such indices are
23 poorly developed.

24 2. In this study, we compare methods to compute multispecies supranational indices and explore
25 different approaches to trend and error estimation, the presentation of indices, and species
26 selection. We do so using population trend data on forest and farmland birds from 28 European
27 countries, 1980 to 2015.

28 3. We find relative stability in common European forest bird populations over this period, but a
29 severe decline in farmland bird populations. Altering the benchmark year affects index
30 characteristics and ease of interpretation. We show that using annual species' indices and their *SEs*
31 to calculate confidence intervals delivers greater precision in index estimates than bootstrapping
32 across species. The inclusion of individual species within indices has limited leverage on index
33 characteristics, but subjective selection of species based on specialisation has the potential to
34 generate bias.

35 4. Multispecies indices are valuable policy-relevant tools for describing biodiversity health. Their
36 calculation and presentation need to be tailored to meet specific policy objectives, and they must be
37 supported by clear interpretative information. We recommend methods for indicator analysis, forms
38 of presentation, and the adoption of an objective species selection protocol to ensure indicators are
39 representative and sensitive to environmental change.

40 **1. INTRODUCTION**

41 Multi-species indices (MSIs) of biodiversity change are used increasingly at national and
42 international scales to report against environmental commitments (Butchart et al. 2010; Tittensor et
43 al. 2014). The most prominent index of species abundance, the Living Planet Index (LPI), tracks
44 trends in thousands of populations of vertebrate species (Collen et al. 2009; McRae, Deint &

45 Freeman 2017), whilst the related Wild Bird Index (WBI) tracks population trends of hundreds of bird
46 species across several regions (Gregory & van Strien 2010; Wotton et al. 2017; Hoffmann et al.
47 2018). Both indices are based on the geometric mean of the relative abundance of species and
48 several studies have shown this metric to have advantages over traditional indices of biodiversity
49 change (Buckland et al. 2011; van Strien, Soldaat & Gregory 2012; Santini et al. 2016). Nonetheless,
50 multi-species biodiversity indices of this kind can potentially suffer from a number of limitations and
51 need to be interpreted with care (Renwick et al. 2011; Santini et al. 2016; Buckland & Johnston
52 2017). In this paper, we explore some of these issues, from reporting statistical uncertainty around
53 the indicators, choosing which year to set as the benchmark year and quantifying associated trends,
54 to the initial selection of species for inclusion in the indices. We use population trend data on
55 European birds to demonstrate each point. Gregory et al. (2005) first described methods to calculate
56 supranational WBIs using population data from breeding bird surveys. This work has been extended
57 with European and EU versions of the *Forest Bird Index* and *Farmland Bird Index* published by the
58 Pan-European Common Bird Monitoring Scheme (PECBMS) near-annually (see Table S1: Gregory et
59 al. 2007; Gregory & van Strien 2010).

60 **1.1 Reporting statistical uncertainty**

61 Soldaat et al. (2017) described some of the technical challenges in constructing appropriate
62 confidence intervals (CIs) around MSIs and their trends, pointing out that many of the options
63 commonly used were limited. The most robust way to construct CIs around an MSI is to bootstrap
64 the species*sites data as this fully accounts for sampling error (Buckland et al. 2005). However,
65 bootstrapping at the site level cannot be applied if sites are not a random sample, as is often the
66 case, or when site level data are not readily available, for example, when the MSIs are constructed
67 using data from the literature (e.g. the LPI: Collen et al. 2009) or from national analysis (e.g. the
68 European WBIs). Gregory et al. (2005) instead used the standard errors (SEs) of individual species'
69 trends to estimate SEs for MSIs, but this cannot be used if data for any constituent species are

70 missing for any year (Soldaat et al. 2017). A more workable and widely used alternative is to
71 construct CIs by bootstrapping across species, with the trend of each species considered as a
72 replicate of the MSI (Buckland et al. 2005; Collen et al. 2009; Eaton et al. 2016). This approach
73 captures the influence of variation between individual species' trends on the MSI but assumes that
74 the set of indicator species is representative of the trends of the community of interest (Buckland &
75 Johnston 2017) and ignores sampling error in species' indices (Soldaat et al. 2017). Furthermore,
76 bootstrapping across species can yield wide CIs if the trend of just one species differs greatly from
77 the rest, meaning that even large changes in the MSI can remain statistically non-significant.

78 **1.2 Setting the benchmark year and quantifying trends**

79 MSIs tend to be set to a value of 100 (or 1.0) in the first year of a series with a *SE* of zero in that year,
80 making the magnitude of change in the index over the time immediately obvious (e.g. halving
81 index=50, doubling index=200). This also means that the error in subsequent years is related to that
82 zero benchmark. However, this approach has ramifications for interpretation because change in the
83 index can only be assessed against the benchmark year (Buckland & Johnstone 2017; Soldaat et al.
84 2017); statistical change during the most recent and often most policy-relevant period cannot be
85 assessed. Furthermore, inaccurate estimates of abundance indices in the early years of surveys, a
86 common feature of recording schemes, can lead to misleading estimates of population trends later
87 (Buckland & Johnston 2017). Another disadvantage of this convention is that the CIs on the index
88 flare out through time, which appears anomalous, as one would expect precision in the index to
89 increase and the CIs to narrow as more data are added.

90 Methods to quantify index trends include calculation of the difference between the first and last
91 values from unsmoothed or smoothed trends, to linear regression through indices (Buckland et al.
92 2005; Gregory et al. 2007; Gregory & van Strien 2010; Fraixedas, Lindén & Lehikoinen 2015), but
93 statistically smoothed indices are recommended for trend estimation, because they remove short-

94 term variation and reduce the influence of endpoints (Buckland et al. 2005; Buckland & Johnston
95 2017; Soldaat et al. 2017).

96 **1.3 Species selection**

97 Species composition is critical to MSI utility and they must be constructed from the trends of a
98 representative set of species if they are to reflect the community of interest. Thus, robust species
99 selection should be a key part of indicator development (Gregory & van Strien 2010; Wade et al.
100 2013, 2014). Methods used to select species for inclusion in MSIs range from expert opinion
101 (Gregory et al. 2005) to more evidence-led approaches based on measures of species' habitat
102 selection or predominant habitat use (Julliard et al. 2006; Renwick et al. 2011; Fraixedas, Lindén &
103 Lehtikoinen 2015; Soldaat et al. 2017). Any influence of either individual species, or the resultant
104 distribution of included species across functional groups, on index characteristics is rarely tested. For
105 example, the current Forest (34 species) and Farmland Bird Indices (39 species), whose composition
106 was dictated largely by expert opinion, comprise 27% and 41% long-distance migrant species
107 respectively (hereafter LDMs: Table S2). These species winter in sub-Saharan Africa or Asia and many
108 have declined (Vickery et al. 2014), but these trends may not have been driven by changes in the
109 European habitats the indices were designed to represent and it is possible that migrant birds might
110 dominate and drive trends in the WBIs.

111 Beyond understanding the influence of individual or groups of species on an index, it is important
112 that initial species selection should be based on ecological principles and that the index has a
113 defined purpose. Furthermore, specialist species, defined as those where their populations are
114 strongly concentrated in one habitat for breeding or feeding, are prioritised for selection as they are
115 assumed to be most sensitive to environmental change. However, these species do not necessarily
116 fully reflect the wider community (Butler et al 2012; Wade et al 2014). Butler et al. (2012)
117 introduced a novel method that imposes both representativeness and sensitivity on the index, with
118 a selection algorithm (*SpecSel*) published by Wade et al. (2014). The approach builds on a resource-

119 use risk assessment, that draws on a matrix of species' ecological requirements covering
120 components of diet, foraging habitat and nesting habitat to predict the impact of land-use change
121 (Butler et al. 2007; Butler et al. 2010; *Wade* et al. 2013). This framework ensures all resource types
122 used by the bird community are exploited by at least one constituent species and that, within this
123 constraint, the indicator species have the highest degree of specialism; more specialised species are
124 taken to be more sensitive to changes in resource availability (Butler et al. 2007). Of course,
125 resource use may vary across time and space for each species but nonetheless this approach
126 facilitates objective species selection.

127 **1.4 Scope**

128 Here, we present up-to-date indices for the European Forest and Farmland birds, constructed using
129 conventional methodologies of setting the first index value to 100 ($SE=0$) and calculating subsequent
130 CIs by bootstrapping across species trends. We then construct a series of indices for the same
131 species' sets and different base years, using new approaches described by Soldaat et al (2017) to
132 estimate statistical uncertainty and quantify trend, and examine their influence on indicator
133 characteristics and interpretation. We test the influence of each constituent bird species and of
134 migrant birds as a group on indicator characteristics and discuss how species selection for the
135 indices might be improved.

136 **2. MATERIALS AND METHODS**

137 **2.1 Trend estimation**

138 We calculated MSIs for species' groups as the geometric mean of the supranational species' indices
139 in each year with each species weighted equally, taken from the PECBMS (Text S1:
140 <https://pecbms.info/>). These MSIs describe the average trend in the relative breeding season
141 abundance of the constituent bird species. The first index value is set to 100 ($SE=0$) and CIs
142 calculated by bootstrapping across species trends, by resampling individual species' indices with
143 replacement 10,000 times, re-calculating the index each time (Buckland et al. 2005). Trends are

144 reported as the difference between the index values in 1980 and 2015. We then test the influence
145 on index characteristics of the following approaches to MSI construction.

146 **2.2 Estimating statistical uncertainty**

147 We use Monte Carlo procedures within the MSI-tool ([https://www.cbs.nl/en-gb/society/nature-and-](https://www.cbs.nl/en-gb/society/nature-and-environment/indices-and-trends--trim--/msi-tool)
148 [environment/indices-and-trends--trim--/msi-tool](https://www.cbs.nl/en-gb/society/nature-and-environment/indices-and-trends--trim--/msi-tool): Soldaat et al. 2017), to calculate MSIs and
149 associated CIs from annual species' indices and their *SEs*. Each available yearly index for each species
150 is simulated by drawing from a normal distribution $N(\mu, \sigma)$ with μ =the natural logarithm of the index
151 and σ =the SE of the index on the log scale. The tool calculates a mean and *SE* from 1000 simulated
152 MSIs in each year and back-transforms these to an index scale, and repeats that process, here
153 10,000 times. Note that, although derived from the same data, index values for a given year
154 calculated using this approach are likely to be marginally different to those calculated as the
155 geometric mean of the constituent species' indices in each year (described above).

156 **2.3 Benchmark year and quantifying trend**

157 Next, we compare the WBIs calculated using the MSI-tool with a baseline year of 1980 with
158 equivalent indices where a) the last year in the series is set to 100 and b) the average value is set to
159 100. A benefit of benchmarking the final year in a time series is that statistical change can then be
160 assessed relative to the latest year, which can be particularly useful to inform actions. Fixing the
161 average to 100, centres the change around that value and so emphasises relative change rather than
162 absolute. We then use the MSI-tool to calculate smoothed trends (LOESS-regression, span=0.75,
163 degree=2) for the WBIs and compare the percentage change between 1980 and 2015 with the
164 absolute difference in index values from 1980 to 2015. We also test for significant changes in the
165 trend slopes between 1980 and 2015 (hereafter change points: Soldaat et al. 2017). Finally, we test
166 for significant differences in trends between MSIs (1980-2015), based on Monte Carlo procedures
167 (1000 iterations using TREND_DIFF function), reporting the average *difference* in the multiplicative
168 trends with *SE* and the significance of that difference.

169 2.3 Species selection

170 Firstly, we used a jack-knife, leave one-out approach (Freeman, Baillie & Gregory 2001), to examine
171 the influence of individual species on the value and precision of WBIs, quantified as the difference
172 between the final index value or width of CIs of the resulting MSIs and those of the full index.
173 Secondly, we examined whether the trends of LDM species differ from those of the resident and
174 short-distance migrants (hereafter RSDM) in each indicator set, and whether they disproportionately
175 affect the indicator. Thirdly, to assess the influence of species' sensitivity to land-use change, we
176 examined trends among broader groups of species associated with European forest (Wade et al.
177 2014) and farmland (Butler et al. 2010) (Table S2). These two studies each constructed resource
178 requirement matrices detailing species' summer and winter diets, summer and winter foraging
179 habitat and nest site location, and their reliance (major=1, moderate=2 or minor=3) on forest or
180 farmland respectively to deliver those resources. From this, we calculated a measure of species
181 sensitivity to environmental change in the focal habitat as the number of resources it uses multiplied
182 by its reliance, with higher scores attributed to less sensitive species (Butler et al. 2010; Wade et al.
183 2014). Here, we ranked forest and farmland species by their sensitivity scores and calculated MSIs
184 for the full group of species (forest=60, farmland=54), the top 2/3, and top 1/3 of species. We
185 compare the MSIs generated from these species' subsets with i) the average MSI across those
186 derived from 1000 species sets, generated by randomly sampling with replacement, the equivalent
187 number of species from the full set, and ii) the current respective WBI. Finally, we applied the
188 *SpecSel* algorithm (Wade et al. 2014) to the forest and farmland species' pools. For sequentially
189 increasing set sizes, this identifies the set of species with the lowest average sensitivity scores (as
190 above) that offers full resource coverage from the requirements matrices. First, we present the MSI
191 for the species set with the lowest average sensitivity score overall across all potential set sizes
192 (hereafter *SENSITIVE*: forest=31; farmland=24). Second, we present the MSI for the set identified by
193 piecewise regression as the optimal breakpoint when relating indicator set size to average sensitivity
194 (hereafter *BREAKPOINT*: forest=14; farmland=5). The *BREAKPOINT* set reflects a trade-off between

195 sensitivity and potential redundancy in the index. Whilst average sensitivity initially declines with
196 increasing indicator set size, as generalist species are replaced by more specialist species, the rate of
197 change slows at larger set sizes and larger indicator sets have greater redundancy (Wade et al.
198 2014). Analyses were carried out using statistical software R (version 3.4.2, R Development Core
199 Team 2017).

200 **3. RESULTS**

201 **3.1 Estimating uncertainty**

202 The Forest Bird Index remains relatively stable, showing a non-significant increase between 1980
203 and 2015 (Fig. 1a,b: +9% using standard methods & +7% using the MSI-tool), while the Farmland Bird
204 Index showed a significant decline over this period (Fig. 1e,f: -60% using both methods: see
205 Discussion). The MSI-tool shows trends of the Forest and Farmland Bird Indices to differ significantly
206 (difference=-0.02, $SE=0.002$, $p<0.05$). For both the Forest and Farmland Bird Indices, CIs derived
207 from the MSI-tool are narrower (Fig. 1b,f) than those derived by bootstrapping across species (Fig.
208 1a,e). For example, bootstrapping-derived CIs for the 2015 index are 43% and 33% wider than those
209 derived using the MSI-tool for the forest and farmland birds respectively.

210 **3.2 Setting benchmark year and quantifying trend**

211 Changing the benchmark year from 1980 to 2015, or setting the average Index value to 100, has
212 little effect on interpretation of the Forest Bird Index because it has remained relatively unchanged
213 (Fig.1 c,d). However, the influence of the benchmark for the Farmland Bird Index is more
214 pronounced. When the last year is set to 100, the index shows statistical stability in farmland bird
215 populations since the early 1990s (CIs overlap 100) and much greater uncertainty around the index
216 value in the earlier years, as you might expect (Fig. 1g). However, the scale of overall change is less
217 obvious, although it can be calculated. The same is true when the index is set to an average of 100,
218 although the magnitude of change is even less clear (Fig.1h).

219 The smoothed Forest Bird Index shows a stable trend both over the whole period and over the
220 last ten years (Fig.2a: change=5.35%, SE=8.5%, NS & change=4.33%, SE=8.3%, NS respectively), with
221 no significant change points. The Farmland Bird Index shows a major decline over the whole period
222 but statistical stability over the last ten years, although the trend remains negative (Fig. 2b: change=-
223 56.8%, SE=5.2%, $p<0.01$ & change=-3.05%, SE=5.6%, NS respectively). Change points were identified
224 in the Farmland Bird Index in each of the years 1985 to 1998 (Fig. 3, $p<0.05$ in all cases: e.g.
225 multiplicative trend $<1992=0.96$, SE=0.008, $>1992=0.98$, SE=0.005, $p<0.01$), signifying a switch from a
226 relatively steep linear decline in the index (~4% pa), to a lesser rate recently (~2% pa).

227 3.3 Species selection

228 Exclusion of individual species affects the resulting Forest Bird Index to varying degrees, but the
229 leverage of individual species is modest (Table 1a). The mean absolute difference in the 2015 index
230 value from that of the Forest Bird Index when excluding one constituent species is 3.29%, SE=0.37%
231 (Table 1a, Fig. 3a). Exclusion of *Picus canus* pulls the index down most, with the 2015 value excluding
232 this species 4% lower than that of the full index, whilst the exclusion of *Emberiza rustica* pushes the
233 index up most, by 9% by 2015. On average, excluding a species widens the CIs on the MSIs (mean
234 absolute difference from Forest Bird Index in 2015=5.32%, SE=0.54%) but, at the individual species
235 level, the direction of change depends on the precision of that species' index (Table 1a). The
236 inclusion of *Leiopicus medius*, *P. canus* and *Coccothraustes coccothraustes* adds most imprecision to
237 the Forest Bird Index (Fig.3a), because their indices are associated with higher sampling error. There
238 is a strong positive correlation between the extent of impact of excluding an individual species on
239 Forest Bird Index value and precision (Spearman $\rho=0.85$, $p<0.0001$).

240 The exclusion of individual species from the Farmland Bird Index has a similar impact overall
241 (mean absolute difference from it in 2015=2.75%, SE=0.55%; Table 1b, Fig. 3b) but the leverage of
242 individual species tends to be greater. Exclusion of *Corvus frugilegus* pushes the index down by 9%
243 compared to the full index in 2015, whilst the exclusion of *Galerida cristata* pushes the index up by

244 18%. Excluding species has mixed effects on the CIs (mean absolute difference from Farmland Bird
245 Index in 2015=4.40%, $SE=0.97\%$, Table 1b). Inclusion of *Upupa epops*, *Anthus campestris* and *C.*
246 *frugilegus* adds most imprecision to the index because their indices have greater sampling error and
247 indices for the first two do not cover all years (Table 1b). The impact of excluding each species on
248 the Farmland Bird Index is positively correlated with the impact on precision (Spearman $\rho=0.62$,
249 $P<0.0001$).

250 Exclusion of individual LDM forest species tends to push the trajectory of the MSI upwards
251 slightly (Table 1a) but the impact of excluding individual LDM species is not significantly different
252 from excluding individual RSDM (mean difference from 2015 Forest Bird Index value: excluding LDM:
253 $n=9$, mean change=3.8%, $SE=0.90\%$; excluding RSDM: $n=25$, mean change=2.3%, $SE=0.58\%$, $t_{30}=1.34$,
254 $p=0.20$). There is also no significant difference in the change in precision when excluding individual
255 LDMs or RSDMs ($n=9$, difference=5.19%, $SE=0.88\%$ & $n=25$, difference=2.75%, $SE=1.2\%$ respectively,
256 $t_{30}=1.67$, $p=0.11$). Similarly, the mean difference in 2015 MSI values compared to the Farmland Bird
257 Index, when excluding either individual LDM or individual RSDM farmland species, is not significantly
258 different (mean difference from 2015 Farmland Bird Index value: excluding LDM: $n=16$, mean
259 change=-0.48%, $SE=0.88\%$; excluding RSDM: $n=23$, mean change=-0.19%, $SE=1.0\%$ respectively, $t_{21}=-$
260 0.21, $p=0.83$); excluding LDM individually pushes the index down very slightly. Likewise, the mean
261 difference in the precision of MSI values compared to the 2015 Farmland Bird Index value, when
262 excluding either individual LDMs or individual RSDMs, is not significantly different ($n=16$,
263 difference=-2.38%, $SE=2.4\%$ & $n=23$, difference=1.05%, $SE=1.2\%$ respectively, $t_{21}=1.30$, $p=0.21$).

264 MSIs for the LDM and RSDM species are similar (Fig. 4). Whilst neither the MSIs for LDM or RSDM
265 forest species exhibit significant trends ($n=9$, change -5.13%, $SE=11.7\%$, *NS* & $n=25$, change=9.82%,
266 $SE=11.61\%$, *NS* respectively), the trend of forest LDMs oscillates and is significantly more negative
267 than that for forest RSDMs (difference=-0.01, $SE=0.003$, $p<0.05$). However, the number of species is
268 small. MSIs for both groups of farmland birds exhibit steep and significant declines (LDMs: $n=16$,

269 change=-51.18%, $SE=13.87\%$, $p<0.01$; RSDM: $n=23$, change=-59.47%, $SE=3.33\%$, both $p<0.01$), but
270 again, the trend of LDMs is significantly more negative than that for RSDMs (difference=-0.015,
271 $SE=0.003$, $p<0.05$). There are no significant change points for either group of forest birds (Fig.4a), nor
272 among LDMs of farmland. In contrast, the MSI-tool identifies significant change points RSDMs of
273 farmland in the years 1985 to 2005 (as in the Farmland Bird Index above), from a steeper to a less
274 steep decline.

275 The MSI for 60 species associated with forests in Europe sits slightly lower than the current Forest
276 Bird Index (change=-1.8%, $SE=5.0\%$, *NS*) but there is no significant difference between the two trend
277 slopes (difference=-0.0003, $SE=0.002$, *NS*: Fig.5a). The MSI for the top 2/3 of these species ranked by
278 decreasing sensitivity to land-use change, shows a slightly stronger decline ($n=40$, change=-8.2%,
279 $SE=6.6\%$, *NS*: Fig.5b) and does not differ from the Forest Bird Index (difference=-0.0038, $SE=0.002$,
280 *NS*). The MSI for the top 1/3 of species in terms of sensitivity shows a steeper but still non-significant
281 decline ($n=20$, change=-15%, $SE=9\%$, *NS*: Fig.5c), but this trend is significantly steeper than that of
282 the Forest Bird Index (difference=-0.007, $SE=0.003$, $P<0.05$). Both the MSIs for the top 2/3 and 1/3 of
283 species, show a greater decline than MSIs based on the same number of randomly selected species
284 (Fig.5b,c). This suggests that species identified as being more sensitive to habitat change have
285 declined more.

286 The MSI for 54 species associated with farmlands in Europe shows a significant decline (change=-
287 35.3%, $SE=5.9\%$, $p<0.01$) but is significantly less negative than that of the Farmland Bird Index
288 (difference=0.010, $SE=0.003$, $p<0.05$, Fig.6a). The MSI for the top 2/3 of these species ranked by
289 decreasing sensitivity, shows a stronger decline ($n=36$, change=-40.8%, $SE=7.1\%$, $p<0.01$ Fig. 6b), but
290 is again significantly less negative than the Farmland Bird Index (difference=0.007, $SE=0.003$, $p<0.05$
291 Fig. 6b). The MSI for the top 1/3 of species in terms of sensitivity shows a large decline ($n=18$,
292 trend=-43.2%, $SE=10\%$, $p<0.01$) that is not significantly different from the Farmland Bird Index
293 (difference=0.008, $SE=0.004$, *NS*, Fig. 7c). Whilst lower, these MSIs do not differ greatly from MSIs

294 based on the same number of randomly selected species (Fig. 7b,c). This suggests that while more
295 sensitive species have declined more, that declines are a generic feature of farmland bird
296 populations, and further that the species included in the current index have shown strong declines.

297 Finally, for forest birds the *SENSITIVE* set MSI shows a non-significant decline (n=31, change=-6.4%,
298 SE=7.5%, NS) whilst the *BREAKPOINT* set shows a non-significant increase (n=14, change=35%, SE=19%,
299 NS), but neither trend differs significantly from the Forest Bird Index (Fig. 7a,b: difference=-0.004,
300 SE=0.002 & difference=0.004, SE=0.003 respectively, both NS). For farmland birds, both the *SENSITIVE* and
301 *BREAKPOINT* MSIs show significant declines (Fig. 8 c,d, n=24, change=-42%, SE=7.4% & n=5, change=-34%,
302 SE=7.6% respectively, both $p < 0.01$), but both are significantly less steep than the Farmland Bird Index
303 (difference=0.007, SE=0.003 & difference=0.011, SE=0.003 respectively, both $P < 0.05$). The wide CIs reflect
304 the small number of species and some of those species having imprecise trends (see Table 1).

305 4. DISCUSSION

306 4.1 Population trends

307 Our analyses reveal contrasting population trends of abundant breeding birds associated with
308 forests and agricultural habitats in Europe. On average, common forest bird populations show a
309 degree of stability in trends, though specialist species seem to be declining (Fig. 6), as reported
310 previously (Gregory et al. 2007). Common farmland bird populations have declined precipitously, the
311 Farmland Bird Index falling by nearly 60% between 1980 and 2015. While the decline was steepest
312 1980-1995, and the trend is statistically stable over the last ten years, the decline continues at a
313 lesser rate (Fig. 1, e-h, 2b). Comparison with previous studies (Gregory et al. 2005, 2007; Gregory
314 and van Strien 2010) is complicated by changing timescales, species sets and the number of
315 countries contributing data. Gregory et al. (2005) reported a sharp decline in widespread farmland
316 birds, but relative stability in birds of woods, parks and gardens, 1980-2002, using data from 18
317 countries. Gregory et al. (2007) showed farmland birds in falling in number but also reported a
318 moderate decline in specialist forest species (>60% of which are in the current Forest Bird Index),

319 1980-2003, using data from 18 countries. Whereas, Gregory and van Strien (2010) reported no
320 obvious trend among forest birds, but a very considerable decline in farmland birds 1980–2007 using
321 data from 22 countries. Our analysis supports these broad patterns, of extensive decline in common
322 farmland birds but relatively stability in common forest birds using a larger and extended dataset
323 (Fig. 1 & 2), and we also find evidence of modest decline among the most specialist forest species
324 too (Fig. 5c).

325 **4.2 Reporting statistical uncertainty**

326 The MSI-tool computes CIs using the *SEs* of the annual species' indices and so error around the MSI
327 reflects noise in the estimation of the species' indices (Fig. 1b, f). When bootstrapping across
328 species' trends, the CIs reflect differences in the trajectory and variability of the individual species'
329 trends (Fig. 1a,e). In our examples, CIs calculated using the MSI-tool are narrower than the
330 bootstrapped estimates (Fig. 1), however, inference is unchanged as both methods show relative
331 stability in forest bird populations and declines among farmland birds. Yet it is possible in certain
332 circumstances for one approach to indicate significant decline or increase, and the other show no
333 significant change. Such mixed messages could easily undermine the policy use of the metrics.
334 Therefore, we recommend the use of the MSI-tool, where possible, to test for statistical change in
335 MSIs. However, given that the two methods convey different but complementary information about
336 uncertainty around the indices, we see merit in presenting MSIs using a bootstrap method as
337 supporting information, provided the differences in inference are explained.

338 **4.3 Setting the benchmark year and quantifying trends**

339 Changing the benchmark year has implications for ease of interpretation of MSIs and we
340 recommend that the default should be to set the starting index value to 100 (or 1) as this
341 demonstrates change over time most intuitively. Moreover, benchmarking against anything other
342 than a fixed year, such as the latest year in a time series or setting the average to 100, means that
343 index values for specific years will change each time the index is updated, which could impact on
344 ease of understanding and communication (the same being true when new data are added to the

345 time series). However, we recognise that fixing the last year to 100 ($SE=0$) allows recent change in
346 the index to be interpreted (Fig. 1d,h), and we suggest presenting additional indices in this format,
347 when practical. We also recommend presenting statistically smoothed indices to best describe the
348 overall index trend, minimising noise (Buckland & Johnston 2017).

349 Note that MSIs calculated in a conventional manner, as the geometric mean of the constituent
350 species indices, will be marginally different from those calculated in the same fashion but using
351 Monte Carlo procedures. This is perceptible in forest birds (Fig. 1a,b) but arguably not for farmland
352 birds (Fig. 1e-f), and the differences are extremely small. We did not set out to test the rigour of the
353 two index methods as that was beyond the scope of our paper.

354 **4.4 Species selection**

355 WBIs appear relatively robust to changes in species selection as the exclusion of individual species
356 had relatively little influence on index characteristics and should not compromise their policy use,
357 given recognised levels of variability and tolerances (e.g. UK government use a 5% threshold to
358 evaluate the significance of change: [www.gov.uk/government/statistics/wild-bird-populations-in-](http://www.gov.uk/government/statistics/wild-bird-populations-in-the-uk)
359 [the-uk](http://www.gov.uk/government/statistics/wild-bird-populations-in-the-uk)), but regular checks are advisable. The exception was *G. cristata*, a rapidly declining species
360 whose inclusion lowers the Farmland Bird Index and reduces overall precision. Whilst smaller sample
361 sizes for rarer species may increase the imprecision of trend estimates, the estimates themselves are
362 not necessarily biased. The inclusion of rare species in an MSI needs careful consideration in terms
363 of the accuracy and precision of the trend estimates, and whether such species are representative of
364 the community the index describes. We show that species adding most imprecision also tend to
365 have the greatest impact on the index values, so species selection should consider index precision
366 alongside other factors. Rarity is also an issue if a species undergoes significant declines over time
367 and it raises questions over whether it should continue to be included in an MSI. This is the case
368 when a declining species becomes so rare that it cannot be monitored reliably (partly because one
369 cannot take a geometric mean of zero). The MSI-tool overcomes this problem by fixing the lowest

370 index value to one and other programmes do similar (e.g. Collen et al. 2009). Renwick et al. (2012)
371 showed WBIs were sensitive to the exclusion of rarer, often declining species, and their exclusion led
372 to more positive trends. So, excluding a rapidly declining (or increasing) species from an index can be
373 problematic and create bias, and some rules are needed. In the case of *G. cristata*, there is no
374 compelling reason to remove the species, as the index would be more positive if the species was
375 lost, and independent evidence suggests that its population has collapsed in Europe (BirdLife
376 International 2017). Note however that its inclusion is likely to reduce the precision of the index.

377 We show that LDMs do not overly influence the WBIs, although their population trends were slightly
378 more negative. Somveille et al. (2013) show that the proportion of migratory bird species in
379 communities follows a strong latitudinal gradient globally, increasing with latitude. Some 37% of
380 species covered by the PECBMS are LDMs and they represent an important component of breeding
381 bird communities in Europe, although it is sensible to check that their trends, likely driven by factors
382 inside and outside Europe, do not drive change in the MSIs.

383 MSIs containing subsets of species judged to be more sensitive to environmental change showed
384 slightly greater declines, as you might predict (Clavel, Julliard & Devictor 2011), but differences from
385 current WBIs were modest (Figs. 5-6). Species selection for current indices was based on expert
386 opinion that prioritised specialists and Reif, Jiguet & Šťastný (2010) showed that expert assessment
387 of species' specialization is highly correlated with independent measures. However, the case for
388 adopting more objective species selection approaches remains. Renwick et al. (2012) argue against
389 species selection based on expert opinion and previous research suggests that indices selected in
390 this manner may not be representative of wider bird communities (Butler et al. 2012; Wade et al.
391 2014). We therefore recommend approaches that impose the required characteristics of reactivity,
392 representativeness and predictability of response on MSIs (Gregory et al 2005). For example, the
393 *SpecSel* algorithm we applied here prioritises representativeness over maximising the specialisation
394 of constituent species, with resultant indicator sets including less specialist species where necessary

395 to ensure all resource types used by the wider community are also exploited by selected species
396 (Wade et al 2014). Here the indices with the most sensitive species outperformed the breakpoint
397 set, which proved to more uncertain (Fig. 7). Although Renwick et al. (2012) showed that trends in
398 WBIs based upon objective selection were very similar to the existing trends, we suggest adopting
399 such formal approaches will improve MSI utility for many taxa, makes species selection more
400 defensible and should ensure a level of future-proofing in terms of reactivity to environmental
401 change. This may be easier to achieve for well-studied taxa, like birds, but the principle of objective
402 species selection remains (Butler et al. 2009).

403 **5. CONCLUSIONS**

404 We show relative stability among common and widespread birds of forests in Europe, but a
405 precipitous and ongoing decline in birds living on farmland. Current WBIs appear relatively robust to
406 changes in species selection but the inclusion of species with more extreme trends can adversely
407 affect index precision and the prioritisation of specialist species for inclusion can lead to non-
408 representative indicator sets. We therefore recommend employing objective species selection
409 frameworks that ensure the critical indicator characteristics of reactivity, representativeness and
410 predictability are imposed. Once an appropriate set of species has been selected, numerous
411 approaches to the construction and presentation of indices are available and, given the potential
412 influence of alternative approaches on index interpretation, each step needs careful consideration.
413 We recommend anchoring indices (unsmoothed or smoothed) to start at 100 in the first year to aid
414 communication, but also recommend, when practical, presenting indices anchored to 100 in the last
415 year of the series to their aid interpretation and policy actions. CIs around the MSIs should ideally
416 reflect error of the annual species' indices and we recommend the MSI-tool as a practicable and
417 effective tool to calculate CIs in this way; particularly given its additional functionality for generating
418 unsmoothed and smoothed MSIs and testing for differences in indicator trends. Most importantly,

419 given the growing influence of MSIs on conservation policy development, the method of calculation
420 of MSIs and CIs must always be clearly presented to facilitate appropriate interpretation.

421

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427

428 **AUTHORS CONTRIBUTIONS**

429 RDG led the study, indicator analyses and writing, JS and PV computed the species' indices, PV and
430 SB contributed to the study design and shaped analyses; all helped write and approved the final
431 paper.

432

433 **DATA ACCESSIBILITY**

434 Data available from <https://pecbms.info/use-of-the-results/data-access-policy/>.

435

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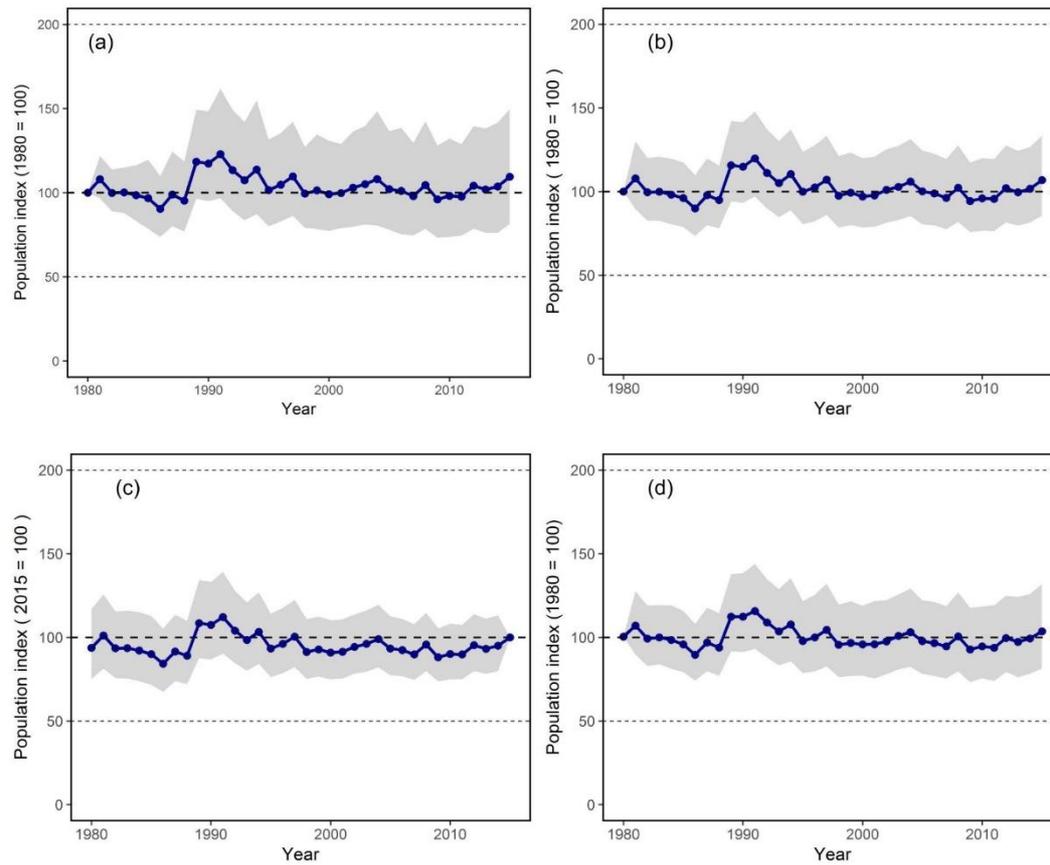
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FIGURE 1 MSIs for European forest (a-d: n=34) and farmland bird species (e-h: n=39) with shaded 95% CIs calculated by bootstrapping (a, e), otherwise using the MSI-tool. Indices set to 100 ($SE=0$) in 1980 in a, b, e and f. Indices set to 100 ($SE=0$) in 2015 in c & g, and to an average of 100 in 1980-2015 ($SE=0$ in 1980) in d and h.



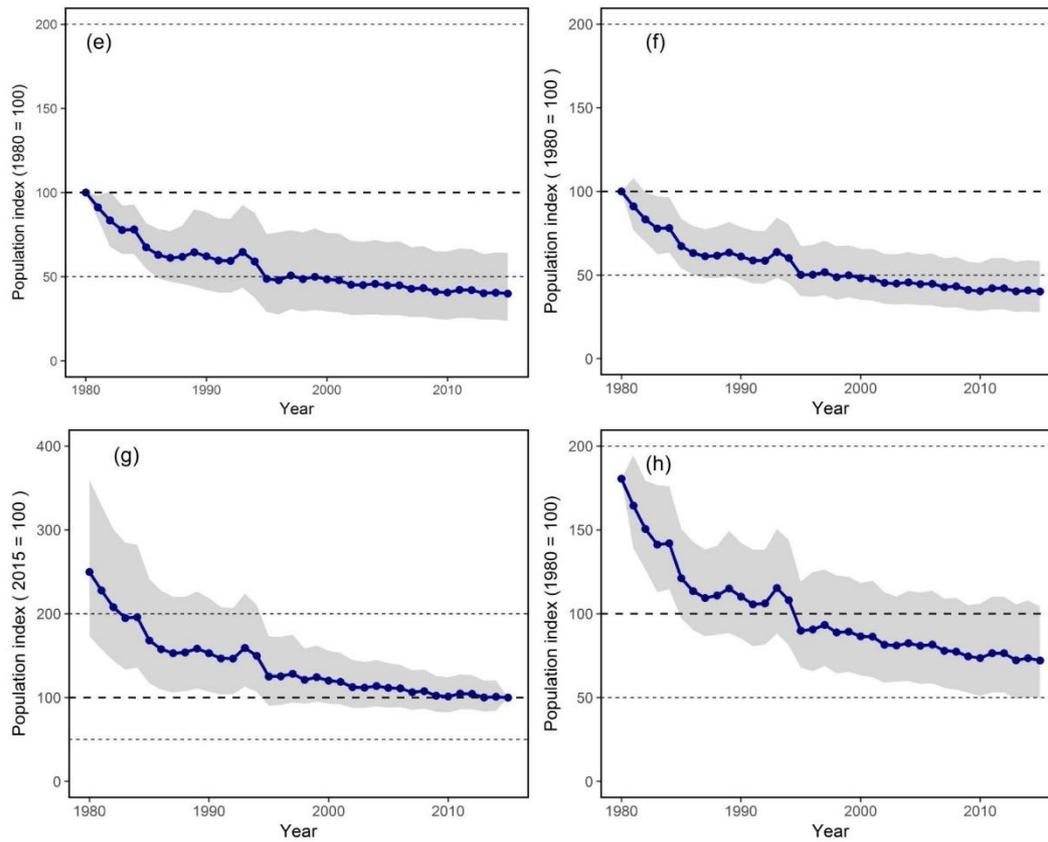


FIGURE 2 Smoothed MSIs for (a) European forest ($n=34$) and (b) farmland bird species ($n=39$) with 95% CIs shaded. Indices set to 100 in 1980. The arrows in (b) indicate periods when there is a significant change detected in the trend.

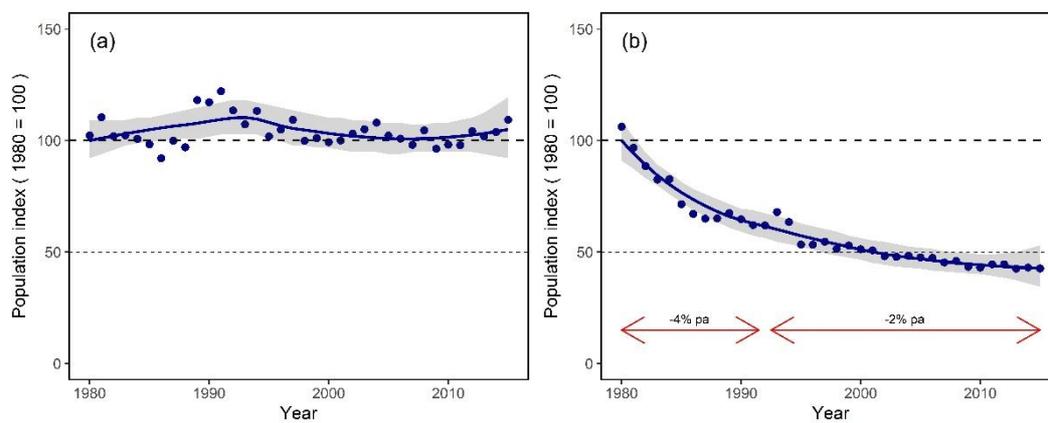


FIGURE 3 MSIs constructed based upon species subsets leaving one species out at a time, (a) European forest bird indices constructed based upon 33 species subsets, and (b) farmland bird

indices constructed based upon 38 species subsets. Species missing from each MSI is given in the legend. Indices are set to 100 in 1980.

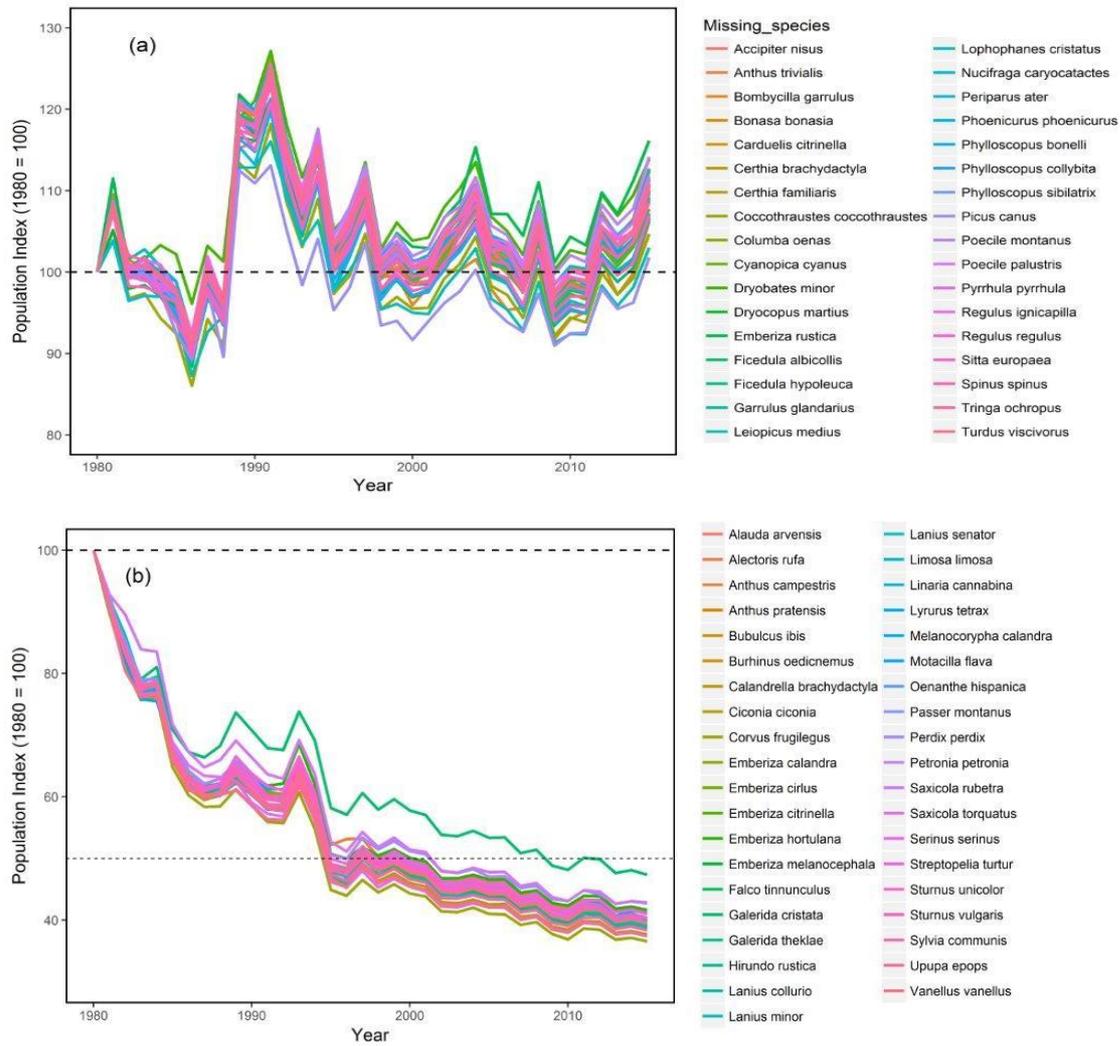


FIGURE 4 Smoothed MSIs for long-distance migrants (black) versus residents and short-distance migrant birds (blue) for (a) forest (n=9 & 25 species respectively) and (b) farmland species (n=16 & 23 species respectively). Indices set to 100 in 1980 with shaded 95% CIs.

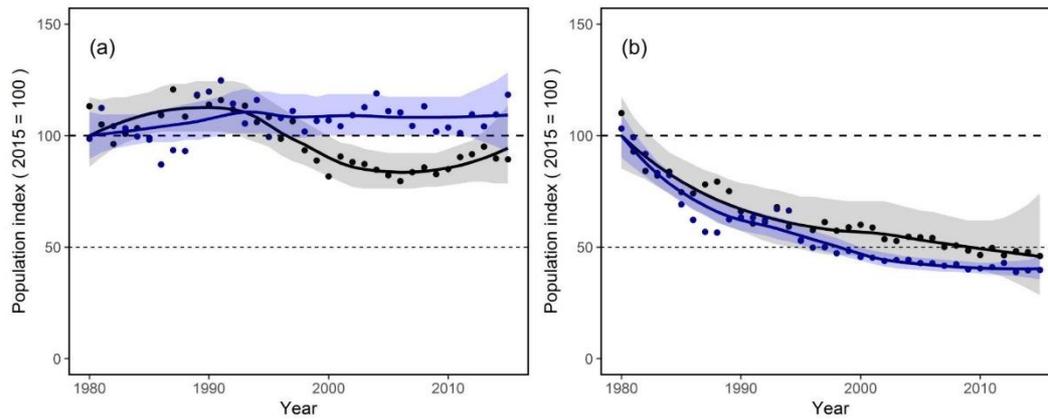


FIGURE 5 MSIs for species associated with forest (a: $n=60$), the top 2/3 (b: $n=40$), and the top 1/3 of these species (c: $n=20$) most sensitive to forest alteration. Grey line is the Forest Bird Index. Red lines are MSIs constructed by drawing with replacement random samples of 40 or 20 species from the 60 species to match the number in the respective index. Indices set to 100 ($SE=0$) in 1980 with shaded 95% CIs.

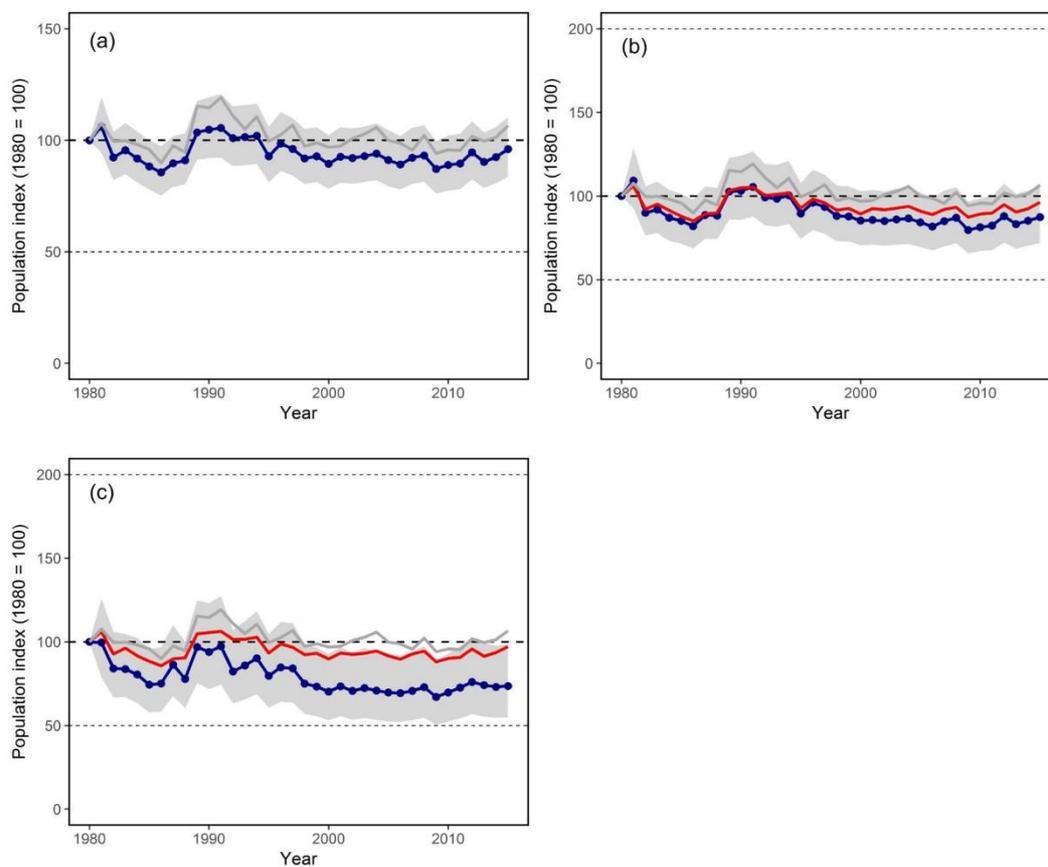


FIGURE 6 MSIs for a group of species associated with farmland (a: n=54), the top 2/3 (b: n=36), and the top 1/3 (c: n=18) of these species most sensitive to farmland alteration. Grey line shows the Farmland Bird Index. Red lines are MSIs constructed by drawing with replacement random samples of 36 or 18 species from the 54 species to match the number of species in the respective index. Indices set to 100 ($SE=0$) in 1980 with shaded 95% CIs.

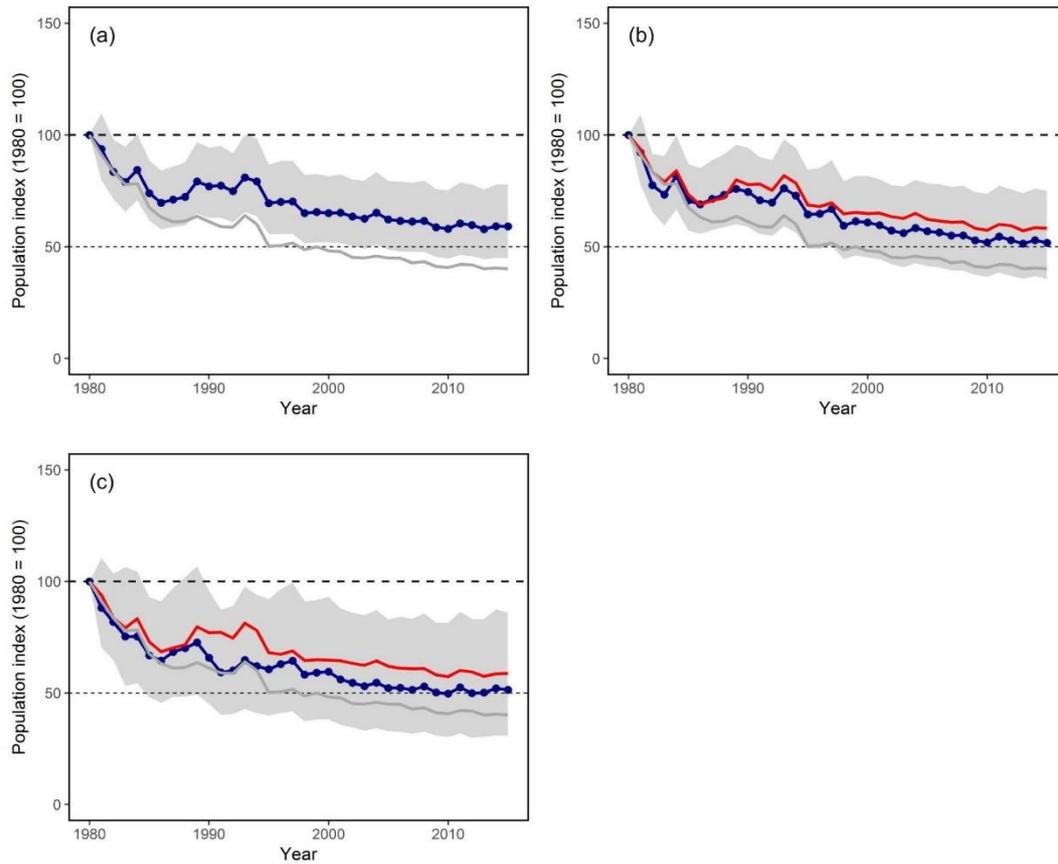


FIGURE 7 MSIs for forest (a-b) and farmland birds (c-d) with species selected according to a species' selection algorithm. This identifies the species set with the lowest overall sensitivity (a=31 forest species & c=23 farmland species), and the optimal breakpoint set covering all resources (b=14 forest species & d=5 farmland species). Indices set to 100 ($SE=0$) in 1980 with shaded 95% CIs. Grey lines show the Forest (a-b) and Farmland Bird Indices (c-d).

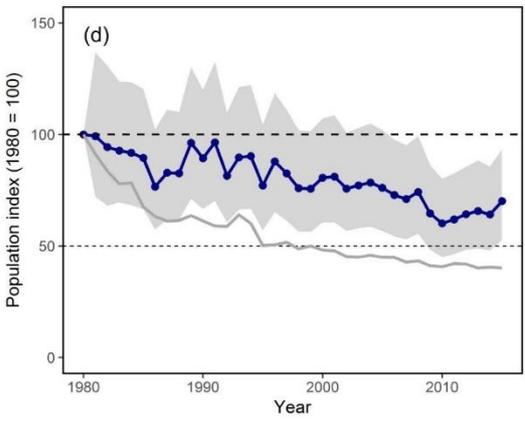
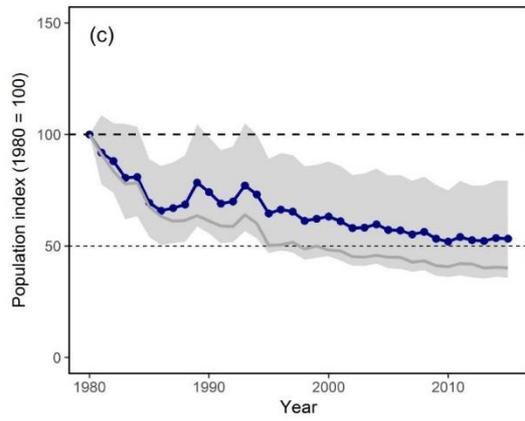
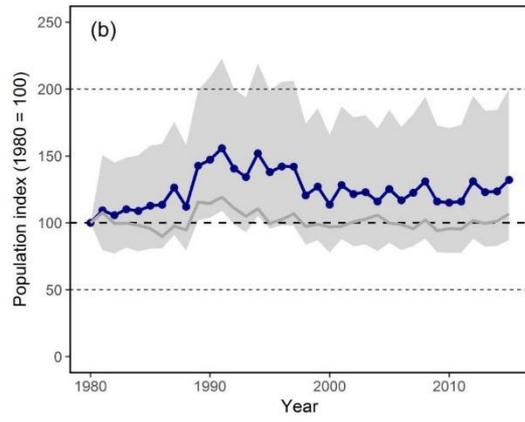
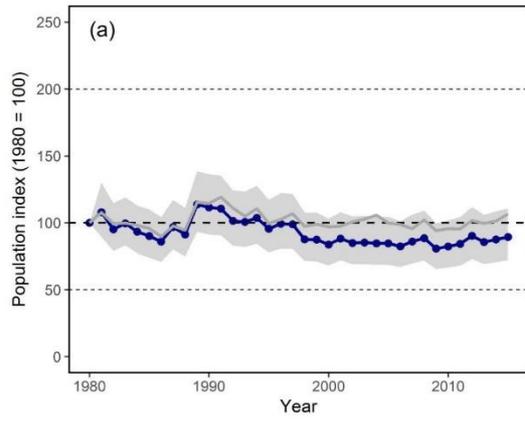


Table 1. Analysis of the impact of excluding individual species from (a) the Forest and (b) the Farmland Bird Indices.

a) Species omitted from Forest Bird Index	First year	Last year	Span in years	Deviation in value from index in 2015 (%)	Difference in precision from index in 2015 (%)	Migratory status
<i>Accipiter nisus</i>	1980	2015	35	2.43	2.08	Non-migrant
<i>Anthus trivialis</i>	1980	2015	35	5.79	7.00	Migrant
<i>Bombycilla garrulus</i>	1988	2015	27	-0.36	-1.76	Non-migrant
<i>Bonasa bonasia</i>	1980	2015	35	5.47	6.35	Non-migrant
<i>Carduelis citrinella</i>	1999	2015	16	2.38	3.23	Non-migrant
<i>Certhia brachydactyla</i>	1982	2015	33	2.8	4.80	Non-migrant
<i>Certhia familiaris</i>	1980	2015	35	3.36	5.62	Non-migrant
<i>Coccothraustes coccothraustes</i>	1980	2015	35	-1.8	-5.67	Non-migrant
<i>Columba oenas</i>	1980	2015	35	2.06	5.28	Non-migrant
<i>Cyanopica cyanus</i>	1998	2015	17	1.09	1.27	Non-migrant
<i>Dryobates minor</i>	1980	2015	35	6.82	7.32	Non-migrant
<i>Dryocopus martius</i>	1980	2015	35	0.11	2.04	Non-migrant
<i>Emberiza rustica</i>	1980	2015	35	8.96	10.17	Migrant
<i>Ficedula albicollis</i>	1982	2015	33	-0.09	1.44	Migrant
<i>Ficedula hypoleuca</i>	1980	2015	35	4.61	7.66	Migrant
<i>Garrulus glandarius</i>	1980	2015	35	2.43	5.14	Non-migrant
<i>Leiopicus medius</i>	1983	2015	32	-3.37	-17.78	Non-migrant
<i>Lophophanes cristatus</i>	1980	2015	35	5.62	6.54	Non-migrant
<i>Nucifraga caryocatactes</i>	1980	2015	35	0.57	0.53	Non-migrant
<i>Periparus ater</i>	1980	2015	35	3.04	4.92	Non-migrant
<i>Phoenicurus phoenicurus</i>	1980	2015	35	3.19	4.41	Migrant
<i>Phylloscopus bonelli</i>	1989	2015	26	3.12	4.37	Migrant
<i>Phylloscopus collybita</i>	1980	2015	35	0.52	3.18	Migrant
<i>Phylloscopus sibilatrix</i>	1980	2015	35	4.38	4.31	Migrant
<i>Picus canus</i>	1982	2015	33	-4.49	-7.92	Non-migrant
<i>Poecile montanus</i>	1980	2015	35	7.09	8.96	Non-migrant
<i>Poecile palustris</i>	1980	2015	35	3.91	5.92	Non-migrant
<i>Pyrrhula pyrrhula</i>	1980	2015	35	4.91	7.13	Non-migrant
<i>Regulus ignicapilla</i>	1982	2015	33	3.72	5.01	Non-migrant
<i>Regulus regulus</i>	1980	2015	35	3.89	6.83	Non-migrant
<i>Sitta europaea</i>	1980	2015	35	0.36	2.93	Non-migrant
<i>Spinus spinus</i>	1980	2015	35	1.84	3.71	Non-migrant
<i>Tringa ochropus</i>	1980	2015	35	3.29	4.14	Migrant
<i>Turdus viscivorus</i>	1980	2015	35	4.03	6.20	Non-migrant

b) Species omitted from Farmland Bird Index	First year	Last year	Span in years	Deviation in value from index in 2015 (%)	Difference in precision from index in 2015 (%)	Migratory status
<i>Alauda arvensis</i>	1980	2015	35	-1.04	1.2	Non-migrant
<i>Alectoris rufa</i>	1998	2015	17	0.33	0.13	Non-migrant
<i>Anthus campestris</i>	1991	2015	24	3.38	-19.47	Migrant
<i>Anthus pratensis</i>	1980	2015	35	0.1	4.38	Non-migrant
<i>Bubulcus ibis</i>	1998	2015	17	-0.65	-0.75	Non-migrant
<i>Burhinus oedicnemus</i>	1998	2015	17	-0.09	0.45	Non-migrant
<i>Calandrella brachydactyla</i>	1998	2015	17	-1.52	-2.47	Migrant

<i>Ciconia ciconia</i>	1980	2015	35	-5.95	-3.44	Migrant
<i>Corvus frugilegus</i>	1980	2015	35	-8.81	-9.96	Non-migrant
<i>Emberiza calandra</i>	1980	2015	35	0.59	4.74	Non-migrant
<i>Emberiza cirrus</i>	1989	2015	26	-4.15	-3.73	Non-migrant
<i>Emberiza citrinella</i>	1980	2015	35	-1.62	0.94	Non-migrant
<i>Emberiza hortulana</i>	1980	2015	35	3.9	6.07	Migrant
<i>Emberiza melanocephala</i>	2000	2015	15	-0.01	1.46	Migrant
<i>Falco tinnunculus</i>	1980	2015	35	-3.21	-1.2	Non-migrant
<i>Galerida cristata</i>	1982	2015	33	18.16	17.81	Non-migrant
<i>Galerida theklae</i>	1998	2015	17	-2.44	-1.59	Non-migrant
<i>Hirundo rustica</i>	1980	2015	35	-3.08	-1.56	Migrant
<i>Lanius collurio</i>	1980	2015	35	-1.81	-1.65	Migrant
<i>Lanius minor</i>	1999	2015	16	-0.68	0.26	Migrant
<i>Lanius senator</i>	1998	2015	17	-0.17	-1.33	Migrant
<i>Limosa limosa</i>	1984	2015	31	-0.75	2.34	Migrant
<i>Linaria cannabina</i>	1980	2015	35	-0.3	0.58	Non-migrant
<i>Lyrurus tetrix</i>	1998	2015	17	2.49	2.27	Non-migrant
<i>Melanocorypha calandra</i>	1998	2015	17	0.51	-1.1	Non-migrant
<i>Motacilla flava</i>	1980	2015	35	0.73	4.41	Migrant
<i>Oenanthe hispanica</i>	1998	2015	17	0.5	-0.65	Migrant
<i>Passer montanus</i>	1980	2015	35	0.49	4.8	Non-migrant
<i>Perdix perdix</i>	1980	2015	35	6.92	8.5	Non-migrant
<i>Petronia petronia</i>	1998	2015	17	-1.54	-1.36	Non-migrant
<i>Saxicola rubetra</i>	1980	2015	35	6.56	5.97	Migrant
<i>Saxicola torquatus</i>	1984	2015	31	-6.66	-7.69	Non-migrant
<i>Serinus serinus</i>	1982	2015	33	-1.29	-0.26	Non-migrant
<i>Streptopelia turtur</i>	1980	2015	35	2.13	5.06	Migrant
<i>Sturnus unicolor</i>	1998	2015	17	-1.36	-1.36	Non-migrant
<i>Sturnus vulgaris</i>	1980	2015	35	0.66	4.25	Non-migrant
<i>Sylvia communis</i>	1980	2015	35	-4.33	-2.56	Migrant
<i>Upupa epops</i>	1982	2015	33	-6.63	-30.53	Migrant
<i>Vanellus vanellus</i>	1980	2015	35	-1.56	3.15	Non-migrant

Supplementary Material

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