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Citizen science rapidly delivers extensive distribution data for birds in a key tropical biodiversity area

Thomas M. Squires ^{a,*}, Pramana Yuda ^b, Panji Gusti Akbar ^c, Nigel J. Collar ^d, Christian Devenish ^a, Imam Taufiqurrahman ^e, Waskito Kukuh Wibowo ^c, Nurul L. Winarni ^f, Ahmad Yanuar ^c, Stuart J. Marsden ^a

- ^a Department of Natural Sciences, Manchester Metropolitan University, Chester Street, Manchester, UK
- ^b Universitas Atma Jaya Yogyakarta, Yogyakarta, Indonesia
- ^c Birdpacker Indonesia, Batu, East Java, Indonesia
- ^d BirdLife International, Cambridge, UK
- e Tangerang Selatan, Banten, Indonesia
- ^f Universitas Indonesia, Depok, West Java, Indonesia

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ABSTRACT

Citizen science projects remain rare in biodiverse yet data-poor countries, contributing to a shortfall in data for biodiversity monitoring and promoting public stewardship of nature. We document and analyse BigMonth2020, a month-long birdwatching event across Java and Bali, publicised through social media and incentivised with grants and competitions. Over 20,000 lists containing 100,000 bird records were submitted to the 'Burungnesia' phone application. Spatial coverage extended to 71% of the islands' 3408 atlas grid squares (6.9 \times 6.9 km), including 1613 previously undocumented squares, with 353 bird species recorded, representing 74% of Java and Bali's avifauna excluding vagrants; 27 threatened species were recorded, with new records for 204 grid squares. Almost 25% of contributors were female, 72% were under 30 years old, and most were graduates and members of birdwatching clubs. The project cost less than US\$10,000 to run, and serves as a model for rapidly establishing a distributional baseline for monitoring biodiversity trajectories in the tropics.

1. Introduction

Obtaining broad-scale ecological data to evaluate species distributions and their responses to environmental change requires resources unavailable to most researchers (Dickinson et al., 2010). Citizen science is a practical way to bridge the resource gap, with projects typically mobilising volunteers to gather and/or classify data following a protocol developed by experts (Dickinson et al., 2012). Ecology-related citizen science projects vary widely, ranging from online exercises (Shamir et al., 2014; Swanson et al., 2015; Rosenthal et al., 2018) to field surveys (Preston, 2013; Gillings et al., 2019). Scientists benefit from citizen science by obtaining large datasets with higher coverage, the volunteers experience direct involvement in science and enhance their skills (Dickinson et al., 2010), and wider society benefits, as volunteers often share their knowledge, increasing levels of scientific literacy and environmental advocacy among peers (Johnson et al., 2014).

E-mail address: tom.squires@stu.mmu.ac.uk (T.M. Squires).

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^{*} Corresponding author.

Citizen science has recently proliferated in developed countries but remains rare in developing countries (Chandler et al., 2017). This is problematic for conservation, since biodiversity hotspots predominantly coincide with data-poor, highly threatened areas (Brooks et al., 2006; Fisher and Christopher, 2007). Barriers to citizen science in developing countries include low awareness of opportunities (for both participants and institutions) (Pocock et al., 2019), low appreciation of its environmental and societal value (Chandler et al., 2017), and low levels of expertise, time, money and perceived personal benefits (Requier et al., 2020). By way of counterbalance, the global rise in smartphone ownership and internet coverage in many developing countries gives citizen science both practicality and appeal (August et al., 2015; Taylor and Silver, 2019).

Indonesia is one of the most biodiverse nations on earth, but habitat loss through land-use change is a major threat to wildlife and habitats, while illegal trapping of wild birds has triggered an 'Asian Songbird Crisis' (Margono et al., 2014; Lee et al., 2016; Hughes, 2017). This trade affects at least 32 threatened species in Indonesia and many common species (Eaton et al., 2015; BirdLife International, 2021), with households in Java, Indonesia's most populous island, keeping some 74 million cage-birds (Marshall et al., 2020). Baseline distribution data for widespread Javan species are now urgently required to identify future changes. To date, such data have been gathered by Indonesian birdwatchers for the first Indonesian Bird Atlas ('Atlas Burung Indonesia'; Taufiqurrahman et al., 2016), and through eBird (Sullivan et al., 2014). However, these data are predominantly gathered in urban centres, ecotourism hotspots and protected areas, leaving large intervening spaces. To develop baseline distribution models for common birds, data need to cover the range of habitats and land-use types within the study area (Phillips et al., 2006).

To this end, we developed 'BigMonth2020', a citizen science project held in Java and Bali during January 2020 which aimed to engage Indonesian society, expand the coverage of bird distribution data, and incidentally contribute to the Indonesian Bird Atlas. Here we outline the scope and design of BigMonth2020, the data collection and validation protocols followed, and the promotional campaign and incentive scheme intended to attract participation. We then assess the bird data collected for their novelty, composition and quality, and examine the demographics of those who contributed to BigMonth2020. Finally, we review the project's outcomes and the benefits and pitfalls of a citizen science event, providing lessons learnt for similar initiatives and the continuation of the work on Java and Bali.

2. Methods

2.1. Inception

We developed an outline plan for an incentive-driven inclusive birdwatching event, to be promoted primarily through social media, and enlisted the involvement of two Indonesian partner organisations: the Indonesian Ornithologists' Union (IdOU), whose members are predominantly academics or work for conservation NGOs, and Birdpacker, a grassroots birdwatching community whose citizen science phone application 'Burungnesia' (burung, Indonesian 'bird'; -nesia from Indonesia) was released in 2016. This application enables birdwatchers to submit georeferenced bird lists in support of efforts to produce Atlas Burung Indonesia, the country's first national bird atlas.

2.2. BigMonth2020

The event's scope was limited to Java and Bali to ensure its logistics were manageable and it lasted a full month to maximise data accumulation within the constraint of limited administrative resources. This gave contributors ample opportunity to log data yet was short enough to maintain social media interest. We timed the event to coincide with university and national holidays, when participants had more free time and were dispersed from large urban centres.

A competition was promoted via social media. We purchased ornithological equipment (binoculars, telescope, field guides, etc.) as prizes for various categories, including the overall top-ten contributors of bird lists, the best social media influencer, and the best photograph. We also established a small grant scheme, administered online with simple bank transfers, to cover transport and subsistence for trips to under-recorded areas. After the third week, we identified the five largest remaining unrecorded areas and offered grants to people to visit them. A total of IDR 27M (US\$1850) was divided among 51 applicants, in grants ranging from US\$6.80 for one person on a day trip to US\$200 for a seven-day trip by eleven students. Overall operational costs, including a small team assembled by Birdpacker to administer the various aspects of the event (i.e. social media, data handling and expert validation), were covered by US \$7000 from the Oriental Bird Club (OBC) and US\$400 by Idea Wild. Other indirect project-related costs included the incidental funding of TMS and SJM, as well as the in-kind cost of developing and running the data-logging application.

2.3. Promotion

In November 2019, partners from Manchester Metropolitan University (MMU) and Birdpacker presented BigMonth2020 at the annual Indonesian birdwatchers' conference. Thereafter, promotion was carried out on social media. We posted Indonesian-language promotions via Facebook and Instagram, and English-language promotions via Twitter. We directly contacted 33 naturalist clubs (22 of them university societies), eleven Indonesian NGOs, two Indonesian zoos, and the European (EAZA) and North American (AZA) zoo associations via email and social media. Thirty-four organisations became official supporters and their logos featured on promotional material.

Social media promotions began with a digital project poster (Fig. 1) on Facebook, Instagram and Twitter two weeks before the event, followed by information about its aims and objectives, the data collection protocol, and the competition rules. A BigMonth2020

webpage provided tutorials for data collection and input, as well as identification guides for lookalike species. Once BigMonth2020 commenced, social media posts were made almost daily on Instagram and Facebook, providing updates on the prize competition, data accumulation, unusual findings, and priority grid squares. Many participants shared our promotions or created their own content, increasing the project's reach (Fig. A.1). The MMU partners visited the Birdpacker team in Malang, East Java, in mid-January and collected data alongside students, NGO staff and government officials, while the OBC chairman recorded data with members of the Birdpacker team in East Java.

2.4. Data collection

Participants were asked to focus their efforts on low-elevation land (< 800 m altitude) outside protected areas, because the largest gaps in data occur in these relatively accessible areas, and to use the Burungnesia phone application to submit their data; we did promote the use of eBird but no participants chose to use this during BigMonth2020. Participants compiled lists of bird species recorded at a unique location as either presence-only or count data (sample data and full protocol in Appendix B). Participants were encouraged to search for birds around the start location for at least one hour and to begin a new list if they travelled 3 km away from the start point. As Burungnesia currently lacks the functionality to record extensive list metadata, we could not obtain data on survey



Fig. 1. From top left clockwise: BigMonth2020 promotional poster used on social media; Instagram promotion of competition prizes; Big-Month2020 competition winner being awarded his prize; and young participants wearing their BigMonth2020 T-shirts with field guides they won as prizes.

effort (distance travelled, survey duration) or list completeness (i.e. whether all species encountered were recorded).

We increased the resolution of the Indonesian Bird Atlas grid system $(0.25^{\circ} \times 0.25^{\circ})$, WGS 84) by dividing each square into 16 cells $(0.0625^{\circ} \times 0.0625^{\circ})$; 6.9×6.9 km), resulting in 3408 grid squares. Using existing data from eBird and the Indonesian Bird Atlas, we categorised squares as unvisited (no bird lists) or visited at two levels (1-5) bird lists, (0.5) bird lists). Data for the Indonesian Bird Atlas were collected manually until the Burungnesia application was released in 2016; here, both datasets are combined and referred to as 'Indonesian Bird Atlas data'. BigMonth2020 participants could download the map as a (0.5) kmz file. Trips to unvisited squares were incentivised using a weighted point-scoring system for the competition, with extra points awarded if five bird lists were submitted from an unvisited grid square. The map and grid square status were updated every three days and a new download made available.

2.5. Data validation

Six experts validated submitted data throughout and after the event. A bird list was flagged for further review if (1) a location description did not match the GPS coordinates; (2) the habitat description did not match the habitat depicted on Google Earth; or (3) a species record was deemed unusual in terms of location, time of year or habitat. For flagged records, the observer was asked for supporting evidence, and depending on the response the record was either retained in or removed from the database. Records without coordinates were omitted. All records were adjusted so that taxonomy followed HBW and BirdLife International (2019).

2.6. Participant questionnaire

An Indonesian-language questionnaire (Appendix C) was posted online to learn more about the event's participants, with a free BigMonth2020 T-shirt (Fig. 1) offered to all respondents. Participants provided demographic data (age, education level, employment status) and information on their birdwatching expertise, motivations and perceptions of conservation issues.

2.7. Ethical statement

The questionnaire was administered by Universitas Atma Jaya Yogyakarta, followed their research guidelines and conformed to standards in BSA (2017). It explained its objectives at the start and participants provided informed consent by answering the questions. Questionnaire data were accepted from adults only (> 18 years) and anonymised before analysis.

2.8. Data analysis

The species recorded were classified into six functional groups to examine differences in data recording. Birds were categorised as either raptors, aerial feeders or waterbirds based on taxonomy and feeding strategy, while all species outside those categories were grouped by preferred habitat (woodland, open/agriculture or scrub/savanna) using BirdLife Data Zone information (BirdLife International, 2020; see Table D.1). We calculated Shannon's evenness (E_H) (Peet, 1974) for the six classes to measure the within-group relative abundance of records for each species, with values ranging from 0 (group dominated by few taxa) to 1 (records evenly distributed among taxa).

To identify participant attributes associated with high survey effort and data composition, we fitted two generalised linear models (GLMs) using the dataset of 134 participants' questionnaire responses combined with the bird data they submitted to Burungnesia. The survey effort model used the number of grid squares visited as the dependent variable, while the data composition model used a 'rarity recording' metric, calculated following August et al. (2020): every species was ranked according to the number of times it was recorded and assigned a rarity value from 1 = most common to 100 = most rare; we then subtracted the median rarity value across all observations in the dataset from the median rarity value across all records for the participant, so that negative values of the metric indicate that the participant recorded common species more frequently than expected and positive values show that the participant recorded rare species more frequently than expected. The predictors used in both models were age in years, gender, occupation (formal employment, freelance-type work, student), birdwatching experience in years, and bird club membership; the number of grid squares visited was included as a predictor in the data composition model. All statistical analyses were conducted in R (4.0.2, R Core Team,

Table 1
Summary statistics for two existing citizen science bird distribution datasets for Java and Bali and the BigMonth2020 dataset.

Characteristic	eBird	Indonesian Bird Atlas	BigMonth2020	
Years covered	1970-2020	2003–2020	2020	
Number of records	180,975	39,011	102,887	
Number of bird lists	11,666	4130	22,055	
Species recorded (threatened)	517 (39)	469 (38)	353 (27)	
Median species recorded per bird list (IQR)	9 (3–19)	6 (2–13)	4 (3–6)	
Grid squares (exclusive to dataset)	594 (67)	827 (135)	2417 (1613)	
Contributors	1241	483	218 ^a	
Median number of lists per contributor	4 (1–11)	2 (1–6)	8.5 (3–27)	

^a unique Burungnesia users who submitted data. Some people recorded in groups and the total number of participants is estimated at 373. IQR: interquartile range.

2020) using package 'MASS' (Venables and Ripley, 2002).

3. Results

3.1. Data accumulation

A total of 22,055 bird lists were submitted across Java and Bali during BigMonth2020 comprising 102,887 bird records (Table 1). The daily number of bird lists submitted grew throughout the event, punctuated by peaks in submissions at weekends (average 55% increase vs. preceding weekdays) (Fig. 2). The difference in data accumulation between the first (2564 lists, 11.6%) and last (8470 lists, 38.4%) seven-day period was particularly sharp.

During BigMonth2020 218 unique users submitted data to Burungnesia, although the total number of participants was an estimated 373 because some worked in groups with only one member submitting data. Ten contributors collected 72% of all bird lists (16,090), 25 contributors submitted over 100 bird lists, and 99 submitted at least ten. A median of four species (IQR 3–6 species) per bird list was slightly lower than the eBird and Indonesian Bird Atlas datasets (Table 1).

3.2. Data coverage

At least one bird list was recorded in 2417 (70.9%) of the 3408 grid squares across Java and Bali (Fig. 3). Data were initially concentrated around major cities, but coverage steadily expanded to remoter areas (Fig. E.1). Many low-elevation agricultural areas were surveyed for the first time. Coverage was greatest in Central Java and least in remote parts of West and East Java, with limited road access and a higher proportion of forested uplands.

Prior to BigMonth2020, bird occurrence data were available for 1092 (32% overall; eBird 17.4%; Indonesian Bird Atlas 24.2%) of the grid squares across Java and Bali (Table 1). BigMonth2020 extended bird distribution data to a further 1613 (47.2%) grid squares, representing a 147% increase in coverage. Combined with eBird and the Indonesian Bird Atlas data, total coverage is now 79.3% of grid squares (Fig. 4). Coverage increased by over 50% for 72 species and over 100% for 37 (Table D.1).

3.3. Data composition

There were 353 bird species recorded during BigMonth2020, representing 74% of those known from Java and Bali excluding vagrants (Lepage, 2020). Cave Swiftlet (*Collocalia linchi*), Eurasian Tree Sparrow (*Passer montanus*) and Sooty-headed Bulbul (*Pycnonotus aurigaster*) made up 16.2%, 10.2% and 6.0% of the 102,887 records, respectively. Twenty-seven species on the IUCN Red List

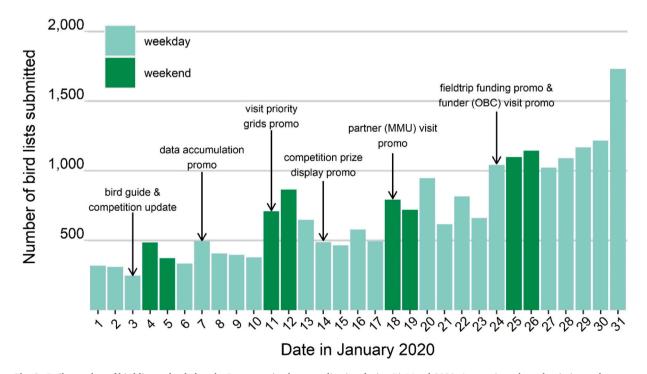


Fig. 2. Daily number of bird lists uploaded to the Burungnesia phone application during BigMonth2020. Annotations show the timing and content of popular social media posts by Birdpacker. Submission peaks on 13 and 20 January are probably data-reporting lags from weekends, and the peak on the final day is probably contributors entering data before the competition cut-off time.

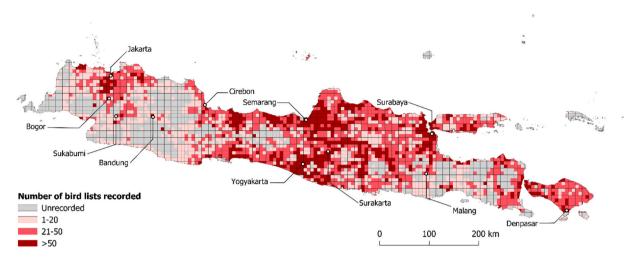


Fig. 3. Data coverage for BigMonth2020. Grid squares $(6.9 \times 6.9 \text{ km})$ are coloured according to the number of bird lists recorded within them. Major cities in Java and Bali are shown.

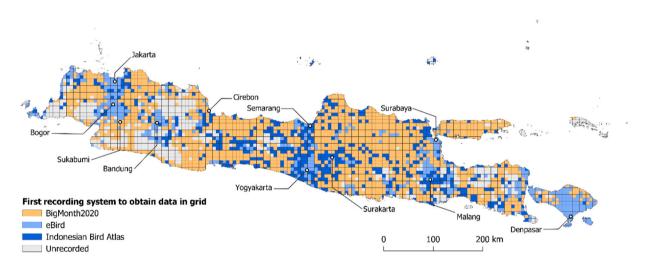


Fig. 4. Bird distribution data coverage for Java and Bali. Grid squares $(6.9 \times 6.9 \text{ km})$ are coloured according to which recording system was first to obtain data there: BigMonth2020 (n = 1613; 47.3%); Indonesian Bird Atlas (n = 575; 16.9%); eBird (n = 514; 15.1%); unrecorded (n = 706; 20.7%).

(14 Vulnerable, 9 Endangered, 4 Critically Endangered) were recorded, ten of which are significantly affected by the cage-bird trade (BirdLife International, 2020). Six threatened species were recorded on > 20 lists: Javan Myna (Acridotheres javanicus) (142 lists), Javan Coucal (Centropus nigrorufus) (101), Sangkar White-eye (Zosterops melanurus) (66), Ruby-throated Bulbul (Rubigula dispar) (62), Milky Stork (Mycteria cinerea) (33) and Java Sparrow (Lonchura oryzivora) (23). Threatened species were recorded for the first time in 204 grid squares, and seven species were recorded for the first time in at least ten squares, with grid square coverage for these increasing by 15.5–69.8% (Table D.1).

Table 2
Summary of bird data recorded during BigMonth2020, with species grouped based on taxonomy and feeding strategy (raptors, waterbirds and aerial feeders) or preferred habitat (woodland birds, birds of open country/agricultural areas, and scrub/savanna birds).

Group	Species	Percentage of all species	Percentage of records	Threatened species	Evenness (E_H)
Open country/agriculture	31	8.8	31.4	3	0.57
Woodland	172	49.0	26.7	15	0.50
Aerial feeders	15	4.3	24.1	0	0.42
Scrub/savanna	21	6.0	9.3	2	0.56
Waterbirds	91	25.9	7.9	6	0.66
Raptors	21	6.0	0.6	1	0.70

Species of open country and farmland were most frequently observed (Table 2), with Eurasian Tree Sparrow, Scaly-breasted Munia (Lonchura punctulata) and Javan Munia (L. leucogastroides) comprising 70.8% of these records. Nearly half the species inhabit woodland but accounted for only a quarter of observations. Aerial feeders were over-represented in the dataset (4.3% of all species recorded accounting for 24.1% of all observations), as were scrub and savanna birds; waterbirds and raptors were under-represented.

3.4. Data quality

During data validation, 845 bird lists (3.8%) were flagged for review. Data from 494 (58.5%) lists were retained in the database following verification, 253 (29.9%) were retained with updated location or species data, and 98 (11.6%) were removed for lack of supporting evidence. Some easily misidentified species commonly required review, notably tailorbirds (*Orthotomus* spp.): 19 of 60 records of Ashy Tailorbird (*O. ruficeps*) were reviewed, of which 13 were accepted with evidence, five re-identified as Olive-backed Tailorbird (*O. sepium*) and one as Common Tailorbird (*O. sutorius*).

3.5. Participant characteristics

Of the estimated 373 participants, 188 (50.4%) answered the questionnaire, all of whom were Indonesian. Of these, 23.4% were female and 71.8% were under 30 years old. Most respondents lived in East Java (28.2%), Yogyakarta (21.8%) and Central Java (14.9%), with fewer in West Java (12.8%), Jakarta (5.3%), Banten (2.1%) and Bali (2.1%), and the remainder (12.8%) lived elsewhere in Indonesia. Most were members of a bird club (67%) and discovered BigMonth2020 through their club (39%) or social media (20% Instagram; 9% Facebook); 36.2% owned a camera but not binoculars, 30.3% had both a camera and binoculars, 16.5% used binoculars alone and 17% had no equipment. Top-ranking motives for their participation in BigMonth2020 were 'contributing to conservation' (74% of respondents) followed by 'seeing new bird species' (64%) (Fig. F.1a). The cage-bird trade and habitat loss were considered equally important threats to birds in Java, followed by climate change (Fig. F.1b). The number of grid squares visited by participants (sampling effort) was significantly higher for participants with more birdwatching experience ($z = 2.79 \pm 0.03$, p < 0.01) and who were male ($z = 2.32 \pm 0.28$, z = 0.02). In terms of rarity recording, participants who visited more grids during BigMonth2020 tended to record common birds more frequently than expected (z = 0.006, z = 0.001). Full GLM parameters are provided in Appendix G.

4. Discussion

BigMonth2020 demonstrates the viability of citizen science in Indonesia and could be replicated in other countries where citizen science projects are scarce and biodiversity seriously under-recorded (Meyer et al., 2015). Over 300 Indonesians (Appendix H) generated a dataset comprising over 100,000 bird records, half of which were collected in previously unsurveyed areas (see https://bigmonth2020.shinyapps.io/shinyappy.).

4.1. Data coverage and composition

BigMonth2020 has more than doubled bird distribution data coverage on Java and Bali, extending to almost 80% of grid squares. Sampling biases related to contributor distribution are a common and expected feature of citizen science data (Dennis and Thomas, 2000; Romo et al., 2006), and the spatial distribution of data here broadly reflects the accessibility of squares and the distribution of contributors, the most prolific of whom mainly lived in Central Java, Yogyakarta and East Java. Consequently only one in ten bird lists were submitted in western Java (Banten, Jakarta and West Java provinces) despite half Java's population residing there (Badan Pusat Statistik, 2016). While inaccessible upland areas in western Java account for the largest remaining gaps in data coverage, some accessible areas close to urban centres were unvisited. In part this is because Central Java and Yogyakarta possess more bird clubs, which are associated with the region's cluster of biology-focused universities. It may also reflect cultural differences in interest in birds between the Sundanese in western Java and the Javanese in central and eastern Java (Jepson and Ladle, 2005). Moreover, it could be linked to the rapid urbanisation of western Java (Firman, 2017), producing a human–nature disconnect and reduction in pro-environmental feeling (Cleary et al., 2020).

The considerable increase in data coverage for many commoner species will enable us to develop robust distribution models to establish a distributional baseline against which to monitor the stability of the environment, as changes in the distribution of common species representative of major habitat types can reveal patterns of wider ecosystem health (Caro and O'Doherty, 1999). Distribution models for common species, which contribute most to patterns of overall species richness (Vázquez and Gaston, 2004), could be used to identify areas of relatively high biodiversity value in under-recorded regions of Java. Estimating the distribution of rare and threatened species is another important aspect of biodiversity monitoring (BirdLife International, 2021), and BigMonth2020 delivered valuable data for 27 threatened species, for nine of which we obtained at least the minimum number of records needed to build accurate distribution models (Proosdij et al., 2016). However, some of Java's Critically Endangered species, such as Black-winged Myna (A. melanopterus) and Javan Pied Starling (Gracupica jalla), were conspicuous absentees from the dataset, highlighting the disastrous declines of some species due to bird trapping in the region.

4.2. Participation and demographics

BigMonth2020 engaged with over 300 Indonesian citizens (Appendix H), a level of participation comparable to similar schemes in Africa and Taiwan (Ko et al., 2014; APLORI, 2020). BigMonth2020 had more participants under 30 years old than projects in countries where birdwatching has a longer tradition with a wider spectrum of cohorts (Wright et al., 2015; MacPhail and Colla, 2020). It also attracted people who were not already birdwatchers, suggesting that such events can promote engagement with nature and conservation issues. Although this demographic may present challenges relating to capacity to participate (e.g. less disposable income, limited transport) and data quality (i.e. less birdwatching experience, limited access to equipment), it indicates a growing community of nature enthusiasts who could rapidly become a significant body of conservation advocates. Retaining participants is, however, critical if BigMonth2020's baseline is to serve its purpose, because participant expertise can be expected to increase over time, especially if project goals and data use are effectively communicated (Forrester et al., 2017). This is best achieved by continuing to appeal to peoples' varied initial motivations for participating (Clary and Snyder, 1999; Bruyere and Rappe, 2007).

Birds have a deep cultural significance in Indonesia (Jepson and Ladle, 2005), but bird-keeping and songbird competitions are almost exclusively male-dominated activities (Marshall et al., 2020); encouragingly, however, a quarter of questionnaire respondents for BigMonth2020 were female. Nevertheless, female participants visited fewer grid squares than average, suggesting that gender-specific barriers to participation still exist and initiatives to encourage female participation are warranted. Even so, we speculate that birdwatching could develop as an inclusive pursuit in Indonesia, irrespective of sex, age or social class, and events like BigMonth2020 are ideally placed to promote this. The distribution of contributors to BigMonth2020 mirrors the prevalence of bird-keeping across Java (Jepson and Ladle, 2009; Marshall et al., 2020), suggesting that people from bird-keeping households could be attracted to birdwatching and conservation as an alternative means to enjoy birds, thereby helping to reduce the threat from the cage-bird trade.

4.3. Project design and data collection

Some adjustments to the sampling strategy we used for BigMonth2020 could help address the spatial bias and remaining gaps in data coverage. Besides the bias we introduced by asking volunteers to visit low-elevation unprotected areas, survey bias was linked to human population density and accessibility, a common problem when *ad hoc* sampling is used, reflecting the trade-off between protocol complexity (data quality) and ease of participation (Bird et al., 2014; Geldmann et al., 2016). While it should be minimised, spatial bias does not preclude the accurate estimation of species distributions (Johnston et al., 2020). Moreover, the uptake of our small incentives to explore under-recorded areas suggests that further such incentives to visit grid squares remote from major roads would help reduce the current spatial bias.

Some issues related to the data collection protocol can be addressed by modifications to the data-logging application. First, the number of taxa recorded per bird list for BigMonth2020 was low relative to other reporting systems for the same area, suggesting that either sampling effort per list (not recorded) or bird detection frequency was lower. The design of the competition, kept simple to promote engagement, probably contributed to this by awarding points for every bird list submitted, thereby encouraging low sampling effort; this is corroborated by our finding that participants who submitted most data tended to record commoner birds more frequently than expected. Requiring a minimum sampling effort for every bird list could resolve this issue, and highlights the need to design incentives carefully. Second, contributors may not have reported all species they encountered—possibly ignoring common species or those posing identification challenges (Snäll et al., 2011; Tulloch et al., 2013)—so inferring species absence was not possible. If absences and sampling effort are known, biases can be accounted for statistically, so these metadata should be required by future versions of the application (Fink et al., 2020). Finally, we manually validated photographic evidence requested from users after bird records were flagged. To expedite this process in future, users should be able to attach photographic evidence to their records during data submission, and the proportion of correctly identified photographs could be used as a data quality metric (Vantieghem et al., 2017).

4.4. Biodiversity monitoring in Java

BigMonth2020 delivered high geographic coverage of the study region and valuable distribution data for most of Java's bird species. The immediate aim following the event is to widen the network of citizen science birdwatchers and improve the utility of the data collected, in order to establish distributional baselines for birds across Indonesia. Extending survey effort beyond the populous islands of Java and Bali poses a logistical challenge given Indonesia's geography, but, beyond simply replicating the efforts described here, in more remote regions organisers could seek to engage with local stakeholders and integrate forms of traditional and indigenous knowledge into the project (Leach and Fairhead, 2002). It would also be desirable to extend the monitoring protocol to better enable the calculation of population trends for common birds from the dataset, which as previously discussed is not possible with the data collected in BigMonth2020. To achieve this, a repeated samples protocol is needed consisting of a random selection of fixed sites, stratified by habitat type, to be surveyed at regular intervals. Meanwhile, the *ad hoc* sampling adopted for Bigmonth2020 would be retained because it is inclusive, offers training opportunities for less experienced volunteers, and helps recruit, retain and involve more casual participants (Higby et al., 2012). Finally, spatiotemporal data coverage can be extended and duplication of effort avoided by establishing closer connections with existing initiatives including the Asian Waterbird Census (International Waterbird Census, 2020), eBird and Raptor Watch (Yuda, 2017).

5. Conclusion

We have demonstrated the potential of citizen science to address gaps in biodiversity distribution data coverage that are unlikely to be filled by traditional fieldwork, as well as its ability to engage with a young demographic, not all of whom were seasoned birdwatchers. Our approach was based on a tailored incentive scheme and targeted social media promotion campaign and stimulated a data collection approach built on existing local efforts. We have identified key aspects of the incentive scheme and data collection protocol that can be adapted to improve data quality, and what would be required to monitor population trends as well as distributions. Considering the popularity of citizen science among funders (Gura, 2013) and the benefits that can be derived from it (McKinley et al., 2017), we hope that the findings and processes reported here will prove a basis, guide and stimulus to similar endeavours across the tropics.

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Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.gecco.2021.e01680. The following supplementary data are available: social media posts by BigMonth2020 participants (Appendix A), the data recording protocol using the Burungnesia application (Appendix B), the feedback questionnaire (Appendix C), a summary of species data recorded during BigMonth2020 (Appendix D), spatiotemporal data accumulation during BigMonth2020 (Appendix E), questionnaire responses related to motivations to participate in BigMonth2020 and threats to Javan birds (Appendix F), GLM parameters (Appendix G), and contributors to BigMonth2020 data collection (Appendix H). Pre- and post-BigMonth2020 data coverage for species recorded (excluding 'sensitive species') can be viewed at https://bigmonth2020.shinyapps.io/shiny.app/.

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