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Short communication

Conservation birding: A quantitative conceptual framework for prioritizing citizen science observations

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ABSTRACT

Despite impressive growth in global biodiversity data, knowledge about the occurrence of species in many parts of the world remains incomplete because of major gaps in the underlying data. This can lead to ill-informed conservation decisions. The collective effort of citizen scientists can generate a great deal of data quickly, but how might we prioritize the powerful — but finite — effort? We argue that instead of simply filling empty spots on the map based solely on where biodiversity information is incomplete, near-term threats to the integrity or persistence of biodiversity assemblages could also be incorporated to prioritize citizen science sampling. Here we develop a quantitative framework illustrating how citizen science sampling and initiatives can be prioritized when simultaneously considering both the completeness of biodiversity sampling and the risk of habitat conversion. We illustrate this framework for birds using global citizen science data from the eBird platform and a global model of the risk of habitat conversion. We find that regions in Africa and southeast Asia would rank as the highest priorities for new and expanded citizen science initiatives. Our framework provides a mechanism to quantify where new biodiversity data are most urgently needed, ultimately helping to improve environmental decision-making. We anticipate this framework can be used in the future at a suite of relevant planning scales, ranging from local to regional to global.

1. Introduction

Biodiversity loss is accelerating globally (Butchart et al., 2010; IPBES, 2019), and targeted monitoring is crucial for implementing effective conservation (Yoccoz et al., 2001; Groves et al., 2002). Yet for monitoring to be effectively integrated into a conservation strategy, a clear understanding of the distribution and abundance of species needs to be established. At a global scale, there has been a tremendous increase in biodiversity monitoring, resulting in large open-access biodiversity databases such as the Global Biodiversity Information Facility (GBIF) which now hosts more than 1.5 billion biodiversity records.

Despite the impressive volume of global biodiversity data, estimates of biodiversity in many parts of the world remain at best imprecise, and at worst non-existent because of a lack of underlying data (Stork, 1993; Boakes et al., 2010; Scheffers et al., 2012; Essl et al., 2013; Cornwell et al., 2019; La Sorte and Somveille, 2020). In such regions, biodiversity data are inadequate to support conservation decision-making. Our understanding of biodiversity is typically biased taxonomically (e.g., more observations for charismatic fauna and flora), temporally (more data in recent decades coinciding with the rise of online citizen science programs), and spatially (e.g., more observations in more populated regions). Spatially, our understanding of biodiversity is biased towards sites in two categories: first, accessible areas (i.e., sites that are accessible to either professional or citizen scientists), and second, "hotspots" — sites already known to support high levels of biodiversity. In many cases those hotspots are already protected areas (Boakes et al., 2010; Martin et al., 2012). These biases leave many parts of the world poorly sampled, and specifically, we are often unsure of total species richness and the number and identity of threatened species in these parts of the world. This fundamental lack of understanding of which species exist

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where is highlighted by modern day 'rediscoveries' (e.g., Nguyen et al., 2019; Scheffers et al., 2011).

An incomplete understanding of biodiversity estimates can lead to rash development decisions, allowing development to proceed uninformed by an understanding of biodiversity distributions in that given region. For example, the southern subspecies of Black-throated Finch *Poephila cincta cincta* is a critically endangered bird in eastern Australia, and development activities — ranging from mining to urbanisation to agriculture — throughout its range are ongoing at least in part because there is a lack of fundamental understanding of the distribution of biodiversity in much of the region (Ramesh et al. 2017; Reside et al., 2019). Unfortunately, however, the current pace of funding for professional conservation and ecology is not compatible with the increasing need for robust biodiversity monitoring (Bakker et al., 2010).

So how do we combat the pervasive lack of complete species' inventories? Citizen science — scientific research conducted in whole or in part by people for whom science is not their profession — has clear potential to deliver comprehensive monitoring of biodiversity in both space and time (Tulloch et al., 2013a; Danielsen et al., 2014; Chandler et al., 2017a, 2017b; McKinley et al., 2017). Indeed, data from citizen science projects have shifted our ability to understand spatiotemporal dynamics of many species' populations (e.g., Schuster et al., 2019). Nevertheless, these data are still far from complete: there are still many spatial and temporal biases in these datasets (Boakes et al., 2010; La Sorte and Somveille, 2020), reflecting a general bias in global understanding of biodiversity towards areas with high human population density and hotspots of both ecotourism and scientific activity (Boakes et al., 2010; Cornwell et al., 2019). Many researchers and/or practitioners have suggested that to ensure more robust estimates of biodiversity, citizen scientists could serve to 'fill the gaps' in biodiversity datasets in regions that are not well surveyed (e.g., Tulloch et al., 2013a; Chandler et al., 2017a, 2017b; McKinley et al., 2017). Exactly how these gaps are filled, however, is still up for debate. Previous studies, for example, have used species distribution models to target the places with the highest probability of finding target species (e.g., Udyawer et al., 2020); designed prioritization approaches for bird surveys with the highest benefits to specific project goals (e.g., Tulloch et al., 2013b); used Value of Information from experts to highlight the critical knowledge gaps to be filled (e.g., Nicol et al., 2018); and quantified where data are most important for informing conservation decisions using various mathematical models (e.g., Kujala et al., 2018).

Crucially, to be of maximum conservation utility, this strategy of gap-filling could be further targeted towards areas with known or projected threats to the integrity or persistence of an assemblage; particularly important given the lack of adequate resources available for biodiversity monitoring. Here we produce a conceptual quantitative framework that can be used to prioritize citizen science observations based on both the biodiversity survey completeness of a region and the level of threats in a region. This framework is intended for citizen science practitioners, environmental managers hoping to leverage citizen science data, and those involved in various citizen science projects. We provide an example of how this framework could be operationalized, conducting a global analysis of where new citizen science observations of birds are most likely to have the greatest return on understanding biodiversity in areas at risk of loss through development. We call this "*conservation birding*".

2. A conceptual example

Choosing where and how to implement effective conservation strategies fundamentally requires information about which species occur where, combined with information about threats to the integrity or persistence of an assemblage. Consider two different, equally sized, habitat patches equidistant from a large city in which reside dedicated birdwatchers who could choose to allocate their surveying to either patch. For both patches, we can estimate how well we understand the biodiversity of that patch based on already-submitted citizen science observations; referred to as 'survey completeness' (i.e., a value, such as percentage probability, representing our confidence of how much we know about the biodiversity in that patch; see details in the following section). Assume Patch A has 5000 citizen science observations and that survey completeness has been estimated at 60%. In contrast, assume Patch B has only 2000 citizen science observations with an estimated survey completeness of 20%. Most practitioners and biologists would intuitively encourage citizen scientists to submit samples from Patch B as opposed to Patch A because we know less about the biodiversity of that area. But what if we knew that Patch A has a 90% chance of being cleared to make way for a development, while Patch B has only a 5% chance of being developed? From a conservation perspective, it is arguably more beneficial to allocate new citizen science sampling effort to Patch A providing conservationists with the necessary data to argue against inappropriate development, or design appropriate conservation mitigation and offset strategies. In other words, because of the low risk of development, Patch B can 'wait' until we more fully understand the biodiversity of Patch A.

3. Illustrating the framework

We can generalize this example by defining two axes: (1) survey completeness — i.e., how well-sampled the biodiversity is in an area, and (2) risk of habitat conversion — i.e., development pressure in an area. As illustrated in our conceptual example, as risk of habitat conversion in an area increases, so should the importance of improving our understanding of the biodiversity present in that area, especially where survey completeness is low (Fig. 1).

To illustrate an example of how this conceptual framework could be used, we use a global citizen science project — eBird — and a global model of risk of habitat conversion. We used eBird to illustrate our framework because it is a globally relevant, successful, citizen science project and the data are openly available. Further, survey completeness has been previously quantified using eBird data (La Sorte and Somveille, 2020). As a result of relying on eBird to illustrate our framework, our analysis is restricted to birds, but we highlight two key points: (1) birds are often considered an effective surrogate to represent biodiversity more broadly (Gregory et al., 2003; Larsen et al., 2012); and (2) our framework can easily be adapted to other taxa such as amphibians, mammals, plants, and insects for which there are citizen science datasets available.

3.1. Survey completeness

eBird is arguably one of the most successful biodiversity citizen science projects in the world. In May 2019 alone, eBird averaged 7.5 observations per second. With >800 million observations globally of >99% of the world's known avifauna, there is clearly the potential to use these data to fundamentally enhance our understanding of conservation need at a global scale, and these data are continuously available to decision-makers and planners around the world through an open-access portal. We used a recently published assessment of eBird survey completeness (La Sorte and Somveille, 2020), based on data submitted between 2012 and 2018. La Sorte and Somveille (2020) estimated survey completeness by modelling the relationship between the number of species and sampling effort to develop a species accumulation curve describing the relationship between the accumulated number of species and survey effort (for full details see La Sorte and Somveille, 2020 and Lobo et al., 2018). We used the equal-area hexagonal cells (49,811 km^2) from La Sorte and Somveille (2020) to derive an average completeness score — rounded to the nearest integer between 0 and 100 — across all months. We restricted our analysis to those hexagonal cells that are terrestrial (Fig. S1).

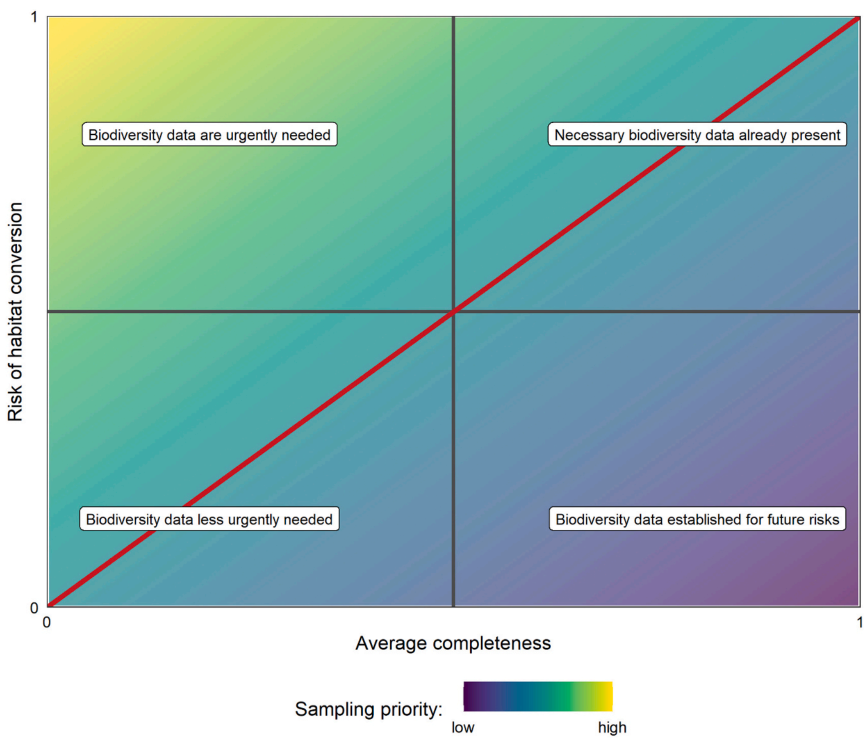

Fig. 1. Conceptual framework illustrating the basis for prioritizing citizen science sampling based on existing sample completeness (x-axis) and the risk of habitat conversion (y-axis). The priority of a citizen science observation becomes increasingly important moving from the bottom right-hand corner of the space to the top left-hand corner. The red line represents the 1:1 slope, and the distance of a site below or above this line indexes its sampling priority from a conservation perspective. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

3.2. Risk of land conversion

We used a recently published global model of the risk of habitat conversion in 30 km^2 planning units (Allan et al., 2019). This map used spatially explicit data on future land-use scenarios from the Land Use Harmonisation Dataset v2 (Hurtt et al., 2020) and projections under socioeconomic pathway 3 (RCP7.0; AIM), a business-as-usual pessimistic scenario where land use change is poorly regulated. The harmonised land-use data contains 12 state layers for the years 2015 and 2030, and we used the difference between these to estimate the proportion of intact habitat projected to be converted to human uses by 2030 in each 30 km^2 planning unit. If a planning unit had >50% probability of conversion to human uses, it was defined as being ‘at risk’ of conversion (see Allan et al., 2019). This thresholding approach recognizes the considerable uncertainty in land-use projections given that our aim was to derive broad estimates of the risk of habitat conversion for a given region, rather than calculating exact amounts of habitat lost. We were left with a binomial representation of whether a planning unit was associated with the potential for conversion to human uses. For our analysis, we spatially aggregated the values (i.e., at risk = 1, or not at risk = 0) of risk of habitat conversion (at 30 km^2 planning units) to each hexagonal cell by taking the mean value of the binomial planning units within a hexagonal cell.

3.3. Assigning sampling priority

We calculated a sampling priority score for each hexagonal cell in the two-dimensional space given by our two axes (survey completeness and risk of habitat conversion; Fig. 1). This was done by plotting completeness vs. risk for each hexagonal cell and calculating the Euclidean distance to the 1:1 slope line, whereby the furthest distance was in the top left and top right corners. Based on our conceptual figure, any value that fell above the 1:1 slope line was assigned a positive value (i.e., highly important regions), whereas any value that fell below the 1:1 slope line was assigned a negative value (i.e., less important regions). These values were then scaled from 0 to 1 after adding the absolute value of the minimum value (i.e., those in the bottom right of Fig. 1), leaving us with each hexagonal cell assigned a sampling priority score ranging from 0 (lowest sampling priority) to 1 (highest sampling priority).

4. Results & discussion

Our analyses revealed that large swathes of terrestrial Earth (53% of hexagonal cells) had virtually no recorded eBird data (see La Sorte and Somveille, 2020). Many of these same areas are at risk of conversion to more intensive human uses (Fig. 2), with 16% of terrestrial Earth being at high risk of conversion (Fig. S2). Our results indicate strong potential to prioritize where citizen scientists could contribute future biodiversity sampling (e.g., Figs. 1, 2a), where those cells with high risk of habitat conversion receive the greatest allocation of effort. While our current illustration is limited to eBird only, we highlight that different regions have different bird monitoring schemes that may not have data available in eBird, and our work is currently only applicable to birds. More work is necessary to generalize these findings to other taxa. But importantly, our framework can easily be adapted to focus on or incorporate other taxa. Regardless, our framework offers one way to differentiate the conservation value of additional citizen science sampling efforts: biodiversity conservation strategies could aim to incorporate information about threats to the integrity or persistence of an assemblage.

Our results showed that some of the highest priority regions in the world for biodiversity sampling — and thus developing citizen science infrastructure — are in Africa, parts of central and southeast Asia, Mongolia, parts of the Middle East, and parts of Brazil (Fig. 2b; interactive version here). Across the world there was high variability in the sampling priority, with different cells in our analysis in markedly different regions of our conceptual space (e.g., Fig. 2a), and this was true even within specific regions (e.g., Australia). Areas with a high risk of habitat conversion and low average completeness (e.g., regions in Guinea, Congo, Brazil, Central African Republic) are where biodiversity data are most urgently needed. Conversely, some regions have relatively low sampling priority either because the risk of habitat conversion is low, or their biodiversity is relatively well known (e.g., relatively less-diverse regions such as the boreal in Canada, or part of Europe). These

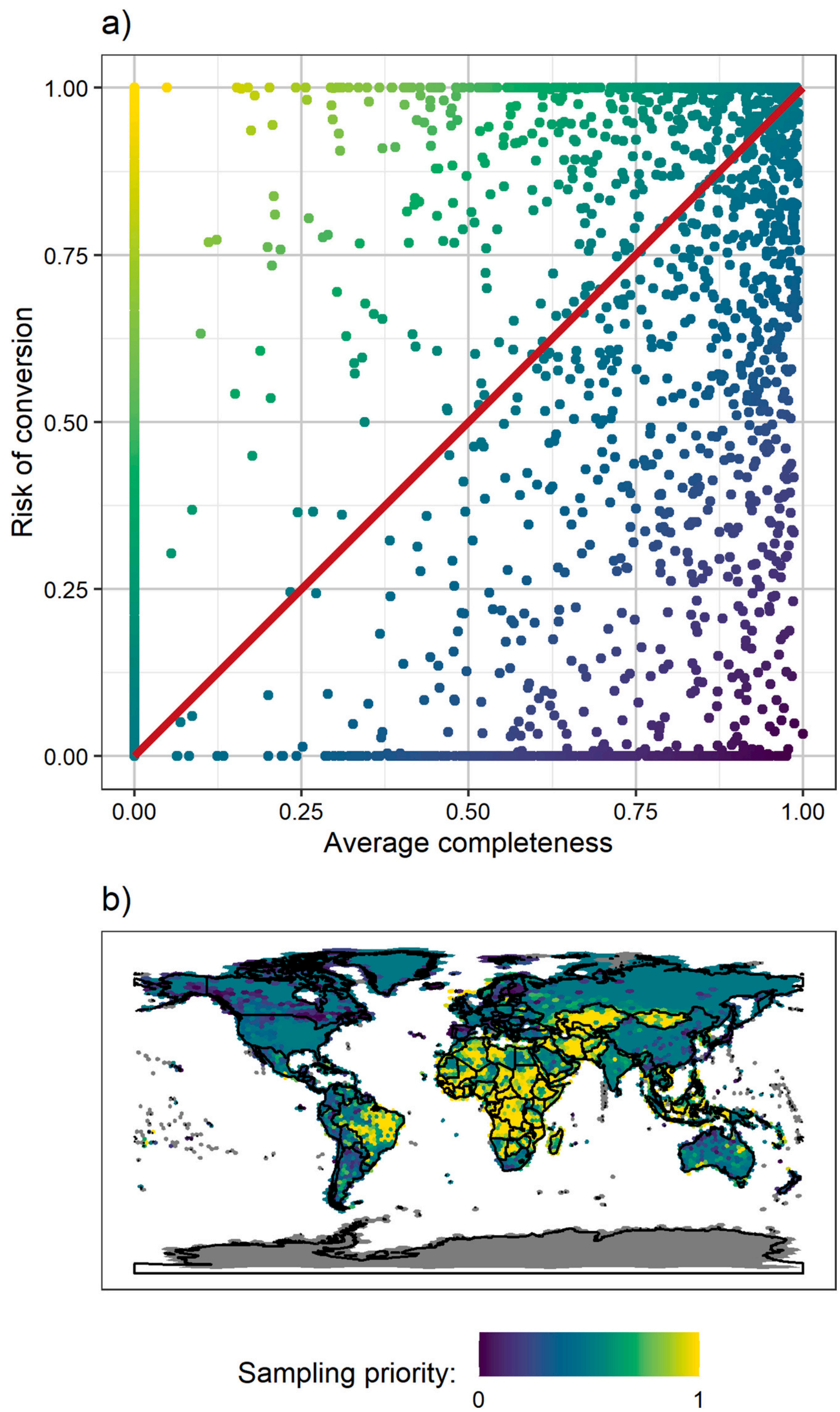

Fig. 2. a) Real-world data placed into our conceptual space, from eBird average completeness (x-axis) and the risk of habitat conversion (y-axis). As illustrated in Fig. 1, cells in the top left of our conceptual space have the highest sampling priority and cells in the bottom right have the lowest sampling priority. b) The sampling priority of a cell mapped across the world (see here for an interactive version).

results highlight the differences among regions in their current understanding of biodiversity relative to the current projections in risk of habitat conversion until the year 2030.

The ranking of sampling priority regions, at a global scale, could be used as a basis for incentivizing and expanding coverage by both international and local citizen science programs and as a means to move citizen science beyond the 'western world' through a combination of participatory, contributory, and field-based projects (Pocock et al., 2019). While the potential downsides of excessive carbon footprints need to be considered, the increase in global ecotourism holds much potential to increase biodiversity sampling in high priority regions (see examples in Callaghan et al., 2020). Such international initiatives could be coupled with local-scale investment and collaboration since this is a proven technique for biodiversity monitoring in traditionally data-poor regions (Ortega-Álvarez et al., 2012). For example, community-based monitoring has successfully helped monitor tropical forest diversity (Chandler et al., 2017a, 2017b) and large carnivores in remote montane landscapes (Farhadinia et al., 2018). Further, some global citizen science projects (e.g., eBird and iNaturalist) have proved successful on a global scale by providing local-scale community curation with infrastructure and initiatives (e.g., websites in the relevant languages). As an example, Taiwan, despite its relatively small geographic area, is currently ranked number eight in terms of eBird submissions (https://ebird.org/home) due in large part to a local portal which provides relevant news to Taiwanese birders (https://ebird.org/taiwan/home). As another example, iNaturalist has truly global reach due in part to their concerted effort to highlight global biodiversity through initiatives such as the iNaturalist World Tour (https://inaturalist.github.io/internationals_all.html). Importantly, there is not a 'one-size-fits-all' recipe to engage with local citizen scientists, due to many different — and complicated — issues; such as access and literacy surrounding smartphones (e.g., Leibenberg et al., 2017; Pejovic and Skarlatidou, 2020). To truly reach a global vision for citizen science (Pocock et al., 2018), many different types of projects will be necessary (Pocock et al., 2019), and for example different recruitment strategies are likely necessary to engage with different types of volunteers (Requier et al., 2020). Nevertheless, our results suggest that similar efforts could be spearheaded in areas such as Africa or southeast Asia (Pocock et al., 2018, 2019) — where it might be difficult to acquire local funding — to increase the biodiversity sampling in these parts of the world in the face of potential threats.

Although we currently provide an illustration of our quantitative conceptual framework at a global scale, the applicability of the framework will likely be more powerful at a local scale. There is currently strong correlation between our sampling priority scores and the completeness scores by La Sorte and Somveille (2020), likely as a result of the coarseness of our analysis (i.e., 50,000 km^2 cells). This is because of the heterogeneity of threats and completeness that occurs at a spatial scale less than the size of the specific cells used here in our case study. We highlight, however, that our conceptual framework can still shift the sampling priority of some cells more or less, depending on the level of threat — even at the large spatial scale used. Nevertheless, there still exists variability among these scores (see Fig. 2a) highlighting regions with relatively greater sampling priority (Fig. 2b). In New Zealand, for example, most cells are unsurprisingly well-sampled, but after accounting for the level of threat, grid cells are more variable in terms of their sampling priority (see interactive figure here). Citizen science practitioners and conservationists could operationalize the conceptual framework we present here at more localized scales; for example, within regional or state management units, or even within more localized areas such as cities, nature reserves, or wetlands where practitioners may be worried about threats to the habitat. At a local scale, it may also be more likely that practitioners will be able to successfully incentivize and interact with local citizen scientists, promoting uptake of a prioritization scheme for citizen science sampling (Callaghan et al., 2019a). In addition, data on development pressures/ecological threats are likely more reliable and robust at smaller spatial scales. Importantly, other metrics could also be integrated into our framework in the future such as the cost of conservation interventions and mechanisms, or the accessibility of a site. The accessibility of a site/region is important to consider because professional monitoring will continue to be necessary in areas that are difficult to get to by citizen scientists (e.g., remote parts of Australia), and some regions of the world will continue to be difficult to monitor with citizen science due to socioeconomic limitations (e.g., technology or limited education). Importantly, we expect that the correlation between sampling priority and average completeness will be lessened at smaller spatial scales, but this needs to be formally tested.

The approach presented here is somewhat static: dependent on a snapshot of our understanding of survey completeness and risk of habitat conversion. But citizen science observations are dynamic, constantly updated and are continuously being amassed (Callaghan et al., 2019b). Similarly, the threat of habitat development can also be dynamic, shifting with political regimes for instance. We see the next steps in this research space being: (1) aggregating data necessary to prioritize citizen science observations (e.g., development pressure at regional or state scales) at more localized scales; (2) extending these analyses to biodiversity more broadly, for example through the use of GBIF data; and (3) developing predictive frameworks which are continuously updated as citizen science observations are submitted (e.g., Callaghan et al., 2019a).

A robust understanding of biodiversity is essential to protect against development of natural areas and effectively plan conservation strategies. Biodiversity monitoring is likely to rely on citizen science data, at least in part, in the future (Danielsen et al., 2014; Chandler et al., 2017a, 2017b; McKinley et al., 2017). We argue that citizen science projects could focus on the highest priority observations, by encouraging or incentivizing participants to sample in the most meaningful way (e.g., Callaghan et al., 2019b). Biodiversity monitoring will continue to rely on a diverse set of end-users and contributors (Bayraktarov et al., 2019), ideally working together to further our understanding of biodiversity, and what threatens it, in space and time. The capacity to prioritize where biodiversity data are most urgently needed will provide the fundamental data to improve environmental decision-making.

CRediT authorship contribution statement

Corey T. Callaghan: Conceptualization, Methodology, Investigation, Writing - Original draft preparation, Visualization. **James E. M. Watson**: Methodology, Data Curation, Writing – Review & Editing. **Mitchell B. Lyons**: Visualization, Methodology, Investigation, Writing – Review & Editing. **William K. Cornwell**: Investigation, Writing – Review & Editing. **Richard A. Fuller**: Conceptualization, Investigation, Visualization, Writing – Review & Editing.

Data availability

Data to illustrate our framework were extracted from Allan et al. 2019 and La Sorte and Somveille 2020 as described above. Code and aggregated data to reproduce Figures 1 and 2 in this paper can be found here: https://doi.org/10.5281/zenodo.4316543.

Declaration of competing interest

The authors declare no conflict of interest.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.biocon.2020.108912.

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