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# Improving Online Citizen Science Platforms for Biodiversity Monitoring

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## ABSTRACT

**Background:** Monitoring biodiversity is crucial in biogeography. Citizen science and biodiversity platforms have revolutionized data access across taxa, but they struggle to provide robust raw data essential for conservation decisions.

**Aims:** This study addresses data gaps for under-represented species and locations, observer expertise variability, and the lack of absence data and sampling effort information to improve data representation and suitability for statistical analyses.

**Materials & Methods:** We collected, compared to IUCN-recognized taxonomic groups, all worldwide living being (animal, plant and fungi) observations held by four major biodiversity platforms: eBird, GBIF, iNaturalist, and Observation.org. We also organized such observations by country of origin and based on their Human Development Index (HDI).

**Results:** We found that, while GBIF, iNaturalist, and Observation.org cover all life forms, birds are the most observed (eBird is a bird-specific platform), whereas fish, other marine organisms, arthropods, and invertebrates are dramatically underrepresented. Moreover, none of the above-mentioned biodiversity platforms considered or directly analysed expertise variability among observers and, apart from eBird, the other three biodiversity platforms do not accommodate data on species absence and sampling effort.

**Discussion and Conclusion:** Finally, we found that species observations on biodiversity platforms considered in this study are skewed towards high HDI countries, primarily North America and Europe. By enhancing the effectiveness of biodiversity platforms, this study has the potential to significantly advance the field of biogeography, paving the way for more informed and effective conservation strategies. Overall, our findings underscore the untapped potential of these platforms in contributing to our understanding of the spatial and temporal patterns of biodiversity.

## 1 | Introduction

Over the past decade, the use of citizen science (CS) data, collected by non-specialist volunteers across various scientific disciplines, has seen an exponential increase. This surge has been particularly noticeable in the fields of ecology, biogeography, and computer science, where CS data has been instrumental in monitoring species occurrence (Chandler et al. 2017; Brown and Williams 2018) and predicting future distribution patterns (e.g., Kéry 2011; Guillera-Arroita 2017; Della Rocca and Milanesi 2022). Moreover, CS contributes to enhancing stewardship of resources by larger sectors of society, a powerful and valuable concept given that all citizens have a vested interest in conservation. Three main factors have contributed to this rapid development:




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1. The escalating need to monitor biodiversity, which is crucial for the conservation and sustainable use of natural resources.
2. Technological advancements in the use of the internet, social media, mobile/handheld computers, smartphones, and tablets (Wang, Xiang, and Fesenmaier 2014), which have greatly simplified the procedures for uploading records onto online platforms (Pocock et al. 2014).
3. The limited availability of resources for long-term biodiversity assessments, both in terms of funding and involvement of professional scientists (Bland et al. 2015; Kelling et al. 2018) –limitations that are particularly evident for urgently needed large-scale assessments (Peterson, Navarro-Siguenza, and Benıtez-Dıaz 2008; Milanesi, Mori, and Menchetti 2020).

In this context, CS provides ecologists with a cost-effective source of species occurrence information at large spatial scales, which would otherwise be prohibitively expensive (Feldman et al. 2021). The high number of occurrences recorded over large areas (i.e., countries or continents) and time spans are fundamental for researchers working on large-scale and geographically diverse projects (Paul et al. 2014; Willemen et al. 2015; Hobson, Smith-Vidaurre, and Salinas-Melgoza 2017; Mori et al. 2017). Indeed, thanks to CS-collected data, researchers can estimate the richness and distribution of vulnerable or invasive species on a broad scale (e.g., continental or global), species' biogeography and habitat use, alien species' colonization, species' natural history, and interspecific interactions (Mori and Menchetti 2014; Sullivan et al. 2014; Chandler et al. 2017; Mori et al. 2018; Vendetti et al. 2018; Menchetti, Guéguen, and Talavera 2019). Observations from citizen scientists are thus becoming crucial to inform policy on biodiversity conservation challenges (Milanesi, Mori, and Menchetti 2020) and thus support the ambitious goals of the recently adopted Kunming-Montreal Global Biodiversity Framework (CBD 2022) to halt and reverse nature loss by 2050. These include stopping human-caused species extinction, promoting the sustainable utilization of biodiversity, ensuring the fair distribution of benefits, and focusing on implementation and finance.

For some taxa, a massive amount of data collected using mostly non-standardized protocols is currently available on online biodiversity platforms, through efforts collectively labelled as CS, whereas a huge variety of CS programs are currently being implemented globally involving a wider range of taxa (van Strien, van Swaay, and Termaat 2013). Among them, the most important and widely used emerging in the last decade are Global Biodiversity Information Facility (GBIF; https://www.gbif.org), iNaturalist (https://www.inaturalist.org), eBird (https://ebird.org/home), Observation.org (https://observation.org). With 2,580,385,219 total observations (accessed on 2 November 2023), GBIF is a global network funded by governments to provide open access to life data on Earth. It is the largest online biodiversity platform, incorporating thousands of smaller platforms, and allows free data download. Although a significant portion of the hosted data (ca. 308.466.842 records) comes from scientific collections, most of them are still derived from citizen observations. iNaturalist, with 178,313,927 total observations of over 395,000 species (accessed on 2 November 2023), is one of the largest and most successful CS projects to date (Unger et al. 2020). It's a platform where volunteers upload photos or sound records for community identification. Once identified and confirmed, data are uploaded to GBIF and can be freely downloaded. With 84,700,000 total observations collected by 684,300 observers (accessed 2 November 2023), eBird is a bird-focused CS platform. Volunteers submit the checklists of bird observations, following various protocols. Users must include all identified species, allowing scientists to infer non-detections. Checklists include duration and distance travelled. eBird data, used for research, monitoring, and conservation planning, can be downloaded after a simple access request. Similar to eBird, but not included among our target platforms, are Ornitho (Italian platform focusing on birds and available for an increasing number of European Countries) and FrogID (Australian platform focusing on frogs, https://www.frogid.net.au/), benefitting from the development of rigorous protocols.

Observation.org, with 41,825,417 total observations (accessed on 2 November 2023) is part of the Observation International Foundation. It accepts data on 19 taxonomic groups, with the majority from birds, plants, butterflies, mammals and dragonflies. It provides opportunistic observations, similar to iNaturalist. Data can be downloaded after a simple access request.

While all these CS platforms can store a large amount of data in a cost-effective way with the potential to remarkably increase our biodiversity knowledge (Pimm et al. 2014; Davis et al. 2023) they are still far from being a really effective tool in the study of biogeography and animal ecology. Specifically, they can provide useful information regarding species name, locations and dates but these data are still challenging to analyse due to intrinsic issues such as non-standardized protocols and/or poor sampling effort details, that can affect the reliability and quality of the inference to be obtained (Tulloch et al. 2013; Cooper, Shirk, and Zuckerberg 2014).

For instance, the growth of CS platforms such as iNaturalist and Observation.org can be largely attributed to their less structured nature. Actually, these platforms allow participants to engage in initiatives without the need for adherence to fixed protocols or long-term commitments. This flexibility may attract a larger number of participants and generate a greater volume of data, but it causes numerous analytical challenges when it comes to extracting robust ecological insights. Indeed, the lack of structure and protocols can lead to inconsistencies in the data, making it difficult to derive meaningful and reliable conclusions. Conversely, eBird (and similar platforms above mentioned), while also accepting unstructured data, adopts a different approach, allowing for the inclusion of refined protocols that contribute to the robustness and reliability of its data. This specificity narrows the scope of the platforms but make it a valuable resource for scientific studies. As a result, it is not surprising that the majority of CS researches used the eBird and similar database, which; however, focuses only on a specific taxon.

Previous studies have tackled the different sources of error and bias in CS data (Ward 2014; Hugo and Altwegg 2017). Quantifying them can aid in (1) enabling researchers to account for these biases when drawing ecological conclusions, (2) informing the design and implementation of future CS projects, and (3) identifying species or regions that may require additional data collection from professional scientists. Ignoring these CS data biases can negatively influence the accuracy of the biogeography patterns to be inferred and of any biodiversity assessment (Fithian et al. 2015). Thus, in this paper, we tackle the main sources of error and bias in CS data, along with proposed practical solutions for their mitigation to improve the online biodiversity platforms above mentioned (and their dedicated mobile Apps) with structural changes and/or in light of the development of brand-new online biodiversity platforms. Our study aims to further the use of CS data in biogeography, enhancing our understanding of biodiversity patterns and informing more effective conservation strategies.

## 2 | Main Sources of Error in Citizen Sciences Data

### 2.1 | Taxonomical Bias

#### 2.1.1 | The Issue

CS observations can be taxonomically biased because volunteers are usually attracted to large and common species, to species that are brightly coloured, easy to detect and to more charismatic groups (Ward 2014; Amano, Lamming, and Sutherland 2016; Boakes et al. 2016; Newbold 2010). This involves a taxonomic imbalance not only in terms of species representativeness, but also in terms of species abundance, since a species that is easier to observe is also observed more frequently (Boakes et al. 2016).

Compared to the list of species currently accepted by the International Union for Conservation of Nature (IUCN 2023; Figure 1), those reported on the main CS platforms belong almost exclusively to a few taxonomic groups (Figure 2).

Among the platforms investigated in this study, eBird was designed and used only for a specific taxonomic group: Birds. The other three platforms: GBIF, iNaturalist and Observation.org are much more complete in terms of representativeness of the different taxa. Indeed, in these three platforms, observations relate to all the kingdoms of life (Figure 3a,b).

However, both in GBIF and in Observation.org, bird observations are over-represented compared to other taxa, while in iNaturalist, although the observations are numerically more distributed among the different taxonomic groups (Figure 3a), the most observed species are mainly attributable to birds (Figure 3b). Thus, birds are among the most popular taxa likely due to their recognizable plumages and vocalizations, medium-large dimensions and, for some species, their gregarious behaviour which make them easily detectable (Steen, Elphick, and Tingley 2019; Caley, Welvaert, and Barry 2020; Henckel et al. 2020; Callaghan et al. 2021). Therefore, people tend to notice a bird more easily than another animal and, within the other taxa, to detect the more attractive and/or abundant organisms (Callaghan et al. 2021).

This taxonomical disparity in the online platforms is further exacerbated by the different geographic distribution of species, with some animals extremely localized and/or linked to less accessible habitats (e.g., aquatic ones) and others much more widely distributed and/or linked to habitats more frequented by the users (e.g., terrestrial ones; Garcia-Soto et al. 2021). A clear example is provided by fishes and other aquatic organisms, especially those living in marine environments (Cigliano et al. 2015; note little representation in Figures 2 and 3). Similarly, Roy et al. (2012) surveyed more than 200 CS projects and found that marine and coastal species were clearly underrepresented. In all platforms considered in our study, fishes are extremely underrepresented even if the total number of existing species accepted by the International Union for Conservation of Nature is three times greater than that of birds

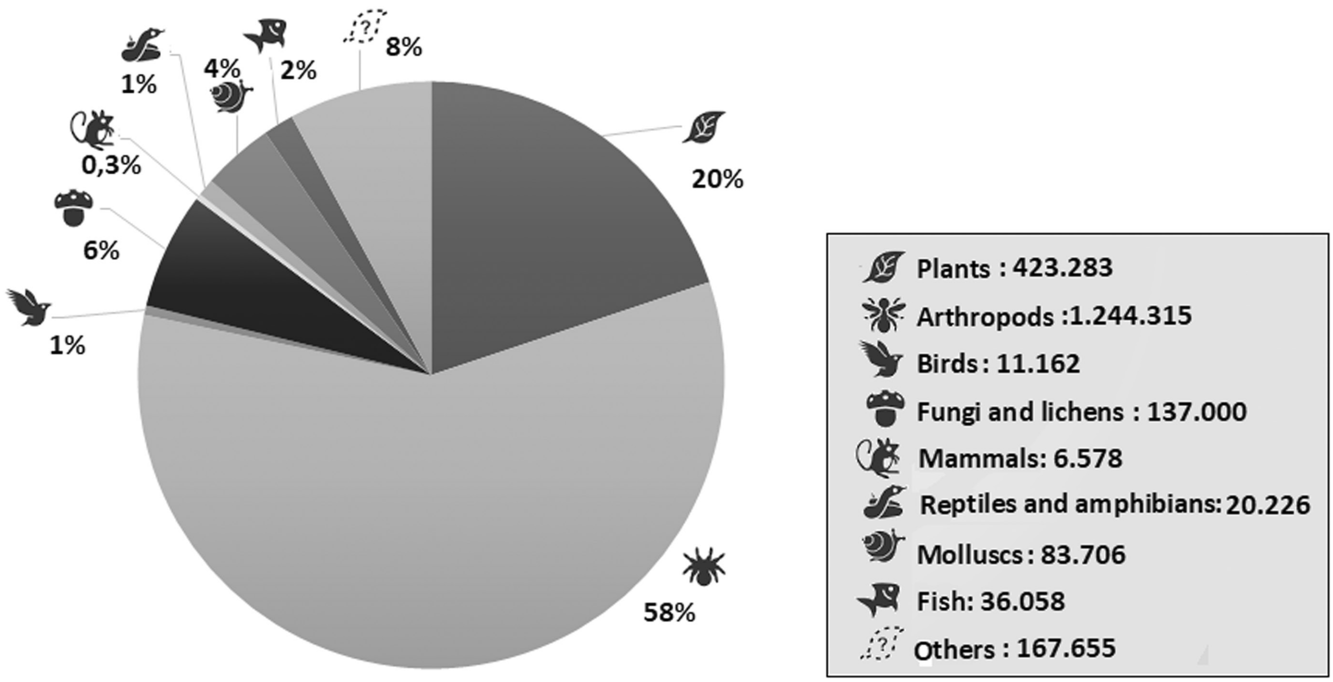


**FIGURE 1** | Number and percentage of total species currently described worldwide. Data derived by the IUCN Red List version 2022-2: Table 1a (IUCN 2023).

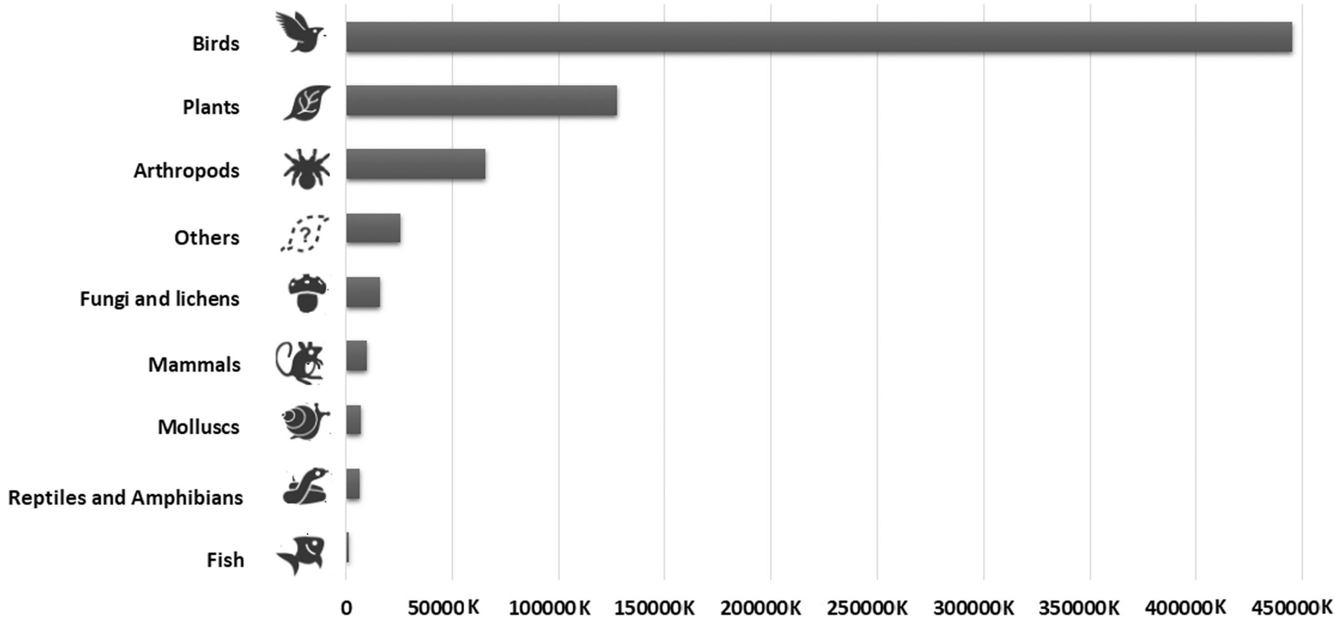


**FIGURE 2** | The number of observations per taxonomic group calculated as average values of the four major biodiversity platforms investigated (eBird, GBIF, iNaturalist and Observation.org).

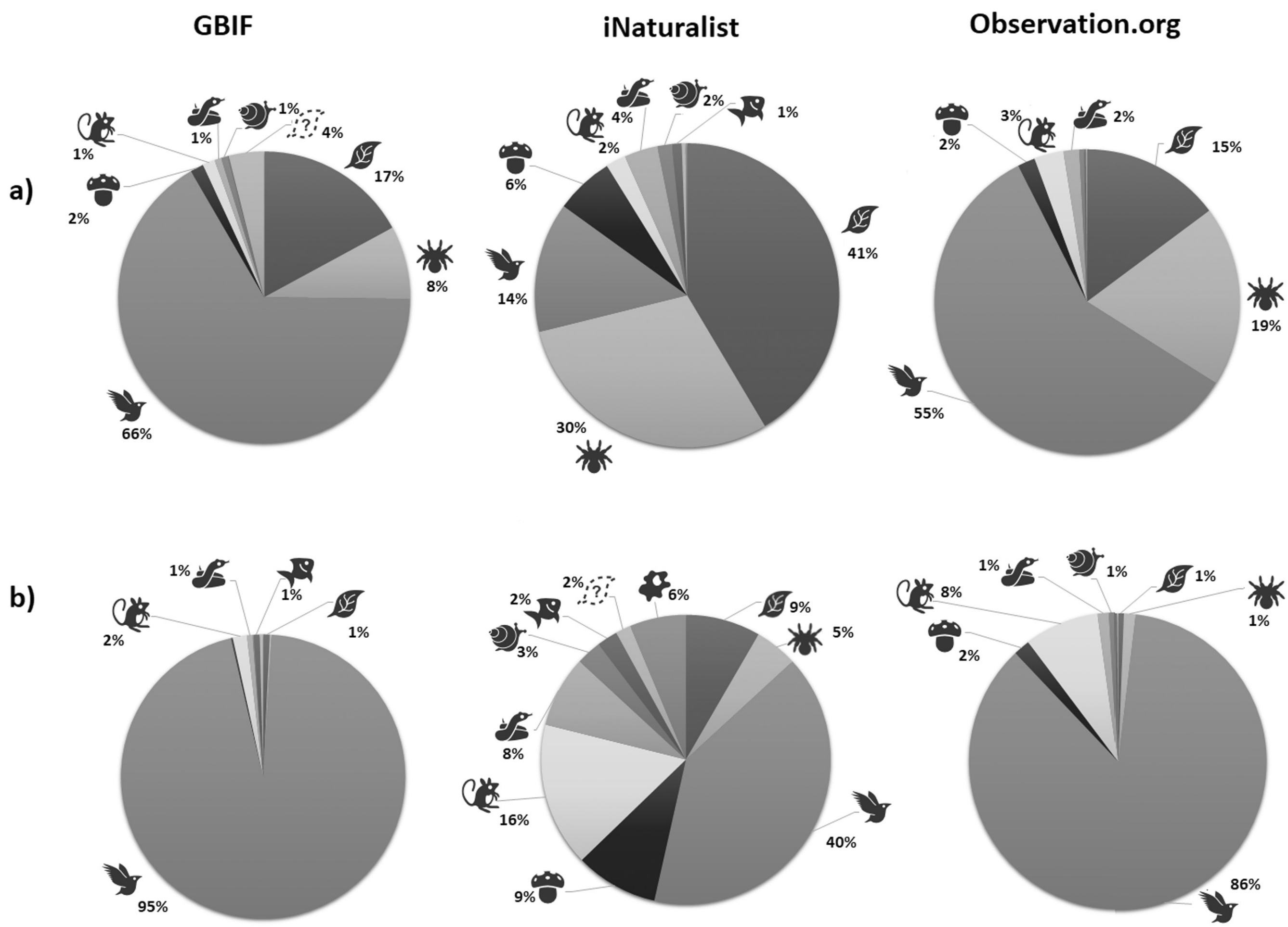


**FIGURE 3** | Graphical representation of the taxonomic imbalance of citizen science data reported in the investigated platforms (eBird was excluded as it contains only birds' records): (a) Percentage of observations for each taxonomic group and (b) percentage of observations of each species in each taxonomic group (calculated as the average value of observations of each species belonging to each of the taxonomic groups considered).

(IUCN 2023). In aquatic/marine contexts citizen scientists encounter difficulties not faced in terrestrial environment, which significantly reduce the probability of observing species, such as the need of expensive boats, diving gear, or transportation along the coast, the ability to swim and practice water sports, which is still uncommon for some cultures, and the lack of visibility in water bodies.

On the other side, arthropods and more generally invertebrates are extremely underrepresented in the biodiversity platforms investigated (Figures 2 and 3). Indeed, such groups comprise a significant percentage of all life on Earth (Figure 1, IUCN 2023), but receive much less attention compared to large mammals and birds (Cardoso et al. 2011; McKinley et al. 2017; Sanderson, Braby, and Bond 2021). Among the platforms investigated, the one with the largest number of arthropods species compared to the other taxa is iNaturalist. However, even in iNaturalist the frequency of observations of arthropod species is disproportionately low compared to other less globally prevalent groups, such as birds. The taxonomical unbalance in the online platforms investigated leads to large amounts of data gathered on relatively well-known groups and a reduced amount of data on species that often are rare, little vagile or cryptic. Given that neglected taxa have a high diversity and play crucial roles in several ecosystems (Cardinale et al. 2012; Gascon et al. 2015) this issue will inevitably result in an unbalanced knowledge of biodiversity and, as a result, in uninformed conservation decisions (Feeley, Stroud, and Perez 2016; Troudet et al. 2017).

#### 2.1.2 | Theoretical Solution

However, improvements are possible. A recent research carried out by Thompson et al. (2023), aimed to assess the willingness of citizen scientists to adapt their data collection methods to contribute more effectively to collective scientific discovery, found that citizens might be open to alter their sampling methods if they were educated on how to make their contributions more valuable. However, this was true within a given taxonomic group of interest (e.g., frogs) and may not hold true across group, although the majority of users of general-scope platforms (51.3%) show only slight preferences for specific groups (Di Cecco et al. 2021). Thus, in these cases the detection of under-sampled species could be enhanced by prompting users of the platform (and App) to search for underrepresented species known to exist in the area under investigation (e.g., based on IUCN assessments/maps), in order to potentially increase their detection. This could be supported by a gamification approach that publicly awards an increasing recognition to users providing data from under-sampled species prompted by the platform (Callaghan et al. 2023; Speelman et al. 2023), although these outcomes need to be further evaluated.

#### 2.1.3 | Technical Solution

From a technical point of view, once the App is activated (along with the GPS system), a pop-up window could appear, providing a list of unsampled species in the surrounding area (the radius would be specified by the user or fixed within a given distance, e.g., 1 km). This could be accompanied by useful tips about these unsampled species, including guidance on how, where, and when to find them, stressing the importance and thus the need to collect data also of these species (e.g., their ecological role and importance in maintain natural ecosystems and biodiversity at a whole). To avoid dealing with an extremely long list of all species, these could be categorized based on different biological groups. Additionally, to mitigate the potential for taxonomic bias, the App could promote unsampled groups in the categorized lists, not only species, to encourage users in contributing. On the other side, to avoid discouraging observers (Skarlatidou et al. 2019) simply want to share or identify a species record (without the need of opening lists), the design of the App would allow users to skip 'unsampled species lists' to quickly upload their observations. However, to encourage the collection of unsampled species, the App could award a special 'contributor badge' to users that provided observations of the taxa prompted in the list. This approach could significantly improve the value of data collected by citizen scientists by reducing significantly the taxonomical bias (Callaghan et al. 2023; Speelman et al. 2023).

### 2.2 | Expertise Variability Among Observers

#### 2.2.1 | The Issue

Another source of variation in CS data includes the variation in skills and expertise among observers, primarily due to the participation of a wide range of volunteers (Fitzpatrick et al. 2009). Thus, the accuracy of CS-generated data may vary depending on the knowledge and/or experience of the participants and the ability of observers to correctly detect and identify species (Kosmala et al. 2016). This inter-observer sampling variation increases for species that are harder to identify (Fitzpatrick et al. 2009; Kelling et al. 2015). Several techniques have been undertaken to minimize error and/or biases and thus increase the robustness of CS data. These include training participants to use standardized protocols, verifying data (i.e., checking observations by experts) and comparing data collected by citizen scientists and professional scientists (Zettler et al. 2017; Clare et al. 2019; Rambonnet et al. 2019; Baker et al. 2021). However, all these actions involve significant interactions with CS users, often providing to be time-consuming and not entirely effective (Gollan et al. 2012).

While the biodiversity platforms investigated in this study (except for GBIF) provide a unique observer ID, none of them directly provide information regarding their expertise and experience. Only on data available in eBird, observer expertise has been considered and proved to be an important parameter to account for in estimating statistically robust patterns of species distribution (Johnston et al. 2018, 2021; Johnston, Matechou, and Dennis 2023).

Specifically, Johnston et al. (2018, 2021); Johnston, Matechou, and Dennis (2023) estimated the skills of observers from their data uploaded on eBird, not directly within the platform. Therefore, incorporating the variability in expertise remains an unresolved issue across all online biodiversity platforms.

#### 2.2.2 | Theoretical Solution

To improve the accuracy and precision of biogeographical patterns derived by CS data, it is crucial to deal with variations in observer skills, ideally by incorporating an index of observer expertise directly into online biodiversity platforms. This index could be computed based on two key parameters: the total number of observations submitted by an observer (often referred as the 'reporting rates'; Farmer, Leonard, and Horn 2012) and the duration (e.g., in years) of the observer's engagement with the biodiversity platform. The former provides a measure of the observer's activity level, while the latter offers insight into their experience and familiarity with the platform and its protocols. For instance, an observer who has been active for several years and has submitted a large number of observations would have a higher expertise index compared to a new user with fewer submissions. Such an index would be usable in data analysis as it would permit checking whether commitment to the platform and/or accumulated experience influence the type of information contributed, for example identification of species, numbers identified, spatial distribution. This type of information could be not publicly displayed in order to fully respect the privacy of the users, who may prefer personal data to be kept reserved (Johnston, Matechou, and Dennis 2023), unless they specifically opt for their level of experience to be shared in the community of observers.

Thus, we would foster the organization of local working groups, also to better estimate expertise variability among observers by providing standardized training, involving experts, encouraging local community participation, and maintaining ongoing feedback.

#### 2.2.3 | Technical Solution

From a technical point of view, when a user searches for observations of a given species or within a given area (via the App or on the website) and selects a given observation, a pop-up window would appear. This window would provide information about the observed species (e.g., date, latitude and longitude coordinates, photos), as well as the nickname of the observer (i.e., the 'Observer ID'). Clicking on the Observer ID would open an 'Observer card' providing an index of the observer's experience (e.g., total number of observations divided by years of engagement with the biodiversity platform, ranging between 0 and $+\infty$; the higher the value, the greater the experience). The card would also display the total number of observations collected and the year the observer engaged with the biodiversity platform. Additionally, a plot (e.g., histogram) showing the number of observations per year and a trend line would be displayed to provide an overview of the observer's participation in the biodiversity platform. A number of observations for each taxon (e.g., birds, mammals, etc.) could also be listed at the bottom of the observer card–that is, an important information to account for as an observer is unlikely to be an expert in all life forms. Overall, this approach would ensure data quality while also explicitly acknowledging the contributions of observers, thereby fostering a sense of community and commitment that is vital to the success of CS initiatives, but should be aligned to the will of each single observer to have this type of personal information shared with the community.

### 2.3 | Lack of Absence Data and Sampling Effort Information

#### 2.3.1 | The Issue

CS platforms usually consist of presence-only data (i.e, 'detections'), not their absences (i.e., 'non-detections'). However, the use of presence-only data to estimate species occurrence lead to limited interpretations of the patterns of species distribution (Ottinger 2010; Conrad and Hilchey 2011; Bird et al. 2014; Guillera-Arroita 2017). While the biodiversity platforms considered in this study include species occurrences (locations of the detections), only eBird allows for absences derived by complete checklists (of species), where a given species has not been observed (i.e., non-detections). Thus, on most current CS platforms, we cannot distinguish between missing sampling (e.g., no sampling and thus no observations) and real absences (e.g., where sampling has been carried out but no observations have been recorded).

Moreover, the sampling methods used to collect observations, including the time spent and the distance travelled during surveys, the number of observers and other information regarding sampling effort (e.g., use of 'line transect', 'point counts', 'traps', or even if the observation was obtained from a vehicle, with binoculars, using mimetic clothes, etc.) are often lacking in the online CS biodiversity platforms. So far, only on eBird complete checklists are allowed, together with information regarding the time spent, the distance travelled and the number of observers during surveys (Kelling et al. 2015; Johnston et al. 2018).

Thus, the lack of absence data and sampling effort information is very relevant and the role of scientists for the correct analysis and interpretation of CS data is fundamental. Scientists need to identify statistical approaches for drawing reliable inferences from CS data. For instance, Milanesi, Mori, and Menchetti (2020) considered occurrences of non-target species as absences and used the total number of observations, observers and collection days as proxies for sampling effort. Moreover, scientists could apply additional filters to derive absence data, such as taxa-based filtering (Van Eupen et al. 2021) and sampling effort measures (Mair and Ruete 2016).

#### 2.3.2 | Theoretical Solution

We strongly encourage to carry out complete checklists of species, for which all the species observed are reported, instead of casual records (e.g., presence-only data) in order to derive absence data (non-detections), that is, if a species is not reported within a given complete checklist, it is absent then. At the same, all the information regarding the sampling effort should be included in order to provide robust data on the species assessment, that is, if a species is reported or not within a given complete checklist, it also depends on the time spent, area investigated during surveys, number of observers, etc. Thus, to reduce the lack of absence data and sampling effort information, we would develop detailed sampling plans, actively involving local communities in reporting also absence data (non-detections) and sampling effort information.

### 2.3.3 | Technical Solution

When an observer collects an observation of a species, the App could pop-up a window showing two buttons specifying 'Type of data' (i.e. 'presence-only' or 'complete checklist'). In case the option 'complete list' is selected, a list of species expected to be detected (e.g., based on IUCN range maps) would appear and the observer would flag those observed during the survey. This could be accompanied by useful but standardized tips about these species, including guidance on how, where, and when to find them. If only a single species is the target, the observer could select the complete checklist mode a priori and if not detected, the App would however record the checklist but with no species data in it. The observer could also fill these new buttons with information regarding the sampling effort:

1. Sampling method: 'line transect', 'point counts', 'traps', etc.;
   - in case of 'line transect' additional information will be filled in an *ad hoc* button, i.e., 'transect length/distance travelled' (in meters),
   - in case of 'point counts' and 'traps' additional information will be filled in an *ad hoc* button, i.e., 'number of points/traps' (the number of points/traps investigated),
2. Sampling duration: time spent in a survey (in minutes).
3. Number of observers: the number of persons involved in the survey.

## 2.4 | Data Biased Towards Highly Frequented Areas and Developed Countries

### 2.4.1 | The Issue

CS datasets are typically biased towards human population centres, areas that are easy to access, protected areas or regions frequently investigated by active observers (Reddy and Davalos 2003; Botts, Erasmus, and Alexander 2011; Martin, Blossey, and Ellis 2012; Feldman et al. 2021). Moreover, geographical coverage of CS data can be biased towards well-financed and more industrialized countries, mainly in North America and Europe (Schmeller et al. 2009; El-Gabbas and Dormann 2018). These problems lead to knowledge gaps in under-sampled areas (Phillips, Anderson, and Schapire 2006; Hugo and Altwegg 2017; Jiménez-Valverde et al. 2019).

If we take into account the Human Development Index (HDI), which assigns a value between 1 and 4 (1 representing the highest level and 4 representing the lowest level) based on the life expectancy, education, and income of each county, in all the platforms considered, a clear prevalence of observations come from those countries with a very high Human Development Index (Group = 1; Figure 4a, Stanton 2007; UNDP 2022; Supporting Information) belonging mainly to North America and Europe (Figure 4b).

The marked spatial bias in CS can be largely attributed to the concentration of prominent platforms in affluent countries. For instance, iNaturalist and eBird are based in the USA, while GBIF and Observation.org have their roots in Europe. The substantial financial resources of these developed countries, facilitate the establishment and expansion of CS platforms (Pocock et al. 2018; Feldman et al. 2021). Moreover, the implementation of similar platforms in developing countries is often hindered by the lack of necessary infrastructure. Finally, the tradition of CS is deeply rooted in North America and, driven by some iconic platforms and surveys such eBird, has spread globally only recently (Havens and Henderson 2013).

### 2.4.2 | Theoretical Solution

It is essential to promote data collection in under sampled areas (i.e., novel environmental conditions) to provide species/taxon-specific maps there too. The degree to which novel environmental conditions are encountered has been assessed with the Multivariate Environmental Similarity Surface (MESS, Elith, Kearney, and Phillips 2010).

Specifically, MESS provides an index of environmental similarity between all pixels of a study area and those of cells to be surveyed, considering a set of spatial predictor variables (e.g., topographic, climatic and land use characteristics). MESS identifies sites where at least one predictor variable (or the most dissimilar variable if more than one) has a value outside the range of those of the surveyed cells, that is, under sampled areas where the ecological contest is not represented in the already surveyed sites. MESS approach is valuable, but limited by its use of the most dissimilar variable as indicator of overall similarity. This means that the most dissimilar variable at one pixel is the only one having an effect (weight) in the calculation of the MESS index for this pixel. Thus, we suggest to calculate a modified version of MESS (mMESS) that does not rely on the use of the most dissimilar variable as indicator of overall similarity but rather considers all predictors (see Milanesi et al. 2017 for details). However, it is essential to develop complementary initiatives to promote data collection in areas identified by mMESS as underrepresented. This could be done by promoting local CS activities and facilitating sampling efforts through the provision of training and resources to local communities. Such efforts could be supported by launching collaborative initiatives with local actors (institutions, conservation organizations, Universities and civil society) to spread the participation of citizens in data collection, funding these outreach activities as part of wider research projects, as it was done in the previous years in countries that currently collect the most of the CS data (Squires et al. 2021; Callaghan et al. 2023; Palma et al. 2024).

### 2.4.3 | Technical Solution

The resulting maps of mMESS should be provided on online biodiversity platforms. The maps could be displayed in a dedicated section of the website or as a background information layer (e.g., in pulsing red colour) on the observation map. These maps should also be accessible on the App. For instance, when the App is activated along with the GPS system, a pop-up window could appear. This window would provide a list of the closest unsampled areas to the mobile device (ranked from the closest to the farthest), together with a message on the importance of filling sampling gaps to monitor biodiversity. This could be accompanied by useful tips

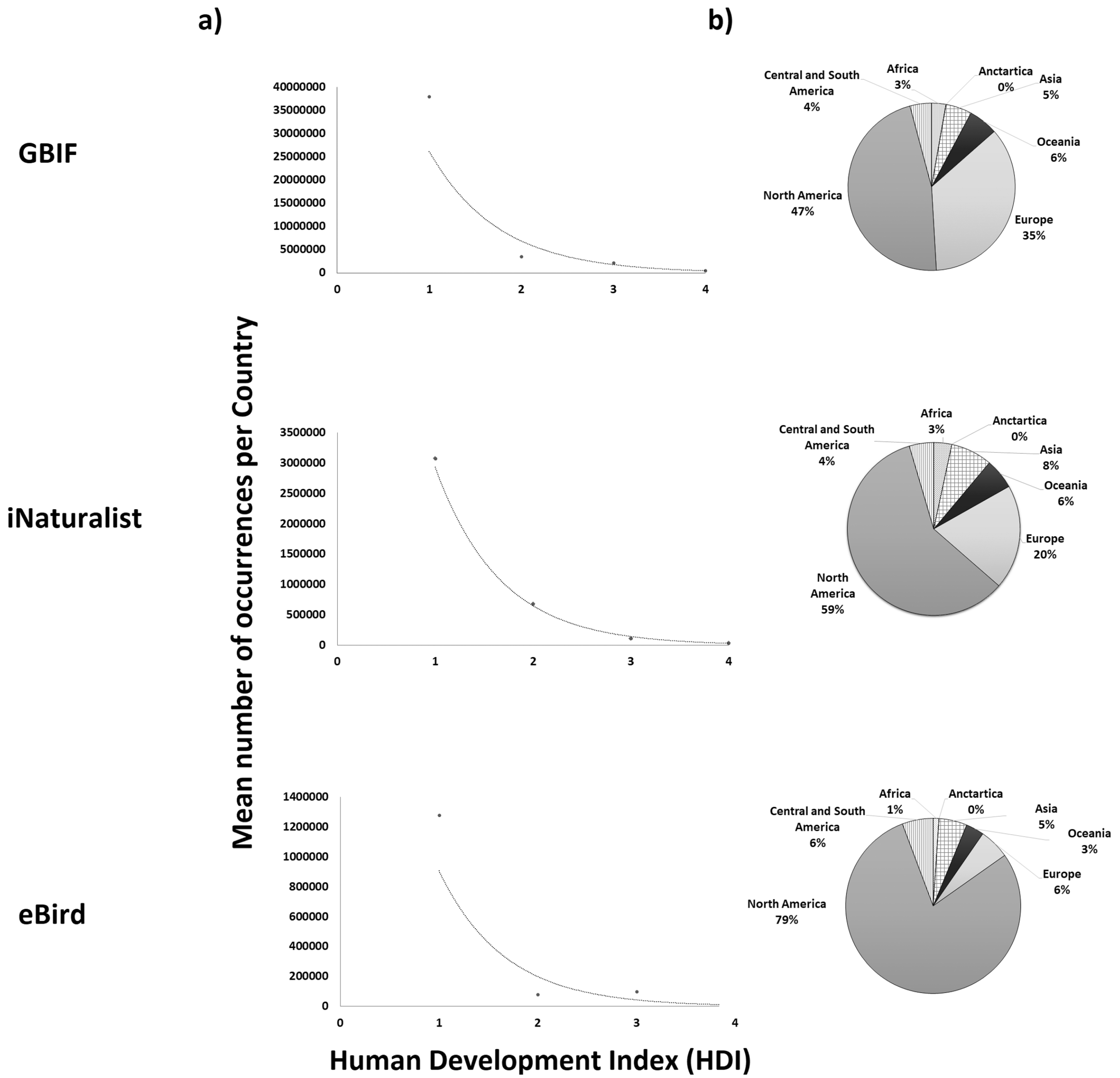


**FIGURE 4** | Graphical representation of the geographic imbalance of citizen sciences data reported in the GBIF, iNaturalist, and eBird platforms (Observation.org platform was excluded as it related only to European data): (a) average number of observations carried out in each country of the world based on its Human Development Index (UNDP 2022), it assigns values between 1 and 4 (1 = highest level and 4 = lowest level) based on the life expectancy, education and income of each country (Supporting Information); (b) percentage of the observations in each continent (calculated as the average number of observations per country).

to reach the selected under-sampled areas, including guidance on how, where, and when to find them.

## 3 | Discussion

Highlighting the main limitations of platforms making CS data available online, in this study we emphasized their role in fostering broader societal involvement in resource stewardship, which is of significant value given the global interest in conservation. We determined strengths and weaknesses of widespread platforms including GBIF, iNaturalist, and eBird, considering their different focuses, and how to improve them. Actually, only a few platforms allow for complete checklists, providing species absence data (non-detections) when a given species has not been observed, and are capable of including details such as time spent, distance travelled, and the number of observers during surveys (Kelling et al. 2015; Johnston et al. 2018), providing direct measures of sampling effort, and considering observer expertise in post-process analysis, which is crucial for estimating statistically robust patterns of species distribution (Johnston et al. 2018, 2021; Johnston, Matechou, and Dennis 2023). Moreover, these platforms focus only on specific taxa (e.g., birds) and data collected are still strongly biased towards the regions where they were developed (mostly North America and Europe), resulting in challenges to monitor biodiversity and assess biogeographical patterns due to taxonomical and spatial bias, lack of robust absence data and sampling effort information, nor account for observer expertise. When compared to data from scientific collections (i.e., specimens collected, identified, and stored in natural history collections, museums, or herbaria, providing tangible records with details about when and where the organism was found, and other information such as age and sex—also available in global platforms such as GBIF), CS can provide a higher amount of data, but their robustness should be tested through quantitative comparisons between these two sources in order to assess their overall efficacy and efficiency (Gollan et al. 2012). Therefore, our survey revealed that existing platforms have *pros* and *cons*, but overall show a few gaps that need to be addressed in order to support robust biodiversity and biogeographic data collection. First, we suggest gathering additional information regarding sampling effort (e.g., use of 'line transect', 'point counts', 'traps', etc.) as these factors might also influence the data collected. Additionally, standardized sampling schemes and maps of unsampled areas should be prioritized. Finally, also incorrect taxonomic identification can have a strong impact on biogeographical analyses and thus we stress the importance of comparing and quantifying the impact of incorrect taxonomic identification, through data filtering and comparison with verified datasets/standardized professional data collection, likewise Arias-Maldonado (2015).

Moreover, all the platforms considered in this study need to improve data coverage towards poorly frequented areas and under-developed countries, as well as to develop robust tools to account for expertise variability among observers. For platforms like iNaturalist and Observation.org, which are rooted in less structured initiatives without fixed protocols or long-term commitments, there is a need to promote the collection of robust data following sampling protocols. This would help derive absence data (non-detections) and sampling effort information. On the other hand, platforms like eBird (Ornitho and FrogID), which focus on specific taxa and often have more rigorous protocols, should consider encouraging the collection of under-sampled species to reduce taxonomical bias within those groups.

To these regards, developing interactive tools to guide observers in collecting robust and representative biodiversity data can provide an effective solution. These tools could include intuitive pop-up windows listing under sampled species in a given area, information on observers' experience, species expected to be detection during surveys, and details about sampling effort. Moreover, they can be fostered by a gamification approach and by dedicated CS initiatives to spread this opportunity to involve and sensitize citizen towards the importance of collecting biodiversity data (Squires et al. 2021; Callaghan et al. 2023; Palma et al. 2024). Indeed, technical improvements need to be paralleled by collaborative initiatives with local actors, ranging from institutions to civil society, aimed to spread the participation of citizens in data collection, as the several types of bioblitzes can contribute to (Meeus et al. 2023) and verify on the field the efficacy of the proposed solutions.

This study represents an initial step towards improving data quality on biodiversity platforms, and we recommend continued experimentation with new features beyond those here discussed to monitor biodiversity and assess biogeographical patterns.

## Author Contributions

F.D.R. led the writing. P.M. and F.D.R. designed and drafted this perspective. F.D.R., M.M. and P.M. contributed to the conceptualization and alternatively commented and revised this manuscript. All authors contributed substantially and critically reviewed drafts and approved the final version of the perspective.


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## Conflicts of Interest

The authors declared no conflicts of interest.

## Data Availability Statement

The authors have nothing to report.

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## Supporting Information

Additional supporting information can be found online in the Supporting Information section.