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Monitoring the world's bird populations with community science data

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ABSTRACT

Systematic monitoring of species across their geographic ranges is a critical part of conservation but it is resource-intensive, costly, and difficult to organize and maintain in the long-term. Large-scale community science programs like eBird may improve our ability to monitor bird populations, particularly in tropical regions where formal studies are lacking. Here, we estimated population trends for nearly 9000 bird species using global eBird birdwatching data and compared our trends to the population trends designated by BirdLife International. We calculated the rate of agreement between eBird and BirdLife trends and examined the effects of latitudinal affiliation, threat status, number of eBird checklists, eBird trend, BirdLife trend and BirdLife trend derivation on the rate of agreement. We also used a randomization approach to compare observed rates of agreement with the rates of agreement expected by chance alone. We show that the rate of agreement was marginally better than expected by chance and improved significantly for temperate region species of Least Concern with more checklists, and species that eBird or BirdLife identified as increasing. Our results suggest that eBird data are not currently adequate for monitoring populations of the majority of the world's bird species, especially in the developing world where systematic surveys are essential. Increased local participation in community science initiatives like eBird may improve our ability to effectively monitor species. Furthermore, it is important to assess the accuracy of BirdLife trends and the manner in which they are derived, especially for species where BirdLife and eBird data trends disagree.

1. Introduction

Systematic long-term monitoring of species' populations is a critical component of their conservation (Ralph et al., 1995; Sauer et al., 2014). Accurate population trends are crucial for identifying species of concern as well as measuring the efficacy of conservation programs (Kleiman et al., 2000; Tear et al., 1995). Monitoring a species across its geographic range can be difficult and resource intensive, but is essential for measuring global trends and taking the necessary conservation measures. Birds are important ecological indicators that are critical to many environmental monitoring schemes, bidiversity assessments and conservation decision-making (Kati and Şekercioğlu, 2006). Recent large declines in bird abundance, particularly among common and widespread birds (Inger et al., 2015; Rosenberg et al., 2019), can also impact natural ecosystems when avian ecosystem functions such as seed dispersal, pollination, scavenging, and predation are reduced (Şekercioğlu, 2006). These declines can have economic costs because some birds help control pests and are a key component of the ecotourism industry (Şekercioğlu, 2002, 2006).

In a few countries, birds are monitored using government-coordinated surveys that produce reliable national-level population trends (Sauer et al., 2014), most notably the Breeding Bird Surveys in North America (United States Geological Survey), Europe (European Bird Census Council) and the United Kingdom (British Trust for Ornithology). However, formal surveys such as these are often lacking in tropical developing nations due to the resources required (Seak et al., 2012). This is especially concerning because these regions harbor the majority of the world's bird species (del Hoyo et al., 2019), many of which are specialized species with higher risk of extinction (Şekercioğlu, 2011). Opportunistic community science can be used to monitor species on a broad scale for comparatively little resource investment (Abolafya et al., 2013; Boersch-Supan et al., 2019; Bonney et al., 2009; Fink et al., 2020; Horns et al., 2018; Silvertown, 2009), and therefore has the potential to fill in some of these data gaps. In

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particular, semi-structured community science data have been used successfully to compare bird population trends with estimates from formal breeding bird surveys (Boersch-Supan et al., 2019; Horns et al., 2018). However, community science can suffer from poor data quality, high inter-observer variation, and spatial heterogeneity (Isaac et al., 2014; Kamp et al., 2016; Kelling et al., 2015; La Sorte and Somveille, 2020), and these issues need to be addressed before using a community science scheme for assessing population changes (Aceves-Bueno et al., 2017; Bayraktarov et al., 2019; Fink et al., 2020).

eBird is a community science database that contains a large and growing volume of bird count data (hereafter “checklists” or “lists”; Sullivan et al., 2009). With over 800 million submitted observations from around the world, eBird has the potential to be a substantial resource for monitoring birds on a large scale. eBird has been used to monitor bird migration (Fournier et al., 2017; Horton et al., 2018), geographic occurrence (Braun and Wann, 2017; Fink et al., 2020), diversity (Callaghan and Gawlik, 2015; La Sorte et al., 2014), and population trends (Boersch-Supan et al., 2019; Clark, 2017; Fink et al., 2020; Horns et al., 2018; Walker and Taylor, 2017). Multiple studies have shown that population trend estimates based on eBird data can reflect trends estimated by formal surveys for focal species (Clark, 2017; Fink et al., 2020), for all species within important conservation regions (Walker and Taylor, 2017), and even for all species at large, continental scales (Horns et al., 2018). However, previous studies verifying population trends based on eBird data have been largely restricted to areas such as North America where there are high volumes of eBird data and reliable structured surveys with which to compare eBird results. Expanding these analyses to a global scale is challenging when there is insufficient information about the species to make accurate trend estimates for comparison.

To address the efficacy of community science to monitor species at the global scale, we used eBird data to estimate world-wide population trends for nearly 9000 bird species over the past 20 years. We then compared our results with the trend estimates made by BirdLife International (2019). BirdLife International (BirdLife) is a world-wide partnership of conservation organizations that seeks to collect information on the threats to global avifauna and to enact conservation action. BirdLife amasses a diverse range of data sources in order to make categorical estimates of population trends for the majority of the world's bird species, classifying each as “increasing”, “stable”, or “decreasing” (Birdlife International, 2019). Where available, species trends are based on empirical survey data such as breeding bird surveys, bird atlas surveys, or targeted species-specific surveys. For most species without empirical data, trends may be based on expert opinion or on indirect evidence of population-level threats (i.e. extensive habitat loss known to be occurring with the species' range) and public input is encouraged in making these designations (BirdLife's Globally Threatened Bird Forums; Birdlife International, 2019).

In order to assess the accuracy of eBird population trends, we compared the rate of agreement between BirdLife and eBird trends and how agreement varied with increasing volumes of eBird data, IUCN threat level, the latitudinal affiliation of the species (whether the species was primarily tropical, temperate, or found in both regions – “cosmopolitan”), and the formal BirdLife trend assessment and derivation for the species (whether the species is estimated to be increasing, stable, or decreasing). We predicted that concordance would be highest for cosmopolitan species, which by definition have large global distributions and thus a higher chance of occurrence in eBird data, and lowest for species restricted to the tropics where eBird use is less prevalent and formal surveys are less numerous (Horns et al., 2018; La Sorte and Somveille, 2020; Şekercioğlu, 2012). We further predicted that species with decreasing eBird trends would show a higher rate of agreement than species estimated to be stable or increasing. Because the ability of birdwatchers to locate birds is steadily increasing through better information, the growing use of bird calls (playback), and employing professional guides and tour companies, species with a negative eBird trend are likely to be truly declining. Our findings will help assess the utility of community science data to act as a coarse-scale indicator of changes in bird populations over large geographic areas where more traditional survey data are unavailable.

2. Methods

We downloaded the complete eBird world data set on February 18, 2020 (ebd_relJan-2020). This provided data through January 2020.

2.1. Data selection

We first determined the number of species each checklist reported (unique checklists were identified on the basis of the “Sampling Event Identifier”), and eliminated any list with fewer than four species, as these can represent a targeted search for a specific species and can confound results (Szabo et al., 2010). We also eliminated any duplicate checklists (identical checklists shared between two or more people birding together) on the basis of the “Group Identifier” and randomly retained one checklist per group. Next, we removed lists prior to 2000 in order to focus on the 20 most recent years of data. Although eBird launched in 2002, users have been able to submit checklists from prior years. Observers on eBird are required to state whether their list included all bird species detected, so we also eliminated any list defined by users as incomplete. In order to use data from sites that would be comparable over time, we restricted the locality type to eBird “hotspots”, thus removing personal locations that may only be used once. We also restricted the protocol type to “traveling” and “stationary”, the two most common protocols with the most rigorous effort data. For stationary checklists, we fixed the distance traveled at 0 km. Finally, following eBird “best practices” (Johnston et al., 2019), we removed checklists that took place over >5 h, that traveled distances of >5 km, and that involved >10 observers. Additionally, we removed any checklists lacking data for the distance, duration, and number of observers covariates. Our final dataset contained >210 million records.

2.2. eBird trend modeling

We first removed all records not identified to species level, including hybrids and domesticates. To estimate the population trend for each species, checklists were only used if they came from eBird hotspots (based on “Locality ID”) with at least one record of the focal species, a technique which has been shown to produce high concordance with formal breeding surveys (Horns et al., 2018). Each list was assigned a 1 or 0 depending on whether or not it recorded the focal species. Presence/absence data were used instead of abundance data because many eBird lists that fail to report abundance would have to be excluded and previous studies have shown that abundance and occurrence rate in eBird data are tightly correlated (Horns et al., 2018; Walker and Taylor, 2017). Because of potential issues with small sample sizes, we removed species with fewer than 50 possible checklists and fewer than ten encounters over those checklists (Fink et al., 2020).

We ran a multiple logistic regression model for each of the remaining 8883 species. For each species, presence/absence data (encounter probability) were modeled as a function of year, number of species recorded in the checklist, number of observers, distance traveled, and duration. The number of species on each checklist was included as part of list-length analysis which uses the number of species detected to control for inter-observer variation in skill and effort (Boersch-Supan et al., 2019; Horns et al., 2018; Kelling et al., 2015; Szabo et al., 2010). For each eBird trend model, we extracted the model coefficients and *p*-values (Appendix 1), and calculated Cox & Snell's index and Nagelkerke's index, two pseudo-R^2 measures of model fit for logistic regressions (Cox and Snell, 1989; Nagelkerke, 1991). For examples of these logistic regressions see Fig. 1. The volume of eBird data has increased exponentially over time (Fig. 2) and thus the ability of

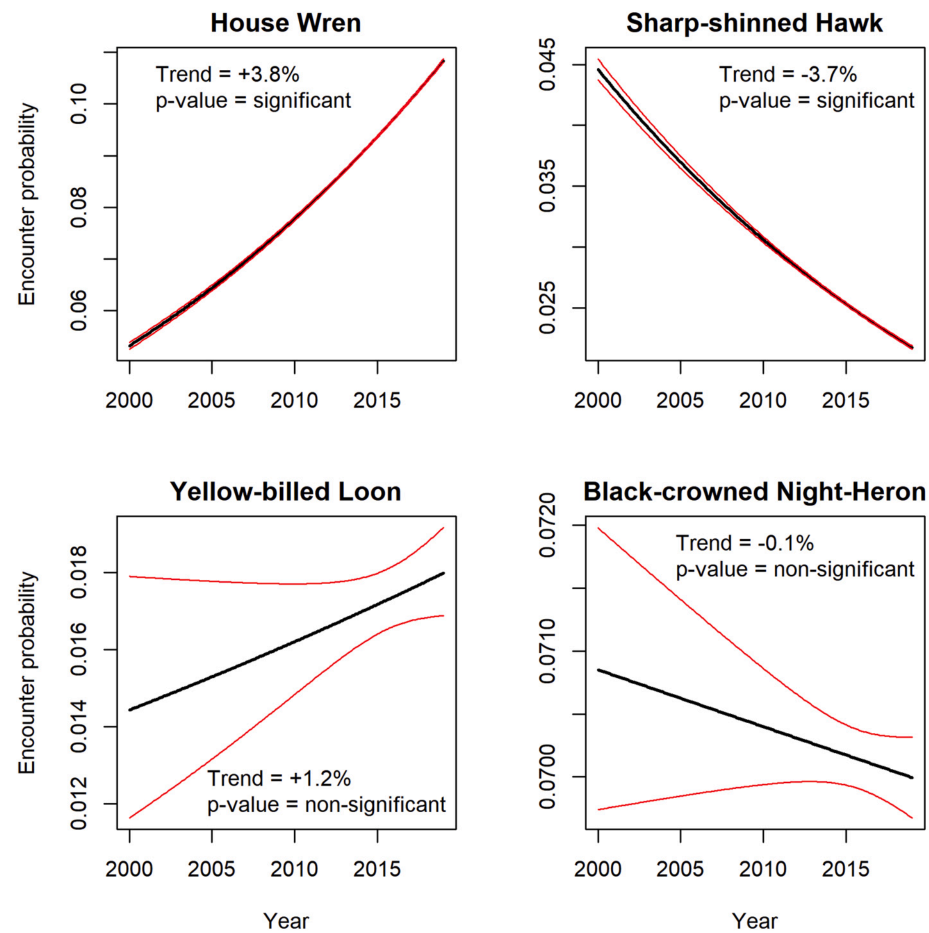

Fig. 1. Examples of logistic regressions conducted on four species with varying results. Trend lines are shown in black with 95% confidence intervals in red. House Wren (*Troglodytes aedon*) increased significantly at a rate of 3.8% per year resulting in the "increasing" designation. Sharp-shinned Hawk (*Accipiter striatus*) decreased significantly at a rate of 3.7% per year resulting in the "decreasing" designation. Yellow-billed Loon increased at a rate of 1.2% per year but this was not significant, resulting in the "stable" designation. Finally, the trend for Black-crowned Night-heron was both below 1% per year and non-significant, resulting in the "stable" designation.

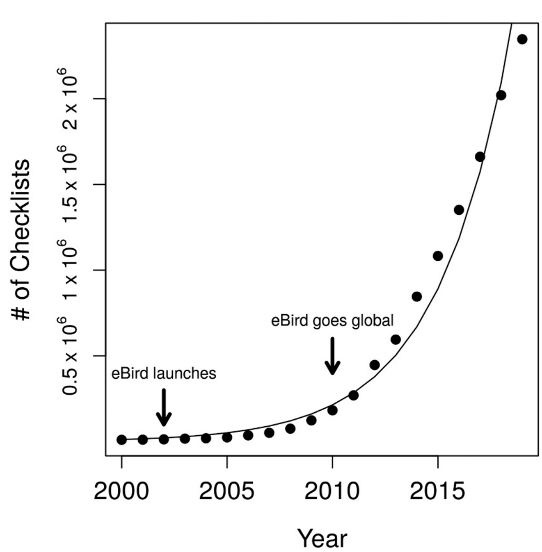

Fig. 2. The number of eBird checklists between 2000 and 2019 used in eBird population trend analyses after data filtering. The curve shows the fitted values from a Poisson Generalized Linear Model.

these data to estimate population trends has likely improved over time. To address this, we re-ran the eBird trend models over two shorter temporal windows: ten years (2010–2019) and five years (2015–2019). We compared our results for these shorter windows with our main results for the 20-year period (2000–2019).

2.3. Comparing eBird trends versus BirdLife International trends

Of the 8883 species with sufficient eBird data to make trend estimates ($\geq$50 checklists, $\geq$10 detections), 8121 have been designated trend estimates by BirdLife International. Because numerical abundance data across years is unavailable for most species, BirdLife only provides categorical estimates, defining all species as either "decreasing", "stable", or "increasing". BirdLife trend estimates are also accompanied by their derivation, classified as "estimated", "inferred", "observed", or "suspected". We hypothesized that the rates of agreement would be higher for estimated and observed trends compared to inferred and suspected trends which are more indirect approaches (Birdlife International, 2019). We used these derivation categories in the subsequent analyses.

Both magnitude and uncertainty are important components in establishing whether a population is undergoing significant directional change. Therefore, we considered eBird trends stable if year did not have a significant effect on the encounter probability or if the absolute value of the magnitude of the trend was under 1%/yr (Van Strien et al., 2001). We used the coefficients from the model outputs to estimate the

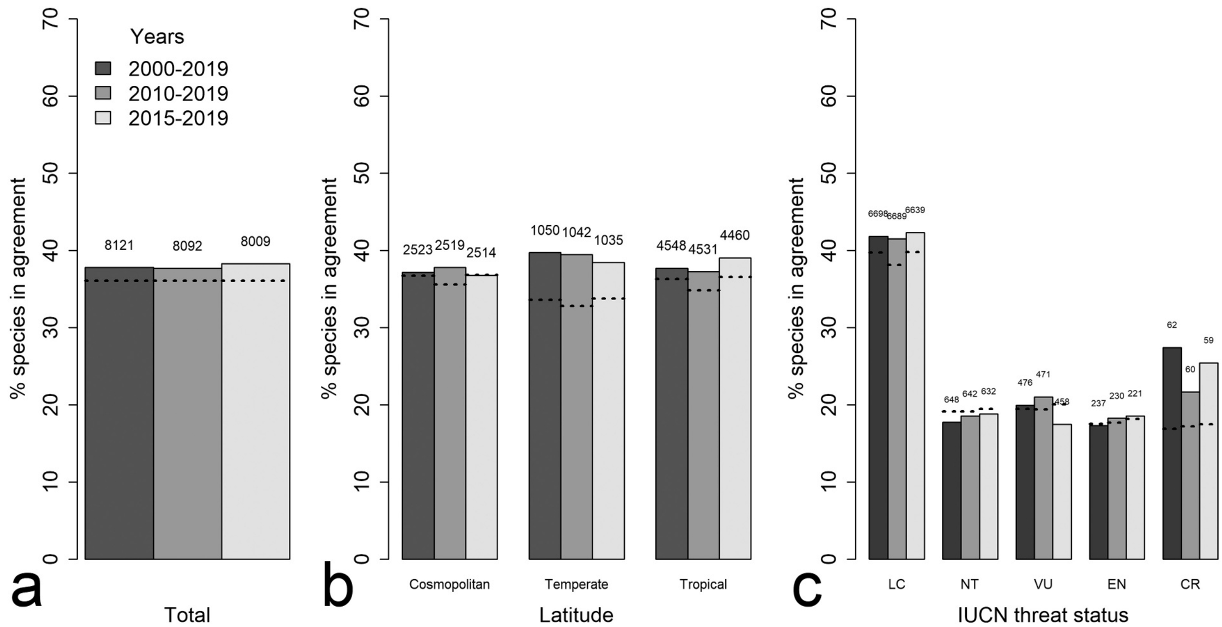

Fig. 3. The (a) overall rate of agreement and the effect of (b) latitudinal affiliation and (c) IUCN threat status on the rate of agreement in population trend estimates between eBird and BirdLife International for three different temporal windows. Numbers above bars represent the total number of species in each category. Dashed lines represent the rate of agreement expected by chance alone. Confidence intervals were so small as to not be visible in the figure. Cosmopolitan species are found both in the tropics (between the tropics of Cancer and Capricorn) and in temperate regions. LC = Least Concern, NT = Near Threatened, VU = Vulnerable, EN = Endangered, CR = Critically Endangered.

magnitude of the trend by calculating the percentage change in encounter probability from year to year. Species with significant year effects and trend magnitudes $>|1\%/\mathrm{yr}|$ were considered decreasing or increasing depending on the directional effect of year (for examples see Fig. 1). We then grouped all species by their latitudinal affiliation, defining each species as primarily found in tropical regions (within the tropics of Cancer and Capricorn), temperate regions (outside of the tropics), or both (cosmopolitan). Range data came from a global bird ecology database (see Şekercioğlu et al., 2019 for details) updated with recent information on the bird species analyzed (del Hoyo et al., 2019).

We calculated the overall rate of agreement as the percentage of species whose eBird trend and BirdLife trend matched. We ran a multiple logistic regression to determine the factors influencing the rates of trend agreement. Agreement (1 or 0) was used as the dependent variable and latitudinal affiliation, IUCN threat status, and the log number of eBird lists from the species' ranges were included as fixed effects. In addition, we included BirdLife trend and derivation, and eBird trend as covariates. The BirdLife trend factor allowed us to test the ability of eBird to predict BirdLife assessments. The eBird trend factor allowed us to test the likelihood that a species with a given trend estimate from eBird will agree with BirdLife. Finally, we included Nagelkerke's index (pseudo-R^2) to determine whether the rate of agreement increased with the amount of variation explained by the eBird trend model. We used likelihood-ratio tests (LRT) to determine the significance of each variable and removed any that were not significant.

2.4. Randomization

When calculating the rates of agreement within categories, it is important to consider the rate of agreement that would occur by chance alone, as the number of species that fall into different categories is not uniform. To do this, we randomized the eBird trend labels across species, keeping the total number in each category ("increased", "decreased" and "stable") constant. We repeated this process 500 times and calculated the mean and 95% confidence intervals for each category (BirdLife trend, BirdLife derivation, eBird trend, latitudinal affiliation and threat status). We compared the observed rates of agreement with the confidence intervals on the means from randomization. An observed rate was greater or less than expected by chance if it was outside the confidence intervals.

All analyses were performed in R version 3.6.1 (R Core Team, 2020).

3. Results

Of the 8121 species with trend estimates from both eBird and BirdLife, BirdLife identified 624 (7.7%) as increasing, 3616 (44.5%) as stable, and 3881 (47.8%) as decreasing. These proportions contrast with the eBird trends of 1974 (24.3%) as increasing, 4942 (60.9%) as stable, and 1205 (14.8%) as decreasing. This comparison suggests that eBird produces trends that are, on average, more positive than BirdLife. Overall, only 37.8% of the bird species had population trends that agreed between these data sources (Fig. 3a) and this was slightly higher than expected by chance (36.1% ± 0.04CI). In the logistic model, Nagelkerke's index did not have a significant effect on the rate of agreement (LRT: $\chi^2 = 0.05$, $p = 0.82$) and so this covariate was dropped from the model. Replacing Nagelkerke's index with Cox & Snell's index as an alternative pseudo-R^2 was also not significant ($\chi^2 = 0.41$, $p = 0.52$). All remaining covariates were significant and so retained.

Species found only in the tropics had lower rates of agreement (37.7%) than temperate species (39.7%) and similar rates of agreement to cosmopolitan species (37.2%; Fig. 3b; $\chi^2 = 8.54$, $p = 0.014$). For all latitudinal affiliations, the observed rate of agreement was higher than expected by chance, and this was particularly the case for temperate species (Fig. 3b). Species of Least Concern showed the highest agreement rate (41.8%) followed by Critically Endangered species (27.4%; $\chi^2 = 13.26$, $p = 0.01$). Species in the intermediate threat categories showed low levels of agreement (17–20%). The observed rate of agreement was higher than expected by chance for Least Concern, Vulnerable, and Critically Endangered species and lower than expected for Near Threatened and Endangered species (Fig. 3c). In particular, the rates of agreement were noticeably higher than expected for Least Concern and Critically Endangered species.

Table 1
A comparison of the trend estimates between those produced by BirdLife International (rows) and those estimated from global eBird data (columns). Bold numbers are those that agree in trend designation.

		eBird trend			
		Increasing	Stable	Decreasing	Total
BirdLife Trend	Increasing	**261**	276	87	624
	Stable	857	**2225**	534	3616
	Decreasing	856	2441	**584**	3881
	Total	1974	4942	1205	8121

For eBird trends ($\chi^2 = 998.05$, $p < 0.0001$) the highest rate of agreement was for decreasing species (48.5%; Table 1) but this was closely followed by stable species (45.0%) with the rate of agreement for increasing species being much lower (13.2%). For all three categories, observed rates of agreement were higher than expected by chance (Fig. 4a). However, while the rates of agreement were only marginally higher than expected by chance for stable and decreasing species, the rate of agreement was much higher than expected for increasing species. The log number of eBird checklists had a positive effect on the rate of agreement (Fig. 4b; $\chi^2 = 4.75$, $p = 0.029$). For BirdLife trends ($\chi^2 = 1591.1$, $p < 0.0001$), the highest rate of agreement was for stable species (61.5%; Table 1), followed by increasing species (41.8%) and decreasing species (15.0%). Again, the observed rates of agreement were higher than expected by chance for all categories (Fig. 4c) but highest for increasing species. These results suggest that BirdLife and eBird tend to agree more when bird populations are increasing. Finally, the rate of agreement was highest for "suspected" BirdLife trends (39.7%), followed by "estimated" trends (36.4%), "observed" trends (26.3%), and "inferred" trends (12.0%; $\chi^2 = 22.23$, $p < 0.0001$). Compared to chance, the rate of agreement was much higher for estimated trends, marginally higher for observed and suspected trends, and lower for inferred trends (Fig. 4d).

Restricting the temporal window to 2010–2019 had little effect on the rate of agreement, but restricting the window to 2015–2019 improved the rate of agreement (Fig. 3a). This result, however, was not consistent across categories of species (Fig. 3 and Fig. 4). In many cases, the difference between the observed rate of agreement and the expected rate of agreement was highest for the 2010–2019 (intermediate) temporal window, but the magnitudes of these differences were relatively small.

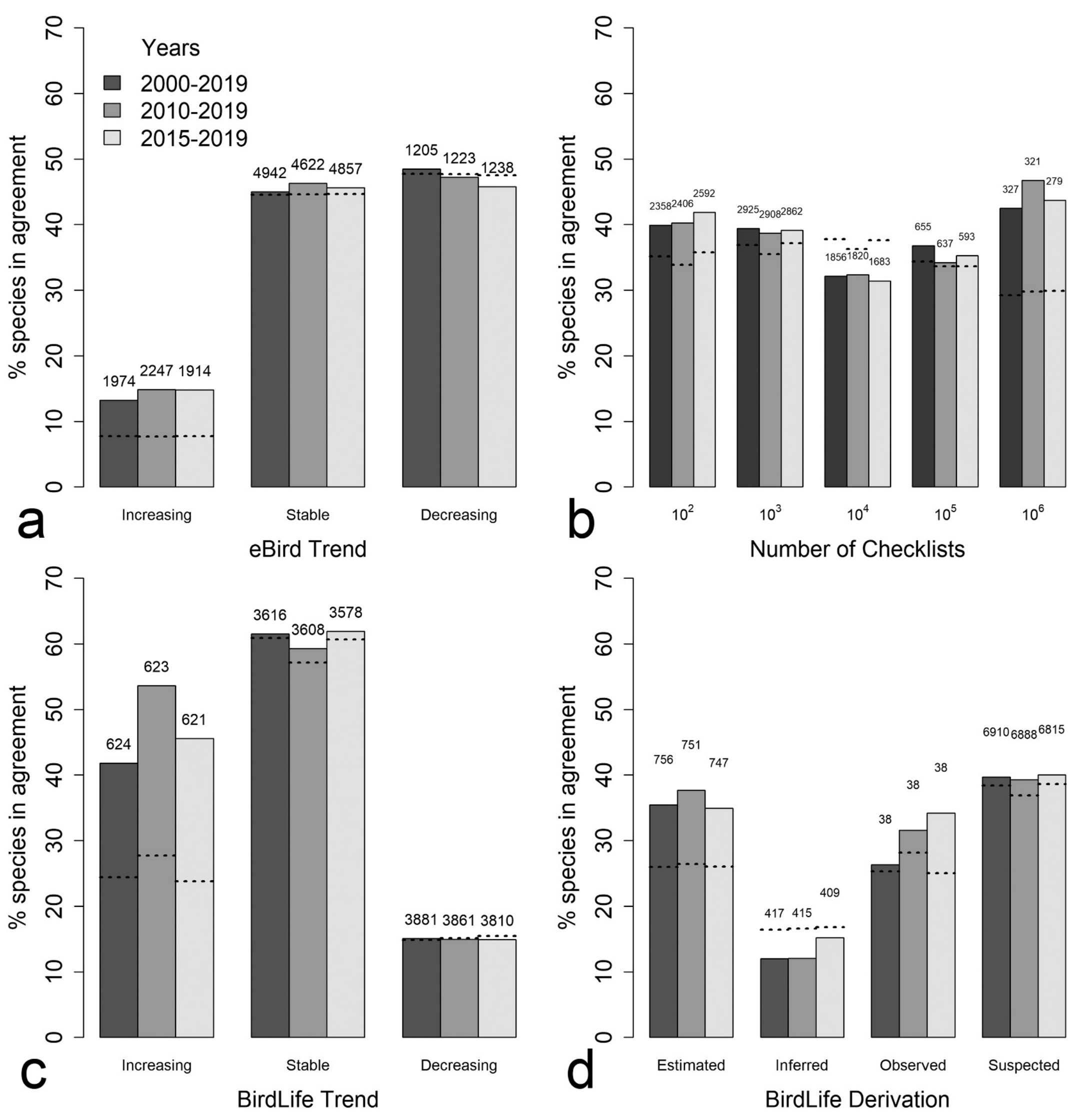

Fig. 4. The effect of (a) eBird trend, (b) number of checklists, (c) BirdLife trend, and (d) BirdLife trend derivation on the rate of agreement in population trend estimates between eBird and BirdLife International for three different temporal windows. Numbers above bars represent the total number of species in each category. Dashed lines represent the rate of agreement expected by chance alone. Confidence intervals were so small as to not be visible in the figure.

4. Discussion

Across the global avifauna, the rate of agreement between population trends based on eBird community science data and those based on traditional conservation assessments by BirdLife International was low (37.8%) but higher than expected by chance (Fig. 3a). eBird data showed increasing trends in more species than did the BirdLife data, suggesting that community science, at least for birds, may provide overly optimistic estimates of population trends. It is reassuring, however, that the rates of agreement for increasing species were considerably greater than expected by chance for both BirdLife and eBird trends. This suggests that trends based on eBird data could be a good way of detecting birds that are increasing in response to anthropogenic change or conservation action. Similar to an analysis of North American eBird data (Horns et al., 2018), the rate of agreement was positively associated with the number of eBird checklists for a species. This result highlights the importance of promoting world-wide participation in community science programs at the local level, especially in developing and tropical countries (La Sorte and Somveille, 2020), in order to increase the volume of data and the probability of detecting accurate trend directions.

The tendency of eBird data to show more positive population trends is likely to be an artifact of increases in focused searches for rare, threatened and/or endemic species that make up the majority of the "target" species birders seek on birdwatching trips. Increased targeting may also be linked with intensive but localized conservation efforts that attract birdwatchers. A converse mechanism may be underlying the higher rate of agreement for birds found in temperate areas (Fig. 3b). The use of eBird is much higher in North America and Europe than in many tropical developing nations (La Sorte and Somveille, 2020), and many of the participants in temperate, developed countries are engaged in more general birdwatching rather than targeted birding trips, with the resulting data providing a more accurate representation of the local bird communities. Similarly, the rate of agreement was highest for species of Least Concern (Fig. 3c), possibly reflecting the disproportionate access that people have to common species versus the significant effort birdwatchers spend to find globally threatened species. However, it is noteworthy that the rate of agreement was much greater than expected by chance for Critically Endangered species. This result could be an artifact of a small sample size or it could indicate that, for the most endangered species, even targeted searching produces declining eBird trends for a group where 92% of the species (for which we had sufficient data) are declining according to BirdLife.

Given the volume of eBird data and the focus of millions of birdwatchers on finding even the rarest bird species on a regular basis, we predicted that bird species with decreasing eBird trends would have significantly higher agreement with BirdLife population trends. Traveling birdwatchers and professional bird tour companies intensively focus on finding rare, range-restricted, endemic, threatened and near threatened species. If, despite this effort, rare species are being recorded less frequently in eBird, these species are likely to be declining. Contrary to our prediction, the rate of agreement for species with decreasing eBird trends was similar to the rate expected by chance (Table 1, Fig. 4a) as was the rate of agreement for species with decreasing BirdLife trends (Table 1, Fig. 4c). These results raise two important considerations for monitoring declining species with community science. First, bird species showing declining trends according to both eBird and BirdLife should be a priority of conservation assessments, especially in understudied tropical regions (Şekercioğlu, 2012). However, likely due to the same increase in effort, actual declines in many species, particularly in common species (Rosenberg et al., 2019), may not emerge as declining trends based on eBird community science.

An important caveat of these results is that we assumed the BirdLife trends to be correct and that a disagreement with the eBird trend was considered a shortcoming of the eBird data in detecting the actual trend. However, while the BirdLife trends are the best available global assessments we have for many bird species, they are not infallible. Many tropical species may lack the data for biologists to accurately estimate population trends. In addition, different species are assessed with different techniques in different habitats. It is therefore difficult in some instances to attribute the disagreement rates to either BirdLife or eBird data. Indeed, we found that the rate of agreement was much higher than expected for species whose BirdLife trends were estimated or observed compared to the inferred or suspected trends (Fig. 4d), indicating that more accurate population trend estimates by scientists are required for higher rates of agreement. Thus, alongside increased community science effort, there is a need for repeatable methods to establish the biodiversity baselines against which future trends will be calculated and community science data can be compared. Given the disparity in data sources and the low levels of agreement, we cannot say whether increasing eBird data alone will be sufficient (Stegman et al., 2017).

Narrowing the temporal window to the past five years did increase the observed rate of agreement above the rate of agreement due to chance, but this trend was not consistent across the various categories of species (Figs. 3 and 4). Many categories (e.g. cosmopolitan and temperate species, Least Concern, Vulnerable and Endangered species, increasing and stable species) actually showed the greatest difference between observed and expected rates of agreement for the intermediate temporal window (2010–2019). This may reflect a trade-off between having more data per year and having more years of data over which to estimate trends. Rates of agreement were highest for species with more checklists, suggesting that greater use of eBird and other community science programs will increase our ability to estimate trends. Birdwatchers should also aim to increase the quality of their data by targeting under-surveyed "coldspots" in addition to popular "hotspots" in order to increase spatial coverage (Callaghan et al., 2019), and by including as many data and meta-data as possible on their checklists to increase the number of checklists that can be used in effort-controlled occurrence and abundance estimation analyses (Johnston et al., 2019). In the tropics, where bird guides and tours are prevalent, we also encourage bird guides to submit complete checklists where possible, even when the target species are not located or in the off-season when tourists are absent. Finally, as new techniques for modeling community science data emerge (Callaghan et al., 2019; Fink et al., 2020), our ability to accurately model population trends will likely increase. For now, we are limited by computing power and data availability in our ability to implement complex models for nearly 11,000 bird species and prudency prioritizes power over model complexity (Fink et al., 2020).

5. Conclusions

Community science may have the potential to provide critical information on the patterns of abundance and distributions of organisms over geographic and temporal scales beyond the scope of traditional scientific studies (Boersch-Supan et al., 2019; Fink et al., 2020; Horns et al., 2018). The use of community science in conservation is rapidly expanding, as is the need to validate the results of such programs. Our results suggest that eBird data are marginally better than chance at predicting BirdLife trends, meaning that eBird data are not currently adequate for monitoring populations of the majority of the world's bird species, especially in the biodiverse developing world where systematic surveys are essential. However, eBird data appear to be good at detecting increasing populations. Additionally, species showing both eBird and BirdLife declines, especially little-known bird species in understudied tropical regions, should be a priority of conservation assessments (Şekercioğlu, 2012). Our results further suggest that increases in local participation in community science programs should increase these programs' efficacy in monitoring populations. Community science initiatives like eBird are becoming increasingly important for biodiversity assessments and further community science participation is critical in the developing world where most of the world's biodiversity resides.

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Credit authorship contribution statement

Montague H.C. Neate-Clegg:Conceptualization, Methodology, Software, Formal analysis, Investigation, Data curation, Writing - original draft, Visualization.**Joshua J. Horns**:Conceptualization, Methodology, Software, Formal analysis, Investigation, Data curation, Writing - original draft, Visualization.**Frederick R. Adler**:Writing - review & editing.**M. Çisel Kemahlı Aytekin**:Resources, Writing - review & editing.**Çağan H. Şekercioğlu**: Conceptualization, Writing - review & editing, Supervision, Project administration.

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References

Abolafya, M., Onmuş, O., Şekercioğlu, Ç.H., Bilgin, R., 2013. Using citizen science data to model the distributions of common songbirds of Turkey under different global climatic change scenarios. PLOS One 8 (7), e68037. https://doi.org/10.1371/journal.pone.0068037.

Aceves-Bueno, E., Adeleye, A.S., Feraud, M., Huang, Y., Tao, M., Yang, Y., Anderson, S.E., 2017. The accuracy of citizen science data: a quantitative review. Bull. Ecol. Soc. Am. 98, 278–290. https://doi.org/10.1002/bes2.1336.

Bayraktarov, E., Ehmke, G., O'Connor, J., Burns, E.L., Nguyen, H.A., McRae, L., Possingham, H.P., Lindenmayer, D.B., 2019. Do big unstructured biodiversity data mean more knowledge? Front. Ecol. Evol. 6, 1–5. https://doi.org/10.3389/fevo.2018.00239.

Birdlife International, 2019. BirdLife data zone. [WWW Document]. URL. http://datazone.birdlife.org/species/search accessed 9.14.18.

Boersch-Supan, P.H., Trask, A.E., Baillie, S.R., 2019. Robustness of simple avian population trend models for semi-structured citizen science data is species-dependent. Biol. Conserv. 240. https://doi.org/10.1016/j.biocon.2019.108286.

Bonney, R., Cooper, C.B., Dickinson, J., Kelling, S., Phillips, T., Rosenberg, K.V., Shirk, J., 2009. Citizen science: a developing tool for expanding science knowledge and scientific literacy. Bioscience 59, 977–984. https://doi.org/10.1525/bio.2009.59.11.9.

Braun, C.E., Wann, G.T., 2017. Historical occurrence of white-tailed ptarmigan in Wyoming. West. North Am. Nat. 77, 204–211. https://doi.org/10.3398/064.077.0208.

Callaghan, C.T., Gawlik, D.E., 2015. Efficacy of eBird data as an aid in conservation planning and monitoring. J. Field Ornithol. 86, 298–304. https://doi.org/10.1111/jofo.12121.

Callaghan, C.T., Poore, A.G.B., Major, R.E., Rowley, J.J.L., Cornwell, W.K., 2019. Optimizing future biodiversity sampling by citizen scientists. Proc. R. Soc. B Biol. Sci. 286. https://doi.org/10.1098/rspb.2019.1487.

Clark, C.J., 2017. eBird records show substantial growth of the Allen's Hummingbird (Selasphorus sasin sedentarius) population in urban Southern California. Condor 119, 122–130. https://doi.org/10.1650/CONDOR-16-153.1.

Cox, D.R., Snell, E.J., 1989. Analysis of Binary Data, 2nd ed. Chapman and Hall, London.

del Hoyo, J., Elliott, A., Sargatal, J., Christie, D.A., de Juana, E., 2019. Handbook of the birds of the world alive. [WWW document]. URL. https://www.hbw.com.

Fink, D., Auer, T., Johnston, A., Ruiz-Gutierrez, V., Hochachka, W.M., Kelling, S., 2020. Modeling avian full annual cycle distribution and population trends with citizen science data. Ecol. Appl. 30, 1–16. https://doi.org/10.1002/eap.2056.

Fournier, A.M.V., Sullivan, A.R., Bump, J.K., Perkins, M., Shieldcastle, M.C., King, S.L., 2017. Combining citizen science species distribution models and stable isotopes reveals migratory connectivity in the secretive Virginia rail. J. Appl. Ecol. 54, 618–627. https://doi.org/10.1111/1365-2664.12723.

Horns, J.J., Adler, F.R., Şekercioğlu, Ç.H., 2018. Using opportunistic citizen science data to estimate avian population trends. Biol. Conserv. 221, 151–159. https://doi.org/10.1016/j.biocon.2018.02.027.

Horton, K.G., Van Doren, B.M., La Sorte, F.A., Fink, D., Sheldon, D., Farnsworth, A., Kelly, J.F., 2018. Navigating north: how body mass and winds shape avian flight behaviours across a North American migratory flyway. Ecol. Lett. 21, 1055–1064. https://doi.org/10.1111/ele.12971.

Inger, R., Gregory, R., Duffy, J.P., Stott, I., Voříšek, P., Gaston, K.J., 2015. Common European birds are declining rapidly while less abundant species' numbers are rising. Ecol. Lett. 18, 28–36. https://doi.org/10.1111/ele.12387.

Isaac, N.J.B., Van Strien, A.J., August, T.A., De Zeeuw, M.P., Roy, D.B., 2014. Statistics for citizen science: extracting signals of change from noisy ecological data. Methods Ecol. Evol. 5, 1052–1060. https://doi.org/10.1111/2041-210X.12254.

Johnston, A., Hochachka, W., Strimas-Mackey, M., Gutierrez, V.R., Robinson, O., Miller, E., Auer, T., Kelling, S., Fink, D., 2019. Best practices for making reliable inferences from citizen science data: case study using eBird to estimate species distributions. bioRxiv 574392. https://doi.org/10.1101/574392.

Kamp, J., Oppel, S., Heldbjerg, H., Nyegaard, T., Donald, P.F., 2016. Unstructured citizen science data fail to detect long-term population declines of common birds in Denmark. Divers. Distrib. 22, 1024–1035. https://doi.org/10.1111/ddi.12463.

Kati, V.I., Şekercioğlu, Ç.H., 2006. Diversity, ecological structure, and conservation of the landbird community of Dadia reserve, Greece. Diversity and Distributions 12, 620–629. https://doi.org/10.1111/j.1366-9516.2006.00288.x.

Kelling, S., Johnston, A., Hochachka, W.M., Iliff, M., Fink, D., Gerbracht, J., Lagoze, C., La Sorte, F.A., Moore, T., Wiggins, A., Wong, W.K., Wood, C., Yu, J., 2015. Can observation skills of citizen scientists be estimated using species accumulation curves? PLoS One 10, 1–20. https://doi.org/10.1371/journal.pone.0139600.

Kleiman, D.G., Reading, R.P., Miller, B.J., Clark, T.W., Scott, M., Robinson, J., Wallace, R.L., Cabin, R.J., Felleman, F., 2000. Improving the evaluation of conservation programs. Conserv. Biol. 14, 356–365.

La Sorte, F.A., Somveille, M., 2020. Survey completeness of a global citizen-science database of bird occurrence. Ecography 43, 34–43. https://doi.org/10.1111/ecog.04632.

La Sorte, F.A., Tingley, M.W., Hurlbert, A.H., 2014. The role of urban and agricultural areas during avian migration: an assessment of within-year temporal turnover. Glob. Ecol. Biogeogr. 23, 1225–1234. https://doi.org/10.1111/geb.12199.

Nagelkerke, N.J.D., 1991. A note on a general definition of the coefficient of determination. Biometrika 78 (3), 691–692.

R Core Team, 2020. R: A Language and Environment for Statistical Computing.

Ralph, C.J., Droege, S., Sauer, J.R., 1995. Managing and monitoring birds using point counts: standards and applications. USDA For. Serv. Gen. Tech. Rep. 149, 161–168.

Rosenberg, K.V., Dokter, A.M., Blancher, P.J., Sauer, J.R., Smith, A.C., Smith, P.A., Stanton, J.C., Panjabi, A., Helft, L., Parr, M., Marra, P.P., 2019. Decline of the North American avifauna. Science 366, 120–124. https://doi.org/10.1126/science.aaw1313.

Sauer, J.R., Hines, J.E., Fallon, J.E., Pardieck, K.L., Ziolkowski, D.J., Link, W.A., 2014. The North American Breeding Bird Survey, Results and Analysis 1966–2013. Version 01.30.2015 [WWW Document]. URL: https://www.mbr-pwrc.usgs.gov/bbs/BBS_Results_and_Analysis_2013.html.

Seak, S., Schmidt-Vogt, D., Thapa, G.B., 2012. Biodiversity monitoring at the Tonlé Sap Lake of Cambodia: a comparative assessment of local methods. Environ. Manag. 50, 707–720. https://doi.org/10.1007/s00267-012-9909-3.

Şekercioğlu, Ç.H., 2002. Forest fragmentation hits insectivorous birds hard. Dir. Sci. 1, 62–64.

Şekercioğlu, Ç.H., 2006. Ecological significance of bird populations. In: del Hoyo, J., Elliott, A., Christie, D.A. (Eds.), Handbook of the Birds of the World. Lynx Edicions, Barcelona, pp. 15–51.

Şekercioğlu, Ç.H, 2011. Functional extinctions of bird pollinators cause plant declines. Science 331, 1019–1020. https://doi.org/10.1126/science.1202389.

Şekercioğlu, Ç.H., 2012. Promoting community-based bird monitoring in the tropics: conservation, research, environmental education, capacity-building, and local incomes. Biol. Conserv. https://doi.org/10.1016/j.biocon.2011.10.024.

Şekercioğlu, Ç.H., Mendenhall, C.D., Oviedo-Brenes, F., Horns, J.J., Ehrlich, P.R., Daily, G.C., 2019. Long-term declines in bird populations in tropical agricultural countryside. Proc. Natl. Acad. Sci. U. S. A. 116, 9903–9912. https://doi.org/10.1073/pnas.1802732116.

Silvertown, J., 2009. A new dawn for citizen science. Trends Ecol. Evol. 24, 467–471. https://doi.org/10.1016/j.tree.2009.03.017.

Stegman, L.S., Primack, R.B., Gallinat, A.S., Lloyd-Evans, T.L., Ellwood, E.R., 2017. Reduced sampling frequency can still detect changes in abundance and phenology of migratory landbirds. Biol. Conserv. 210, 107–115. https://doi.org/10.1016/j.biocon.2017.04.004.

Sullivan, B.L., Wood, C.L., Iliff, R.E., Bonney, D.F., Kelling, S., 2009. eBird: a citizen-based bird observation network in the biological sciences. Biol. Conserv. 142, 2282–2292. https://doi.org/10.1016/j.biocon.2009.05.006.

Szabo, J.K., Vesk, P.A., Baxter, P.W.J., Possingham, H.P., 2010. Regional avian species declines estimated from volunteer-collected long-term data using List Length Analysis. Ecol. Appl. 20, 2157–2169. https://doi.org/10.1890/09-0877.1.

Tear, T.H., Scott, J.M., Hayward, P.H., Griffith, B., 1995. Recovery plans and the Endangered Species Act: are criticisms supported by data? Conserv. Biol. 9, 182–195.

Van Strien, A.J., Pannekoek, J., Gibbons, D.W., 2001. Indexing European bird population trends using results of national monitoring schemes: a trial of a new method. Bird Study 48, 200–213. https://doi.org/10.1080/00063650109461219.

Walker, J., Taylor, P.D., 2017. Using eBird Data to Model Population Change of Migratory Bird Species. pp. 12. https://doi.org/10.5751/ACE-00960-120104.