

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

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## **Key words:**

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

## **Abstract**

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

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

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

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

## **1. INTRODUCTION**

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

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

### **1.1 Reporting statistical uncertainty**

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

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

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

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

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

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

### **1.3 Species selection**

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

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

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

#### **1.4 Scope**

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

## **2. MATERIALS AND METHODS**

### **2.1 Trend estimation**

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

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

## **2.2 Estimating statistical uncertainty**

We use Monte Carlo procedures within the 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 associated CIs from annual species' indices and their *SEs*. Each available yearly index for each species is simulated by drawing from a normal distribution  $N(\mu, \sigma)$  with  $\mu$ =the natural logarithm of the index and  $\sigma$ =the *SE* of the index on the log scale. The tool calculates a mean and *SE* from 1000 simulated MSIs in each year and back-transforms these to an index scale, and repeats that process, here 10,000 times. Note that, although derived from the same data, index values for a given year calculated using this approach are likely to be marginally different to those calculated as the geometric mean of the constituent species' indices in each year (described above).

## **2.3 Benchmark year and quantifying trend**

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

## 2.3 Species selection

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



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

### **3. RESULTS**

#### **3.1 Estimating uncertainty**

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

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

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

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

### 3.3 Species selection

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

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

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

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

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

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

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

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

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

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

## 4. DISCUSSION

### 4.1 Population trends

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

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

#### **4.2 Reporting statistical uncertainty**

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

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

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

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

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

#### 4.4 Species selection

WBIs appear relatively robust to changes in species selection as the exclusion of individual species had relatively little influence on index characteristics and should not compromise their policy use, given recognised levels of variability and tolerances (e.g. UK government use a 5% threshold to evaluate the significance of change: [www.gov.uk/government/statistics/wild-bird-populations-in-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 whose inclusion lowers the Farmland Bird Index and reduces overall precision. Whilst smaller sample sizes for rarer species may increase the imprecision of trend estimates, the estimates themselves are not necessarily biased. The inclusion of rare species in an MSI needs careful consideration in terms of the accuracy and precision of the trend estimates, and whether such species are representative of the community the index describes. We show that species adding most imprecision also tend to have the greatest impact on the index values, so species selection should consider index precision alongside other factors. Rarity is also an issue if a species undergoes significant declines over time and it raises questions over whether it should continue to be included in an MSI. This is the case when a declining species becomes so rare that it cannot be monitored reliably (partly because one 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



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

## 5. CONCLUSIONS

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

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

## ACKNOWLEDGEMENTS

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## AUTHORS CONTRIBUTIONS

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

## DATA ACCESSIBILITY

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

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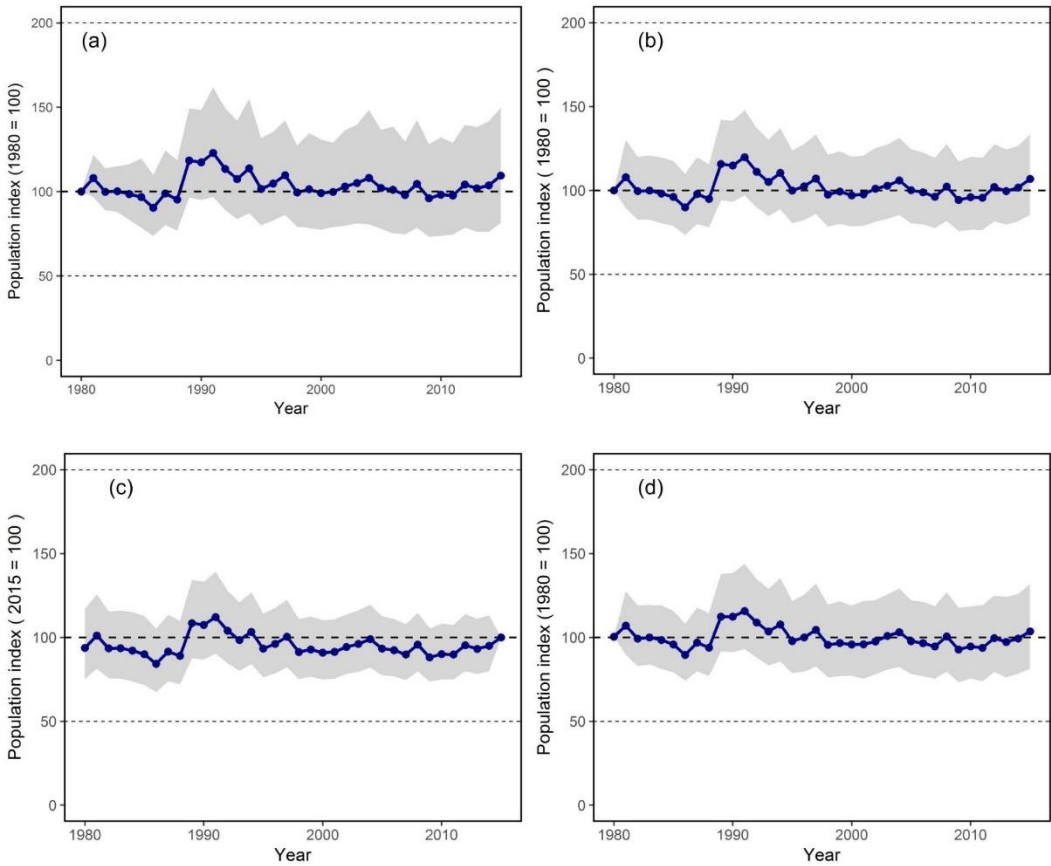
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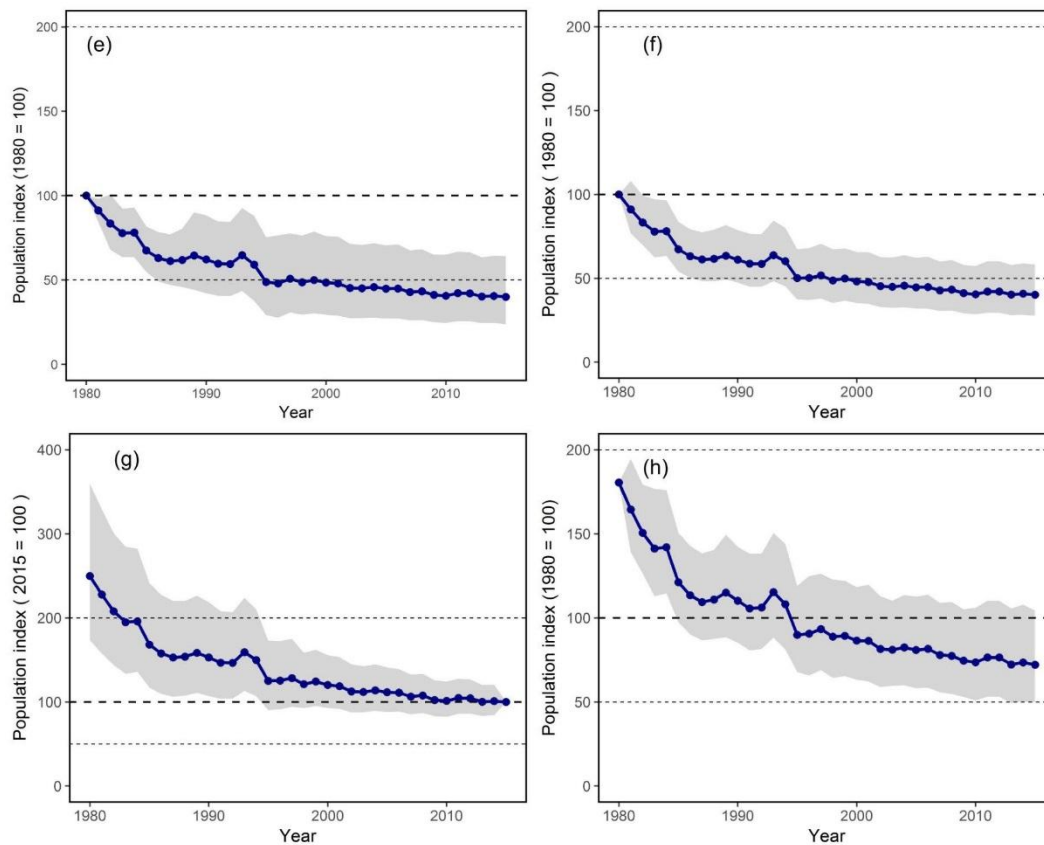
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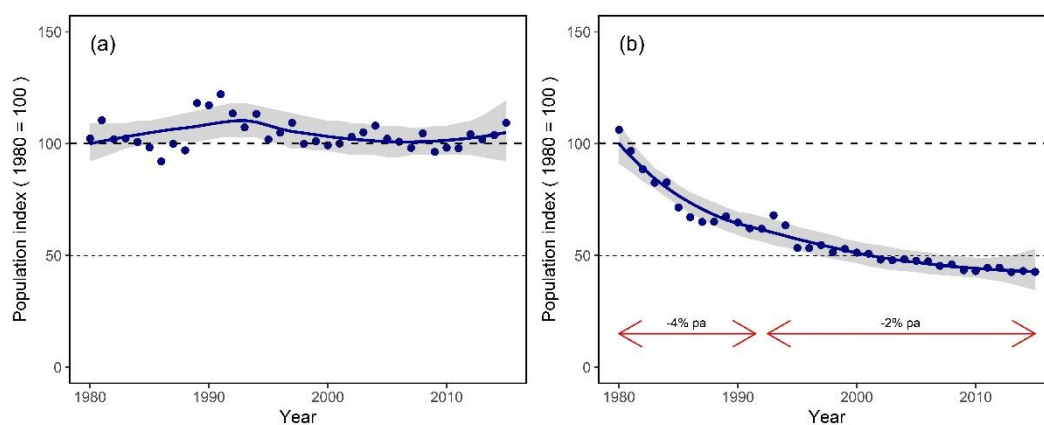
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**FIGURE 1** MSIs for European forest (a-d: n=34) and farmland bird species (e-h: n=39) with shaded 95% CIs calculated by bootstrapping (a, e), otherwise using the MSI-tool. Indices set to 100 ( $SE=0$ ) in 1980 in a, b, e and f. Indices set to 100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





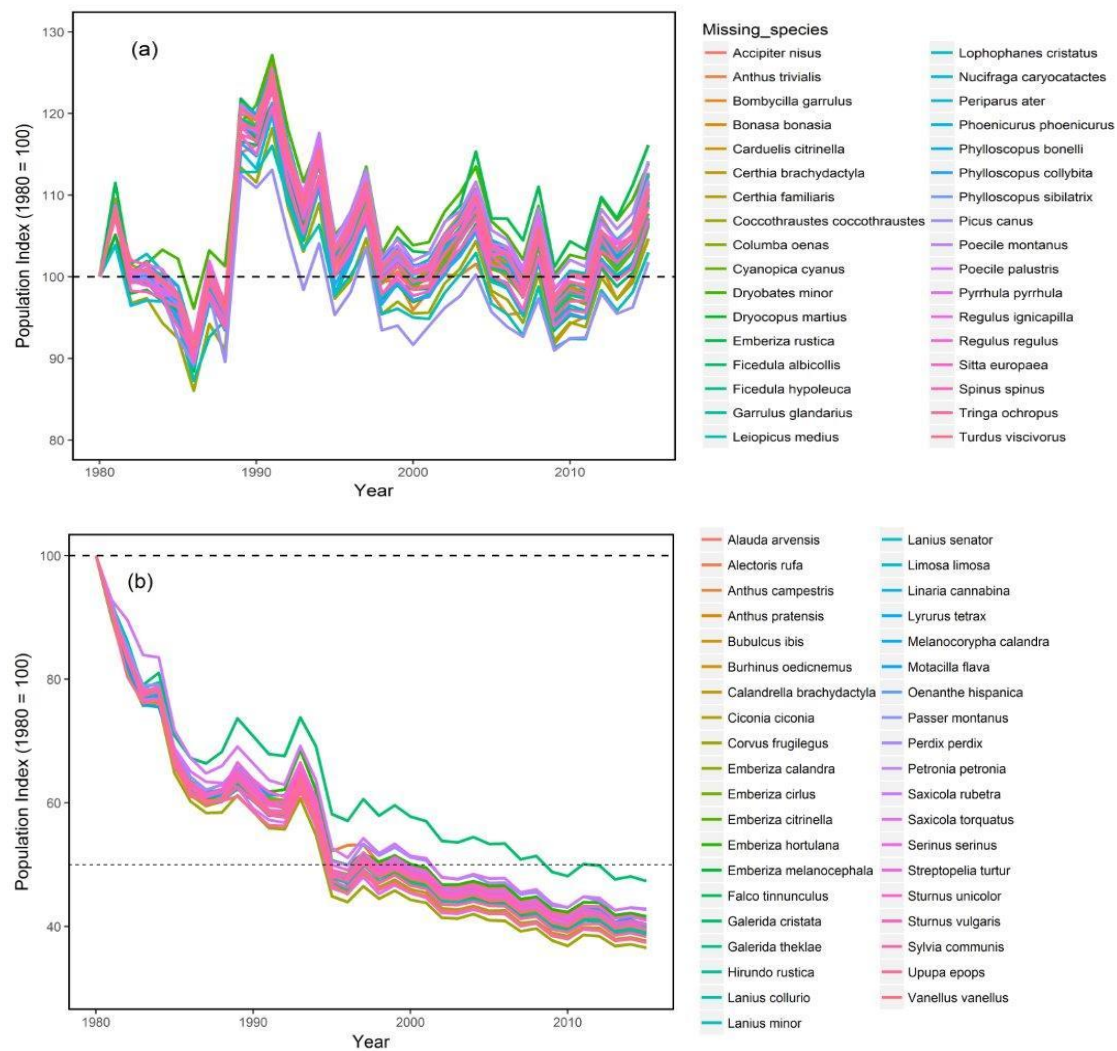
**FIGURE 2** Smoothed MSIs for (a) European forest ( $n=34$ ) and (b) farmland bird species ( $n=39$ ) with 95% CIs shaded. Indices set to 100 in 1980. The arrows in (b) indicate periods when there is a significant change detected in the trend.



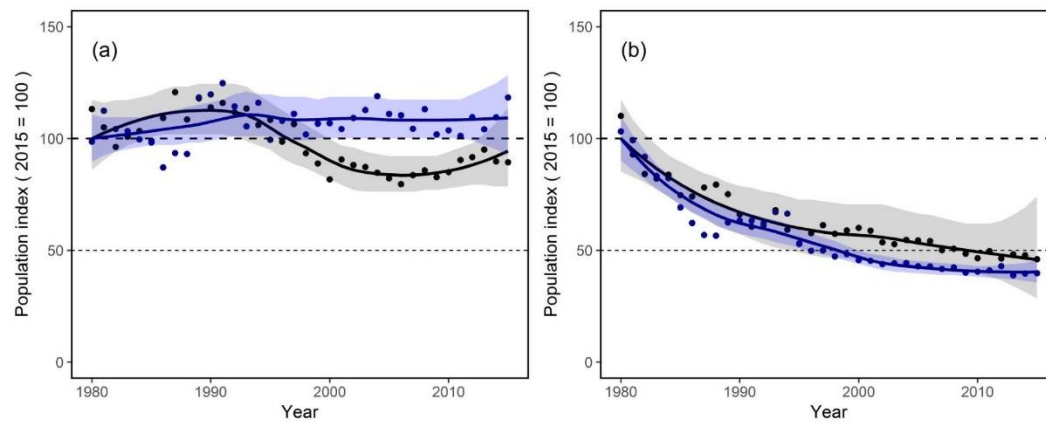
**FIGURE 3** MSIs constructed based upon species subsets leaving one species out at a time, (a) European forest bird indices constructed based upon 33 species subsets, and (b) farmland bird



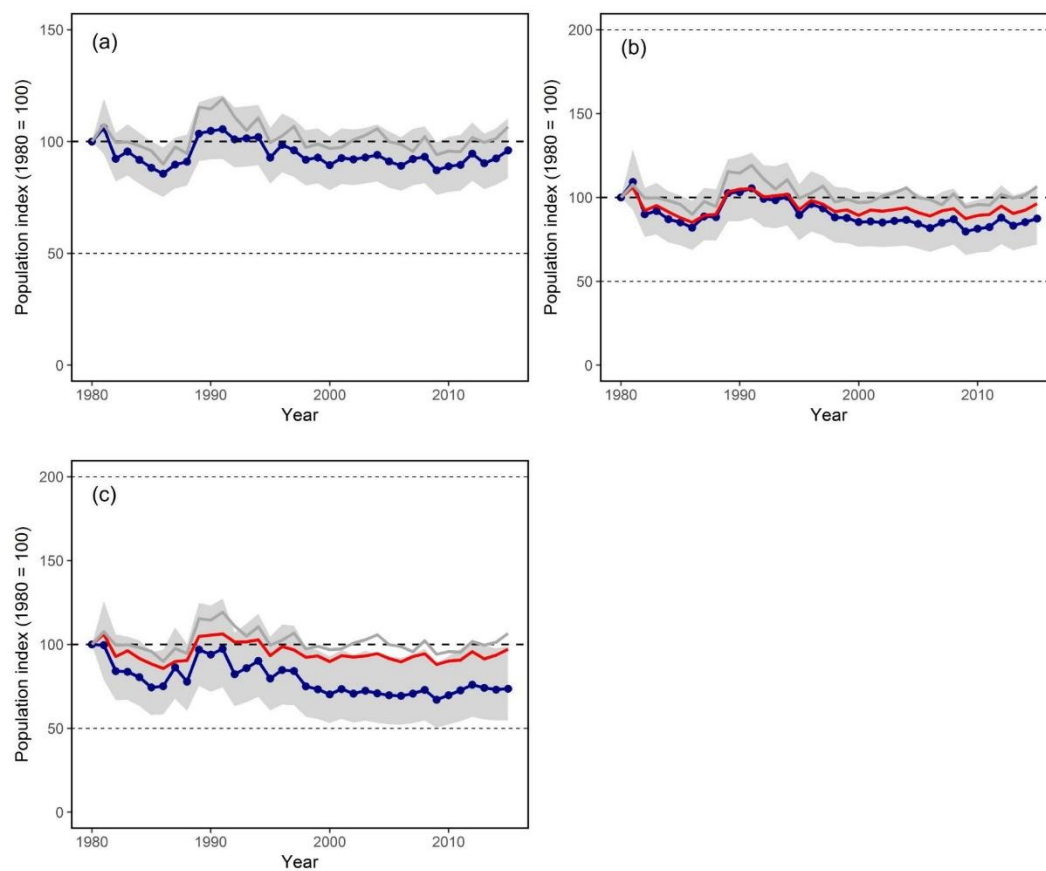
indices constructed based upon 38 species subsets. Species missing from each MSI is given in the legend. Indices are set to 100 in 1980.



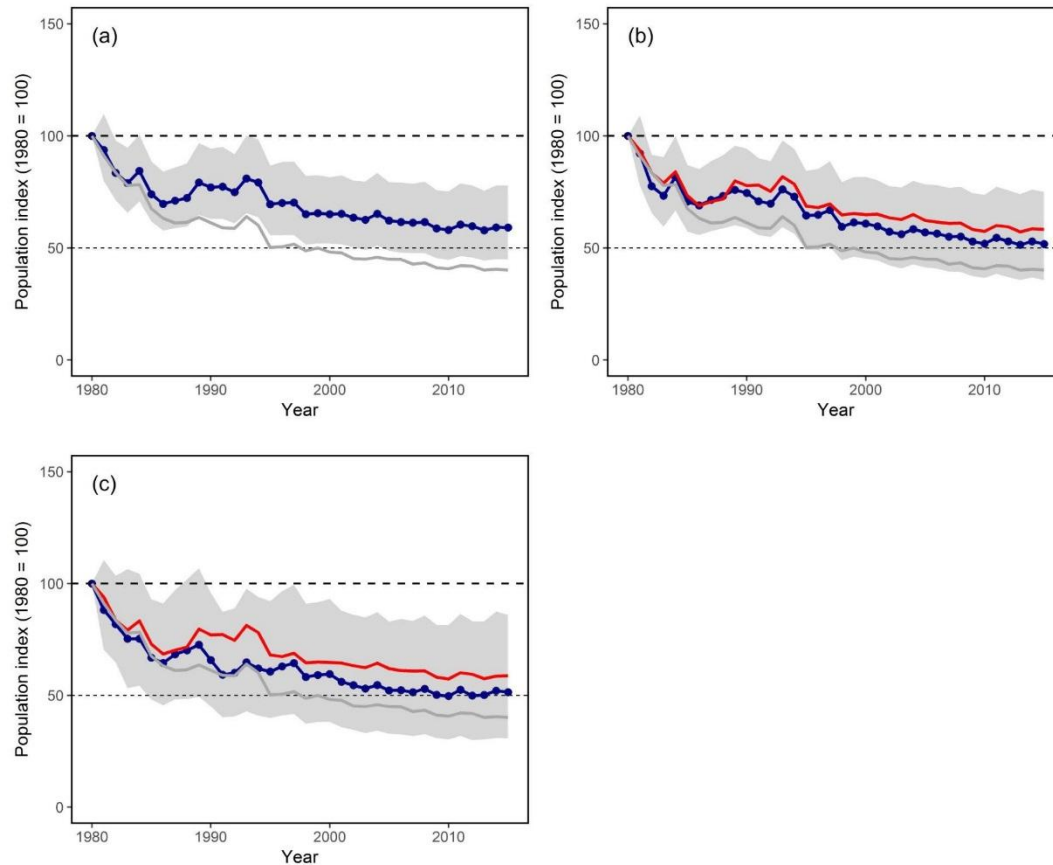
**FIGURE 4** Smoothed MSIs for long-distance migrants (black) versus residents and short-distance migrant birds (blue) for (a) forest (n=9 & 25 species respectively) and (b) farmland species (n=16 & 23 species respectively). Indices set to 100 in 1980 with shaded 95% CIs.



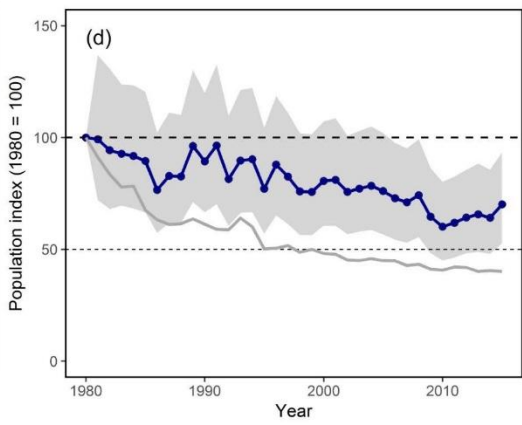
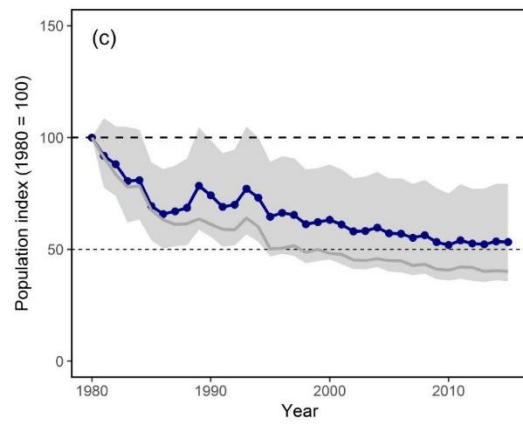
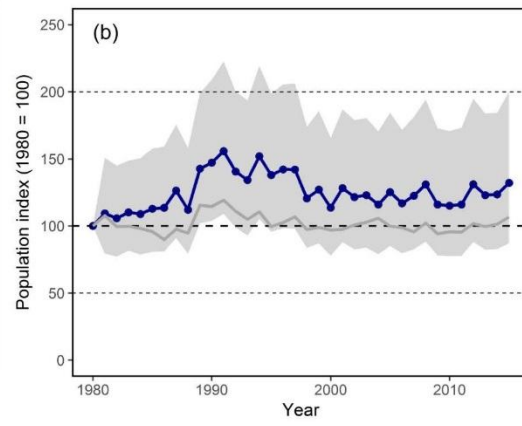
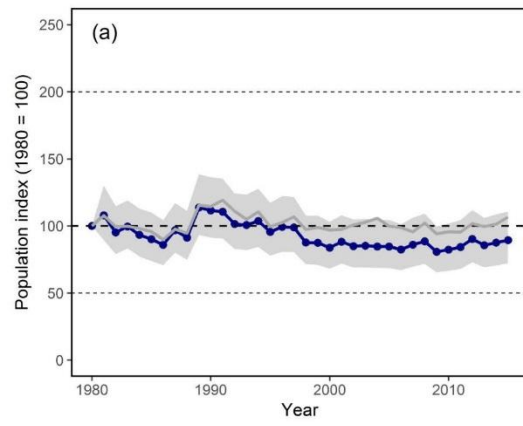
**FIGURE 5** MSIs for species associated with forest (a:  $n=60$ ), the top 2/3 (b:  $n=40$ ), and the top 1/3 of these species (c:  $n=20$ ) most sensitive to forest alteration. Grey line is the Forest Bird Index. Red lines are MSIs constructed by drawing with replacement random samples of 40 or 20 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.

<b>a) Species omitted from Forest Bird Index</b>	<b>First year</b>	<b>Last year</b>	<b>Span in years</b>	<b>Deviation in value from index in 2015 (%)</b>	<b>Difference in precision from index in 2015 (%)</b>	<b>Migratory status</b>
<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>b) Species omitted from Farmland Bird Index</b>	<b>First year</b>	<b>Last year</b>	<b>Span in years</b>	<b>Deviation in value from index in 2015 (%)</b>	<b>Difference in precision from index in 2015 (%)</b>	<b>Migratory status</b>
<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 oedicephalus</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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