2	analysis of trends, uncertainty and species selection
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Contrasting trends of widespread forest and farmland birds in Europe: an

Abstract

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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. Policy implications. 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 a number of 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 for European birds, using population data from 18 national annual breeding bird surveys. The composite indices revealed a pattern of decline in common farmland bird populations, but relative stability in common European birds associated with woodlands. This work has been extended (Gregory et al. 2007; Gregory & van Strien 2010), 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).

1.1 Reporting statistical uncertainty

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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 SEs of individual species' trends to estimate standard errors (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 time series with a SE of zero in that year, with error in subsequent years related to that benchmark, thus making the magnitude of change in the index over the time series immediately obvious (e.g. halving index=50, doubling index=200). 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 & Lehikoinen 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 2). 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 μ =the natural logarithm of the index and σ =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

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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 (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 of 6.6% between 1980 and 2015, while the Farmland Bird Index showed a significant decline of nearly 60% over this period (Fig. 1a,e). Trends of the Forest and Farmland Bird Indices 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 (~4% pa), to a lesser rate recently (~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), reflecting that fact that 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 ρ =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 from the Farmland Bird Index 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 ρ =0.62, P<0.0001).

Exclusion of individual LDM forest species tends to push the trajectory of the MSI upwards slightly (Table 2a) 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_{22} =-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_{22} =1.30, p=0.21).

MSIs for the LDM and RSDM species are broadly similar, but some differences are evident (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 small number of LDMs makes interpretation difficult. 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 farmland LDMs is significantly more negative than that for farmland 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 and shows a marginal but non-significant decline (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) but it is again non-significant 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 on the basis of their specialism 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 this decline 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, the differences are modest and 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 negative than the Farmland Bird Index (difference=0.007, *SE*=0.003 & difference=0.011, *SE*=0.003 respectively, both P<0.05). Note the wide CIs linked to the small number of species in the indices 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 more (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).

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. Given that the two methods convey quite different, but complementary, information about uncertainty around the indices, we see merit in presenting MSIs with each type of error, as long as any resulting differences in inference are explained. However, we recommend the use of the MSI-tool, where possible, to test for statistical change in MSIs.

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).

4.4 Species selection

WBIs appear relatively robust to species selection, with similar patterns of change identified by the various different methods we explored. In general, the exclusion of individual species from the WBIs had relatively little influence on index characteristics. The exception was G. cristata, a rapidly declining species whose inclusion both significantly lowers the Farmland Bird Index and reduces overall precision. Whilst smaller samples sizes for rarer species may increase the imprecision of trend estimates, the estimates themselves may not necessarily be biased. The inclusion of rare species in an MSI therefore 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, which suggests that species selection should consider the precision of species' indices, alongside other factors. Rarity can also impact on index characteristics if a species undergoes significant declines over time and raises questions over whether such a species should continue to be included in an MSI or be removed. This is particularly pertinent when a declining species becomes so rare it cannot be monitored reliably and continued inclusion in an index becomes problematic (partly because one cannot take a geometric mean of zero). The MSI-tool overcomes this problem by fixing the lowest index value to one, and other programmes do similar (e.g. Collen et al. 2009). Renwick et al. (2012) showed that the WBIs were sensitive to the exclusion of rarer, often declining species, and their exclusion from a woodland bird index in England led to more positive trends. So excluding a rapidly declining (or increasing) species from an index can be problematic and create bias, but some limits may need to be set in terms of precision. In the case of G. cristata, there is no compelling reason to remove the species, though its impact on index precision is a concern, and independent evidence suggests that the population of this species has collapsed in Europe (BirdLife International 2017).

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We show that LDMs do not overly influence the WBIs, although their population trends were slightly more negative. Somveille et al. (2013) show that the proportion of migratory bird species in communities follows a strong latitudinal gradient globally, increasing with latitude. Some 37% of

species covered by the PECBMS are LDMs and they represent an important component of breeding bird communities in Europe. Their inclusion within the indices seems appropriate though it is sensible to check that their trends, likely driven by factors inside and outside Europe, do not drive change in the MSIs.

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MSIs containing subsets of forest or farmland species judged to be more sensitive to environmental change showed slightly greater declines, as you might predict (Clavel, Julliard & Devictor 2011), but differences from current WBIs were modest (Figs. 5-6). Species selection for current indices was based on expert opinion that prioritised specialists and Reif, Jiguet & Šťastný (2010) showed that expert assessment of species' specialization is highly correlated with independent quantitative measures, so this is perhaps unsurprising. However, the case for adopting more objective species selection approaches remains. Renwick et al. (2012) identified species selection based on expert opinion as one of the main weaknesses of WBIs and previous research suggests that indices selected in this manner may not be representative of wider bird communities (Butler et al. 2012; Wade et al. 2014). Whilst basing species selection on a more formal ranking of specialisation imposes a degree of objectivity to the selection process, this still does not ensure full representativeness in the resultant indicator. We therefore recommend adopting systematic approaches that impose the required characteristics of reactivity, representativeness and predictability of response on MSIs (Gregory et al 2005). For example, the SpecSel algorithm we applied here prioritises representativeness over maximising the specialisation 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 species set with lowest sensitivity outperformed the breakpoint set, which proved to more variable and uncertain (Fig. 7). Although these MSIs were quite similar to current WBIs (Fig. 7), and Renwick et al. (2012) showed that trends in WBIs based upon objective selection were actually very similar to the existing trends, we suggest adopting such formal approaches improves MSI utility, makes species

selection more defendable and should ensure a level of future-proofing in terms of MSI reactivity to novel environmental change.

5. CONCLUSIONS

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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 nonrepresentative 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. Cls 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.

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418	
419	AUTHORS CONTRIBUTIONS
420	RDG led the study, indicator analyses and writing, JS and PV computed the species' indices, PV and
421	SB contributed to the study design and shaped analyses; all helped write and approved the final
422	paper.
423	
424	DATA ACCESSIBILITY
425	Data available from https://pecbms.info/use-of-the-results/data-access-policy/).
426	
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511	
512	FIGURE 1 MSIs for European forest (a-d: n=34) and farmland bird species (e-h: n=39) with shaded
513	95% CIs calculated by bootstrapping (a, e), otherwise using the MSI-tool. Indices set to 100 (SE=0) in
514	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
515	(SE=0 in 1980) in d and h.

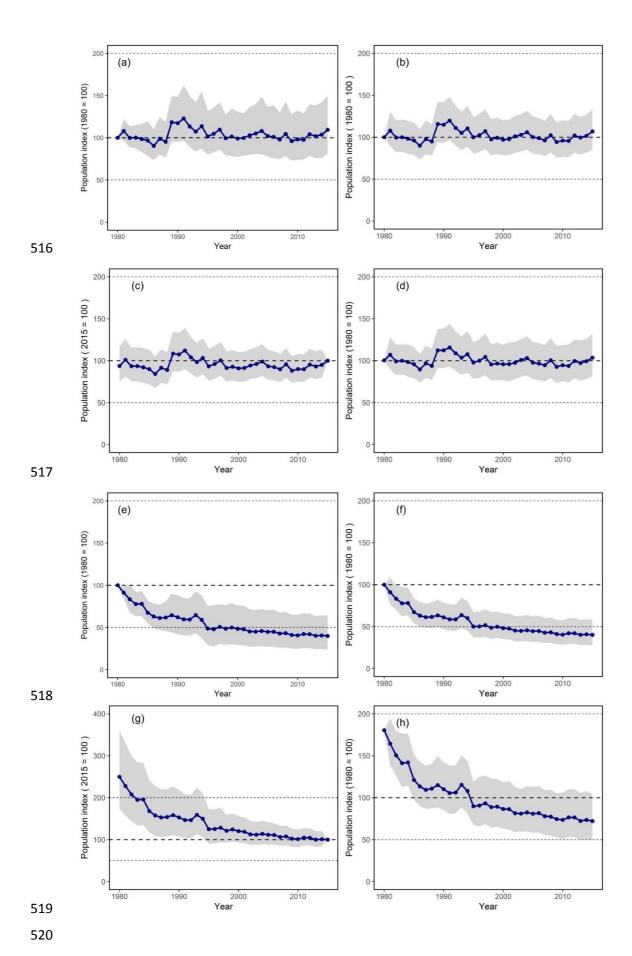


FIGURE 2 Smoothed MSIs for (a) European forest (n=34) and (b) farmland bird species (n=39) with 95% CIs shaded. Indices set to 100 in 1980. The arrows in (b) indicate periods when there is a significant change detected in the trend.

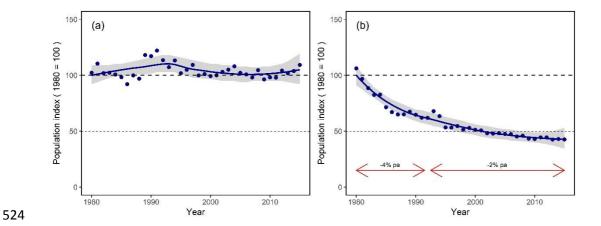
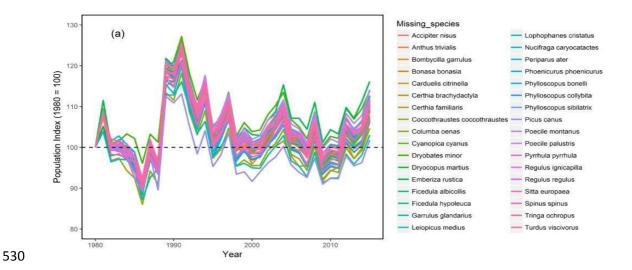


FIGURE 3 MSIs constructed based upon species subsets leaving one species out at a time, (a)

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.



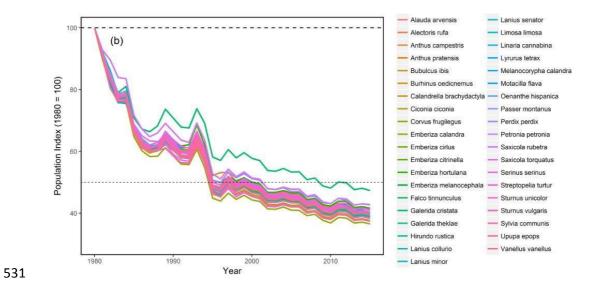


FIGURE 4 Smoothed MSIs for long-distance migrants (black) versus residents and short-distance migrant birds (blue) for (a) forest (n=9 & 25 species respectively) and (b) farmland species (n=16 & 23 species respectively). Indices set to 100 in 1980 with shaded 95% CIs.

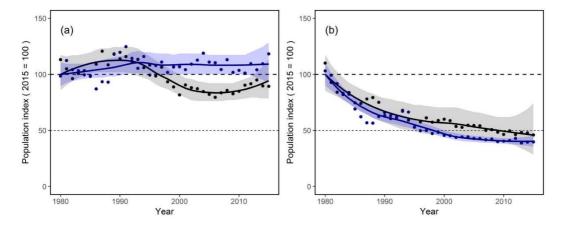


FIGURE 5 MSIs for species associated with forest (a: n=60), the top 2/3 (b: n=40), and the top 1/3 of these species (c: n=20) most sensitive to forest alteration. Grey line is the Forest Bird Index. Red lines are MSIs constructed by drawing with replacement random samples of 40 or 20 species from the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

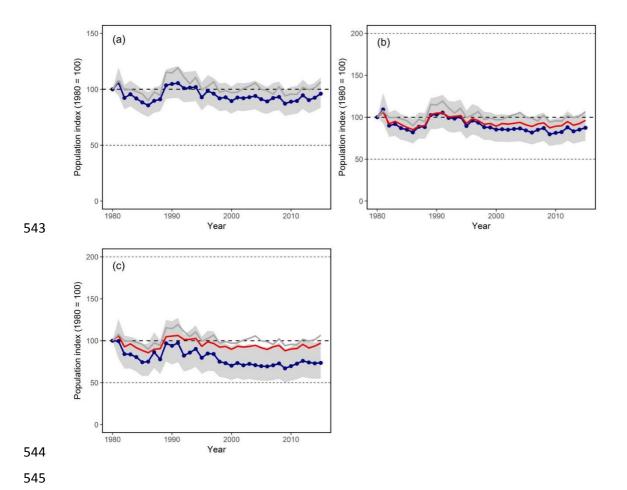
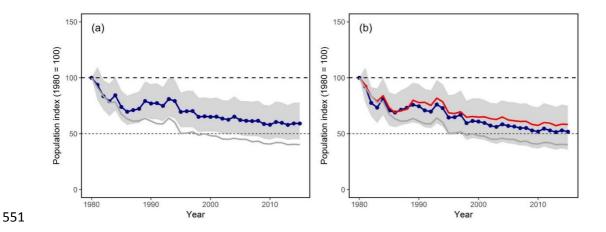


FIGURE 6 MSIs for a group of species associated with farmland (a: n=54), the top 2/3 (b: n=36), and the top 1/3 (c: n=18) of these species most sensitive to farmland alteration. Grey line shows the Farmland Bird Index. Red lines are MSIs constructed by drawing with replacement random samples of 36 or 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.



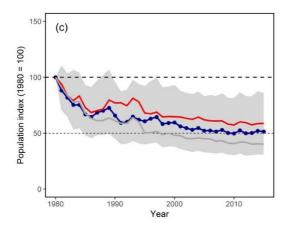


FIGURE 7 MSIs for forest (a-b) and farmland birds (c-d) with species selected according to a species' selection algorithm. This identifies the species set with the lowest overall sensitivity (a=31 forest species & c=23 farmland species), and the optimal breakpoint set covering all resources (b=14 forest 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).

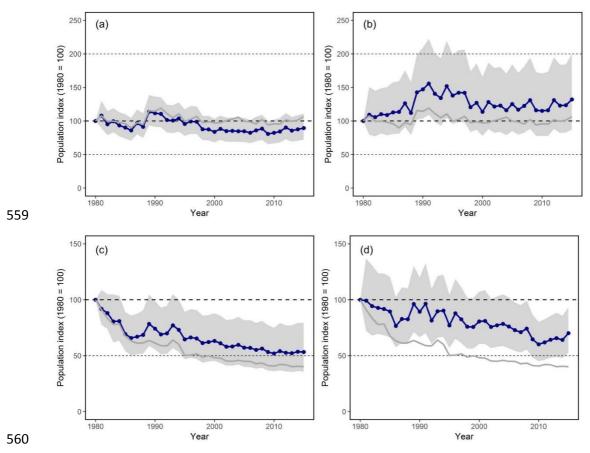


Table 1. Analysis of the impact of excluding individual species from (a) the Forest and (b) the Farmland Bird Indices.

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
Accipiter nisus	1980	2015	35	2.43	2.08	Non-migrant
Anthus trivialis	1980	2015	35	5.79	7.00	Migrant
Bombycilla garrulus	1988	2015	27	-0.36	-1.76	Non-migrant
Bonasa bonasia	1980	2015	35	5.47	6.35	Non-migrant
Carduelis citrinella	1999	2015	16	2.38	3.23	Non-migrant
Certhia brachydactyla	1982	2015	33	2.8	4.80	Non-migrant
Certhia familiaris	1980	2015	35	3.36	5.62	Non-migrant
Coccothraustes coccothraustes	1980	2015	35	-1.8	-5.67	Non-migrant
Columba oenas	1980	2015	35	2.06	5.28	Non-migrant
Cyanopica cyanus	1998	2015	17	1.09	1.27	Non-migrant
Dryobates minor	1980	2015	35	6.82	7.32	Non-migrant
Dryocopus martius	1980	2015	35	0.11	2.04	Non-migrant
Emberiza rustica	1980	2015	35	8.96	10.17	Migrant
Ficedula albicollis	1982	2015	33	-0.09	1.44	Migrant
Ficedula hypoleuca	1980	2015	35	4.61	7.66	Migrant
Garrulus glandarius	1980	2015	35	2.43	5.14	Non-migrant
Leiopicus medius	1983	2015	32	-3.37	-17.78	Non-migrant
Lophophanes cristatus	1980	2015	35	5.62	6.54	Non-migrant
Nucifraga caryocatactes	1980	2015	35	0.57	0.53	Non-migrant
Periparus ater	1980	2015	35	3.04	4.92	Non-migrant
Phoenicurus phoenicurus	1980	2015	35	3.19	4.41	Migrant
Phylloscopus bonelli	1989	2015	26	3.12	4.37	Migrant
Phylloscopus collybita	1980	2015	35	0.52	3.18	Migrant
Phylloscopus sibilatrix	1980	2015	35	4.38	4.31	Migrant
Picus canus	1982	2015	33	-4.49	-7.92	Non-migrant
Poecile montanus	1980	2015	35	7.09	8.96	Non-migrant
Poecile palustris	1980	2015	35	3.91	5.92	Non-migrant
Pyrrhula pyrrhula	1980	2015	35	4.91	7.13	Non-migrant
Regulus ignicapilla	1982	2015	33	3.72	5.01	Non-migrant

Regulus regulus	1980	2015	35	3.89	6.83	Non-migrant
Sitta europaea	1980	2015	35	0.36	2.93	Non-migrant
Spinus spinus	1980	2015	35	1.84	3.71	Non-migrant
Tringa ochropus	1980	2015	35	3.29	4.14	Migrant
Turdus viscivorus	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
Alauda arvensis	1980	2015	35	-1.04	1.2	Non-migrant
Alectoris rufa	1998	2015	17	0.33	0.13	Non-migrant
Anthus campestris	1991	2015	24	3.38	-19.47	Migrant
Anthus pratensis	1980	2015	35	0.1	4.38	Non-migrant
Bubulcus ibis	1998	2015	17	-0.65	-0.75	Non-migrant
Burhinus oedicnemus	1998	2015	17	-0.09	0.45	Non-migrant
Calandrella brachydactyla	1998	2015	17	-1.52	-2.47	Migrant
Ciconia ciconia	1980	2015	35	-5.95	-3.44	Migrant
Corvus frugilegus	1980	2015	35	-8.81	-9.96	Non-migrant
Emberiza calandra	1980	2015	35	0.59	4.74	Non-migrant
Emberiza cirlus	1989	2015	26	-4.15	-3.73	Non-migrant
Emberiza citrinella	1980	2015	35	-1.62	0.94	Non-migrant
Emberiza hortulana	1980	2015	35	3.9	6.07	Migrant
Emberiza melanocephala	2000	2015	15	-0.01	1.46	Migrant
Falco tinnunculus	1980	2015	35	-3.21	-1.2	Non-migrant
Galerida cristata	1982	2015	33	18.16	17.81	Non-migrant
Galerida theklae	1998	2015	17	-2.44	-1.59	Non-migrant
Hirundo rustica	1980	2015	35	-3.08	-1.56	Migrant
Lanius collurio	1980	2015	35	-1.81	-1.65	Migrant
Lanius minor	1999	2015	16	-0.68	0.26	Migrant
Lanius senator	1998	2015	17	-0.17	-1.33	Migrant
Limosa limosa	1984	2015	31	-0.75	2.34	Migrant

Linaria cannabina	1980	2015	35	-0.3	0.58	Non-migrant
Lyrurus tetrax	1998	2015	17	2.49	2.27	Non-migrant
Melanocorypha calandra	1998	2015	17	0.51	-1.1	Non-migrant
Motacilla flava	1980	2015	35	0.73	4.41	Migrant
Oenanthe hispanica	1998	2015	17	0.5	-0.65	Migrant
Passer montanus	1980	2015	35	0.49	4.8	Non-migrant
Perdix perdix	1980	2015	35	6.92	8.5	Non-migrant
Petronia petronia	1998	2015	17	-1.54	-1.36	Non-migrant
Saxicola rubetra	1980	2015	35	6.56	5.97	Migrant
Saxicola torquatus	1984	2015	31	-6.66	-7.69	Non-migrant
Serinus serinus	1982	2015	33	-1.29	-0.26	Non-migrant
Streptopelia turtur	1980	2015	35	2.13	5.06	Migrant
Sturnus unicolor	1998	2015	17	-1.36	-1.36	Non-migrant
Sturnus vulgaris	1980	2015	35	0.66	4.25	Non-migrant
Sylvia communis	1980	2015	35	-4.33	-2.56	Migrant
<i>Upupa epops</i>	1982	2015	33	-6.63	-30.53	Migrant
Vanellus vanellus	1980	2015	35	-1.56	3.15	Non-migrant

SUPPLEMENTARY MATERIALS

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Text S1

Bird population trends came from the PECBMS (https://pecbms.info/). In brief, project coordinators in 28 European countries calculated species' indices from national breeding bird surveys using standardised software (Table S3). Sample surveys record all bird species encountered but are less likely to cover rare species, so trends are for the commoner and more widespread birds. A sample of sites is counted annually (from hundreds to thousands per country) using well-established methods that measure the relative abundance of bird species in the breeding season (Table S2). Schemes differ in how the sample plots are selected, varying from free choice of plots by observers, to systematic and stratified-random choice, and national programmes have operated for different periods. National species' trends are estimated annually using Poisson regression (a GLM model; McCullagh & Nelder 1989), implemented in the https://www.cbs.nl/en-gb/society/nature-andenvironment/indices-and-trends--trim--: (Pannekoek & van Strien 2005), which corrects for overdispersion and serial correlation using Generalised Estimating Equations (McCullagh & Nelder 1989). These are then combined in a hierarchical fashion to produce supranational species' indices using a weighting factor based on the estimated national population size for each species, which means that a change in a larger national population has greater impact on the overall index than a change in a smaller population. Full methodological details of index production are available from the EBCC website (https://pecbms.info/) and all European species' indices and the European/EU multispecies indices are freely available to view and download from this site. Taxonomy follows the HBW and BirdLife International's Illustrated Checklist of the Birds of the World (http://datazone.birdlife.org/species/taxonomy). References

McCullagh, P. & J.A. Nelder, (1989) Generalized Linear Models, 2nd edition. Chapman and Hall, London.

Pannekoek, J. & van Strien, A.J. (2005) TRIM 3 Manual. Trends and Indices for Monitoring Data. CBS
 Voorburg, Statistics Netherlands, The Netherlands.

Table S1 – Links to the policy use of the Wild Bird Indices in Europe

597	Eurostat - Eurobase datasets:
598	http://ec.europa.eu/eurostat/en/web/products-datasets/-/ENV_BIO3
599	http://appsso.eurostat.ec.europa.eu/nui/show.do?dataset=env_bio3⟨=en
600	http://appsso.eurostat.ec.europa.eu/nui/show.do?dataset=env_bio2⟨=en
601	http://ec.europa.eu/eurostat/web/sdi/life-on-land
602	Eurostat - Statistics explained:
603 604	http://ec.europa.eu/eurostat/statistics-explained/index.php?title=Agri-environmental_indicator _population_trends_of_farmland_birds
605 606	http://ec.europa.eu/eurostat/statistics- explained/index.php?title=Archive:Sustainable_development - natural_resources
607	http://ec.europa.eu/eurostat/statistics-explained/index.php/Biodiversity_statistics
608	Statistical books and pocketbooks:
609 610	http://ec.europa.eu/eurostat/documents/3217494/8461633/KS-04-17-780-EN-N.pdf/f7694981-6190-46fb-99d6-d092ce04083f
611 612	http://ec.europa.eu/eurostat/documents/3217494/7735275/KS-06-16-212-EN-N.pdf/8a304ba5- 588a-4cf6-8549-8d000aafc342
613 614	http://ec.europa.eu/eurostat/documents/3217494/8435375/KS-DK-17-001-EN-N.pdf/18d1ecfd-acd8-4390-ade6-e1f858d746da
615 616	http://ec.europa.eu/eurostat/documents/3217494/6975281/KS-GT-15-001-EN-N.pdf/5a20c781- e6e4-4695-b33d-9f502a30383f

Table S2 Species classification. The table indicates whether each species is included in the current indicator set, whether they are long-distance migrants or either short-distance migrants or residents, whether they are broadly associated with either habitat, and whether they are identified in the *BREAKPOINT* or *SENSITIVE* species sets according to the resources they use in that habitat (see text).

	Indicator species	Migratory status	Associated habitat	Breakpoint set	Sensitive set
Acanthis flammea			Forest		

Accipiter nisus	Forest	Non-migrant	Forest	Yes	Yes
Acrocephalus palustris			Agriculture/grassland		
Aegithalos caudatus			Forest		
Alauda arvensis	Farmland	Non-migrant	Agriculture/grassland		
Alectoris rufa	Farmland	Non-migrant			
Anthus campestris	Farmland	Migrant	Agriculture/grassland		
Anthus pratensis	Farmland	Non-migrant	Agriculture/grassland		Yes
Anthus trivialis	Forest	Migrant	Forest		Yes
Bombycilla garrulus	Forest	Non-migrant			
Bonasa bonasia	Forest	Non-migrant	Forest		Yes
Bubulcus ibis	Farmland	Non-migrant			
Burhinus oedicnemus	Farmland	Non-migrant	Agriculture/grassland		Yes
Buteo buteo			Forest	Yes	Yes
Calandrella brachydactyla	Farmland	Migrant	Agriculture/grassland		Yes
Carduelis citrinella	Forest	Non-migrant			
Certhia brachydactyla	Forest	Non-migrant	Forest		
Certhia familiaris	Forest	Non-migrant	Forest		
Cettia cetti			Agriculture/grassland		
Chloris chloris			Forest & Agriculture/grassland		
Ciconia ciconia	Farmland	Migrant	Agriculture/grassland		Yes
Cisticola juncidis			Agriculture/grassland		
Coccothraustes coccothraustes	Forest	Non-migrant	Forest	Yes	Yes
Columba oenas	Forest	Non-migrant	Forest		
Columba palumbus			Forest & Agriculture/grassland		
Corvus corone			Agriculture/grassland		
Corvus frugilegus	Farmland	Non-migrant	Agriculture/grassland		
Corvus monedula			Agriculture/grassland		
Cuculus canorus			Forest		
Cyanistes caeruleus			Forest		
Cyanopica cyanus	Forest	Non-migrant			
Dendrocopos major			Forest	Yes	Yes
Dryobates minor	Forest	Non-migrant	Forest		Yes

Dryocopus martius	Forest	Non-migrant	Forest		
Emberiza calandra	Farmland	Non-migrant	Agriculture/grassland		Yes
Emberiza cirlus	Farmland	Non-migrant	Agriculture/grassland		Yes
Emberiza citrinella	Farmland	Non-migrant	Agriculture/grassland		Yes
Emberiza hortulana	Farmland	Migrant	Agriculture/grassland		
Emberiza melanocephala	Farmland	Migrant			
Emberiza rustica	Forest	Migrant	Forest	Yes	Yes
Emberiza schoeniclus			Agriculture/grassland		
Erithacus rubecula			Forest		
Falco tinnunculus	Farmland	Non-migrant	Agriculture/grassland	Yes	Yes
Ficedula albicollis	Forest	Migrant	Forest	Yes	Yes
Ficedula hypoleuca	Forest	Migrant	Forest		Yes
Fringilla coelebs			Forest		
Galerida cristata	Farmland	Non-migrant	Agriculture/grassland		
Galerida theklae	Farmland	Non-migrant	Agriculture/grassland		
Gallinago gallinago			Agriculture/grassland	Yes	Yes
Garrulus glandarius	Forest	Non-migrant	Forest		
Hippolais icterina			Forest		Yes
Hippolais polyglotta			Forest & Agriculture/grassland		Yes
Hirundo rustica	Farmland	Migrant	Agriculture/grassland		Yes
Jynx torquilla			Forest		Yes
Lanius collurio	Farmland	Migrant	Agriculture/grassland	Yes	Yes
Lanius minor	Farmland	Migrant			
Lanius senator	Farmland	Migrant	Agriculture/grassland		
Leiopicus medius	Forest	Non-migrant	Forest	Yes	Yes
Limosa limosa	Farmland	Migrant	Agriculture/grassland		Yes
Linaria cannabina	Farmland	Non-migrant	Agriculture/grassland		
Locustella fluviatilis			Forest		
Locustella naevia			Agriculture/grassland		
Lophophanes cristatus	Forest	Non-migrant	Forest	Yes	Yes
Lullula arborea			Forest		
Lullula arborea			Agriculture/grassland		

Luscinia megarhynchos			Forest		Yes
Lyrurus tetrix	Farmland	Non-migrant	Forest	Yes	Yes
Melanocorypha calandra	Farmland	Non-migrant	Agriculture/grassland		Yes
Merops apiaster			Agriculture/grassland		
Motacilla alba			Agriculture/grassland		
Motacilla flava	Farmland	Migrant	Agriculture/grassland		Yes
Muscicapa striata			Forest		Yes
Nucifraga caryocatactes	Forest	Non-migrant	Forest	Yes	Yes
Oenanthe hispanica	Farmland	Migrant	Agriculture/grassland		
Oenanthe oenanthe			Agriculture/grassland		
Oriolus oriolus			Forest	Yes	Yes
Parus major			Forest		
Passer domesticus			Agriculture/grassland		
Passer montanus	Farmland	Non-migrant	Agriculture/grassland		
Perdix perdix	Farmland	Non-migrant	Agriculture/grassland		Yes
Periparus ater	Forest	Non-migrant	Forest		Yes
Petronia petronia	Farmland	Non-migrant	Agriculture/grassland		
Phoenicurus phoenicurus	Forest	Migrant	Forest		
Phylloscopus bonelli	Forest	Migrant	Forest		Yes
Phylloscopus collybita	Forest	Migrant	Forest		
Phylloscopus sibilatrix	Forest	Migrant	Forest		Yes
Phylloscopus trochilus			Forest		
Pica pica			Agriculture/grassland		
Picus canus	Forest	Non-migrant	Forest		
Picus viridis			Forest		
Poecile montanus	Forest	Non-migrant	Forest		
Poecile palustris	Forest	Non-migrant	Forest		
Prunella modularis			Forest		
Pyrrhula pyrrhula	Forest	Non-migrant	Forest	Yes	Yes
Regulus ignicapilla	Forest	Non-migrant	Forest		Yes
Regulus regulus	Forest	Non-migrant	Forest		Yes
Saxicola rubetra	Farmland	Migrant	Agriculture/grassland		Yes
Saxicola torquatus	Farmland	Non-migrant	Agriculture/grassland		Yes

Serinus serinus	Farmland	Non-migrant	Forest & Agriculture/grassland	Yes	
Sitta europaea	Forest	Non-migrant	Forest		Yes
Spinus spinus	Forest	Non-migrant	Forest		Yes
Streptopelia turtur	Farmland	Migrant	Agriculture/grassland		Yes
Sturnus unicolor	Farmland	Non-migrant	Agriculture/grassland		
Sturnus vulgaris	Farmland	Non-migrant	Agriculture/grassland		
Sylvia atricapilla			Forest		
Sylvia borin			Forest		Yes
Sylvia communis	Farmland	Migrant	Agriculture/grassland		Yes
Sylvia curruca			Agriculture/grassland		
Tringa ochropus	Forest	Migrant			
Troglodytes troglodytes			Forest	Yes	Yes
Turdus iliacus			Forest		
Turdus merula			Forest	Yes	Yes
Turdus philomelos			Forest		
Turdus pilaris			Agriculture/grassland	Yes	Yes
Turdus viscivorus	Forest	Non-migrant	Forest		
	Farmland	Migrant	Agriculture/grassland		Yes
Vanellus vanellus	Farmland	Non-migrant	Agriculture/grassland		Yes

Table S3 – European data sources and survey designs. Regional grouping and biogeographical region: WE - West Europe ~ Atlantic region, NE - North Europe ~ Boreal region, SE - South Europe ~ Mediterranean region, CEE - Central & East Europe ~ Continental region, Miscellaneous countries: Southeast, East Mediterranean and West Balkan. First year = first year of data time series in a country/region (data available to PECBMS). Last year = last year of data time series in a country/region (data available to PECBMS).

Country/region	Region(group of countries)	Sampling design	Field method	First year	Last year
Austria	WE	Free choice	Point counts	1998	2015
Belgium-Brussels	WE	Stratified random	Point counts	1992	2015
Belgium-Wallonia	WE	Free choice	Point counts	1990	2015
Bulgaria	Southeast Europe	Stratified random	Line transect	2005	2015

		Free choice-	Line transect		
Cyprus	East Mediterranean	Stratified random		2006	2015
Czech Republic	CEE	Free choice	Point counts	1982	2015
Denmark	WE	Free choice	Point counts	1976	2015
Estonia	CEE	Free choice	Point counts	1983	2015
Finland	NE	Free choice & systematic	Line transect & point counts	1975	2015
France	SE	Stratified random	Point counts	1989	2014
Germany East	CEE	Free choice &	Point counts,	1991	2015
Germany West	WE	stratified random	line transects & territory mapping	1989	2015
Greece	Southeast Europe	Stratified random	Point counts	2007	2015
Hungary	CEE	Stratified random	Point counts	1999	2015
Italy	SE	Random	Point counts	2000	2015
Latvia	CEE	Systematic & random	Line transect & point counts	1995	2015
Lithuania	CEE	Stratified random	Point counts	2011	2015
Luxembourg	WE	Stratified random	Line transect & territory mapping	2009	2012
Netherlands	WE	Free choice	Territory mapping	1984	2015
Norway	NE	Free choice & systematic & random	Point counts & line transect	1996	2015
Poland	CEE	Stratified random	Line transect	2000	2015
Portugal	SE	Stratified	Point counts	2004	2014
Republic of Ireland	WE	Stratified random	Line transect	1998	2015
Romania	Southeast Europe	Semi-random	Point counts	2007	2015
Slovakia	CEE	Free choice	Point counts	2005	2015
Slovenia	West Balkan	stratified non- random	Line transect	2008	2015
Spain	SE	Stratified random	Point counts & line transect	1998	2015

Sweden	NE	Free choice & systematic	Point counts & line transect	1975	2015
Switzerland	WE	Systematic	Territory mapping	1999	2015
United Kingdom	WE	Free choice & stratified random	Territory mapping & line transect	1966	2015

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