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Using opportunistic citizen science data to estimate avian population trends

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ABSTRACT

Determining population trends is critical for conservation. For most bird species, trends are based on count data gathered by institutions with formalized survey protocols. However, limited resources may prevent these types of surveys, especially in developing countries. Ecotourism growth and subsequent increases in opportunistic data from birdwatching can provide a source of population trend information if analyses control for inter-observer variation. List length analysis (LLA) controls for such variation by using the number of species recorded as a proxy for observer skill and effort. Here, we use LLA on opportunistic data gathered by eBird to estimate population trends for 574 North American bird species (48% of species declining) and compare these estimates to population trends based on 1) formal breeding bird surveys (54% of species declining) and 2) population estimates from eBird data controlled using more rigorous correction (46% of species declining). Our analyses show that eBird data produce population trends that differ on average by only 0.4%/year from formal surveys and do not differ significantly from estimates using more control metrics. We find that estimates do not improve appreciably beyond 10,000 checklists, suggesting this as the minimum threshold of opportunistic data required for population trend estimation. Lastly, we show that characteristics affecting a species' ubiquity, such as geographic and elevational range, can affect its population trend estimate. Our results suggest that opportunistic data can be used to approximate species population trends, especially for widespread species. Because our protocol uses information present in all checklists, it can be applied to a diversity of data sources including eBird, trip reports, and bird atlases.

1. Introduction

Determining regional and large-scale population trends for species is a critical component of conservation. Accurate population trends are required to identify species of conservation concern and to evaluate the effectiveness of conservation programs (Kleiman et al., 2000; Tear et al., 1995). For most bird species, populations are monitored using point count data (Howe et al., 1989; Robertson et al., 1995; Sauer et al., 2017), which assumes that changes in how often a species is detected are correlated with changes in that species overall abundance.

In North America, the United States Geological Survey (USGS) and the Canadian Wildlife Service (CWS) oversee the annual North American Breeding Bird Survey (BBS) to monitor the populations of many bird species that are breeding residents (Sauer et al., 2017). The BBS maintains thousands of transects where observers record all birds detected visually or aurally at set locations. These counts generate reliable population trends for many bird species at the state and national level (Downes et al., 2016). Monitoring programs such as this require substantial resources and are absent from most developing countries (Seak et al., 2012; Şekercioğlu, 2012a), even though the growing threat of climate change has made such monitoring programs more important than ever (Harris et al., 2011). This paucity of population monitoring is especially true in the tropics, home to the majority of the world's bird species, many of which are specialized, sedentary and threatened with extinction (Şekercioğlu and Sodhi, 2007; Tobias et al., 2013). Only a few tropical and/or developing countries have bird atlas data (Robertson et al., 1995) while in most countries ornithological data primarily come from birdwatching tours, individual birdwatchers, and other forms of opportunistic data (Şekercioğlu, 2012a). The geographical and temporal coverage of these types of data are less systematic than those of the BBS and may result in less accurate population estimates.

The increase in ecotourism and the development of large citizen science programs have resulted in a rapidly growing body of data on birds. Opportunistic data have been previously employed to effectively answer questions about species occurrence at large geographic or temporal scales (Devictor et al., 2010). In some studies, large volumes of opportunistic data have yielded results similar to those of formal

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bird-count surveys when examining spatial or temporal patterns of bird occurrence (Munson et al., 2010; Walker and Taylor, 2017). Others, however, have cautioned against the use of opportunistic data, particularly when estimating population trends for common species (Kamp et al., 2016).

eBird is a large citizen science database that contains a large and growing volume of bird count data (hereafter "checklists" or "lists") (Sullivan et al., 2009). Data from eBird has been successfully used to analyze diversity (Callaghan and Gawlik, 2015; La Sorte et al., 2014), species distributions (Fink et al., 2010), and migration (Supp et al., 2015), as well as monitor population trends (Clark, 2017; Walker and Taylor, 2017). These data are submitted by participants with a wide range of skill and experience, and thus some means of observer quality control must be implemented in any analysis. All eBird checklists are submitted with various metrics that can help control for variation among observers. Each checklist has data on the number of observers, the time spent observing, and the distance travelled. This information plays an important role in standardizing observations across participants, but is not available in many data sources, such as birding tour lists and bird atlas data.

List length analysis (LLA) uses only the number of species recorded on a given list as a proxy for observer skill and effort (Szabo et al., 2010). LLA operates under the assumption that as the number of species recorded on a given checklist increases, the likelihood of that list recording a specific species also increases. Previous analyses of eBird data have confirmed that the number of species reported increases with both time spent observing (effort) and long-term participation continuity (skill) (Kelling et al., 2015). Studies of eBird data have also shown that using the number of species recorded does help to control for inter-observer variability when estimating occupancy (Johnston et al., 2017) Because the number of species observed can be gathered from any birdwatching checklist, the use of LLA would allow for data from a greater number of sources to be used when estimating population trends.

However, using LLA in place of eBird's more complete means of quality control may produce unreliable trend estimates. Population trend estimates can vary widely depending on the method of analysis used (Thomas and Martin, 1996). It has also been suggested that LLA may perform poorly in areas with low diversity (Isaac et al., 2014). Therefore, we use two different methods to estimate bird population trends from opportunistic data (eBird) and compare them with each other and with estimates from more formal surveys (BBS). Our first method of analysis, hereafter "additional parameters," or "AP," uses multiple parameters of effort associated with each eBird checklists, including distance travelled and time spent observing. Our second method, hereafter "list-length-only," or "LO" uses only LLA, testing its ability to serve as a proxy for effort. LLA has previously been used as a means of quality control with eBird data (Walker and Taylor, 2017), though only in conjunction with other metrics. Here, we compare results generated from more complex models to those generated by models that only use LLA as a means of quality control. If results from each analytical method are similar, it may be feasible to use multiple sources of opportunistic data (such as birding tour lists and bird atlas information) for which more standard methods of quality control may be unavailable.

In this paper, we compare avian population trend data gathered by formal surveying (BBS) to those estimated using LLA and eBird data. We estimate population trends from eBird using both AP and LO analytical methods and compare these methods to one another. We also test the ability of citizen science data to estimate overall population trajectories (the proportion of species with increasing or decreasing trends) at a broad regional scale. We then use these results to estimate the volume of citizen science data required to accurately detect these large-scale changes. Finally, we investigate avian ecological characteristics that best predict the potential of a species' population to be reliably estimated using this methodology.

2. Methods

2.1. Data selection and trend calculation

We analyzed population changes for 574 bird species that occur on both the Breeding Bird Survey lists and eBird checklists. All analyses were done using R (Version 3.1.1) (R Core Team, 2014).

2.1.1. BBS trends

We downloaded the complete BBS dataset and reduced it to records from the contiguous 48 United States (Paradiek et al., 2017). We further reduced the dataset to counts conducted from 1997 through 2016. The BBS dataset contains records as far back as 1967, however before 1997 most years contain fewer than 100 records and no years prior to 1997 contain > 10,000. Starting in 1997 all years contain between 128,000 and 141,000 records. Species that were recorded to the sub-species level by the BBS were lumped together. We then generated presence/absence data for each species at each point count station. Analyses were done using presence/absence data rather than abundance to make the results comparable between the BBS and eBird because many eBird lists do not report abundance. Previous studies have found strong linear correlations between the proportion of BBS point count stations at which a species occurred and the reported abundance (Walker and Taylor, 2017). Species population trends were estimated by fitting their presence/absence data to mixed logistic regression models, with year treated as a fixed effect. To reduce error associated with geographic variation, route ID nested within state was treated as a random effect. To ensure that using presence/absence data in place of abundance data did not seriously affect trend estimates, we re-calculated population trends by using BBS abundance data and mixed Poisson regression. The rest of the cofactors from the logistic regression were kept the same. The Pearson correlation coefficient across all species was 0.74, suggesting a high degree of correlation between presence/absence and abundance-based modeling techniques.

2.1.2. eBird trends

We downloaded the complete eBird basic dataset and again reduced it to checklists from the contiguous United States gathered between 1997 and 2016. Checklists were based on unique "sampling event identifiers." eBird users are required to specify if they are reporting all birds detected or whether their list represents only a sample of the present avifauna. We eliminated all checklists that users defined as incomplete. We also eliminated any checklists with fewer than four species, as these short lists often represent a targeted search for a specific species and have the potential to confound results (Szabo et al., 2010). Duplicate lists were excluded by condensing lists on the basis of "group identifier". 11,681,254 eBird lists remained for analysis after duplicate, incomplete, and short lists were removed. When estimating population trends for each species, we only used checklists from eBird locations, as defined by the "locality ID", with at least one record for that species. All checklists that met the criteria for analysis were assigned a 1 or 0 depending on whether they recorded the species of interest. We generated two sets of population trends for each species by fitting this presence/absence data from eBird checklists to either an AP or LO multiple logistic model. Both models included "year", "number of species", and "state" as fixed effects. Every species observed during one observation period receives its own record in eBird's data, but all are associated with the same "sampling event identifier". Therefore we determined number of species recorded as the number of times a unique "sampling event identifier" appeared in the data. AP models also took advantage of the metrics of quality control associated with all eBird checklists by including "distance travelled", and "time spent observing" as fixed effects. We additionally ran the same models but only used the most recent 5, 10, and 15 years of data from eBird (rather than the 20 years included in the original analysis) to identify the necessary timespan of opportunistic data required to elucidate long-term trends.

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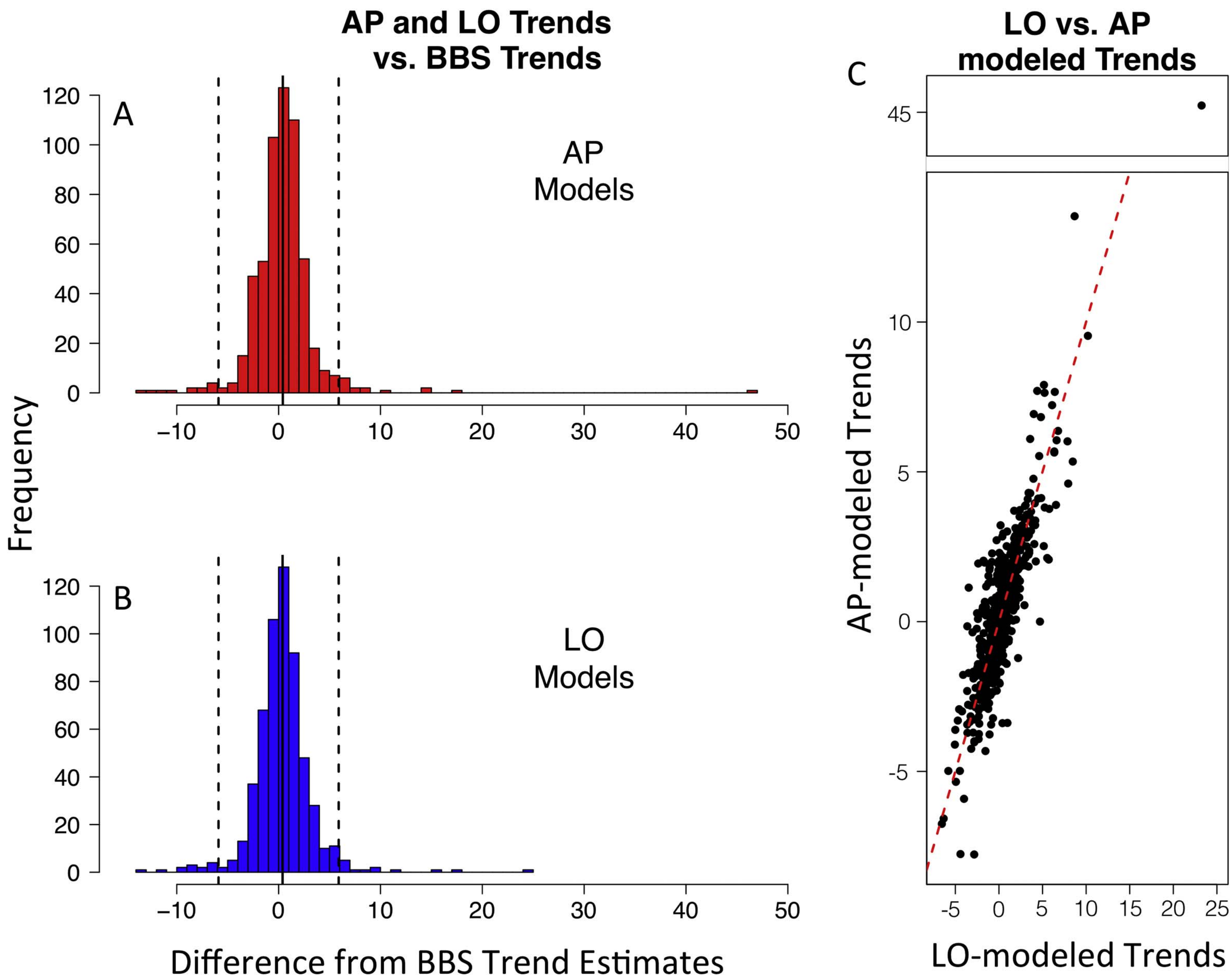

Fig. 1. Comparison of population trends between BBS data and eBird data modeled with different control parameters: A and B) Histograms of the differences in population trends of 574 bird species estimated by the BBS vs. both methods of eBird data analysis. 1A: trends from models using a greater number of quality control metrics (AP). 1B: trends based on list-length alone (LO).). Solid black lines indicate mean trend differences, broken lines indicate 95% of variation from 0. C) Comparison of species' trends estimated using AP and LO modeling techniques. Red line indicates 1:1 relationship ($R^2 = 0.73$).

2.2. Sensitivity-specificity

Next, we performed sensitivity-specificity analyses to test the ability of eBird data to detect national trajectories in avian populations and to approximate the volume of eBird data required before trend estimates did not appreciably improve with more checklists. To determine the overall accuracy of our methods to detect changes at this broad level, all species were assigned to one of the following categories: True Positive if both the BBS and eBird showed increasing populations, False Positive if the BBS reported a decreasing trend while our results suggested an increasing population, False Negative if the BBS reported an increasing trend while our results suggested a decreasing trend, and True Negative if both sources reported a decreasing population trend. Sensitivity-specificity analyses are carried out by comparing the sensitivity (the proportion of species with positive eBird trends that were also considered positive trends by the BBS (true positive rate)) against the specificity (the proportion of species with negative eBird trends that were also considered negative by the BBS (true negative rate)). It is important that this protocol produce reasonable rates for both sensitivity and specificity, as low rates of either metric could have serious conservation consequences. Low sensitivity may mean that our methods are inadequate at detecting increases in a species' population which could result in incorrect assessments of conservation programs and misdirection of funds. Even more seriously, low specificity may mean that our methods are inadequate at detecting declines in a species' population, severely hindering the ability of these methods in monitoring declining and at-risk species.

We randomly selected a subset of checklists from within each species' range without replacement, and calculated new population trends based on the reduced dataset. We randomly sampled between 100 and 1000 checklists by 100 s, between 1000 and 10,000 checklists by 1000 s, between 10,000 and 100,000 checklists by 10,000 s, and between 100,000 and 1000,000 checklists by 100,000 s. At each sampling level we determined the true positive rate and true negative rate across all species to see how using a smaller subset of the overall data set affected our ability to accurately assess national-level increases and decreases in population trends. As more eBird data are added, we hypothesize that the true positive and true negative rates will increase, suggesting an overall improvement in trend estimates.

In order to identify a threshold of checklists above which trend estimates no longer improve, we calculated the straight-line distance between each point based on the randomly selected subset of eBird data and the coordinate (0,1). In sensitivity-specificity analyses, sensitivity (the true positive rate) is generally compared to 1-specificity (the false negative rate). Therefore, (0,1) is the idealized location for a test to fall in a sensitivity-specificity analysis, as it would amount to 100% accurate detection of both increasing and decreasing population trends (Akobeng, 2007). These distances were then plotted against the number of checklists that had been randomly sampled. We used the R package 'segmented' to identify a breakpoint where the improvement of trend estimates slowed considerably (Muggio, 2008).

2.3. Bird characteristics

To test whether particular aspects of a bird's ecology may affect their ability to be reliably recorded, we used multiple linear regression to compare the log absolute value of the difference in trend estimates between the USGS and eBird against a number of covariates that could affect a species' ubiquity. The log of the absolute value of trend differences was used to reduce heteroscedasticity and avoid illogical negative regression extrapolations. Number of habitats used, range of diets consumed, elevational range, geographic range, and population trend were all included as non-interacting cofactors. Ecological data came from a global bird ecology database covering all the bird species of the world (see Şekercioğlu, 2012b) and updated with recent information (del Hoyo et al., 2017). We used the number of BBS routes where a species was detected as a proxy for that species' geographic range. Trend estimates included in these regressions were the outputs of the BBS data analysis described above. We hypothesize that the difference in trend estimation should increase as birds become more specialized and less ubiquitous (use fewer habitats, forage on fewer resources, or tolerate a narrower elevational/geographic range). Conversely, a species may show a larger disparity in trend estimate if their population is rapidly declining, as this may amount to fewer sightings.

3. Results

3.1. Trend estimation

Across all 574 species included in our analyses, the average difference in trend estimates between the BBS and eBird was 0.414%/year (S.D. = 3.33%/year, median = 0.353%/year) for eBird trends estimated using AP models and 0.390%/year (S.D. = 2.88%/year, median = 0.295%/year) for eBird trends estimated using LO models (Fig. 1A and B). The population trends calculated using the two different modeling techniques were tightly correlated (Fig. 1C) and the differences in trend estimate between AP and LO models were not statistically different than zero (paired *t*-test p = 0.703). Accuracy of trend estimation decreased when analyses were performed over shorter timespans. Average difference in trend estimate went from 0.41%/year to 1.48%/year for AP models and from 0.39%/year to 1.97%/year for LO models when using all 20 years of data compared to the most recent 5 years (with 10 and 15 year time spans yielding intermediate values, Fig. 2).

3.2. Sensitivity-specificity

Our sensitivity-specificity analysis revealed that our methodology estimated national trajectories in population with more accuracy than would be expected by chance for both general and reduced-model eBird trends (Fig. 3A). In addition, the accuracy of these population trajectories increased with greater volumes of eBird data. The improvement in accuracy showed an exponentially decreasing pattern (Fig. 3A and B). Our break-point analysis identified 11,677 checklists for AP-modeled trends and 14,119 checklists for LO-modeled trends as the threshold above which the rate of improvement in accuracy slowed considerably (Fig. 3B).

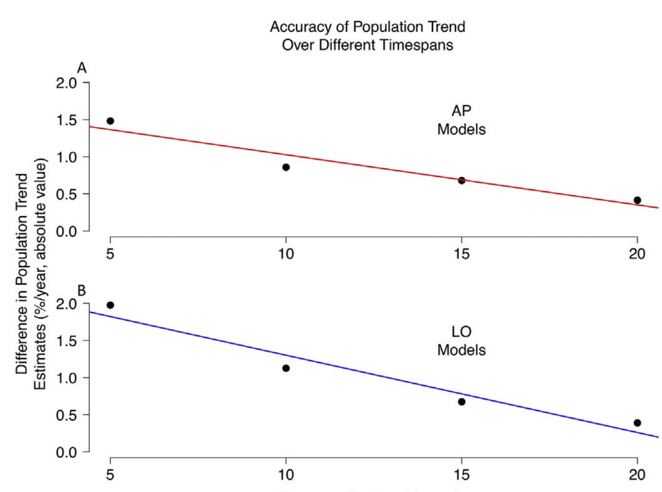

Fig. 2. Accuracy of population trends over different timespans: Average difference between population trends based on BBS data and eBird data when analyzing different timespans. 1A shows results from eBird trends calculated using a greater number of control parameters (AP), 1B shows results from eBird trends calculated using only list-length analysis (LO). Solid lines are linear regressions.

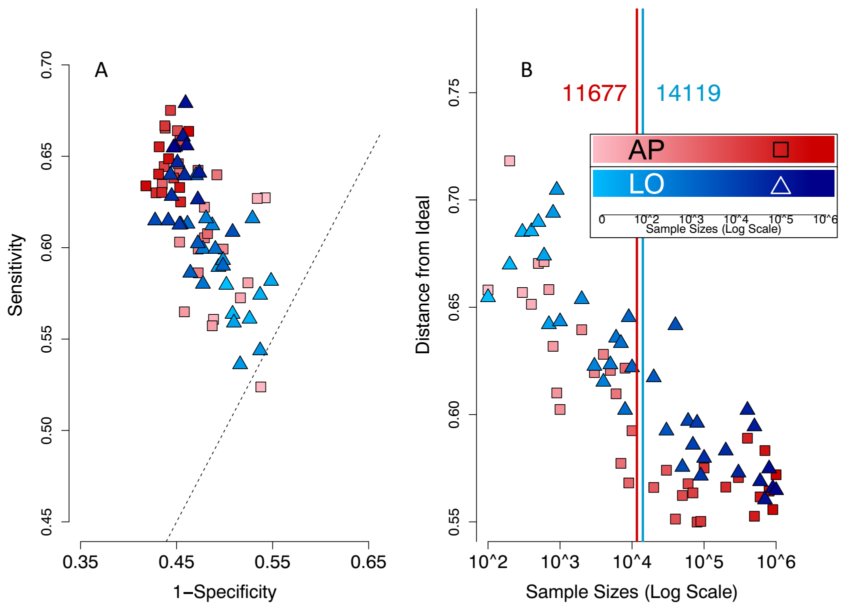

Fig. 3. Sensitivity-specificity analysis: A) Results of a Sensitivity-Specificity analysis when species trends were calculated with incrementally increasing subsets of the entire eBird dataset. Trends calculated using a greater number of quality control metrics (AP) are represented by red squares, trends calculated using only list-length (LO) are represented by blue triangles. Lighter points were estimates generated using small amounts of eBird data, darker points were generated using large amounts of eBird data. Dotted line represents a 1:1 line corresponding to random estimates. Points nearer 0 on the x-axis have a lower false-negative rate. Points nearer 1 on the y-axis have a higher true positive rate. B) The straight-line distance of each point in 2A from the coordinate (0,1) which represents an ideal outcome where all population increases and declines are identified accurately. Points are plotted against the $\log_{10}$ of the number of eBird checklists randomly sampled. Vertical lines and associated values represent the minimum number of checklists required (as estimated by a breakpoint analysis). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

3.3. Bird characteristics

Both elevational range and geographic range significantly affected the accuracy of eBird-based population trends for both AP and LO models (Table 1, Fig. 4). As elevational or geographic range increased, the log absolute value between trend differences decreased significantly in both modeling techniques. Species with larger ranges, such as common grackles (*Quiscalus quiscula*), tended to have similar population trends between the BBS and eBird (*Q. quiscula*: BBS = −1.86%/year, eBird_{AP} = −1.77%/year, eBird_{LO} = −1.65%/year), while species with more restricted rages in the United States, such as white-crowned pigeon (*Patagioenas leucocephala*),tended to differ by wider margins (*P. leucocephala*: BBS = 0.74%/year, eBird_{AP} = 3.89%/year, eBird_{LO} = 6.5%/year). Contrary to expectations, habitat breadth had only a marginally significant effect on trend estimate and diet breadth appeared to have no influence. Population trend of a species (based on BBS data) also had no effect on the accuracy of eBird-based population trends.

4. Discussion

4.1. Trend estimation

Our analyses show that high volumes of opportunistic birdwatching data, after accounting for skill and effort, can approximate population trend estimates based on formally acquired bird-count data. We found that, on average, population trends based on eBird data differed from trends estimated by the BBS by approximately 0.4%/year. The differences between the trends estimated using models with greater metrics of quality control (AP models) and those estimated using only list-length analysis (LO models) were not statistically significant. This suggests that using list-length alone gives reasonable results if other quality-control metrics are unavailable. Though the average difference between the BBS and eBird trends was small, there was some variation. Half of all species had population trends estimated from eBird data that were not > 1.3%/year different from population trends estimated from BBS data (Fig. 1). 95% of species had differences in trend below 6%/year. However there were nine species (1.6%) that differed by > 10%/year between the two data sources. Six of these (1.05%) differed by > 10% in both AP and LO models. One potential contributor to this variation was the coarse-level of geographic control. Though all data came only from eBird locations with at least one record of the species being analyzed (and therefore had the potential to record the species), the models only controlled for variation at the state level. Differences in visitation rates and topography at finer spatial scales may confound these results, though some of this geographic variance, like differences in sampling intensity, may be controlled for through the use of LLA (Isaac et al., 2014).

Additionally, the timespan over which analyses were done had a notable effect on the accuracy of population trend estimates. When we ran the same analyses using 5, 10, and 15 years worth of data, we saw a notable and largely linear reduction in agreement between eBird trends and BBS. This has two important ramifications. First, it confirms that data from areas with a more recent history of birding tourism will produce less accurate population trend estimates. Second, it suggests that population trend estimates from opportunistic data will likely continue to improve beyond 20 years of data. Taken together, these conclusions highlight the importance of long-term continuity for large-scale citizen science programs.

Table 1
Multiple linear regression results comparing population trend accuracy to ecological bird characteristics. Results of two multiple linear regressions (one for each modeling type) with the difference between BBS population trends and eBird population trends as the response variable and ecological bird characteristics (including habitat breadth, diet breadth, elevational range, geographic range, and population trend) as explanatory variables. Variables in bold were found to be significant.

Model-type	Additional parameters (AP)				List-length only (LO)			
Coefficient	Estimate	Std. err.	t-Value	p-Value	Estimate	Std. err.	t-Value	p-Value
Habitat breadth	0.0628	0.183	1.861	0.0633	0.0293	0.0335	0.875	0.382
Diet breadth	−0.0210	0.0464	−0.451	0.652	0.0403	0.0461	0.874	0.382
Elevational range	**-1.10×10^{-4}**	**5.01×10^{-5}**	**−2.194**	**0.0286**	**-1.39×10^{-4}**	**4.98×10^{-5}**	**−2.78**	**0.0056**
Geographic range	**-3.25×10^{-4}**	**5.64×10^{-5}**	**−5.768**	**1.37×10^{-8}**	**-3.20×10^{-4}**	**5.61×10^{-5}**	**−5.70**	**1.96×10^{-8}**
Population trend	0.0261	0.0301	0.869	0.385	0.0368	0.0299	1.23	0.219

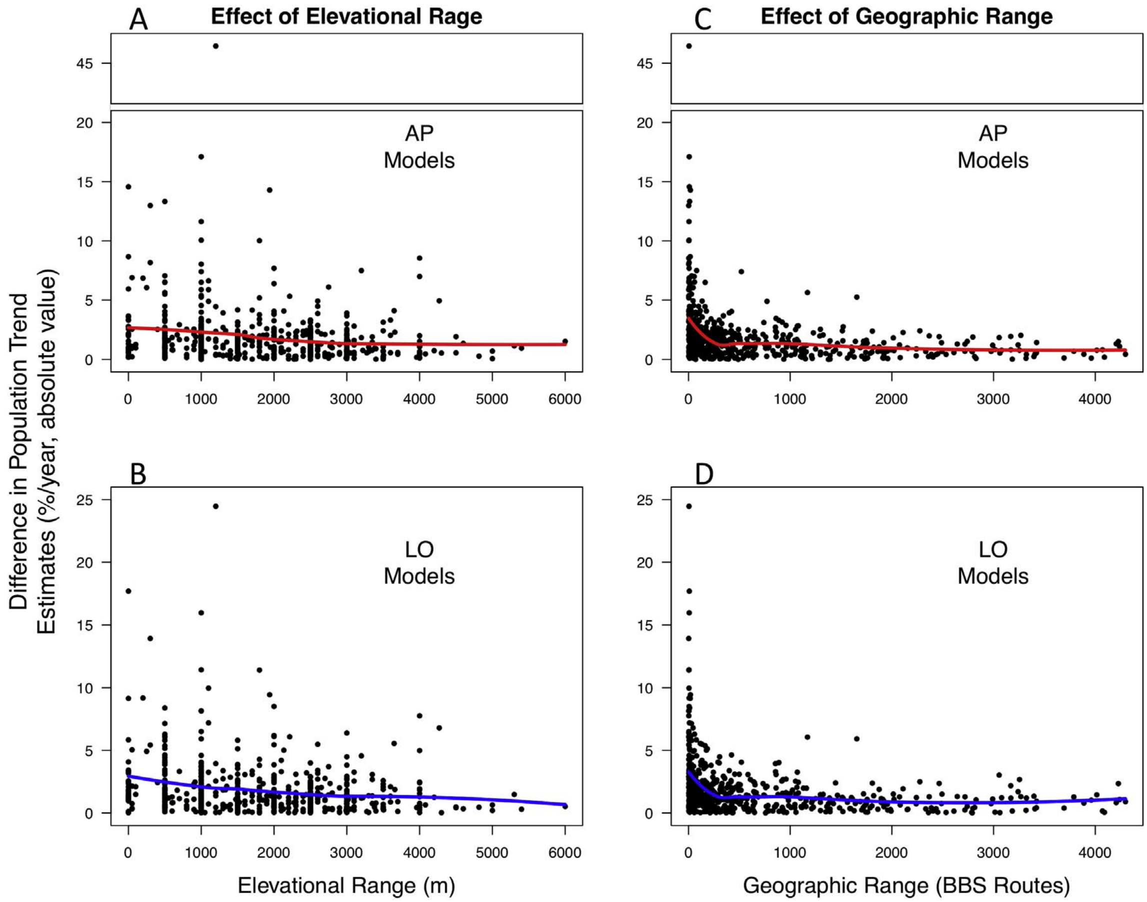

Fig. 4. Factors significantly influencing the ability of species to be monitored using eBird data: The effect of elevational range (4A and B) and geographic range (4C and D) on the similarity in population trend estimate for 574 species between the BBS and eBird using models with a greater number of quality control metrics (AP models, 4A and C) and models incorporating only list-length (LO models, 4B and D). Geographic range is based on the number of BBS survey routes on which a species occurred. Solid lines show loess regression trends. Both elevational range and geographic range for both AP and LO models showed a significant ability to predict how well population trends based on eBird data would match trends based on BBS data when included in multiple linear regression models with other species characteristic cofactors.

4.2. Sensitivity-specificity

When looking at the direction of all population trends, our estimates for the proportion of species increasing and decreasing matched the BBS roughly 22% better than would be expected by chance (Fig. 3A). Additionally, the agreement between eBird estimates and BBS estimates improved as the number of eBird checklists sampled increased, but with diminishing returns above a certain threshold. We identified 11,677 checklists for AP modeled-trends and 14,119 checklists for LO-modeled trends as a reasonable breakpoint where, below this point, national-level trend analyses improve rapidly with increasing numbers of checklists. Above this threshold, however, estimates only improved slightly even when the number of checklists sampled increased by several orders of magnitude. It should be kept in mind that, due to our method of sub-sampling eBird checklists, both of these thresholds fell between the same two sampling levels (samples of 10,000 and 20,000 checklists). Therefore, this difference in threshold between the two modeling methods is unlikely to be significant. We suggest that, based on these results, a minimum of 10,000 birdwatching checklists are required before trends no longer improve appreciably with higher volumes of data. However, our analyses were based over a 20-year timespan as this was the maximum amount of complete data overlap between BBS and eBird. At different time intervals, the number of checklists required may vary.

It is important to keep in mind that this analysis looked only at agreement in the trajectory of population trends at a national level, but gives no indication as to the magnitude of those changes. A species experiencing a decline of < 1%/year would be treated the same as a species declining by 20%/year with obvious consequences for conservation initiatives. Therefore, we calculated the average difference in population trend when sampling only 10,000 checklists to determine the applicability of this threshold as it relates to magnitude of population change. At 10,000 checklists, average difference in population trend was 0.53%/year for AP models and 0.30%/year for LO models, similar to the average differences seen at higher sampling levels. This suggests 10,000 lists as an appropriate threshold for which to estimate both trajectory and magnitude of population trend.

4.3. Bird characteristics

Elevational and geographic range significantly influenced the accuracy of population trend estimates for a given species, regardless of modeling method (Fig. 4, Table 1). As the elevational range of a species increased, the absolute value of the difference in trend estimations decreased for both AP and LO models. Average differences declined from 2.4%/year for AP models and 2.56%/year for LO models for species restricted to elevational bands of < 1000 m (n = 116), to an average difference of 1.17%/year for AP models and 1.04%/year for LO models when species' elevational ranges exceed 4000 m (n = 28). Likewise the absolute value of the differences in trend estimates declined as the geographic range of a species increased; from an average difference of 2.36%/year for AP models and 2.29%/year for LO models when species are found on fewer than 500 BBS routes (n = 359), to an average difference of 0.80%/year for AP models and 1.05%/year for LO models when species are found on over 3000 BBS routes (n = 27). This suggests that a species' ubiquity will improve the accuracy of its populations being monitored using citizen science because species with greater elevational or geographic ranges will be found in more places and will occur more frequently on checklists.

Many widespread species like red-tailed hawk (*Buteo jamaicensis*) and Swainson's thrush (*Catharus ustulatus*) had population trend differences below 0.2%/year. Conversely, most of the nine species with trend estimates that differed by > 10% are highly range- or habitat-restricted in the survey area (Montezuma quail (*Cyrtonyx montezumae*), smooth-billed ani (*Crotophaga ani*), surfbird (*Calidris virgata*), pomarine jaeger (*Stercorarius pomarinus*), Kirtland's warbler (*Setophaga kirtlandii*), and saltmarsh sparrow (*Ammospiza caudacuta*)). This is consistent with the idea that a species' ubiquity may influence its ability to be monitored using citizen science.

Two important considerations for the interpretation of these results are our use of occurrence on BBS survey routes as a proxy for geographic range and the differences between habitat types used. Occurrence on BBS routes allowed us to limit a species' geographic range strictly to where it is found in the contiguous United States and it provides reasonably accurate relative geographic ranges between species (though BBS route density may vary from state to state). However, it cannot be used to determine the exact relationship between square kilometers of geographic range and the ability of eBird data to accurately estimate population trend. Additionally, though our results suggest that using a greater number of habitat types will improve a species' population trend estimate, there is likely variation between a species' preferred habitat type and its occurrence on eBird checklists. Habitats near urban areas or regions known to be high in avian diversity are likely to be disproportionately represented in eBird data while formal surveys are likely to sample habitat types at a rate closer to their geographic extent. We found that agreement between eBird trends and BBS trends did differ when considering species with different habitat preferences (Table 2). Nonetheless, these results indicate that more ubiquitous species, with wider geographic ranges and broader habitat use, can better be monitored using this methodology than species with narrower geographic or ecological niches.

4.4. Implications

Our results suggest that high volumes of opportunistic data can approximate the results of formal surveys for many bird species. This implies that population trends for many bird species throughout the developing world, particularly in the tropics, can be estimated without costly formal surveys, which are often economically unfeasible. Because our models that used only LLA as a means of quality control (LO models) performed as well as models with a greater number of quality indices (AP models), it may be possible to apply this methodology to a diverse range of data sources including eBird lists, bird atlas data, road surveys, birding tour lists, and the like. Most formal surveys that estimate population trends require strict sampling frequencies, sampling intensities, or repetition by the same individual observers (Butcher et al., 1993). Previous analyses of eBird data have incorporated travelling distance and number of observers to help control for variation in effort (Munson et al., 2010). Even when LLA has been applied to eBird data, it has been used in conjunction with additional metrics of quality control (Walker and Taylor, 2017). Here, we show that using only LLA can produce population trend estimates statistically similar to those estimates gathered by both formal surveys as well as more complex modeling methods.

For many regions, particularly in the developing world, no single data source (e.g. eBird, bird atlases, birding groups) has sufficient volume to reliably estimate population trends. As of February 2018, 71% of tropical nations have fewer than 10,000 eBird checklists, the threshold identified as sufficient here. In some tropical regions, such as the Afrotropics, this proportion of nations that fall short of 10,000 checklists rises to 95%. However, these figures are based on the total number of checklists submitted to each nation while our protocol removes incomplete, short, or duplicate lists. If we assume the proportion of lists from tropical nations that do not match our criteria is similar to the checklists from the United States, only 17 tropical nations (19%) still meet this 10,000 list threshold. Fortunately, use of eBird in developing tropical nations is expanding quickly. From February 2017 through January 2018, an average of 5500 checklists were added in tropical countries. However, that figure is highly skewed. Larger more developed nations, like Brazil and India, added tens of thousands of checklists over the previous 12 months, while less populous and less-

Table 2
Percentage of species from different habitat and diet guilds with increasing or decreasing population trends.

Category		BBS			eBird AP		eBird LO	
		# species	% Inc.	% Dec.	% Inc.	% Dec.	% Inc.	% Dec.
Habitat	All Birds	574	46	54	55	46	52	48
	Wetland	105	42	58	65	35	74	26
	Plains	8	50	50	50	50	50	50
	Woodland	88	59	41	57	43	55	45
	Savanna	11	64	36	64	36	64	36
	Forest	129	53	47	59	41	47	54
	Artificial	11	36	64	46	55	46	55
	Shrub	78	36	64	49	51	49	51
	Grassland	65	39	62	48	49	37	63
	Rocky	6	33	67	33	67	17	83
	Coastal	46	33	67	37	63	54	46
	Riparian	12	50	50	50	50	33	67
	Sea	7	71	29	14	86	14	86
	Desert	7	43	57	86	14	86	14
Diet	Fish	51	35	65	57	43	61	39
	Invertebrate	307	49	51	53	47	49	51
	Seed	94	35	65	48	51	48	52
	Vertebrate	33	58	42	55	46	52	49
	Omnivore	32	44	56	63	38	66	34
	Nectar	12	33	67	42	58	58	42
	Fruit	10	60	40	60	40	50	50
	Scavenge	3	67	33	67	33	100	0
	Plant	26	58	42	77	23	65	35

visited nations, like Burundi and Guinea-Bissau, added few or no lists. In regions with limited ecotourism infrastructure, it may be impractical to ever rely on one bird-count data source to monitor populations. Therefore, by using a modeling approach that only incorporates data present in even the most basic checklists (year and number of species), multiple sources of information can be analyzed following the same protocol.

Even though only 21% of the world's countries currently have > 10,000 eBird checklists, 9050 bird species occur in these 53 countries, constituting 87% of the global avifauna. 7914 of these bird species were recorded in the 17 tropical countries with > 10,000 checklists, even when Argentina, Australia, China and South Africa are excluded from tropical countries. Even if we assume that the proportion of usable checklists in other countries is similar to the USA, 7811 bird species occur in the remaining 36 countries with > 10,000 usable eBird checklists, constituting 75% of the global avifauna. 6465 of these species occur in the 17 tropical countries with > 10,000 usable checklists. In 2017, the number of eBird checklists worldwide increased by 30%, and by an average and median of 27% in the 50 most visited tropical countries. Based on the country-specific rates of increase for eBird checklists in 2017, in another year, the countries with > 10,000 usable checklists will account for 83% of the world's avifauna (8444 species), with 7467 of these species occurring in the 21 tropical countries with > 10,000 usable checklists. We estimate that within five years, 73 countries hosting 9434 bird species, or 90% of the world's avifauna, will each have > 10,000 usable checklists.

Our results indicate that the more common and widespread a species is, the more accurate its population trend based on opportunistic data will be. Because specialized species are more likely to be threatened with extinction (Şekercioğlu, 2011), they are often the focus of more intensive monitoring, while large population declines of bird species assumed to be common and widespread can be overlooked due to their ubiquity (Inger et al., 2015). Therefore, using eBird and other types of opportunistic data for widespread species can complement professional monitoring of threatened, specialized and range-restricted species, especially in developing countries where common and widespread species are often not monitored regularly, and whose declines can have disproportionate impact on the important ecosystem services they provide (Şekercioğlu et al., 2016).

4.5. Conclusions

Result edit.

In this study, we show that large volumes of opportunistic birdwatching data collected by citizen scientists can approximate bird population trend estimates based on formal and systematic surveys. Additionally, trends calculated using multiple metrics of effort for correction do not differ significantly from trends calculated using only the total number of species observed as a proxy for skill and effort. Our results also show consistent proportions of species increasing and decreasing at the national level. Moreover, we show that a minimum dataset of 10,000 checklists will produce reasonably accurate trend estimates for both general and simple models, and that these estimates only improve marginally with larger data sets. Lastly, our study suggests that more widespread species may be the best suited for this methodology, as their higher detection rates result in higher quality data and increased sensitivity.

Analyses of citizen science data focused on birds and other species is especially valuable for developing countries lacking the necessary resources to maintain long-term, professional bird-monitoring programs. We find that using only the number of bird species detected as a means of quality control, information inherent to all checklists, will produce population trend estimates similar to those from data sources with more advanced means of reducing variability. This means that many different sources of birdwatching data can be incorporated to increase the quantity of data available for monitoring birds in understudied areas, including most of the world's global biodiversity hotspots.

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