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Review

A state-of-the-art review on birds as indicators of biodiversity: Advances, challenges, and future directions

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ABSTRACT

The current loss of biodiversity has been broadly acknowledged as the main cause of ecosystem change. To halt this trend, several international agreements have been made, and various biodiversity metrics have been developed to evaluate whether the targets of these agreements are being met. The process of developing good indicators is not trivial. Indicators should be able to synthesize and communicate our current knowledge, but they also need to meet both scientific and practical criteria. Since it would not be practical to monitor all species, indicators are mainly built on the monitoring of some well-known taxa, such as birds. Here we systematically review the wide spectrum of bird biodiversity indicators (hereafter indicators) available to: i) evaluate recent methodological advances; ii) identify current knowledge gaps jeopardizing indicator interpretation and use in guiding decision-making; and iii) examine challenges in their applicability across different spatial and temporal contexts. We pay particular attention to indicator characteristics such as site and species selection, spatial, seasonal and habitat coverage, and statistical issues in developing indicators and tools to tackle them, to provide specific recommendations for the future construction of indicators. Several methodological advances have recently been made to enhance the process of indicator development, including multiple ways to select sites and species to increase their robustness. However, we found that there are strong spatial, seasonal and habitat biases among the selected indicators. Most of them are from Europe, using mainly census data from the breeding season and typically covering farmland and forest habitats. The major challenges that we detected in their applicability were related to the modelling of the statistical uncertainty associated to the indicator. We recommend the use of quantitative methods in site and species selection procedures whenever possible. Current indicators should be expanded to areas outside Europe and to less studied habitats and should not neglect monitoring work outside the breeding season. Time-series analyses studying temporal trends and using multi-species data should in general account for temporal autocorrelation as well as for phylogenetic correlation. Multi-species hierarchical models are a good alternative for analysing and constructing indicators, but they need to include annual random effects allowing for unexplained annual variation in the average status of the community, i.e. the indicator target. Despite methodological and context-specific differences in the indicators reviewed, most of them seem to highlight the urgent need of devising strategic climate and conservation policies to improve the status and trends of biodiversity.

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1. Introduction

The current loss of biodiversity has been broadly acknowledged as the main cause of ecosystem change (Hooper et al., 2012; Ceballos et al., 2015) and it has been suggested to undermine the ability of mankind to adapt to global change (Cardinale et al., 2012), accelerating ecosystem degradation (Hooper et al., 2012) and threatening human well-being (Díaz et al., 2006; Hanski et al., 2012). In 2002, signatory states agreed under the Convention on Biological Diversity (CBD) to tackle both human-induced extinction of species and the loss of natural habitats through a significant reduction of the current rate of biodiversity loss by 2010 (CBD, 2002; BirdLife International, 2013). A related target was set by European high-level delegations, who committed to halt biodiversity decline by 2010 (Pereira and Cooper, 2006; Mace and Baillie, 2007; van Strien et al., 2009). However, none of the targets were met (Butchart et al., 2010; Rands et al., 2010), and similar, but more explicit, goals were adopted within the CBD's Strategic Plan for Biodiversity 2011–2020 (CBD, 2010; Henle et al., 2013; Secretariat of the Convention on Biological Diversity, 2014), widely referred to as the Aichi Biodiversity Targets. So far, progress towards these goals has been poor, mainly because of the lack of a clear definition and operational indicators (Tittensor et al., 2014). To determine whether new targets formulated within the post-2020 Global Biodiversity Framework are accomplished, there is a need to develop summary statistics to describe trends in components of biodiversity as accurately and robustly as possible, while being at the same time useful and understandable for decision-makers (Reid et al., 1993; Gregory et al., 2005; Mace et al., 2018; Green et al., 2019).

Birds are a good candidate taxon for monitoring global environmental change, because they have long been monitored worldwide (Bibby, 1999; Pereira and Cooper, 2006; Schmeller et al., 2012). They are relatively easy to detect and identify, census methods are well developed and cheap, and many skilled volunteers are willing to count birds (Koskimies, 1989; Venier and Pearce, 2004; Gregory et al., 2005; Pereira and Cooper, 2006). Our understanding of their population biology, behaviour and life history (except in the tropics; Xiao et al., 2017) is good (Venier and Pearce, 2004; Gregory et al., 2005) and they are known to show predictable population responses to environmental change (Järvinen and Väisänen, 1979). They are also widespread and relatively diverse (~10,000 species globally) and tend to be at, or near, the top of the food chain, making them sensitive to changes at lower trophic levels (Koskimies, 1989; Gregory et al., 2005).

The need to measure biodiversity change has promoted the development of what are known as composite or multi-species indicators (Gregory et al., 2005; Maes and Van Dyck, 2005). The purpose of composite indicators is to integrate data of species and ecosystem change in such a way that information is reduced into simple meaningful, visual summaries or "indices" (Gregory et al., 2003; Pereira and Cooper, 2006; Fraixedas et al., 2015a,b). Some examples are the Biodiversity Intactness Index (BII; Scholes and Biggs, 2005) and the following associated Biodiversity Intactness Variance (BIV; Hui et al., 2008), the Red List Index (RLI; Butchart et al., 2004, 2005, 2007), the Living Planet Index (LPI; Loh et al., 2005), or the more recent Biodiversity Change Index (BCI; Normander et al., 2012).

Composite trend indicators are one example where a group of species population trends are taken together to describe environmental changes. The main goal is to reflect the population response, but also to mirror that of other species reacting to the same human disturbance, therefore acting as a surrogate for ecosystem health (Caro and D'Oherty, 1999; Gregory et al., 2005). Probably the best-known example among birds is the Wild Bird Index (WBI; Gregory et al., 1999, 2003), which is one of the better summary statistics available at a regional scale (Butchart et al., 2010; Tittensor et al., 2014). WBIs have been adopted by the EU and incorporated in the 'abundance and distribution of selected species', one of the Streamlining European Biodiversity Indicators (SEBI) set to address the EU biodiversity targets (EEA, 2012). This indicator (SEBI 01) reflects the general state of common birds in two main habitats (forest and farmland), which together represent the predominant land types in Europe (Gregory et al., 2005; EEA, 2012; Vallecillo et al., 2016). Importantly, these indicators are used to inform and improve current management practices, as is the case of the European Farmland Bird Indicator (EFBI; Butler et al., 2010). WBIs have also been used in global biodiversity syntheses (Butchart et al., 2010; Secretariat of the Convention on Biological Diversity, 2014; Tittensor et al., 2014).

Composite indicators have been further developed to describe the impacts of climate change on biodiversity. Examples, also known as pressure indicators, include the Community Temperature Index (CTI; Devictor et al., 2008, 2012) and the Climate Impact Indicator (CII; Gregory et al., 2009; Stephens et al., 2016). The latter, based on bird data, has been also taken up by the EU (SEBI 011), under the name 'impacts of climate change on bird populations' (EEA, 2012), and used in global biodiversity assessments (Butchart et al., 2010; Tittensor et al., 2014).

Given the degree of integration of bird indicators into national and international policies (Gregory and van Strien, 2010), the present study represents a systematic review of recent scientific literature published on multi-species indicators (i.e. multi-species indices or multi-species annual summaries of a community reflecting changes in space and/or time) including bird data at the global, regional and national levels. We review four different types of indicators (state, benefit, response and pressure; BirdLife International, 2013), specifically focusing on site and species selection methodologies, spatial, seasonal and habitat coverage, and statistical issues in developing indicators and tools to tackle them. For this purpose, we summarise the general characteristics of the selected indicators by evaluating recent methodological advances, identifying current knowledge gaps and recognizing the main challenges in their applicability. We believe that a review such as this one is long overdue, given the proliferation of different indicators, their inconsistent use and applications, and all the knowledge gaps that jeopardize their interpretation across multiple spatial and temporal scales. Based on this analysis, we formulate specific recommendations for the future construction of indicators, including different ways to account for uncertainty.

2. Materials and methods

We used the ISI Web of Science database as a literature search method to access research articles. We carried out an advanced search using two different key word combinations: i) (birds AND indicators* AND biodiversity*); and ii) (birds AND multi-species* AND indices*). We also discarded those studies written in a language other than English. We looked for articles published in the first half of the implementing period of the CBD's Strategic Plan for Biodiversity 2011–2020 (i.e. 2011–2016), including studies up to December 2016. Although we did not consider grey literature (i.e. reports, government documents, etc.), we regard the obtained sample as representative of the current scientific literature available on the subject of study.

Our combined search resulted in a total of 278 studies (269 from the first key word combination, and 9 studies from the second one; searches performed on 13 December 2019). We reviewed the title and abstract of the articles, and chose the studies providing at least one multi-species indicator for birds. Articles involving bird indicators together with indicators for other taxa were likewise selected, but we excluded studies where birds were combined together with other taxa in a single indicator. All the bird-related indicators found in the Biodiversity Indicators Partnership (BIP) website were covered in our literature search, therefore including state, benefit, response and pressure indicators (BirdLife International, 2013).

The final selection comprised a total of 47 articles that met our criteria and were examined in more detail. The majority of the studies reported more than one indicator, and we gathered information separately for each of them. Indicators were collected both from the main text and the supplementary material, obtaining a total of 254 indicators. The geographical extent of the final indicator set ranged from a minimum spatial resolution of a region (e.g. southern Finland), excluding indicators performed at the local scale (e.g. city forests/woodlands), to a global level. We did not consider any indicators for which there was no information available in relation to their outcome (i.e. trend). For each of the indicators, we extracted: 1) the reference of the article (authors and journal abbreviation); 2) type of indicator (state, benefit, response or pressure, or a combination of these); 3) a brief description of the indicator; 4) type of data used (e.g. abundance, presence/absence data); 5) study period; 6) number of species involved; 7) season of the year; 8) study area; 9) type of habitat; 10) driver (type of driver thought to affect the indicator); 11) whether site selection was applied to develop the indicator; 12) whether species selection was applied to develop the indicator; 13) whether expert opinion was used in the species selection procedure; and 14) the general outcome of the indicator (increase, decline or no trend; the latter including well defined non-linear changes without a clear overall increase/decrease over the full study period) (see Table A1).

In addition, we classified the uncertainty measures related to each of the selected indicators, as well as other relevant data (see Table A2) as follows:

1. Inferential approach for detecting temporal changes in indicators:

1a) Annual indicator values and their uncertainties are compared against a reference year (e.g. the first year) or period (e.g. the average of the first five years) with a fixed value, typically one or 100 for ease of communication (Gregory and van Strien, 2010);

1b) Trends in indicator time-series are analysed with a separate model (e.g. linear model, piecewise trend, generalized additive model); this approach, which may include spatial replicates, also applies if indices are first fitted with a reference year or the indicator is illustrated using approach 1a, but after that temporal changes in the indicator are analysed statistically in a separate model;

1c) Hierarchical approach, jointly modelling the raw data of separate species and changes in the indicator (e.g. generalized linear mixed model, dynamic factor analysis, Bayesian approaches). This is a similar approach to 1b) in that a trend is modelled over the whole study period (it also applies even if e.g. figures are made with a reference year), but the analysis is done in only one step and the same model provides the indicator values (the annual multi-species model fit). Even cases ignoring one or many levels of potentially relevant random variation are listed here;

1d) Statistical uncertainty of the indicator or its changes is not assessed at all. Indicator values are presented as naked point estimates (e.g. RLI, where there is no statistical uncertainty given for the categories *per se*, although bootstrap is used to assess uncertainty due to missing data).

2. Technical approach for estimating indicator uncertainty, or for analysing temporal/spatial changes (variation) in the indicator:

2a) Simulation or bootstrap;

2b) Frequentist theory (e.g. null hypothesis tests or confidence intervals – CIs, not obtained through simulation);

2c) Bayesian analysis.

3. Other relevant data:

3a) Accounts for species detectability when constructing the indicator; indicators where species detectability is explicitly modelled;

3b) Accounts for (or tests for) phylogenetic correlation when constructing the indicator; especially with multi-species data, such as the case of the indicators, it can be important to recognise that related species' indices may behave similarly;

3c) Accounts for (or tests for) temporal residual autocorrelation in trend analyses of indicators; in this case autocorrelation only applies to 1b and 1c (not 1a). Even when present in the indicator, autocorrelation is not an issue in pairwise comparisons of two years, and approach 1a consists of several such comparisons (between the reference year and all other values).

For all assessed traits or classification outcomes we reported the proportions of indicators (%) that filled the criteria (binary outcome). Using the function *binom.test* in R (package "stats"; R Core Team, 2018), we obtained the 95% CIs as uncertainties associated with the reported proportions. This was done under the assumption that the selected indicators form a random sample, representing the approach preferred by researchers in these types of studies, and that the proportion of indicators is an estimate of the probability for applying a certain approach. Each of the indicators reviewed was considered as a single data point in the proportion. We used the habitats classification scheme of the International Union for Conservation of Nature and Natural Resources to classify certain habitat types into broader categories (IUCN, 2020).

3. Results

3.1. Indicator typology and drivers

From a total of 254 indicators, we found that the minority were benefit (n = 2) and response (n = 4) indicators, whereas almost half of the cases (CI = 39%–52%; n = 116 of 254) were state indicators. In addition, 30% of the selected indicators were classified into more than one typology (e.g. pressure and state; CI = 24%–36%; n = 76 of 254). The number of pressure indicators was almost half of state indicators (CI = 39%–58%; n = 56 of 116). While the majority of pressure indicators were either related to climate change or to land-use changes (CI = 74%–94%; n = 48 of 56), combined pressure and state (n = 14), and also benefit indicators were all linked to climate and land-use changes. Pressure and response indicators showed a good balance among the three different driver combinations (8 climate-change indicators, 11 land-use change indicators, and 14 climate and land-use change indicators). Combined state and response (n = 29), and response indicators alone only referred to land-use changes. The majority of state indicators were also linked to land-use changes (CI = 83%–95%; n = 104 of 116). Therefore, up to 70% of the selected indicators (CI = 64%–75%; n = 177 of 254) dealt with land-use changes alone, while the percentage of indicators concerning both drivers was less than 20% (CI = 14%–24%; n = 47 of 254) (see Table A1 and Fig. 1).

3.2. Seasonal, spatial and habitat coverage

Regarding the season of the year, more than 80% (CI = 79%–89%; n = 214 of 254) of the indicators used only breeding season data, whereas only four indicators relied on wintering data (2%; CI = 0%–4%; n = 4 of 254). Less than 15% of the indicators were combining both breeding and wintering data (CI = 9%–18%; n = 33 of 254) (Table A1).

At least 5% of the indicators were carried out at the global scale (CI = 3%–9%; n = 13 of 254). The majority of the selected indicators were exclusively focused on Europe (83%; CI = 78%–87%; n = 211 of 254), and many of them were performed at the national level (75%; CI = 69%–81%; n = 159 of 211). Europe was the only continent covering regional indicators (n = 19). All indicators from Oceania were performed at the national level (n = 18), whereas in America almost all indicators were classified as supranational (i.e. involving more than one country; 91%; CI = 59%–100%; n = 10 of 11). Only one indicator came from Africa (see Table A1 and Fig. 2) and none from Asia.

Around 20% of the selected indicators incorporated two or more

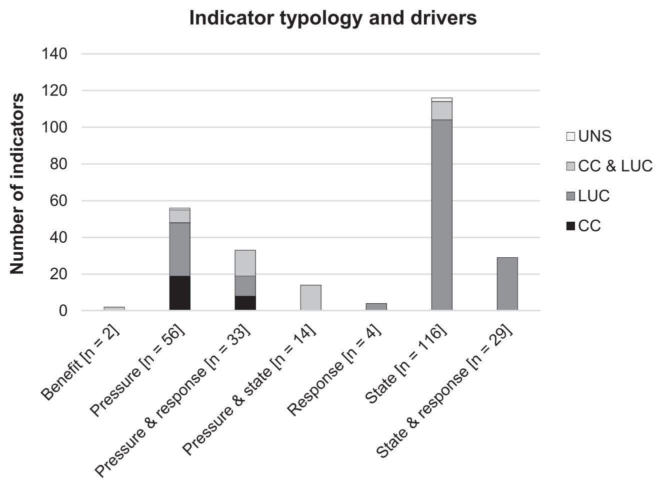

Fig. 1. Indicator typology as defined by BirdLife International (2013) extracted from the literature search and classified into different drivers (UNS = Unspecified; CC = Climate Change; LUC = Land-Use Change).

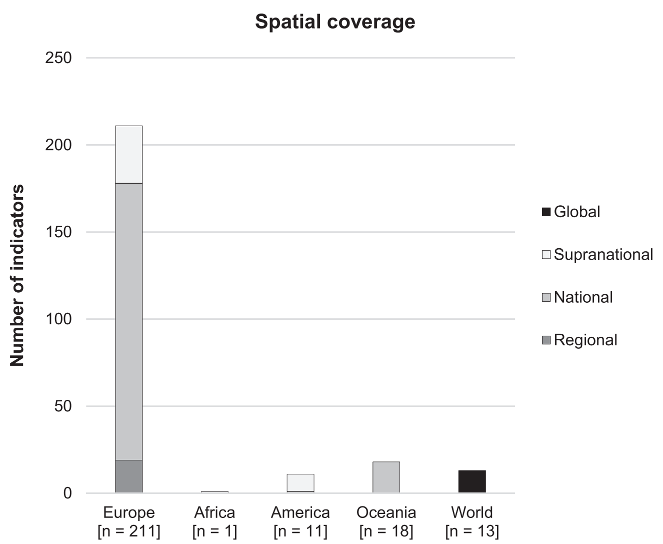

Fig. 2. Spatial coverage of the indicators extracted from the literature search and classified into different continents. The word "supranational" refers to those indicators involving more than one country.

than two habitat types (CI = 16%–26%; n = 52 of 254). A considerable percentage of the indicators did not include information about the habitat type (21%; CI = 16%–27%; n = 54 of 254). Farmland was the most recurrent habitat in our dataset among those indicators including a single habitat type (n = 50), followed closely by forest indicators (n = 41). Forest and farmland habitats made up almost 40% of the indicators (CI = 30%–42%; n = 91 of 254). The worst represented habitats were marine and shrubland (n = 4, and n = 3, respectively). Indicators with no clear habitat classification were mostly pressure indicators (65%; CI = 51%–77%; n = 35 of 54). This was also the case for marine indicators. Half or more than half of farmland, forest and wetland indicators were classified as state indicators (farmland: 50%; CI = 36%–64%; n = 25 of 50; forest: 76%; CI = 60%–88%; n = 31 of 41; wetland: 82%; CI = 57%–96%; n = 14 of 17). All indicators belonging to grassland and shrubland habitats were also state indicators (see Table A1 and Table 1).

Land-use change indicators were dominant among farmland (86%), forest (73%), generalist (i.e. no marked habitat preferences; 67%), grassland (75%), marine (75%) and wetland habitats (88%). They also constituted more than half of the indicators for which no habitat data were available (CI = 41%–69%; n = 30 of 54) (see Table A1 and Table 2).

3.3. Site selection, species selection and expert advice

The majority of the indicators used species selection (85%; CI = 80%–89%; n = 215 of 254), and nearly 50% of them used site selection (CI = 43%–56%; n = 125 of 254). Almost all indicators using site selection also used species selection (96%; CI = 91%–99%; n = 120 of 125). A bit more than 30% of the indicators included expert advice (CI = 26%–38%; n = 81 of 254), and all of them made use of species selection. Indicators using both site selection and expert advice were not very common in our dataset (22%; CI = 17%–27%; n = 55 of 254), but they all included a certain species selection procedure. Almost half of the indicators including species selection methods were state indicators (47%; CI = 41%–54%; n = 102 of 215). It was the same case for those indicators incorporating site, species selection and expert advice (49%; CI = 35%–63%; n = 27 of 55) (Table A1).

The application of site selection was not independent from species selection, meaning that there was an overrepresentation of indicators using both site selection and species selection, or neither one, as compared to indicators using only one selection type (Pearson's Chi-squared test: χ^2 = 22.72, df = 1, $p < 0.0001$). Species selection was not independent from expert advice (χ^2 = 19.87, df = 1, $p < 0.0001$), with more indicators relying on either species selection methods or both species selection and expert advice.

3.4. Outcome of the indicators

In general terms, half of the selected indicators showed declining trends (CI = 44%–56%; n = 127 of 254). From these, more than 60% were pressure and state indicators (CI = 53%–71%; n = 79 of 127). Only about 20% of the indicators increased (CI = 18%–29%; n = 59 of 254), and more than 30% of them were state indicators (CI = 22%–47%; n = 20 of 59). Around 20% of the indicators had no significant trends (CI = 18%–28%; n = 58 of 254), being the majority state indicators (78%; CI = 65%–87%; n = 45 of 58). Almost 5% of the chosen indicators could not be classified into any of the defined categories (i.e. decline, increase or no trend; CI = 2%–7%; n = 10 of 254), and eight of out ten were state indicators (see Table A1 and Fig. 3).

Regarding indicator typology, all benefit indicators (n = 2) declined. More than half of pressure (CI = 50%–77%; n = 36 of 56), and pressure and state indicators showed declining trends (n = 8 of 14). At least 75% of response (n = 3 of 4) and pressure and response indicators declined (CI = 58%–89%; n = 25 of 33). State indicators had approximately the same number of indicators declining and showing no clear trends (n = 43 of 116 and n = 45 of 116, respectively). Contrary to other indicator types, a bit more than half of state and response indicators showed increasing trends (n = 15 of 29) (see Table A1 and Fig. 3).

More than half of farmland indicators and forest indicators showed declining trends (farmland: n = 26 of 50; forest: n = 21 of 41). Together, they summed up almost 40% of the all set of declining indicators (CI = 29%–46%; n = 47 of 127). More than 50% of generalist indicators had increasing trends (n = 5 of 9). However, farmland and forest indicators made up almost 50% of the all set of increasing indicators (n = 28 of 59). More than half of grassland, shrubland and wetland indicators showed no clear trends (grassland: n = 6 of 8; shrubland: n = 2 of 3; wetland = 9 of 17). Approximately 40% of the all set of indicators showing no clear trends was found among farmland and wetland indicators (CI = 24%–50%; n = 21 of 58) (see Table A1 and Table 3).

Almost 60% of the indicators showing declining trends were related to land-use changes (CI = 48%–66%; n = 73 of 127). A similar case was found for indicators with increasing and no clear trends, being the majority land-use change indicators (increase: 68%; CI = 54%–79%; n = 40 of 59; no trend: 93%; CI = 83%–98%; n = 54 of 58). While

Table 1
Indicator typology as defined by BirdLife International (2013) extracted from the literature search and classified into different habitat types. In some cases, the same indicator covered two or more habitat types. We used the habitats classification scheme of the International Union for Conservation of Nature and Natural Resources to classify certain habitat types into broader categories (IUCN, 2020). "UNS" refers to unspecified habitat.

	Typology								
Habitat	Benefit	Pressure	Pressure & response	Pressure & state	Response	State	State & response	Total	%
> 2 habitats	0	5	4	0	2	11	0	22	9
2 habitats	0	2	14	0	0	2	12	30	12
Farmland	0	3	7	3	0	25	12	50	20
Forest	0	3	4	3	0	31	0	41	16
Generalist	0	1	0	2	0	1	5	9	4
Grassland	0	0	0	0	0	8	0	8	3
Marine (*)	0	3	0	0	0	1	0	4	2
Shrubland	0	0	0	0	0	3	0	3	1
Urban	0	1	0	3	0	4	0	8	3
Wetland (**)	0	3	0	0	0	14	0	17	7
Other (***)	0	0	2	1	0	5	0	8	3
UNS	2	35	2	2	2	11	0	54	21
Total	2	56	33	14	4	116	29	254	100
%	1	22	13	6	2	46	11	100	

(*) Including dune/shore, estuaries and sea
(**) Including bog/marsh, freshwater, inland water, lakes and mires
(***) Including artificial, natural, near human and open-water environments

Table 2
Indicator drivers extracted from the literature search and classified into different habitat types. In some cases, the same indicator covered two or more habitat types. We used the habitats classification scheme of the International Union for Conservation of Nature and Natural Resources to classify certain habitat types into broader categories (IUCN, 2020). The meaning of the acronyms is the following: UNS = Unspecified, CC = Climate Change, LUC = Land-Use Change.

	Driver					
Habitat	CC	LUC	CC & LUC	UNS	Total	%
> 2 habitats	7	13	2	0	22	9
2 habitats	2	19	9	0	30	12
Farmland	1	43	6	0	50	20
Forest	6	30	5	0	41	16
Generalist	1	6	2	0	9	4
Grassland	0	6	2	0	8	3
Marine (*)	1	3	0	0	4	2
Shrubland	0	1	2	0	3	1
Urban	1	4	3	0	8	3
Wetland (**)	0	15	2	0	17	7
Other (***)	0	7	1	0	8	3
UNS	8	30	13	3	54	21
Total	27	177	47	3	254	100
%	11	70	19	1	100	

(*) Including dune/shore, estuaries and sea
(**) Including bog/marsh, freshwater, inland water, lakes and mires
(***) Including artificial, natural, near human and open-water environments

70% of climate change indicators and those including both climate and land-use changes were declining (CC: CI = 50%–86%; n = 19 of 27; CC &LUC: CI = 55%–83%; n = 33 of 47), only about 40% of land-use change indicators showed declining trends (CI = 34%–49%; n = 73 of 177) (Table A1).

3.5. Indicator uncertainty

In more than 80% of the cases it was possible to clearly determine the inferential approach used to detect temporal changes in indicators (82%; CI = 77%–86%; n = 208 of 254). The most used inferential approach was 1b, i.e. the indicator time-series were first constructed but their trends were analysed with a separate model (29%; CI = 23%–36%; n = 60 of 208). This included also cases where the trend model was hierarchical, e.g. a mixed model analysing the indicators and including a random effect of site. Only a few of these indicators effectively applied a combination of approaches 1a (i.e. particular years compared against a reference year or period) and 1b (13%; CI = 9%–18%; n = 27 of 208). About 20% of the indicators used hierarchical modelling for constructing and analysing the indicators (approach 1c; CI = 14%–25%; n = 40 of 208). About 60% of cases where mixed effects models were applied, covering cases from both approach 1b and 1c, annual random variation in the indicator was ignored (e.g. no random effect of factor variable year in addition to the trend; CI = 48%–68%; n = 58 of 100). In almost 30% of the cases statistical uncertainty was not assessed at all (approach 1d; CI = 22%–35%; n = 59 of 208). In addition, there were special cases (11%; CI = 8%–16%; n = 29 of 254) where indicators were classified as using approach 1a. These referred to simulated future scenarios not based on statistical models. There was missing information for more than 5% of the indicators (CI = 4%–10%; n = 17 of 254) (Table A2).

Frequentist theory was the most popular technical approach for estimating indicator uncertainty, or for analysing temporal/spatial changes (variation) in the indicator (approach 2b; 43%; CI = 37%–50%; n = 110 of 254), followed closely by simulation or bootstrap (approach 2a; 34%; CI = 28%–40%; n = 87 of 254). Surprisingly, none of the indicators used Bayesian analysis (i.e.

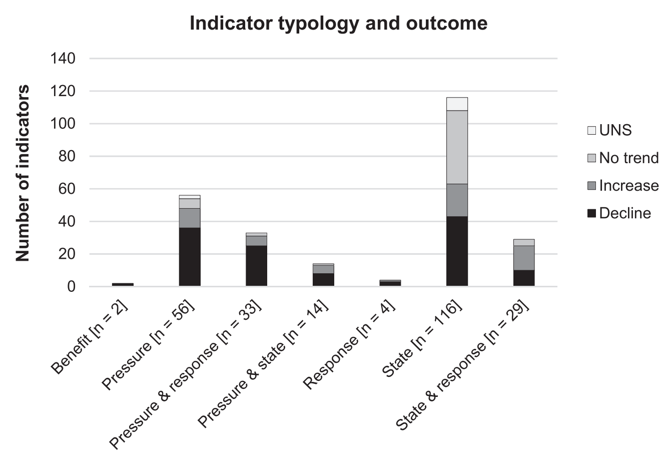

Fig. 3. Indicator typology as defined by BirdLife International (2013) extracted from the literature search and classified into different outcomes. "UNS" refers to unspecified outcome.

Table 3
Indicator outcome (increase, decline or no trend; the latter referring to well defined non-linear changes without a clear overall increase/decrease over the full study period) extracted from the literature search and classified into different habitat types. In some cases, the same indicator covered two or more habitat types. We used the habitats classification scheme of the International Union for Conservation of Nature and Natural Resources to classify certain habitat types into broader categories (IUCN, 2020). "UNS" refers to unspecified outcome/habitat.

	Outcome					
Habitat	Decline	Increase	No trend	UNS	Total	%
> 2 habitats	9	4	5	4	22	9
2 habitats	16	9	5	0	30	12
Farmland	26	12	12	0	50	20
Forest	21	16	4	0	41	16
Generalist	3	5	1	0	9	4
Grassland	2	0	6	0	8	3
Marine (*)	0	1	1	2	4	2
Shrubland	1	0	2	0	3	1
Urban	2	3	3	0	8	3
Wetland (**)	7	1	9	0	17	7
Other (***)	2	2	0	4	8	3
UNS	38	6	10	0	54	21
Total	127	59	58	10	254	100
%	50	23	23	4	100	

(*) Including dune/shore, estuaries and sea.
(**) Including bog/marsh, freshwater, inland water, lakes and mires.
(***) Including artificial, natural, near human and open-water environments.

approach 2c), and in more than 20% of the cases it was not possible to evaluate the technical approach given that uncertainty was not assessed (i.e. indicators previously classified as 1d; CI = 18%–29%; n = 59 of 254) (Table A2).

In addition, only 15% of the indicators accounted for species detectability (approach 3a; CI = 11%–20%; n = 38 of 254), about 1% for phylogenetic correlation (approach 3b; CI = 0%–3%; n = 2 of 254), and less than 20% for temporal autocorrelation, only considering indicators classified as either 1b or 1c (approach 3c; CI = 10%–26%; n = 17 of 100) (Table A2). The modelling of temporal autocorrelation was not relevant when the inferential approach was 1a (see Methods section). Therefore, in the majority of cases indicators did not incorporate any of these features.

4. Discussion

Three main research findings emerge from this study. First, important methodological advances have been made to improve the robustness of the reviewed indicators, as illustrated by the extensive use of site and/or species selection methods in their construction. Second, strong spatial, seasonal and habitat biases have been identified, with most indicators being habitat-specific (mainly covering farmland and forest habitats), mostly focused on Europe and based on data from the breeding season. Third, statistical uncertainty was ignored in a substantial number of the indicators reviewed. We elaborate on these findings and their implications in the subsequent sections.

4.1. Recent methodological advances

Our review shows a notable number of indicators for which site selection, species selection or a combination of both methods are applied, particularly in the case of state indicators. Species selection procedures are key elements when designing indicators. Several studies have demonstrated that indices are more representative of the wider community when species selection criteria are used to identify the potential indicator species pool (Butler et al., 2012; Wade et al., 2014). A good example are studies including methods to quantify species habitat preferences based on habitat data derived from transects (Larsen et al., 2011; Jiguet et al., 2012a; Renwick et al., 2012; Fraixedas et al., 2015b). Other recent methodological advances in species selection include the construction of indicators using a ratio of species positively and negatively affected by a driver, which enables a finer interpretation of the patterns affecting the shape of the final indicators (Herrando et al., 2014, 2016; Palmer et al., 2015; Stephens et al., 2016). However, even in this case, it is necessary to select species positively and negatively affected by the specific driver. Given that species can behave differently within these two groups, it is essential to rely on either evidence-based selection or, if that is not possible, use expert opinion to complement species selection procedures (Roth et al., 2014), or in other cases to simply assign species to a particular habitat (Galewski and Devictor, 2016).

4.2. Current knowledge gaps

We discovered several biases in the indicators reviewed. Most of the indicators analysing drivers of population change only considered land-use changes. The combination of climate and land-use changes was not very common in our dataset, though their interaction is critical in understanding environmental change, as it is to conservation policies (Burns et al., 2016; Oliver et al., 2017). There was also a bias in terms of indicator typology, with the number of state indicators clearly surpassing other indicator types such as benefit or response. Moreover, since many bird species are migratory, population drivers may influence species during different phases of their life cycle. The selected indicators are mostly based on data from the breeding season because territorial bird populations can often be censused more easily, and indicators using data from the non-breeding season are scarce (but see e.g. Godet et al., 2011; Fraixedas et al., 2015a). Another important gap found at the global scale is the spatial coverage of the indicators, since they are mostly focused on Europe, where most of national indicators come from. We specifically found a lack of indicators from Africa and Asia. Out of all published state indicators found in the peer-reviewed literature, the most common are habitat-specific ones, which are biased towards farmland and forests. Although these are the most widespread habitats in Europe, others such as marine or shrubland habitats should not be neglected. Despite the impacts caused by human activities on marine ecosystems and species, the current lack of information on the status of species and habitats limits our understanding of the pressures that may affect biodiversity and ecosystems (EEA, 2017). However, it is known that seabirds are among the most threatened groups of birds (Hoffmann et al., 2018). As for shrubland habitats, most bird populations have been severely declining since the 1950 s (e.g. in eastern North America; Hunter et al., 2001), which highlights the need to measure the effectiveness of conservation programs for these species (Schlossberg and King, 2015).

4.3. Statistical issues in indicator development

The results showed that statistical uncertainty was ignored in several of the indicators reviewed. Realistic measures of uncertainty accompanying the indicator and its trends are essential for reliable inference and sensible interpretation of changes in any indicator (Soldaat et al., 2017). Similarly as for error estimation, the number of indicators accounting for species detectability, phylogenetic correlation and temporal autocorrelation was very low. Variation in detectability between species may not represent a large problem when species included in the indicator analyses are given an equal weight (Lehikoinen, 2013). However, changes in detectability over time due to, for instance phenology, may generate a bias in the estimated abundance (Lehikoinen, 2013; Chambert et al., 2015). Moreover, few studies have considered the importance of spatial variation in species detectability when estimating temporal trends in bird populations (e.g. MacLeod et al., 2012; Massimino et al., 2015). Temporal autocorrelation is another key component of estimating population change (Thomas, 1996). Incorporating a temporally correlated component in the trend analysis can smooth out fluctuations caused by e.g. an anomalous weather year (Harrison et al., 2014), and ignoring it may leave lead to underestimated uncertainly (e.g. too narrow CIs), which is difficult to spot and may actually look like a desired result. The same can happen if phylogeny is ignored, since it is assumed that species are independent from each other even if they may share a common ancestry (Johnston et al., 2014; Sólymos et al., 2018). To account for phylogenetic correlation one could, for instance, weight species according to uniqueness (i.e. a weight that is different for each species), or add several random effects (e.g. family, genus and species) on the intercept and slope when modelling trends (Ives and Helmus, 2011; Tucker et al., 2017).

A separate, and often missing, component of many indicator analyses with multiple species or sites is the modelling of common annual random variation, i.e. between-species synchrony affecting the indicator or spatial synchrony when analysing variation in the indicator. This can be simply modelled by including year as a factor variable with random effects (on the intercept) in the model, and it is particularly important both in log-linear trend models and in models allowing for flexible and more complex trends, such as generalized additive models (Knape, 2016). Although researchers may be reluctant about including year as both a fixed effect (as a continuous variable – describing the trend) and as a random effect in the same model, these variables have very different function and the model is in most cases fully identifiable.

4.4. Major challenges in indicator applicability

There are inevitable challenges concerning the use and development of biodiversity indicators in Europe and beyond (Walpole et al., 2009). One potential explanation for studies not including statistical uncertainty may be that current methods for error estimation are poorly developed in multi-species biodiversity indices (Gregory et al., 2019). Lack of data also constitutes a limiting factor when trying to estimate error in trends, leaving some options out of range (e.g. bootstrapping species*sites data to fully account for sampling error; Buckland et al., 2005). Even when data are available, there are certain technical challenges and limitations when reporting statistical uncertainty (e.g. constructing CIs around indicators and their trends; Soldaat et al., 2017). As an example, there is currently no statistical uncertainty given for the red list categories, which makes difficult to communicate the uncertainty associated to the RLI values and trends (Butchart et al., 2007; Rueda-Cediel et al., 2018). In addition, the ability of statistical models to react to recent changes in indicator trends depends on the length of the time series, among other aspects (Tittensor et al., 2014). This is a major limiting factor to all existing indicators looking at trends, since large-scale land-use changes, and therefore their impacts on vertebrate diversity, have already taken place before the commonly used baselines (e.g. the 1970s; Hoffmann et al., 2018; Fraixedas et al., 2019). Moreover, even in the case of WBIs, where bird observations are collected through systematic annual breeding surveys to provide scientifically robust and representative trend information (Gregory and van Strien, 2010; Hoffmann et al., 2018), data coverage is currently limited to Europe and North America (but see for instance Wotton et al., 2017). Another problem associated with current monitoring schemes is that they may not be able to monitor populations of rarer species, potentially excluding the more sensitive species (Battisti and Fanelli, 2016). The omission of less common species associated with pristine habitats can produce an over-optimistic assessment of the health of the ecosystem (Renwick et al., 2012). At the same time, accounting for detectability will be only possible if we choose monitoring methods that provide data, where requirements for analysing observation process are fulfilled (e.g. Kéry and Schmidt, 2004, 2008). Finally, problems of species selection persist (e.g. differences in the allocation of species into groups based on their habitat preference depending on the region studied), which may strongly affect the trends in indices (Fraser et al., 2017).

4.5. Recommendations and future directions

Several methodological advances have been made in the development of biodiversity indicators. Quantitative methods for species and site selection will likely improve the robustness of existing indicators (Gregory and van Strien, 2010; Wade et al., 2013, 2014), and we strongly advise paying attention to species selection when establishing a new indicator. If expert opinion is required, methods for engaging with experts that enhance the accuracy and calibration of their judgements should be used (Sutherland and Burgman, 2015; Fraser et al., 2017). Currently, there are strong spatial, habitat and seasonal biases in peer-reviewed indicators. Therefore, we call for further studies to fill the gaps, particularly in ecosystems outside Europe (e.g. Szabo et al., 2012; Ingram et al., 2015), and without neglecting the non-breeding season (e.g. Godet et al., 2011; Fraixedas et al., 2015a). There is also a need to integrate the impacts of climate change and land use on biodiversity into the same modelling framework (e.g. Clavero et al., 2011; Eglington and Pearce-Higgins, 2012; Ay et al., 2014), which may prove especially valuable for the assessment of conservation policies. Several of the revised indicators relied on an initial baseline year to measure trends. Poor estimation in the baseline year due to e.g. low sample size or large annual fluctuations in the index usually leads to inaccurate estimates of the population trend, with biodiversity declines being overlooked (Buckland and Johnston, 2017). However, there are methods to reduce the sensitivity to the choice of baseline year, such as smoothing the index using generalized additive models (Fewster et al., 2000; Buckland et al., 2005). It is also possible to fit models with annually separate intercepts, so that all years are associated with their own uncertainty, rather that integrating the uncertainty of the baseline year(s) to be compared with all other years.

Multi-species hierarchical models are a good alternative for constructing and analysing indicators (Amano et al., 2012), but they need to include annual random effects allowing for annual variation in the indicators (Knape, 2016). Another attractive but seldom seen modelling approach that could be used for simultaneously constructing and analysing indicators is dynamical factor analysis (Zuur et al., 2003). Time-series analyses studying temporal trends and using multi-species data should in general account for temporal autocorrelation (e.g. Lindström et al., 2013; Galewski and Devictor, 2016; Schipper et al., 2016). In addition, phylogenetic correlation is an issue worth to consider in modelling decisions (e.g. Jiguet et al., 2012b). At the outset, further efforts should be made to improve monitoring design to obtain high quality data on biodiversity at acceptable spatial and temporal resolutions (de Heer et al., 2005; Normander et al., 2012). By increasing the robustness of monitoring schemes, we hope to see a greater diversification of the indicator typology, including the development of more benefit and response indicators. Moreover, common methods to apply and harmonise data from different monitoring schemes would be highly desirable to optimize sampling effort and be more efficient in the statistical use of data (Normander et al., 2012; Schmeller et al., 2012). Applying monitoring methods that enable accounting for detectability will be most important in studies that cover a wide range of habitat types (Studeny et al., 2013; Harrison et al., 2014). Finally, cross-validation with other biodiversity indicators is a means of improving the interpretation of results (Bailey et al., 2007; European Communities, 2009), because birds may respond differently to environmental factors when compared to other taxa (Gregory and van Strien, 2010).

5. Concluding remarks

To effectively estimate changes in biodiversity and evaluate progress towards global biodiversity targets in the context of the post-2020 Global Biodiversity Framework, greater commitment and increased resources are needed to expand current monitoring schemes in order to improve the spatial representativeness and the habitat and seasonal coverage of the indicators. This will be key to improve our understanding of how ecosystems and the living resources react to environmental changes. Furthermore, to obtain a clear picture of biodiversity trends and being able to communicate the results to policy makers, researchers must find appropriate statistical methods to calculate informative and robust indicators with a realistic level of fluctuations and uncertainty around them. This will ensure the formulation of well-informed conservation programmes and a resource for practitioners to mitigate or even reverse current biodiversity losses. Our results regarding the outcome of the revised indicators give cause for concern, since most of them were more often displaying declining trends in biodiversity than increasing ones. Parties to the CBD prepare to adopt the post-2020 Global Biodiversity Framework and do so facing an overall failure in achieving most of the Aichi Biodiversity Targets. We believe that this review can help to improve indicator development and application, and thereby contribute to ensure a roadmap to monitor success of the next generation of biodiversity goals.

Author contributions

SF conceived the study, carried out the analyses and writing, ALe and ALi supervised the project, ALi and MP helped with data collection; all authors contributed to the study design, write and approved the final version of the paper.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

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