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ORIGINAL PAPER

Citizen science data accurately predicts expert-derived species richness at a continental scale when sampling thresholds are met

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Abstract

Understanding species richness patterns in time and space is critical for conservation management and ecological analyses. But estimates of species richness for a given place are often imprecise and incomplete, even when derived from expert-validated range maps. The current uptake of citizen science in natural resource management, conservation, and ecology offers great potential for extensive data to define species occurrence and richness patterns in the future. Yet, studies are needed to validate these richness patterns and ensure these data are fit-for-purpose. We compared data from a continental-scale citizen science project—FrogID—with expert-derived range maps to assess how well the former predicts species richness patterns in space. We then investigated how many citizen science submissions are necessary to fully sample the underlying frog community. There was a strong positive association between citizen science species richness estimates and estimates derived from an expert-derived map of frog distributions. An average of 153 citizen science submissions were necessary to fully-sample frog richness based on the expert-derived frog richness. Sampling effort in the citizen science project was negatively correlated with the remoteness of an area: less remote areas were more likely to have a greater number of citizen science submissions and be fully sampled. This suggests that scientists will likely need to rely on professionals for data collection in remote regions. We conclude that a citizen science project that has been running for ~ 18 months, can accurately predict frog species richness at a continental scale compared with an expert-derived map based on ~ 240 years of data accumulation. At large-scales, biodiversity data derived from citizen science projects will likely play a prominent role in the future of biodiversity and conservation.

Keywords Citizen science · Species richness · Frogs · Anurans · FrogID

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Introduction

Estimating biodiversity is fundamental to biogeography (MacArthur and Wilson 1963; Whittaker et al. 2001), ecology (Tilman 1999; McGarigal et al. 2016), and conservation (Humphries et al. 1995; Paterson et al. 2008)—especially as we continue to lose biodiversity in the sixth, and largest, mass extinction event (Ceballos et al. 2017). Of the various measures of biodiversity (e.g., Faith 1992; Jost 2006), species richness is the most widely used and intuitive. Understanding which species are where, and which sites are more species-rich than others, is critical for conservation efforts (Yoccoz et al. 2001). Despite the importance of understanding species richness, estimates are still often imprecise and incomplete (Stork 1993; Mora et al. 2011; Essl et al. 2013). This is because estimating species richness by field surveys is expensive, time-consuming, and difficult. In addition, detection probabilities differ among species (White 2005) and remote areas are often poorly sampled.

Conservationists, ecologists, and practitioners are increasingly relying, at least in part, on citizen science data to quantify biodiversity (Theobald et al. 2015; Welvaert and Caley 2016; Pocock et al. 2017; McKinley et al. 2017). Citizen science projects—public participation in professional science (Jordan et al. 2015)—are producing datasets at large spatial and temporal scales (Tulloch et al. 2013). Citizen science data can lead to a better understanding of species richness at local (Lepczyk 2005; Callaghan and Gawlik 2015; Sullivan et al. 2017), continental (Gardiner et al. 2012; Jiguet et al. 2012), and global scales (Pocock et al. 2018). But despite the potential of citizen science (Tulloch et al. 2013; Theobald et al. 2015), many professional scientists remain reluctant to use citizen-derived data in conservation and ecological research because of concerns of data quality and control in citizen science projects (Burgess et al. 2017). There is a need for research which demonstrates the validity and applicability of citizen science datasets for biodiversity and conservation research across various citizen science projects. This is especially true given the various biases often associated with citizen science projects.

Spatial (e.g., disproportionate amount of sightings near human populations), temporal (e.g., weekend sampling when volunteers are more likely to not be working), and taxonomic (e.g., preferences for charismatic fauna and flora) biases, for example, are generally associated with citizen science data (Boakes et al. 2010; Courter et al. 2013; Troudet et al. 2017) influencing certainty surrounding biodiversity estimates. However, informed conservation and management decisions rely on robust estimates of biodiversity. Techniques that statistically assess how well a citizen science project samples a given community are important for providing confidence in biodiversity estimates. One such method is to understand how many sampling events (i.e., citizen science submissions) are necessary to fully sample a given community (Solla et al. 2005; Callaghan et al. 2017). This is important because it provides managers of citizen science projects the ability to minimize wasted effort by encouraging participants to sample in areas where the community has not been fully sampled, thus improving the spatial extent of citizen science data (Pocock et al. 2018).

Amphibians are one of the most threatened groups of animals, with more than 40% of all species globally assessed as threatened or extinct (IUCN 2019). More than one-fifth of all amphibian species have been assessed as Data Deficient, meaning that there is too little information available for a reliable assessment of conservation status (IUCN 2019). Conservation planning generally has a strong focus on the status of individual species (e.g., Roberts 2018), rarely extending into analyses of biodiversity estimates in space and time (Eken et al. 2004). This is partly because biodiversity estimates in space and time for amphibians are rarely available due to a paucity of baseline historic data and difficulties in surveying for amphibians.

Amphibians are difficult to survey due to their nocturnal habits, secretive behavior, cryptic appearance, and their reliance on rainfall events to be active and thus detectable (Penman et al. 2006; Mazerolle et al. 2007). The use of citizen science data to study amphibians has lagged behind other taxa (Geijzendorffer et al. 2016). But recently, amphibians have been the focus of a large number of citizen science projects (Pieterson et al. 2006; Westgate et al. 2015), at global (e.g., iNaturalist) and at continental scales (e.g., FrogID, FrogWatch USA). These projects have increased our baseline knowledge of amphibian distributions (Balaguera-Reina et al. 2019, Rowley et al. 2019), taxonomy (Pavón-Vázquez et al. 2016), conservation status (Westgate et al. 2015; Balaguera-Reina et al. 2019), and biodiversity patterns (Pieterson et al. 2006; Botts et al. 2011).

If data on amphibians from citizen science projects is to form the basis for decisions in conservation management, it is critical to demonstrate how these data compare with professionally collected data. Such analyses demonstrate the value of citizen science data in the future of natural resource management and conservation biology (Burgess et al. 2017). We used an expert-derived map of frog species richness across Australia (Cogger 2018) and compared this with data obtained from a national citizen science project in Australia: FrogID (Rowley et al. 2019). The former is based upon data and knowledge accumulated over the past ~240 years while the latter has been running for ~2 years. Our objective was to compare the results between an expert-derived map of frog species richness and species richness estimated from a national citizen science project. We had three sub-objectives: (1) to quantify how well the FrogID project samples frog species richness compared to expert-derived estimates; (2) to quantify how many citizen science submissions are necessary to sample species richness in an area; and (3) to quantify how the remoteness of an area influences sampling by citizen scientist contributors.

Methods

Cogger: an expert-derived map of frog species richness in Australia

Australia currently has a total of 240 described species of frogs, plus the introduced Cane Toad (*Rhinella marina*). To estimate frog species richness throughout Australia, we used an expert-derived dataset of estimated frog distributions throughout Australia (Cogger 2018). This dataset (hereafter referred to as Cogger) was compiled by estimating polygon distributions of frog occurrences from a variety of sources, including the Atlas of Living Australia (http://www.ala.org.au), museum specimens, published research (e.g., Moore 1954; Littlejohn 1959; Lee 1967; Watson et al. 1971; Roberts and Majors 1993), and expert-solicited advice and opinions. Cogger data are a combination of such species' presence records—visual and acoustic records at and away from breeding sites—and inferences of species' ranges made by experts based on soils, topology, climate, vegetation, and biogeography (Cogger 2018). Based on these data and inferences, each species has a smoothed minimum convex polygon (created using the program WORLDMAP; Williams 2000): the outer geographic limits of the area within which each species has been recorded and/or is assumed to occur. Because of the remoteness throughout most of Australia—and thus the lack of detailed surveys by professionals throughout these remote regions—Cogger data provide the best estimate of frog species richness throughout Australia as we currently understand it.

FrogID: a continental-scale citizen science project

FrogID is a national citizen science project led by the Australian Museum (Rowley et al. 2019). Participants submit 20–60 s audio recordings of calling frogs using a smartphone app, and the app adds associated metadata (time, date, latitude, longitude, and an estimate of precision of geographic location) to each submission at the time of recording. A team of experts then independently identifies any frog species heard calling in the recordings. Importantly, recordings with identifiable frog calls typically include multiple species (an average of 2.2 species with a current maximum of 11 species per recording; Rowley et al. 2019). Hence, we define a 'submission' as a submitted recording and an 'observation' as a single record of a frog originating from a submission for a particular site/date/time combination. Since its inception in November 2017, FrogID has collected over 100,000 validated occurrence records from 188 species—78% of frog species known in Australia. These data collected are approaching one-fifth of all frog records reported in the Atlas of Living Australia, a national aggregate database of biodiversity data, collected over the last ~ 240 years. We excluded any submissions whose coordinates were not on mainland Australia and submissions that had a geolocation accuracy > 3 km, because these represent submissions which indicated the app was unsure of the location (i.e., potentially > 100 km away; Rowley et al. 2019). We used FrogID data collected between November 17th, 2017 and May 31st, 2019, contributed by 8809 volunteer citizen scientists from 39,881 unique locations (i.e., latitude/longitude combinations).

Statistical analysis

Species richness comparisons

Our analyses focused on frog species richness in space, comparing FrogID data—data at a given point of known occurrence—with broadly drawn polygons from the expert-derived maps, which likely include areas in space (i.e., unsuitable habitat) that do not represent true occurrences of particular species. The Cogger expert-derived map represents the areas where a species can be expected to occur, although within these areas the species will only be found in suitable habitat: overestimation of species richness is a feature of expert-derived maps (Graham and Hijmans 2006). Thus, Cogger potentially overestimates species richness (Graham and Hijmans 2006). Conversely, FrogID data are typically constrained to frog breeding sites: water bodies—sometimes permanent and sometimes temporary. Thus, FrogID may sample a smaller proportion of the whole landscape for many species, whilst providing important data on frog breeding habitats. Despite these biases, we feel that these comparisons between the datasets are valid as Cogger data are the best-available data for comparisons with FrogID and are used by conservation practitioners to infer the presence of frogs in a given region.

To compare species richness patterns throughout Australia between FrogID and Cogger, we summarized species richness using 30-min grid cells and found the total species richness in each of these grid cells for each respective dataset. Only grid cells in which the centroid fell within mainland Australia and where Cogger estimated frog species richness were included in these analyses (N = 2746). These grid cells have been used to describe frog diversity throughout Australia (Slatyer et al. 2007; Cogger 2018) allowing us to make direct comparisons between FrogID data and these earlier approaches. Further analyses and statistical tests were then at the level of these grid cells. Cogger species richness estimates are available in each of the 2746 grid cells, but we are unable to estimate sampling effort in these grid cells because of the variety of sources used to compile these species' range estimates. However, many grid cells have not been sampled by FrogID. To overcome these biases between the two datasets, and to generalize FrogID's ability to sample species richness throughout Australia, we stratified our analyses to two levels: (1) we assessed the relationship between species richness generated from FrogID and Cogger at each grid cell ($N=2746$), and (2) we assessed the relationship between species richness generated from FrogID and Cogger at only those grid cells which have at least one sample by FrogID. This provides us with an understanding of how FrogID will compare with Cogger as more grid cells continue to be sampled in the future.

To assess these two different relationships between FrogID and Cogger we used linear models. We then *estimated* species richness in each grid cell for FrogID only, using the 'specpool' function from the vegan R package (Oksanen et al. 2018). We used the first-order jackknife (Smith and Belle 1984) estimate of species richness for this approach because we had many grids with relatively few samples, given by the equation: $S_{pool} = S_{observed} + A_1*(N - 1)/N$, where S_{pool} is the extrapolated species pool for that grid, $S_{observed}$ is the observed number of species in that grid, A_1 is the number of species occurring in one submission in that grid, and N is the number of submissions from a grid (Smith and Belle 1984; Oksanen et al. 2018). For Cogger, the species richness throughout our analyses was treated as the maximum number of species in a grid cell as there are no underlying samples or sampling effort which would allow further estimation of species richness. We then re-assessed the relationship between *estimated* species richness (from the first-order jackknife) from FrogID and species richness from Cogger, repeating the two linear models from above.

Assessing number of samples necessary to meet thresholds of Cogger

For grid cells sampled by both FrogID and Cogger, we assessed how well FrogID sampled these grid cells, based on species richness derived from Cogger. We aimed to estimate how many submissions were needed to meet thresholds that represent 50%, 60%, 70%, 80%, 90%, and 100% of the species richness from Cogger. This approach assumes that Cogger represents the maximum detectable number of species in a grid cell. We counted how many grid cells met each of these thresholds and the number of associated submissions from each of these grid cells. This approach allowed us to estimate how 'complete' a given grid cell was. We then assessed how many submissions were necessary to meet each of the above thresholds using the 'specaccum' function from vegan (e.g., Figure S1), with the rarefaction method (Oksanen et al. 2018). We empirically summarized this information, providing the number of samples, on average, to meet each of these thresholds.

Assessing predictors of how well grids are sampled

For grid cells sampled by both FrogID and Cogger, we summarized the absolute difference (i.e., the difference between Cogger and FrogID) and the relative difference: the absolute difference divided by Cogger's species richness. By using the relative difference, we were able visualize the differences in space and test predictions of what factors influence differences detected between the datasets. In a given grid cell, we investigated the influence of remoteness and ecoregion on sampling by FrogID users. For a measure of remoteness, we used a published dataset of accessibility which encompasses spatial locations of roads, railroads, rivers, water bodies, elevation, slope angle, and land cover to produce a measure of travel time to the nearest city (Weiss et al. 2018). This product is negatively correlated with population density, and encompasses many aspects of what may limit scientists from sampling a site in addition to population density. We took the mean accessibility measure (in minutes) for each 30-min grid cell in the analysis, using Google Earth Engine (Gorelick et al. 2017). Each grid cell's centroid was also assigned to an ecoregion, relying on the WWF terrestrial ecoregions of the world map (Olson et al. 2001).

We then investigated the relationship between remoteness of a grid cell and the number of FrogID samples using a linear model with log-transformed variables for the number of FrogID submissions and the remoteness of a grid cell. To test what predicted the relative difference between the FrogID and Cogger datasets, we first used a generalized linear model with a binomial distribution where the response variable was whether a grid was sampled and the predictor variable was log-transformed remoteness values. Lastly, we investigated whether remoteness, ecoregion, or the interaction between the two influenced the relative difference between the two datasets. To do so, we first transformed the relative difference by adding a constant (to remove negative values from the distribution) and taking the inverse of the values (to make the distribution right-skewed as opposed to left-skewed). This provided us with a zero-inflated continuous distribution which we then modelled using a tweedie distribution and a Generalized Additive Model, from the 'mgcv' package (Wood 2004).

Data accessibility

All analyses were performed within the R statistical environment (R Core Team 2018) and relied heavily on the tidyverse workflow (Wickham 2017). R code necessary to reproduce these analyses are available in a permanently archived Zenodo repository: https://zenodo.org/record/3610732.

Results

A total of 91,773 FrogID records were initially assessed, but after excluding records associated with a grid whose centroid landed in the ocean and records with low accuracy in geolocation, a total of 87,870 observations (N = 50,886 submissions) were used in analyses. This accumulated to a total of 185 species throughout continental Australia—77% of the known frog species richness from Cogger. A total of 2746 grid cells had frog occurrences from Cogger, whereas 577 grid cells had samples from FrogID (Fig. 1). When investigating all grid cells with estimates of species richness by Cogger, there was strong evidence of a positive relationship ($t = 32.79$, $df = 2744$, $p < 0.001$, $R^2 = 0.28$) between FrogID and Cogger species richness (Fig. 2a). This relationship remained strongly positive after confining the analysis to the subset of cells that had data from both Cogger and FrogID (Fig. 2b; $t = 20.70$, $df = 575$, $p < 0.001$, $R^2 = 0.42$). When we estimated species richness based on FrogID submissions using the first-order jackknife estimation—as opposed to simply taking the total observed species richness by FrogID in a grid cell—the results remained similar and there was still strong evidence of FrogID species richness

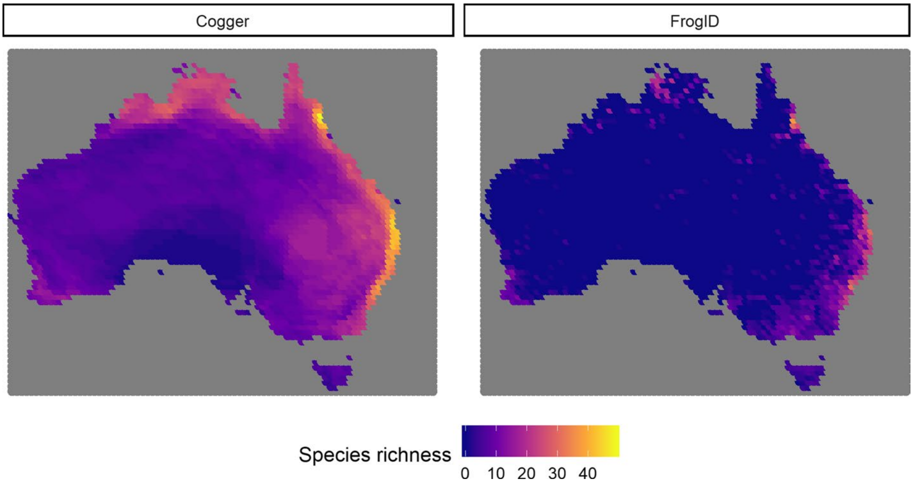

Fig. 1 Species richness throughout continental Australia from both Cogger's expert-validated map, the cumulative product of many sources, and from FrogID, since November 2017

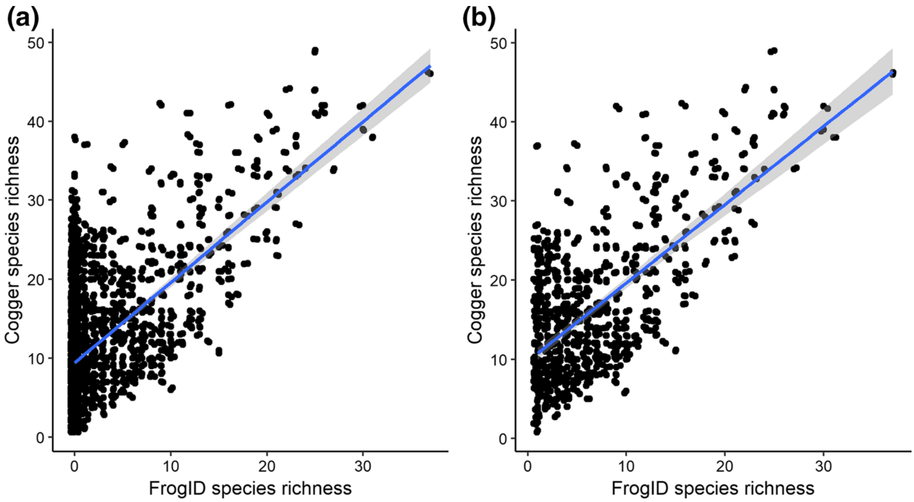

Fig. 2 The relationship between species richness from FrogID and Cogger's expert-validated map for **a** all grid cells known to have frog occurrences (N = 2746) and **b** only those grid cells that were sampled by both FrogID and Cogger's expert-validated map. Points are shown using 'geom_jitter' from ggplot2 to demonstrate where points overlap along the discrete richness levels

predicting Cogger species richness (Figure S2). This was true while investigating all grid cells ($t = 32.86$, $df = 2744$, $p < 0.001$, $R^2 = 0.28$) and only those grid cells sampled by both datasets ($t = 20.79$, $df = 575$, $p < 0.001$, $R^2 = 0.43$).

The majority of sampled grid cells from FrogID (N = 577) under-represented species richness, compared with Cogger (Figure S3, Figure S4). The median difference between Cogger and FrogID was 8 species, with a mean of 9.5 ± 6.1 sd. Six grid cells had a greater species richness estimate from FrogID than Cogger, with the highest difference being 4 more species from FrogID than Cogger. In particular, FrogID data under-represented species richness along the Great Dividing Range of eastern Australia, in tropical north Queensland, the Northern Territory, and the Kimberley of Western Australia (Figure S4). When investigating the relative difference between the two datasets using all grid cells sampled by Cogger (N = 2746), those grid cells sampled by FrogID underestimated diversity most throughout inland Australia (Figure S5).

There was a positive relationship between the number of FrogID submissions in a grid cell and the associated species richness in the grid cell (Figure S6; t = 13.17, df = 575, $p < 0.001$, $R^2 = 0.23$). The number of grid cells which met the threshold of Cogger species richness increased with a decreasing threshold (Fig. 3, Figure S7), from 44 (for 100% threshold) to 275 (for 50% threshold). And the median number of submissions needed generally decreased with decreasing threshold from 195, 168, 86, 64, 55, and 43, for 100%, 90%, 80%, 70%, 60% and 50% thresholds, respectively. But because grid cells are not uniformly species-rich (Fig. 1), we assessed how many submissions were needed on a per-grid basis by investigating all possible grid cells (N = 2746; Figure S7). On average, 153, 163, 119, 63, 43, and 41 submissions were needed to meet the 100%, 90%, 80%, 70%, 60%, and 50% thresholds respectively. For each grid cell which

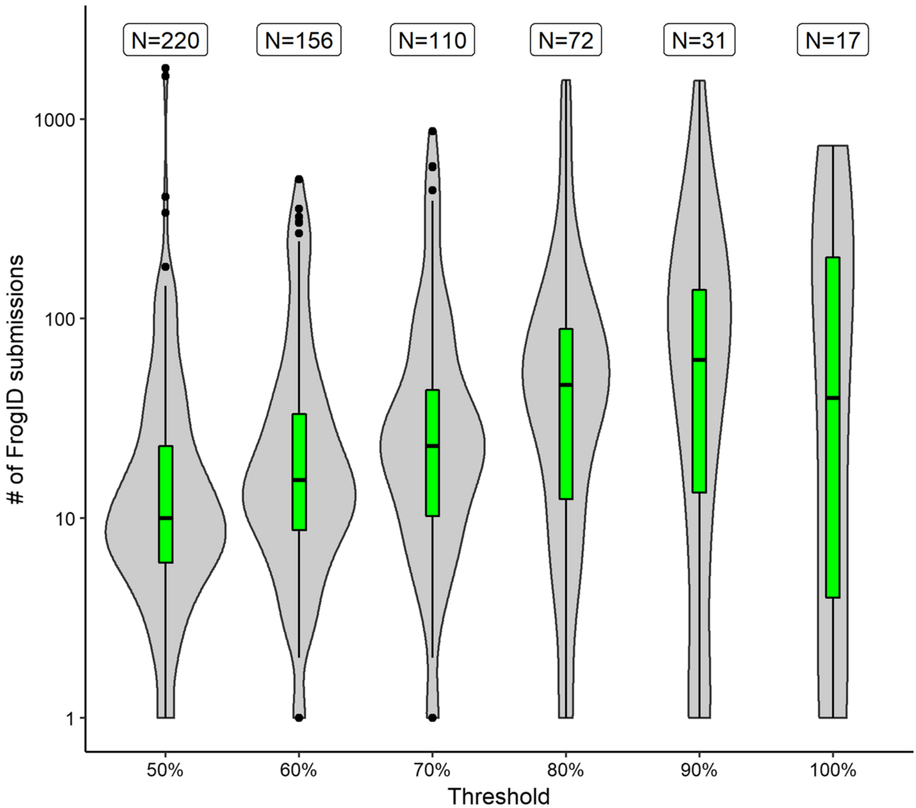

Fig. 3 The number of FrogID submissions (on a log-scale) within each grid cell required to meet each threshold (i.e, FrogID species richness as a % of the Cogger species richness). The number of grid cells that meet each threshold are listed. The median and quartiles are shown in the boxplots

met the associated threshold level, there was a positive relationship between the Cogger richness and the number of samples needed to meet that threshold (Figure S8).

There was strong evidence ($t = -17.02$, $df = 575$, $p < 0.001$, $R^2 = 0.33$) that the remoteness of a grid cell negatively influenced the number of samples which were submitted by FrogID users from that grid cell (Fig. 4). The remoteness of a grid cell was also a strong predictor (Table S1) of whether a grid cell was fully sampled by FrogID users when compared with Cogger species richness—at all threshold levels (Figure S9). Lastly, the remoteness of a grid cell strongly influenced the relative difference between Cogger and FrogID species richness (Fig. 5, Figure S9). There were significant differences in sampling among ecoregions (Fig. 5, Figure S10): sampling was most complete (i.e., lowest relative difference between Cogger and FrogID) in Temperate Broad & Mixed Forests (e.g., east coast of Australia) and least complete (i.e., greatest relative difference between Cogger and FrogID) in Desert & Xeric shrublands (e.g., inland Australia).

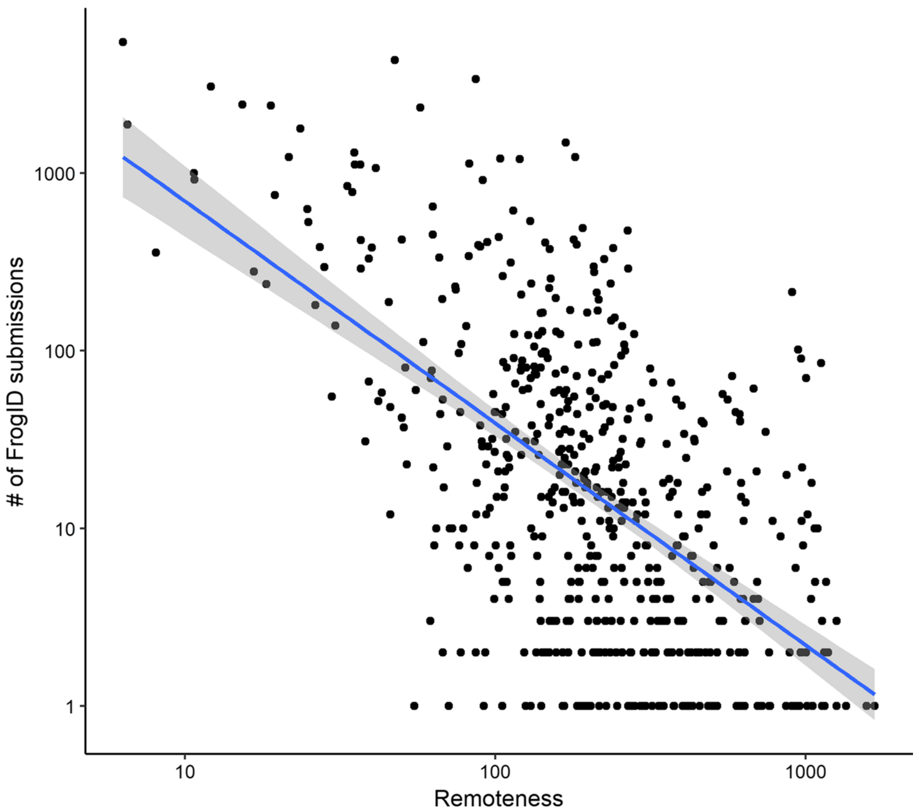

Fig. 4 The remoteness of a grid cell was negatively associated with the number of FrogID submissions in the grid cell. A smoothed linear model line is shown, and both axes are on a log-scale

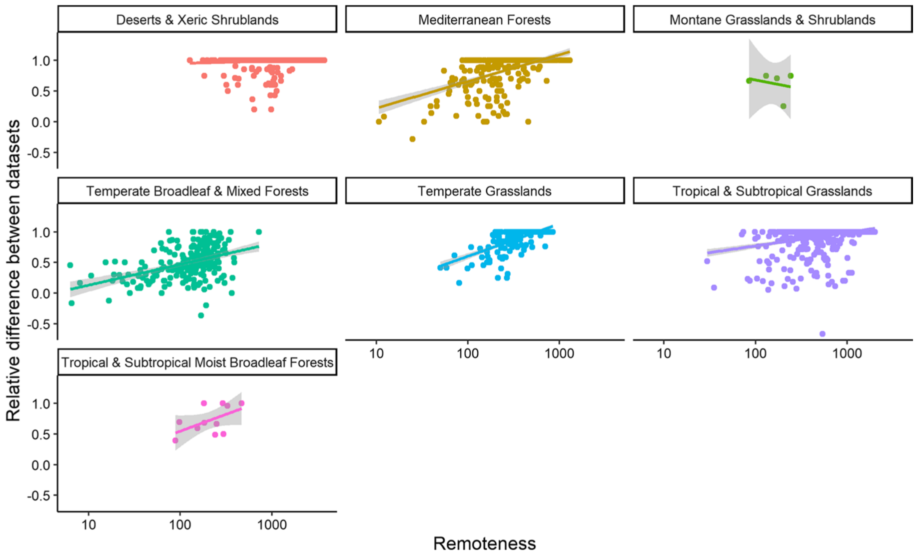

Fig. 5 The relative difference of a grid's Cogger and FrogID species richness, taken by dividing the absolute difference by the Cogger species richness level, regressed against the remoteness of the grid cell (on a log-scale). Linear model fits are shown, but models were fitted with Generalized Additive Models to account for data effects (Fig. S9)

Discussion

We empirically and statistically demonstrated that citizen science data accurately predicts expert-validated species richness patterns at a continental scale. Across those grid cells sampled by FrogID, an average of 153 citizen science submissions was necessary to fully-sample frog species richness based on the expert-derived frog species richness. Sampling effort in the citizen science project was negatively correlated with the remoteness of an area: less remote areas were more likely to have a greater number of citizen science submissions and be fully sampled. These results provide further support to the unsurprising, but strong bias in citizen science datasets towards sampling in areas with high human populations (Boakes et al. 2010; Dickinson et al. 2010; Botts et al. 2011; Theobald et al. 2015; Mair and Ruete 2016). This is probably exaggerated in Australia, compared with other continents, given the highly urbanized population and given 86% of Australia is classified as remote or very remote (i.e., difficult to access; Glover and Tennant 2003). Despite this strong bias, these citizen science data provide a promising outlook for understanding species richness patterns of frogs throughout continental Australia.

True biodiversity values are rarely known, even for professionally collected datasets (Gotelli and Colwell 2001; Graham and Hijmans 2006; Colwell 2009; Jarzyna and Jetz 2016). No matter the methods (cf. citizen science datasets and expert-derived maps), there is inherent noise and over and under estimations of species richness (Graham and Hijmans 2006). For example, we found that six grid cells had greater species richness than Cogger, with the highest being four more species than Cogger. Ultimately, our results suggest that citizen science data may have the ability to reshape our understanding of species richness, especially when we understand what influences sampling regimes in citizen science projects. Our analysis was strictly focused on community-level analyses (i.e., species richness), but further work should investigate how these citizen science data refine our understanding of species-specific associations throughout Australia (e.g., species distribution models). Such analyses should investigate the biases between the two datasets, comparing broad minimum convex polygons and presence-only citizen science data (Van der Wal et al. 2015). When citizen science data are combined with datasets defining species' boundaries, this allows an immediate picture of changes in status for many species. Repeated collection of citizen science data may also generate early recognition of single taxon or particularly cross-species patterns of decline.

The number of citizen science projects is increasing throughout the world (Welvaert and Caley 2016; Pocock et al. 2017), and natural resource management will undoubtedly rely on citizen science data—at least in part—into the future (McKinley et al. 2017). Understanding, and correcting for, the biases in citizen science datasets is only one step in the workflow (Bird et al. 2014). Citizen science projects should also seek to increase the information content from these growing datasets (Hochachka et al. 2012). One way is to understand how many citizen science observations are necessary to provide robust estimates of species richness estimates when compared with professionally collected data (Solla et al. 2005; Embling et al. 2015; Callaghan et al. 2017). We found that on average ~ 150 FrogID submissions for any particular 30-min grid cell are needed to fully sample the underlying species richness as presented by Cogger. There are many biases which could impact these results, such as differing detection probabilities among habitat types and species (Gascon et al. 1999; Rowley and Alford 2007), differential responses of frog species to weather patterns (Penman et al. 2006), and differing breeding seasons of frogs (Lemckert and Mahony 2008). We acknowledge that future work should further investigate the relationship between these biases and frog occurrences at a finer scale using a combination of citizen science data and professionally-collected data. Nevertheless, by understanding the number of submissions necessary to sample a community, citizen science managers could then work to prioritize certain areas, filling in the gaps in associated datasets (Scholes et al. 2012). For instance, FrogID receives on average 1732 submissions per week, and we know that ~ 150 submissions are necessary to sample the known species richness in a grid cell. If the current submission trend continues, and if the effort could somehow be prioritized among grid cells based on the aforementioned aspects of frog sampling (Callaghan et al. 2019a, b), then all 2746 grid cells could theoretically be fully sampled within 238 weeks: by 2024.

Of course, this simplistic extrapolation can only be taken as a theoretical exploration. Nevertheless, it highlights that by comprehending the minimum effort sampling by citizen scientists (Embling et al. 2015), we can begin to better plan for the future of citizen science projects (Pocock et al. 2018, Callaghan et al. 2019a). We also recognize that there is an ongoing interplay with professional scientists both in the initial recognition, recording, and description of species-specific calls, and in the use of experts to identify species calling in FrogID submissions (Rowley et al. 2019). Our analyses also assume that species richness is constant in space and time—something we know not to be true (Yoccoz et al. 2001; Wiens 2011). Thus, when and where a citizen science observer samples is important, and this is especially true for frogs as most species are highly dependent on specific climatic conditions to be detectable (Penman et al. 2006; Heard et al. 2006). Our analytical approach did not account for these variable impacts on detection, and in some areas more FrogID submissions may be necessary than we estimated. But in other instances, if sampled under optimal climatic conditions (e.g., the arid zone after a significant rainfall event), then fewer submissions may be necessary. In remote regions with overall low diversity (e.g., the arid zone of Australia) not all grid cells may need to be sampled, as a nearest-neighbor sampling approach may be sufficient. Conversely, remote areas with known high diversity (e.g., the wet tropics in North Queensland or Kimberley in Western Australia) or regions with species that have very limited geographic ranges should have more-focused sampling because a nearest-neighbor grid-cell approach is unlikely to be sufficient to pick-up small differences in species richness throughout the landscape. Remoteness of a site will always be a barrier for citizen science observers, and this highlights where the best value could be spent by professional monitoring schemes: professionally-collected data should be augmented with citizen science data (Lepczyk 2005; Proença et al. 2017).

Conclusions

Many citizen science projects have been validated by comparing citizen science results with data collected by professionals (See et al. 2013; Van der Wal et al. 2015; Austen et al. 2016; Roman et al. 2017; Callaghan et al. 2018). Our results—albeit restricted to frogs in Australia—confirm these general trends: citizen science data can perform as well as professionally collected data (Aceves-Bueno et al. 2017). FrogID is a national citizen science project providing large amounts of data on frogs throughout Australia, capitalizing on frog behavior and identifying species based on vocalizations, likely minimizing disturbances (Rowley et al. 2019). Citizen science participation rates (Pocock et al. 2017), and thus the use of these data, are likely to continue to increase at global and local scales (Theobald et al. 2015; Pocock et al. 2018). Here we demonstrate that FrogID—with ~18 months of data—accurately predicts species richness throughout continental Australia, when compared with an expert-validated map of species richness—accumulated over ~240 years. Citizen science projects must be considered by governments and professional scientists as a powerful tool for aiding the conservation of biodiversity and promoting community engagement with the broader conservation effort.

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