

RESEARCH ARTICLE

Realising the Promise of Large Data and Complex Models

Outstanding challenges and future directions for biodiversity monitoring using citizen science data

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Abstract

1. There is increasing availability and use of unstructured and semi-structured citizen science data in biodiversity research and conservation. This expansion of a rich source of 'big data' has sparked numerous research directions, driving the development of analytical approaches that account for the complex observation processes in these datasets.
2. We review outstanding challenges in the analysis of citizen science data for biodiversity monitoring. For many of these challenges, the potential impact on ecological inference is unknown. Further research can document the impact and explore ways to address it. In addition to outlining research directions, describing these challenges may be useful in considering the design of future citizen science projects or additions to existing projects.
3. We outline challenges for biodiversity monitoring using citizen science data in four partially overlapping categories: challenges that arise as a result of (a) observer behaviour; (b) data structures; (c) statistical models; and (d) communication. Potential solutions for these challenges are combinations of: (a) collecting additional data or metadata; (b) analytically combining different datasets; and (c) developing or refining statistical models.
4. While there has been important progress to develop methods that tackle most of these challenges, there remain substantial gains in biodiversity monitoring and subsequent conservation actions that we believe will be possible by further research and development in these areas. The degree of challenge and opportunity that each of these presents varies substantially across different datasets, taxa and ecological questions. In some cases, a route forward to address these challenges is clear, while in other cases there is more scope for exploration and creativity.

KEY WORDS

citizen science, community science, detectability, multi-species models, observation process, occupancy models, presence-only, statistical ecology

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1 | INTRODUCTION

Monitoring biodiversity is a critical step in understanding the status and dynamics of the natural world. Citizen science or community science (CS) data, collected by volunteers, are often used to meet this objective (Dickinson et al., 2012; Pocock et al., 2018; Theobald et al., 2015). For decades, volunteer observers have contributed to extensive ecological monitoring through designed surveys of plants, butterflies, coral reefs, birds and many other taxa (Delany, 2005; Lau et al., 2019; Pescott et al., 2015; van Swaay et al., 2019). However, the recent rapid growth in CS data is largely due to observers participating in less structured projects, without fixed protocols, requirements for observer knowledge, or long-term observer commitment (Pocock et al., 2017). This vast growth of CS data can potentially contribute substantially to biodiversity monitoring and is potentially transformational for monitoring biodiversity, particularly in parts of the world with little or no formal data collection (SoIB, 2020).

Less structured CS projects attract more observers and have more data, but present several analytical challenges in order to derive robust ecological knowledge from the data. For example, bias, variation and error are all more prevalent in less structured CS data (Dickinson et al., 2010; Isaac et al., 2014; Kelling, Fink, et al., 2015). To obtain accurate ecological knowledge from these data, analyses must address the challenges inherent in the data (Altweig & Nichols, 2019; Johnston et al., 2021). Despite important analytical developments, there remain a number of outstanding challenges in the analysis of CS data. The large and growing volume of data provides motivation to address these challenges and to further unlock the power of CS data to increase our ecological understanding.

We classify the analytical challenges with CS data within four categories (Table 1). These categories group challenges that arise as a result of (a) observer behaviour; (b) data structures; (c) statistical models; and (d) communication. The categories are not independent and many of the challenges within this paper have elements of more than one category. There is a need to understand the degree to which all of these challenges can impact ecological conclusions,

TABLE 1 List of challenges for the use of citizen science data for monitoring biodiversity. There are four broad categories and 10 individual challenges

Category	Challenge
Observer behaviour	Spatial bias
	Observer differences
	Reporting preferences
	False positive errors
Data structures	Validation
	Detectability
Statistical models	Multi-species models
	Data integration
	Computational limitations
Communication	Communication

which varies by taxon, location, time and ecological question. The solutions to most of these challenges fall into three groups: (a) collecting additional data or metadata; (b) analytically combining different datasets; and (c) developing or refining statistical models. Many of the challenges outlined here can be addressed with a combination of these solutions and often there is a trade-off between the solutions; for example, additional data or metadata may reduce the need for novelty in analytical methods.

Here we summarise our perspectives of the key analytical challenges that could be addressed with CS data. The list of these challenges may be useful to inform the design of new CS projects, to target the collection of additional data, or to target the development of new statistical or analytical methods. We believe that progress towards addressing each of these challenges will help to leverage the most robust ecological knowledge from CS data that are available now and in the future.

2 | BIODIVERSITY CS DATA

Citizen science (increasingly also called 'community science') is a broad term which includes many different types of data and can be challenging to define (Haklay et al., 2021). Here we define citizen science as 'active engagement of the general public in scientific research tasks' (Vohland et al., 2021). The scope of citizen science data in ecology includes a broad suite of data types. This includes data from structured protocols, and observers collecting acoustic recordings (Newson et al., 2015; Rowley et al., 2019), eDNA samples (Biggs et al., 2015), or identifying species in camera trap photographs (Clare et al., 2019). Here we focus on a narrower range of CS data; direct species observations from unstructured and semi-structured protocols, where observers choose where, when, how and whether to record different species. For brevity, we refer to these data as 'CS data' throughout this manuscript.

CS data with direct species observations are obtained from a variety of project types. Species observations are generally collected in three different ways. First, individual species observations contain information on species presence, and together they produce presence-only data. Second, incomplete lists contain information on a list of species observed during an observation period. However, incomplete lists only include species that an observer chose to record. Third, complete lists contain information on all species that were detected and identified by an observer during an observation period. Complete lists enable inference of non-detections, which are particularly valuable for statistical analysis. Both types of lists can additionally have associated metadata on the observation process, creating semi-structured CS data (Boersch-Supan et al., 2019; Kelling et al., 2019).

A number of data characteristics can exacerbate the challenges outlined below. In particular, presence-only data are particularly difficult to analyse, because the data structure confounds the ecological and observation processes (Elith et al., 2011). The main hurdle when analysing presence-only data is inferring where

effort was expended but a species was not reported, and a number of different modelling approaches have been proposed to address this (Chefaoui & Lobo, 2008; Hill, 2012; Phillips et al., 2009; van Strien et al., 2013). However, all these approaches make strong assumptions (Hastie & Fithian, 2013). Presence-only data compound the effect of all the challenges listed in this paper. However, this is also the most abundant CS data type, so resolving the challenges below for presence-only data would vastly increase the potential impact. Given the greater complications of these data, we do not recommend degrading list data to presence-only data for analysis (Johnston et al., 2021). Other data characteristics that can also compound the challenges below are insufficient data or insufficient metadata to account for heterogeneity in the observation process.

3 | OBSERVER BEHAVIOUR

The unstructured and semi-structured CS data described above have an inherent dependence on the choices of participants. The choices and behaviours of individual and collective observers can introduce bias, error and variation, into the resultant datasets. The challenges in this section can be addressed by any of the three solution categories above, with an emphasis on collecting additional data.

3.1 | Spatial bias

In the CS data that are the focus of this paper, observers select where they want to record species, leading to strong spatial bias in the data. Observers may select locations for their accessibility, such as those close to home or near to roads (Dennis & Thomas, 2000; Kadmon et al., 2004; Mair & Reute, 2016; Tiago, Ceia-Hasse, et al., 2017) or for ecological reasons, for example selecting locations with protected areas, high species diversity, or particularly rare species (Boakes et al., 2010; Botts et al., 2011; Hijmans et al., 2000; Tulloch et al., 2013). Often, the decision about where to record species may be a trade-off between these two components (Johnston et al., 2020; Kolstoe & Cameron, 2017). Due to the strong influence of observer choice, the spatial bias in CS data is greater than in designed surveys and conventional ecological data.

Spatial bias can lead to incorrect inference because the sampled population is not representative of the target population (Zhang & Zhu, 2018). This is particularly a challenge if the drivers of observer site selection are aligned with the ecological process of interest, and if there are no variables that describe this preference in the model (Chakraborty et al., 2011; Diggle et al., 2010). Spatial bias may also present a greater challenge if certain habitats are represented very sparsely in a dataset or not at all (Johnston et al., 2020). A further complication is that spatial bias itself can also be time-varying (e.g. Hochachka et al., 2021), which can confound the measurement of temporally varying processes, such as phenology or population trends.

There are several ways to mitigate or accommodate spatial bias in ecological analyses. When analysing presence-only data, it is important to explicitly consider the spatial bias in the observation process (Beck et al., 2014; Chakraborty et al., 2011; Fithian et al., 2015; Phillips et al., 2009). When analysing list data, spatial bias is less critical, but can still create erroneous ecological conclusions (Boakes et al., 2010; Yang et al., 2013). To reduce spatial bias with list data, analysts can conduct spatial subsampling before analysis (Araújo & Guisan, 2006; Kramer-Schadt et al., 2013). However, in many situations, spatial subsampling has had only a negligible impact on ecological conclusions (Beck et al., 2014; Geldmann et al., 2016; Kadmon et al., 2004) and it can also lead to problems of class imbalance for rare species (Steen et al., 2021). Alternatively, the sampling intensity can be used as a propensity weight in analyses, which may only have a large effect where data density is very low (Johnston et al., 2020). Another framework of analyses jointly models the spatial bias in survey locations and the ecological response (Conn et al., 2017; Diggle et al., 2010; Pati et al., 2011), however, these model-based approaches can limit the analysis to simpler statistical models for the underlying processes.

Future work could develop statistical models to further separate the complex and time-varying spatial sampling bias from the ecological process, and to account for its impact on ecological estimates and associated uncertainty. A potential direction of solutions is data integration of CS data with structured data which may help to address the issues of spatial bias (Gelfand & Shirota, 2019; Robinson et al., 2020; Steger et al., 2017). Another direction of work is the theoretical framework and implementation for incentives for observers to visit different sites (Callaghan et al., 2019; Xue et al., 2016). This can be treated as an experimental change in bias, which is useful for statistical calibration of the bias and for better understanding of observer behaviour.

3.2 | Observer differences

Observers in many CS projects vary hugely in their skills, experience, behaviour and equipment, leading to large differences in observers' skills for detection and identification of different species (Moyer-Horner et al., 2012; Sauer et al., 1994; Sunde & Jesson, 2013). Many CS projects have also demonstrated that individual observers learn to identify more species as they continue to participate (Jiguet, 2009; Kelling, Johnston, et al., 2015; Kendall et al., 1996; Sharma et al., 2019). There are also changes over time in the aggregated pool of observers; as CS projects expand, they often seek to attract new participants who may have less experience than existing participants.

As a demonstration of elements of this challenge, we explored observer differences within a subset of eBird data (Sullivan et al., 2014). We selected eBird data from New York state collected each May, from 2002 (when the eBird project started) to 2020. We selected only complete checklists, reducing the impact of observer preferences. For computational efficiency, we randomly selected

a subset of 2,000 observers from this dataset. We wanted to understand how the average number of species recorded per hour has changed over this 19-year period. We first modelled the number of species recorded on a checklist in a Poisson GLM with three continuous covariates: year, duration and square root of duration (Model 1). Second, to track whether these changes were also evident within individuals, we added an observer random effect to Model 1 (creating Model 2).

Model 1 estimated that over the whole population of observers, later years were associated with on average fewer species recorded per hour (Figure 1a). Model 2 estimated that, for individual observers, later years were associated with on average more species recorded per hour (Figure 1a). These opposing patterns arise because observers that join as the project expands generally record fewer species per hour (Figure 1b).

Previous work shows that accounting for variation in observers improves ecological inference of species distributions (Erickson & Smith, 2021; Johnston et al., 2018). However, temporal changes within observers and within the observer pool present a particular challenge for inferring ecological changes over time from CS data, for example when estimating shifting species distributions, tracking species phenology or estimating population trends.

Most potential solutions to this challenge require identification of individual observers in the data, which could be through a unique code rather than a name. However, in this line of research it is imperative to consider that CS projects rely on the trust and voluntary

contribution of observers, many of whom may not want their individual data assessed (Anhalt-Depies et al., 2019; Mahr et al., 2018). Additionally, some observers may adjust their ways of observing in order to 'improve' their data, which could create additional temporal bias. It is critical that further work on observer variability works with project coordinators and carefully considers the impact on the analyses, the project and the observers themselves.

3.3 | Reporting preferences

In many CS projects, observers select which species to record, either with presence-only data or incomplete lists. Even when using complete lists, observers may choose to start a list because they detected an interesting species. When observers report species preferentially, the preference of the observer becomes an additional part of the observation process, which can further confound the ecological and observation processes. Further understanding of observer preferences would enable a huge volume of presence-only or incomplete list CS data to be useful for ecological analysis.

Observers in CS projects may more readily record some species, due to preference, interest or their ability to detect and identify the species. For example, large species are recorded proportionally more often than small species in some CS datasets (Callaghan et al., 2021; Steger et al., 2017; Stoudt et al., 2021). Rare species may also be more interesting to CS observers, who travel further

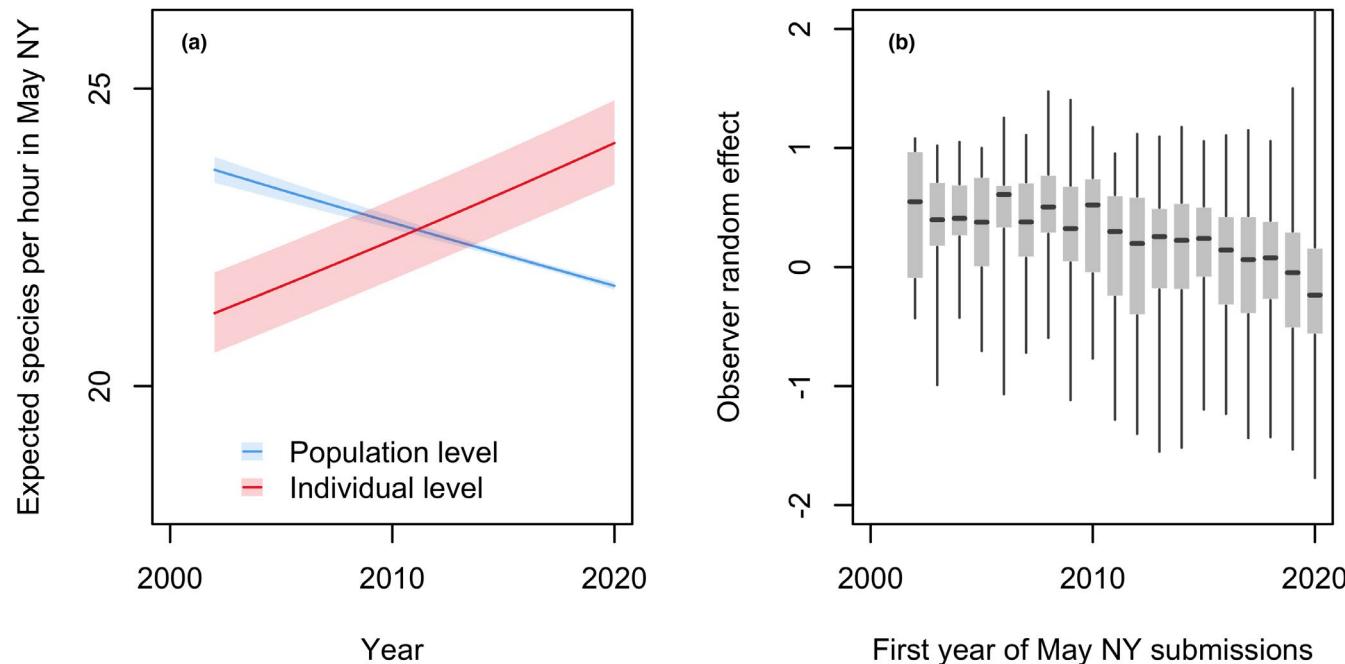


FIGURE 1 Relationships between eBird observers and average number of species recorded per hour in New York state in May from 2002 to 2020. (a) Population-level (Model 1) and individual-level (Model 2) expected species per 1 hr complete checklists in each year. Population-level estimate is from a GLM and individual level estimate is from a GLM with random intercept for observer. Confidence limits are shown only for the fixed-effects components of the model. (b) Observer random effects from the individual model (Model 2) plotted against the first year that observers submitted data in New York state in May

to observe them (Boakes et al., 2010; Kolstoe & Cameron, 2017; Tulloch et al., 2013), although the degree of interest in rare species varies among observers (August et al., 2020).

As a demonstration of this challenge, we explored rarity and observer preference within a subset of eBird data (Sullivan et al., 2014). We selected eBird data from New York state and years 2010–2020. For each species, we calculated the proportions of complete and incomplete lists on which it was reported. We calculated the ratio of incomplete to complete list proportions as a measure of preference and, as expected, found higher preference for rarer species (Figure 2). This demonstrates that the inter-specific prevalence of species on incomplete lists or in presence-only data is not a reflection of prevalence on complete lists, with one dimension of this bias being regional species rarity.

This challenge is particularly problematic when comparing different species, as the relative frequency of each species in the data is a function of both the species prevalence and of the reporting preference (Steger et al., 2017). However, additional challenges can arise if species preferences vary temporally and spatially. For example, if interest in species changes over time (Schuetz & Johnston, 2021) or if species prevalence changes and reporting preferences change in response (Figure 2; Boersch-Supan et al., 2019). Development of statistical methods that estimate spatio-temporal variation in preferential reporting would be extremely useful for analysis of presence-only or incomplete list CS data.

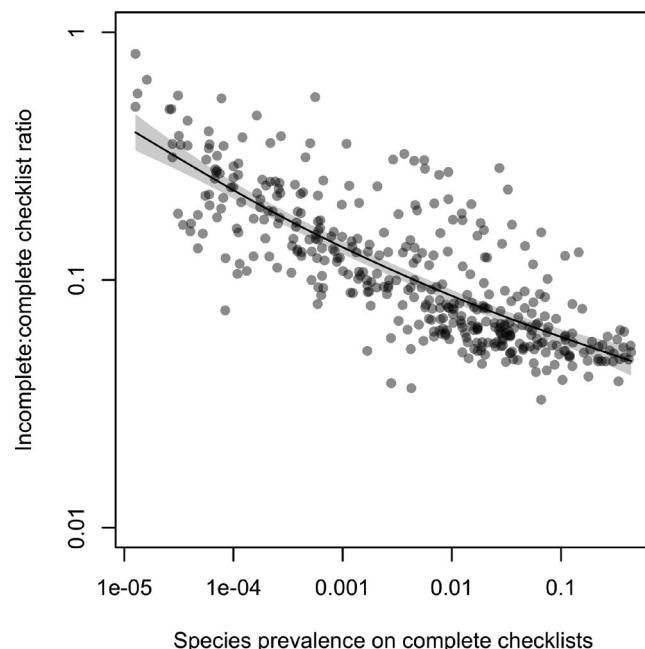


FIGURE 2 For each species in New York state, we show the average species prevalence plotted against the ratio of incomplete to complete list proportions. Each dot represents a single species. The y-axis can be interpreted as an index of species preference. Species that are rarer have higher preference. The line and shaded polygon are a fitted GAM with maximum four degrees of freedom and associated 95% confidence intervals

3.4 | False positive error

False positive errors occur when a species that was not actually present is reported. Although ecological analyses now routinely account for false negative errors (MacKenzie et al., 2002; Royle & Link, 2006), false positive errors present an additional challenge that is not typically accommodated. The rate of false positives in data may increase as beginner naturalists increasingly contribute to CS surveys (Farmer et al., 2012; Fitzpatrick et al., 2009).

False positive errors regularly occur within data of species observations (Chambert et al., 2015; Cruickshank et al., 2019; Gardiner et al., 2012; Kéry & Royle, 2021). Even low rates of false positive errors can lead to considerable bias in the estimation of occupancy rates (Altweig & Nichols, 2019; Miller et al., 2011; Rempel et al., 2019), since all sites with at least one positive observation are classified as being occupied by the species. The increasing volume of CS data and many repeat surveys in single locations can lead to more consequential impacts of false positive records (Kéry & Royle, 2021) and substantially biased inference of species distributions (Cruickshank et al., 2019).

Statistical models that account for false positive observation error have mostly been developed for occupancy data (Chambert et al., 2015; Royle & Link, 2006), and recently environmental DNA data (Griffin et al., 2020). Some research has also focussed on modelling the probability that a species is mistaken for another, which is particularly relevant in multi-species models (Conn et al., 2013, 2014; section 5.1 multi-species models). However, accounting for false positive errors can lead to model identifiability issues, and consequently most models that account for false positive error rely on additional data without false positives. To avoid this requirement of additional data, Griffin et al. (2020) employed informative prior distributions within a Bayesian framework to overcome this identifiability issue. Clearly, additional data are not always available, especially for large-scale projects, and hence statistical solutions, such as this, provide a unifying framework for routinely accounting for both types of error in CS data. A complementary direction to partially solve this challenge, is for projects to validate species observations or enable reporting observations at a higher taxonomic level than species (section 4.1 validation).

4 | DATA STRUCTURES

The opportunistic nature of much of the data collected for CS projects creates an unstructured and heterogeneous set of observations. This creates challenges for data validation and estimating detectability. As with section 3, the challenges in this section can be addressed by any of the three solution categories, however, in this category of challenges there is an emphasis on combining data.

4.1 | Validation

Validation is a critical component of all analytical projects, but some elements of validation are particularly relevant when dealing with

CS data. Here, we define three stages of validation that are relevant for CS data; (a) validation of data; (b) validation of statistical models; and (c) validation of results.

First, validating that the data are correct can be a particular challenge in CS data (Austen et al., 2016; Crall et al., 2011). There are several elements of a species observation that could be incorrectly recorded (e.g. location; Balázs et al., 2021), but here we focus on validation of the species or other taxonomic identification (Austen et al., 2016). Validation can either happen before or during data analysis. For example, validating before analysis, some projects only share confirmed data, such as eBird or Project Feederwatch, which have automatic filters followed by expert reviews of unusual observations (Bonter & Cooper, 2012; Kelling, Fink, et al., 2015) or iNaturalist that denotes as 'research grade' observations those which have consensus identification (Di Cecco et al., 2021). One potential solution to aid data validation before analysis is collecting additional data to validate the identification, for example photos or recordings (Terry et al., 2020). However, there are also analytical approaches to validating data, for example estimating the error rate of misidentification (section 3.4 false positives; Chambert et al., 2015; Conn et al., 2013). A hybrid between these two approaches uses a pre-analysis estimate of uncertainty, which is included in subsequent statistical models. A pre-analysis estimate of identification uncertainty is available from many automatic species identification tools (Newson et al., 2015; van Horn et al., 2018), or different taxonomic levels of identification by observers (Johnston et al., 2015). These avenues of methodological development for observational data are relatively new and there is scope for much future work.

Second, validating the statistical models can present a challenge. Often, internal model validation is conducted with subsets of the same data that are removed before model fitting. However, the subset of the CS data used during the validation stage usually has the same biases and challenges as the whole dataset (Matutini et al., 2021). For example it is difficult to validate the spatial patterns produced from biased data when the validation data are also spatially biased in the same way. Carefully selecting subsets of the data that evaluate the model performance for the target ecological inference with the least bias is an important element of analysing CS data (Valavi et al., 2018). Validating models is also possible using simulations, where the simulated data replicate realistic characteristics of both the ecological and observation processes (Zurell et al., 2010). In general, the models that analytically separate the ecological and observation processes (e.g. occupancy models), may be the most difficult to validate. Further investigations on the impact of validation data selection will be a valuable future avenue of research.

Third, validating the results of the statistical models with external data can be particularly valuable. Using independent data can provide a robust validation of the target ecological inference (Matutini et al., 2021), however, this requires good quality structured data from the same species, locations and times, which are often lacking (Bayraktarov et al., 2019). Common examples of this type of validation include comparing species distributions (e.g. Tiago, Pereira, & Capinha, 2017) or species population trends (e.g. Boersch-Supan

et al., 2019). There is also a growing opportunity to validate the results from analyses of very different data structures. For example, comparing results from CS data to those from acoustic telemetry (Vianna et al., 2014) or tracking data (Heim et al., 2020). Model results can also be assessed by experts, providing an alternative perspective on their quality. Alignment between results from analyses of CS data and other datasets has been highly variable across species and regions, so care is required when extrapolating inference from these studies in limited geographic regions to other parts of the world or taxonomic groups.

4.2 | Detectability

All surveys, including structured surveys, suffer from imperfect detectability (Mazerolle et al., 2007; Miller et al., 2011; Wintle et al., 2005). However, two separate definitions of detectability are commonly used in ecology. The first is species detectability; probability of detecting a species given that it occurs in a location. This is estimated in statistical models that estimate the probability of species occurrence, for example occupancy models (MacKenzie et al., 2002). The second definition is individual detectability; probability of detecting an individual given that it is present in a location and available for detection (Buckland et al., 2015). This is used in models that estimate species abundance or density. Species density is a more sensitive metric for monitoring biodiversity, because density can change when species occupancy does not change. To be able to estimate species density, we need estimates of individual detectability, however, estimates of species detectability are much more common.

Estimates of both species and individual detectability typically require a more complex and structured data-collection protocol than exists with CS data (Buckland et al., 2015; MacKenzie & Royle, 2005). However, in some cases, CS data can be manipulated post hoc to approximate the data required to estimate species detectability, for example, by using temporally close observations from the same location as repeat visits in an occupancy model. However, where these repeat visits are available, they are often conducted by different observers (section 3.2 observer differences), which adds complexity to the observation process between repeat visits. Another approach to constructing repeat visits is space-for-time substitution, using spatial replication as a proxy for temporal replication (Srivaths et al., 2018), although this approach has assumptions that may not hold (Kendall & White, 2009).

Observations of species counts can provide additional information to estimate species detectability (Royle & Nichols, 2003) or individual detectability (Royle, 2004). However, these approaches also require strong assumptions that may not be met by CS data (Barker et al., 2018; Dennis et al., 2015; Kéry, 2018). An additional challenge encountered when analysing CS data with these methods is that there is typically not a well-defined sampling unit, so estimates of detectability and subsequent occupancy or abundance are not within a known area.

Population size is an important metric in ecology and conservation as it can be linked to a species' propensity to maintain its population (O'Grady et al., 2004). Development of tools to estimate individual detectability from CS data would enable estimates of density or abundance. Data integration may provide opportunities to estimate detectability with CS data, for example following work combining different protocols for single-observation point counts (Lele et al., 2012; Solymos et al., 2012). Alternatively, collecting additional metadata would allow detectability to be formally estimated, which would be valuable even if these metadata were collected only for a subset of locations and times. Future directions could explore creative ways to estimate both individual and species detectability from various types of CS data.

5 | STATISTICAL MODELS

The high degree of bias, error and variation in CS data are challenges for the statistical models used for analysis. Here we do not advocate for a particular modelling approach, but list a few classes of models or modelling frameworks that hold huge potential for the analysis of CS data. Overall, the challenges in this section will be largely addressed by developing and refining analytical approaches.

5.1 | Multi-species models

Multi-species models estimate the distributions of several species in the same model, enabling sharing of information between species and inference of species co-occurrence or interactions. These models have been developed through two key directions; joint species distribution models (jSDMs; Ovaskainen, 2020) and multi-species occupancy models (MSOMs; Devarajan et al., 2020). Broadly, jSDMs do not account for observation error but allow for a flexible explanation of community composition, accounting for species' environmental preferences, as well as interactions between species, and spatial autocorrelation (Warton et al., 2015). On the other hand, MSOMs account for observation error by estimating detectability, but generally assume simpler models for community structure. The two fields are slowly merging, with new models being proposed that account for both observation error and correlation between species (Tobler et al., 2019), but more work is needed in this area to fully leverage CS data for monitoring biodiversity on a large scale.

Joint species distribution models (jSDMs) can be fitted to fairly large datasets, but without accounting for the observation process, results can be unreliable (Guillera-Arroita, 2017; Guillera-Arroita et al., 2014). Additionally, there is an ongoing debate about the interpretation of the inferred species correlation matrix and its use when predicting species distributions (Poggianti et al., 2021). Finally, fairly strong assumptions need to be made on how environmental responses and observation processes vary between species in both jSDMs and in MSOMs.

The main challenge, especially as the number of species grows, is to build statistical models that identify species with shared environmental preferences and/or observation processes. For example, recent novel approaches group species according to their covariate effects (Swallow et al., 2016) or use a deep neural network for feature extraction (Chen et al., 2016). More flexible and computationally efficient multi-species models of these types are needed. These models need to provide reliable inference on community structure, to quantify the effect of landscape characteristics on community composition, account for observation error, and fit to large CS datasets.

5.2 | Data integration

Data integration provides opportunities to maximise the use of available data sources with the goal of improving accuracy and precision of parameter estimates. With growth in not only the volume of CS data but also in the data types collected, statistical models that combine differently structured data are increasingly of interest. Various methods for combining information from multiple datasets exist (Besbeas et al., 2002; Fletcher Jr. et al., 2019), but here we focus on formal integration using joint likelihoods to estimate shared parameters. Integrated modelling is well-recognised in ecology (Besbeas et al., 2002; Besbeas & Morgan, 2019; Fletcher Jr. et al., 2019; Schaub & Abadi, 2011), historically with an emphasis on combining demographic data and structured count data (Schaub & Kéry, 2021; Zipkin & Saunders, 2018), but with a more recent focus on integrating big CS datasets (Isaac et al., 2020; Miller, Pacifici, et al., 2019). Applications of integrated models with CS data typically seek to benefit from combining the depth of smaller, structured datasets and the breadth of larger semi- or unstructured datasets (Robinson et al., 2020; Steger et al., 2017).

Several of the integrated modelling approaches with CS data involve combining presence-only data with list data, enabling inference of species non-detections. This data combination is quickly growing in application in species distributions (Fletcher Jr. et al., 2019; Miller, Pacifici, et al., 2019). However, simulation-based studies have shown that poor estimates can be obtained when biases in presence-only data are unknown and hence not accounted for (Ahmad Suhaimi et al., 2021; Simmonds et al., 2020). When estimating population trends, data integration of large CS list data and structured data can reduce bias (Boersch-Supan & Robinson, 2021; Hertzog et al., 2021; Pagel et al., 2014).

Integrated statistical models may have an implicit assumption that larger datasets will carry more weight and contribute more to the joint likelihood (Kéry & Royle, 2021). However, this can lead to inference that is dominated by the larger, potentially biased, data source, thus overwhelming the smaller but informative dataset. Weighting of likelihoods provides one possibility to address this issue (Fletcher Jr. et al., 2019).

There is a need for greater understanding of where integrated modelling is most suitable and beneficial for CS data. Integrated

modelling with large CS datasets has potential costs, as well as outstanding questions (Isaac et al., 2020). For example, computational challenges for large CS data (section 5.3 computational limitations) are amplified for integrated models, thus hindering wide-scale use and presenting barriers for model development. Validation of results is an additional challenge for integrated models (section 4.1 validation). However, integrated models are an important direction for improved analysis (Kéry & Royle, 2021) and hence more research is needed on integrated models for CS data and to consider where additional data collection may benefit the analysis.

5.3 | Computational limitations

CS data present many 'big data' problems; storing and modelling large datasets, that are also sparse and messy (Dobson et al., 2020; Hampton et al., 2013; Kelling, Fink, et al., 2015). With more data and increasingly complex models, ecological analyses require more computing power and more efficient algorithms. This is particularly the case within a Bayesian framework, where the choice of algorithms can have considerable impact on computation times (Betancourt, 2017; Robert et al., 2018).

As CS model complexity and data volumes increase, different model-fitting methods may be necessary to enable convergence. For example, the Polya-Gamma (PG) data-augmentation scheme for logistic regression models (Polson et al., 2013) is orders of magnitude more efficient than standard Metropolis–Hastings algorithms for occupancy models with a logit-link function (Clark & Altweig, 2019). Similarly, several advancements have been made for probit-link occupancy models accounting for spatial and spatio-temporal autocorrelation using efficient algorithms (Hepler & Erhardt, 2021; Johnson et al., 2013; Mohankumar & Hefley, 2022). Finally, implementing the PG scheme within a variational Bayes framework (Diana et al., 2021) leads to additional and substantial savings in computation time. Algorithms of this type could be more widely employed and implemented to enable fitting complex CS models to large datasets.

In addition to selection of algorithms, variable selection methods can also have substantial impacts on computation time in Bayesian models. Efficient variable selection allows for identification of important predictors for all model parameters even in complex models (Griffin et al., 2020; Wan & Griffin, 2021). Variable selection in CS models is key for our understanding of the drivers of ecological processes and hence efficient approaches could improve ecological inference from CS data (Morin et al., 2020; Swallow et al., 2016).

Integrated Laplace approximations are another statistical tool that enables efficient fitting of complex Bayesian models to large datasets. For example, the INLA framework can efficiently fit complex spatio-temporal models (Kraainski et al., 2018; Rue et al., 2017) and inlabru is a recent R package that has been specifically developed with ecological data in mind and hence for cases where detection probability is unknown (Bachl et al., 2019). Future work could consider more complex models for heterogeneous detectability and

models for time-varying processes that underlie species presence in space, such as phenology.

There will always be a trade-off between model complexity and computational feasibility. Therefore, to enable continued fitting of complex models to growing CS data, ecological modellers and statisticians should aim to develop and implement more efficient algorithms, learning from the latest developments in mainstream statistics.

6 | COMMUNICATION

Communication is critical in many elements of CS. These include communication of results with observers (de Vries et al., 2019), communication between analysts and project organisers to refine data collection (Kühl et al., 2020), and communication of analytical approaches from statisticians to a wider group of ecologists. All of these types of communication are essential for solutions to the challenges that require either additional data collection, or dissemination of new statistical methods, and here we focus on the last of these.

For CS data to reach their potential in contributing to biodiversity modelling, robust appropriate statistical methods need to move beyond the reach of technical groups. The increasing move towards open science is useful for code availability (Beck et al., 2020; Powers & Hampton, 2019), but complex models and code alone may not be accessible to ecologists. Making methods truly accessible requires developing software, workshops, tutorials and guidebooks (Cooch & White, 2017; Miller, Rexstad, et al., 2019; Strimas-Mackey et al., 2020), which typically requires funding and incentives specifically for this dissemination. Longer term, there is also a need to provide more quantitative training for ecologists (Cooke et al., 2021; Ellison & Dennis, 2010; Koenig, 2011), to align with the more complex and sophisticated analytical approaches increasingly used for big data in ecology (Hampton et al., 2013; McCallen et al., 2019; Touchon & McCoy, 2016). Citizen science democratises data collection, and accessible communication of novel methods could also democratise analysis of these data by enabling CS data to reach their broadest potential.

7 | CONCLUSIONS

Opportunistic and semi-structured CS data will play an increasingly important role in the future of biodiversity monitoring, yet there are many remaining challenges with CS data. Continued use of this 'big data' resource for ecology and conservation without due care and attention to these challenges, can affect ecological conclusions and lead to poor conservation decisions (Clarke, 2016; Dobson et al., 2020; Harry & Braccini, 2021; La Sorte et al., 2018). Analytical innovation and creativity in all of the areas listed above would lead to improved ecological inference and the ability to use more of the large and diverse pool of CS data.

We have not attempted to rank the challenges according to their importance or level of urgency because these will depend on both the questions being asked and the type of data. In some cases, we have expressed our views about possible directions for solving the problem but often there will be a trade-off in these two elements of advance; improved data reduce the requirement for new models, whereas new models may be more critical in cases where data cannot be improved or augmented.

Finally, we have focused on the types of data that are currently widely collected by direct observation of the species, but increasingly, data collection uses new technologies, for example eDNA, telemetry, camera traps or acoustics. We anticipate that they will become increasingly adopted and intertwined with more conventional CS data (Davies et al., 2012; Newson et al., 2015; Swanson et al., 2016; Terry et al., 2020). These new technologies will likely help to solve some challenges, but increase the magnitude of other challenges.

CS data have tremendous potential to monitor and track biodiversity on a global scale. Despite the inherent challenges of dealing with such data as outlined in this paper, with good statistical models, refinements to project data collection, and accessible analytical tools, CS data can be a powerful tool for sustainable monitoring of biodiversity on a global scale (Bush et al., 2017; Pocock et al., 2018).

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CONFLICT OF INTEREST

The authors have no conflict of interest to declare.

AUTHOR CONTRIBUTIONS

All authors conceived the ideas and contributed to the writing. A.J. conducted the analysis and led the writing of the manuscript.

DATA AVAILABILITY STATEMENT

The original full eBird datasets are available from <https://ebird.org/science/use-ebird-data>. Code and processed data are available at https://github.com/ali-johnston/mee_future_directions/ and <https://doi.org/10.5281/zenodo.5919811> (Johnston et al., 2022).

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