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COVID-19 impacts on participation in large scale biodiversity-themed community science projects in the United States

Theresa M. Crimmins[a,b,*], Erin Posthumus[a,b], Sara Schaffer[a,b], Kathleen L. Prudic[a,**]

[a] *School of Natural Resources and the Environment, University of Arizona, 1604 E. Lowell St., Tucson, AZ 85721, USA*
[b] *USA National Phenology Network, 1311 E. 4th St., Ste. 325, Tucson, AZ 85721, USA*

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ABSTRACT

Shutdowns associated with the COVID-19 pandemic have had extensive impacts on professional and volunteer-based biodiversity and conservation efforts. We evaluated the impact of the widespread pandemic-related closures in the spring of 2020 on participation patterns and rates on a national and a state-by-state basis in the United States in four biodiversity-themed community science programs: eBird, eButterfly, iNaturalist, and *Nature's Notebook*. We compared the number of participants, observations submitted, and proportion of observations collected in urban environments in spring 2020 to the expected values for these metrics based on activity in the previous five years (2015–2019), which in many cases exhibited underlying growth.

At the national scale, eButterfly and *Nature's Notebook* exhibited declines in the number of participants and number of observations submitted during the spring of 2020 and iNaturalist and eBird showed growth in both measures. On a state-by-state basis, the patterns varied geographically and by program. The more popular programs – iNaturalist and eBird – exhibited increases in the Eastern U.S. in both the number of observations and participants and slight declines in the West. Further, there was a widespread increase in observations originating from urban areas, particularly in iNaturalist and eBird. Understanding the impacts of lockdowns on participation patterns in these programs is crucial for proper interpretation of the data. The data generated by these programs are highly valuable for documenting impacts of pandemic-related closures on wildlife and plants and may suggest patterns seen in other community science programs and in other countries.

1. Introduction

The COVID-19 pandemic has had extensive impact on all facets of human society (Bates et al., 2020; Diffenbaugh et al., 2020). To limit virus transmission, swift closures of public spaces including college campuses, K-12 schools, theaters, sports venues, and parks and recreation facilities swept through the United States in March 2020 and remained in place for variable durations across states through subsequent months. Consequently, tourism, recreation behaviors, and other forms of human activity patterns have been dramatically impacted (Bakar and Rosbi, 2020; Nicola et al., 2020). The dramatic shifts in human activities have had clear effects on wildlife and biodiversity; anecdotes suggest some wildlife may be moving into new areas or changing their behavior, while others may be at risk of increased exploitation or disturbance (Corlett et al., 2020; Rutz et al., 2020).

Community science – also referred to as citizen science, volunteer science, and public participation in scientific research – provides significant value to conservation efforts in both urban and non-urban areas (Cooper et al., 2007; Devictor et al., 2010; McKinley et al., 2017; Sullivan et al., 2017). Community science programs are characterized as scientific research conducted at least in part by amateur or volunteer scientists (Bonney et al., 2009; Dickinson et al., 2012). Designed to engage non-professionals in the act of science and data, these programs frequently yield data at spatial and temporal scales far beyond what professional scientists can achieve when working alone. Community science programs lead to increases in science literacy and an understanding of the process of "doing science", a deepened sense of place, and a greater understanding and appreciation for the plants and animals they are observing (Dickinson et al., 2012; Evans et al., 2020). As such, community science programs were widely advertised during early weeks of the shutdown in the U.S. as stimulating and meaningful activities for children and adults alike during school and office closures (Bowman and

* Correspondence to: T M. Crimmins, School of Natural Resources and the Environment, University of Arizona, 1604 E. Lowell St., Tucson, AZ 85721, USA.
** Corresponding author.
E-mail addresses: theresa@usanpn.org (T.M. Crimmins), klprudic@arizona.edu (K.L. Prudic).

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Gibson, 2020; Crimmins, 2020; Piñon, 2020) as well as an alternative approach for data collection that might mitigate the shutdown of formal research and monitoring activities (Bowser et al., 2020; Kornfeld, 2020; Zellmer et al., 2020).

In the weeks immediately following the issuance of COVID-related shutdown orders in the U.S., several community science programs reported spikes in participation. Zooniverse, City Nature Challenge, and Stall Catchers – all large scale community science programs or platforms – reported an increase in participation in March and April 2020 (Bowser et al., 2020; Kubis, 2020; Dinneen, 2020; Young, 2020). Several of these programs, which can be undertaken by individuals on personal computers at home, reported an increase in participation of three to five times the rate of previous years during the same time period (Bowser et al., 2020; Kubis, 2020). Zooniverse participants completed classifications of galaxies, animal photos, and more at three times the rate of previous years as of April 3, 2020 (Bowser et al., 2020), and participants in the Stall Catchers project assisted with Alzheimer's research at levels 38% higher than in 2019 (personal communication, P. Michelucci, July 24, 2020). SciStarter, which connects participants with thousands of community science programs, reported increased interest in projects focused on environmental health and identifying and observing birds during the shutdown (Kornfeld, 2020).

Whether the boost in community science project participation documented among some programs early in the shutdown extended to all types of community science programs remains unknown. Here, we explore the impact of the shutdown on participation in four biodiversity-themed community science programs in the U.S.: eButterfly (e-butterfly.org), iNaturalist (inaturalist.org), *Nature's Notebook* (naturesnotebook.org), and eBird (ebird.org). Each of these programs exists to document and share biodiversity observations to support science and conservation. Because participants in these programs typically step outside to identify and assess plants and animals, we anticipate these programs may show different patterns in participation and data submissions from those reported by community science programs that are undertaken completely online. An understanding of the impacts of the pandemic on participation in biodiversity-themed programs is necessary for analysts exploring these data in future studies, as shifts in the intensity or geographic scope of participation may necessitate statistical techniques that account for consequential irregularities in the datasets. The rich and geographically extensive volunteer-contributed reports of plants and animals originating from these programs have the potential to provide important insight into wildlife responses to pandemic-related closures, provided that data interpretation accounts for the impacts of lockdown on data collection. Further, a clearer understanding of changes in program participants' contributions during lockdown is valuable to program staff aiming to support participants as fully as possible. Finally, the findings specific to these four programs in the U.S. may point to what might be expected regarding patterns in participation and consequent impacts on resultant data in other community science programs and in other countries.

We predicted that the shutdown would lead to a drop in the number of participants contributing to the four biodiversity-themed community science programs as well in the amount of observations submitted, due to the increased demands in other parts of participants' lives during this period. Second, we expected the locations where participants collected observations to change during the shutdown, due to the closure of parks and reserves, natural spaces, and facilities such as nature centers and arboreta. Specifically, we expected to see a greater proportion of observations submitted from urban areas than prior to closures, due to stay-at-home orders limiting participants' movement. Finally, we hypothesized that the number of active participants, the amount of data submitted, and the proportion of observations submitted from urban areas in each state would all be affected proportionally by the amount of time a state was formally under lockdown.

2. Materials and methods

2.1. Community science programs

The data evaluated in this study represent four popular biodiversity-themed community science programs in the U.S. The programs vary in their aims, complexity in participating, and levels of standardization, though all contribute critical data and information for documenting and tracking status and trends in biodiversity (Kelling et al., 2019). Data from all four programs are frequently utilized by scientists, conservation organizations, and land management agencies to understand distributions and trends in species and to inform decisions (Cooper et al., 2007; Ellwood et al., 2017).

eButterfly engages participants in documenting checklists of butterflies across North America (Prudic et al., 2017). Participants submit their observations for a new or existing location on a web browser; all locations are stored to encourage repeated observations from established locations. Similar to eBird, participants choose from one of four types of sampling protocols and are presented with a checklist of butterfly species known to occur in the state or province; participants are invited to report presence or absence for all species on the list. Participants are encouraged to submit photos of their observations so that species identification can be verified by other participants in the community. Over 1000 species of butterflies and moths have been contributed to eButterfly to-date (eButterfly, 2020).

iNaturalist engages participants across the globe to photo document plants, animals, fungi, and algae (Seltzer, 2019). Photos are uploaded through a web browser or mobile application to an online community where other participants verify the species identification (Nugent, 2018; Unger et al., 2020). Species identification is also facilitated by a machine learning algorithm which evaluates the submitted photo and makes suggestions on species identification to the participant (Van Horn et al., 2018). Since the program's launch, over 300,000 species have been documented worldwide through iNaturalist (Loarie, 2020). Projects and events can also be created within the platform, such as bioblitz and City Nature Challenge events in which participants survey the biodiversity of a specific area during a defined time period. Dozens of such events took place across the U.S. in spring 2020, despite pandemic lockdowns.

Nature's Notebook, coordinated by the USA National Phenology Network (USA-NPN), engages individuals and groups of participants observing collectively in documenting plant and animal phenology across the U.S. (Denny et al., 2014). Participants first register one or more locations (sites) at which they make repeated observations, then register individual plants and/or a checklist of animal species to observe at each site. Participants collect observations of the status of seasonal growth and development (conditions such as presence of leaves, open flowers, or ripe fruits in plants and presence of individuals, mating, courtship calling, or egg laying in animals) via a web browser or mobile application. Participants are encouraged to make observations 2–3 times per week during the season when plants and animals are active and indicate the presence or absence of each phenological stage at each visit (Rosemartin et al., 2014). Protocols are currently available for participants to track the phenology of over 1000 species of plants and nearly 400 species of insects, fish, amphibians, reptiles, birds, and mammals (USA National Phenology Network, 2020a).

eBird engages a global network of participants who submit observations of birds to a central data repository via a web browser or the eBird Mobile application (Sullivan et al., 2014). Participants report bird species identity, occurrence, and relative abundance at either predefined birding hotspots or observer-specified locations; locations can be saved and returned to for repeat observations. Participants choose from one of four types of sampling protocols and are presented with a checklist of bird species most likely to be observed at their selected location; participants are invited to report presence or absence and number of individuals for all species on the list. Some participants report only occasionally; others complete daily checklists (Sullivan et al., 2009). As of 2019, eBird boasted 10,721 bird species in the program's taxonomy (Team eBird, 2019).

Citizen science programs generally have shown growth in recognition and participation over the past decade (McKinley et al., 2017). Three of the four programs examined – iNaturalist, *Nature's Notebook*, and eBird – similarly experienced either steady or exponential growth in participation in recent years (Fig. 1a, b).

2.2. Data preparation

We downloaded the prepackaged eBird "basic sampling event dataset" from the eBird website on August 15, 2020 (eBird Basic Dataset, 2020). This dataset includes all validated observations and unique participants from checklists entered into eBird as well as covariates entered into the checklists regarding location and effort, but not species (Sullivan et al., 2014).

We accessed iNaturalist "research grade" observations through the Global Biodiversity Information Facility filtering by state, month, year, and unique participant (GBIF, 2020). Research grade observations are observations with a date, latitude/longitude coordinates, and a consistent species identification made by at least two reviewers (Ueda, 2020), which is analogous to the internal vetting processes of eBird and eButterfly. We accessed eButterfly data through the eButterfly database. All records for observations within the United States were retained.

For *Nature's Notebook*, we downloaded all "status and intensity" records collected 2015–2020 from the USA-NPN National Phenology Database using the rnpn package (USA National Phenology Network, 2020b). Status and intensity records reflect each time an observer recorded data on an individual plant or an animal at location over the course of the season (Rosemartin et al., 2018). We excluded data contributed by the National Ecological Observatory Network (NEON) and records contributed at locations outside of the U.S. We treated each instance of observing a single organism on a single date as an "observation," consistent with the definition of an observation in the other community science programs in this study.

For each program-specific dataset, we excluded all records collected in months other than March, April, May, and June and we removed all observations falling outside of the United States. Next, we intersected observation locations with a shapefile representing the boundaries of urban areas (U.S. Census Bureau, 2017) and assigned a binary value of urban/non-urban to each observation based on its latitude/longitude reported location. Finally, we tallied the number of observations and the number of unique participants for each program in each year, and then again by state in each year. Similarly, for each program, we calculated the percentage of observations within each year that fell within urban areas as well as the percentage of observations within urban areas in each state in each year.

2.3. Statistical analyses

To determine the impact of the shutdowns on participation in community science programs, we examined the number of individuals

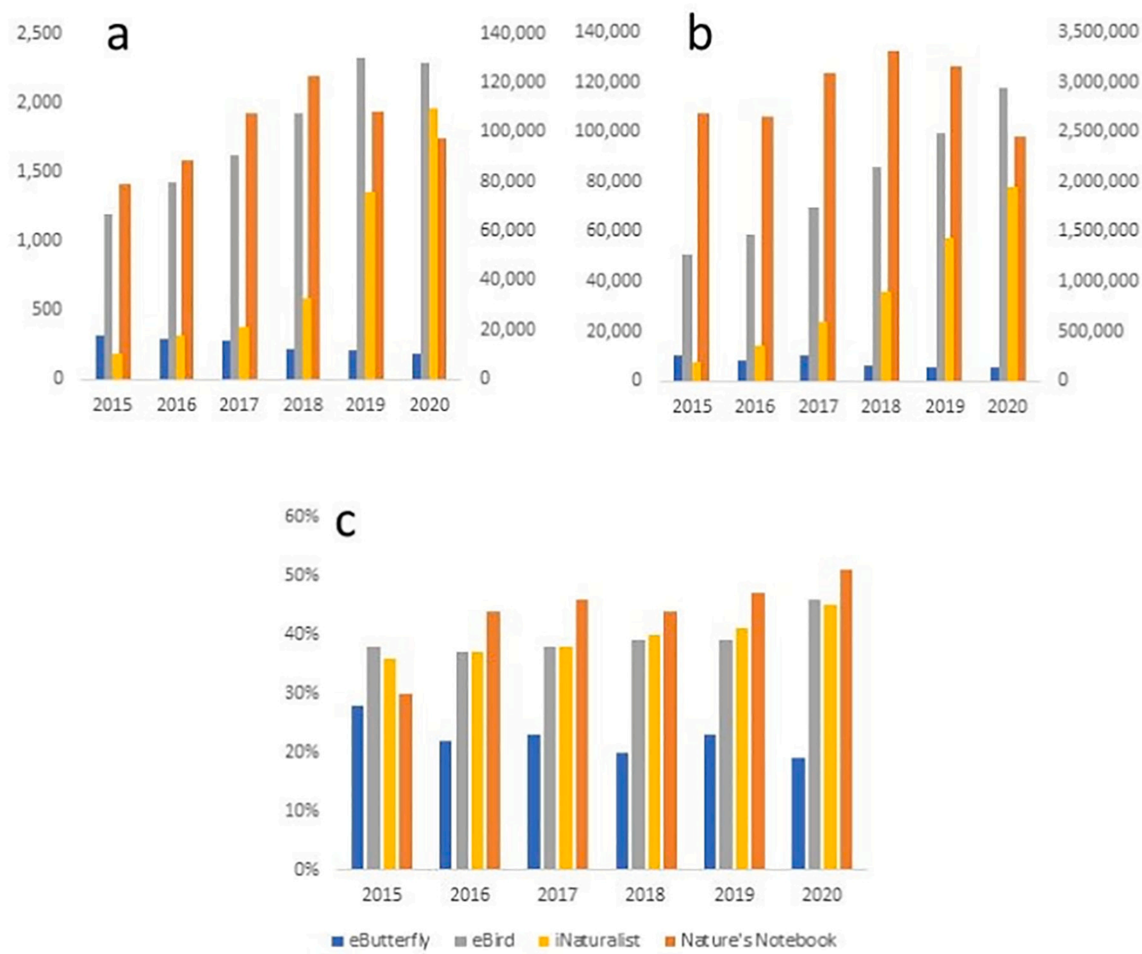

Fig. 1. Long-term patterns in participation among four biodiversity-themed community science programs. a) Number of participants, b) observations submitted, and c) percentage of observations originating from urban areas contributed to eButterfly, iNaturalist, *Nature's Notebook*, and eBird in the U.S., March–June 2015–2020. In a) and b), eButterfly and *Nature's Notebook* are plotted on the primary y-axis and iNaturalist and eBird are plotted on the secondary y-axis.

contributing observations and the number of observations submitted. Because several of the variables under examination exhibit growth over the past five years (Fig. 1, Table A.1), we performed a likelihood ratio test to select between linear and polynomial models for each program. Residuals were normally distributed as determined by a visual inspection of a QQ plot. We tested homogeneity of variance by plotting fitted values versus residuals. The final models selected appear in Table A.2. We then constructed a model between 2015 and 2019 and used this model to create an expected 2020 value with a 95% prediction interval for 2020 (Knowles and Frederick, 2016). We then compared the predicted 2020 value to the observed 2020 value, calculated the percent difference between the two, and then assessed whether the observed fell outside of the predicted 95% interval as our measure of significance (Knowles and Frederick, 2016). We evaluated both the number of unique participants contributing to the program and the number of observations submitted in each of the programs (eButterfly, iNaturalist, *Nature's Notebook*, and eBird) for the entire U.S. as well as for each state in the U.S. For the state-by-state analyses, iNaturalist and eBird data were log transformed, and *Nature's Notebook* and eButterfly data were square root-transformed. We also used this approach to evaluate whether a larger proportion of records originated from within urban areas in the spring of 2020.

For all three metrics (number of observations, number of unique participants, percent urban observations), we evaluated the effect of stay at home orders on the percent change between the observed and expected 2020 values in each of the programs (eButterfly, iNaturalist, *Nature's Notebook*, and eBird) for the entire U.S. as well as for each state. Number of stay at home days by state were acquired from the National Academy for State Health Policy (2020).

All analyses were performed in Rv3.5.3 with RStudio v1.2.5001 as the integrated development environment. Both data and R code are archived in Zenodo (DOI: https://doi.org/10.5281/zenodo.4430966).

3. Results

Spring (March-Jun) participation rates vary dramatically across the four programs evaluated in this study (Fig. 1, Table A.1). iNaturalist and eBird engage tens to hundreds of thousands of participants each spring - far more than *Nature's Notebook*, which engages thousands, and eButterfly, which engages hundreds of individuals each spring. Accordingly, the quantities of incoming observations also vary among the programs: eButterfly participants report thousands of observations each spring, where eBird participants report millions of observations. Participants in iNaturalist and *Nature's Notebook* contribute hundreds of thousands of observations each spring. *Nature's Notebook* boasts the highest rate of observations originating from urban areas; eButterfly's observations are submitted primarily from non-urban areas.

In 2020, two of the four programs, eButterfly and *Nature's Notebook*, experienced fewer participants than expected, and *Nature's Notebook* saw significantly fewer observations than expected (Fig. 2, Table A.1). In

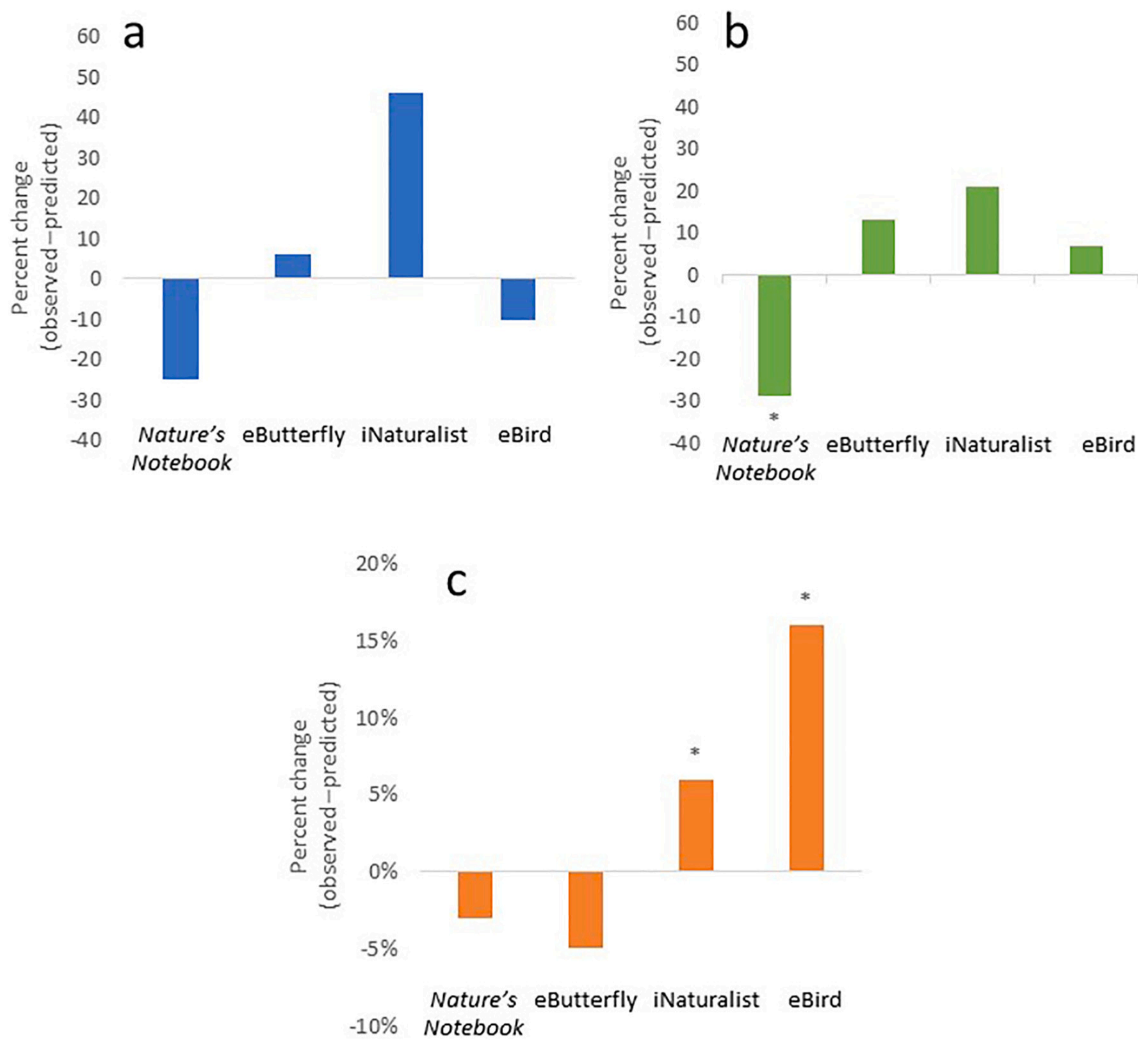

Fig. 2. Difference between predicted and observed values in a) the number of participants, b) observations submitted, and c) percentage of observations originating from urban areas contributed to eButterfly, iNaturalist, *Nature's Notebook*, and eBird in the U.S., March–June 2015–2020.

contrast, both iNaturalist and eBird show sustained activity or increases in these variables across the nation, though gains over what was predicted were non-significant (Fig. 2a, b). All programs but eButterfly experienced more observations originating in urban areas in 2020 than expected, and this proportion was significantly greater than expected for iNaturalist and eBird (Fig. 2c).

The number of participants and amount of data coming into each program is markedly greater in certain states (Table A.4). California is among the top five states in all four programs in terms of participants and observations contributed 2015–2019, and Texas and New York are in the top five states for both metrics in three of the four programs during the pre-COVID springs. The extent to which the number of participants and amount of incoming data from these states was impacted in spring of 2020 was not consistent among programs. For example, the levels of participation in California and Texas declined noticeably across programs in 2020, though the measures changed little for New York.

3.1. Contributing participants

State-by-state analyses revealed widespread decreases in participation across all four programs, though spatial patterns in changes varied by program. eButterfly exhibited significant drops in participation in Alaska, Hawai'i, and through the Great Plains states and also showed sharp increases in participation in other states, though the increase over expected levels of participation were only significant in Utah (Fig. 3a, Table A.4). iNaturalist demonstrated decreases in participation in 2020 over expected numbers nearly nationwide, with significant decreases in many western states as well as decreases in states that contribute the largest proportions of observations and participants (Fig. 3b, Table A.4). Changes in participation in *Nature's Notebook* were spatially patchy (Fig. 3c). California, a top-contributing state in *Nature's Notebook* pre-COVID, saw a significant decline in participation in 2020, though other top-observing states, including Massachusetts and New York, remained steady in 2020 (Table A.4). Similar to iNaturalist, eBird showed a significant decrease in participation over what was expected based on previous years in many western states as well as significant decreases in Eastern Seaboard states (Fig. 3d).

3.2. Observation activity

Overall patterns of change in observations in 2020 paralleled the patterns seen in participants. For all states combined, *Nature's Notebook* participants contributed significantly fewer observations in 2020 (98,256 observations) compared to what was expected (95% prediction interval: 105,980–170,849; Table A.3). eButterfly, iNaturalist, and eBird each exhibited a non-significant increase in the number of participants over what was expected based on 2015–2019 patterns (Table A.3).

Spatial patterns of change in observations submitted to the eButterfly program (Fig. 3a, Table A.4) paralleled changes observed in participants (Fig. 3a). Changes in observations contributed to iNaturalist and eBird both exhibited a fairly clear east-west gradient, where western states generally showed decreases in observations and states east of the

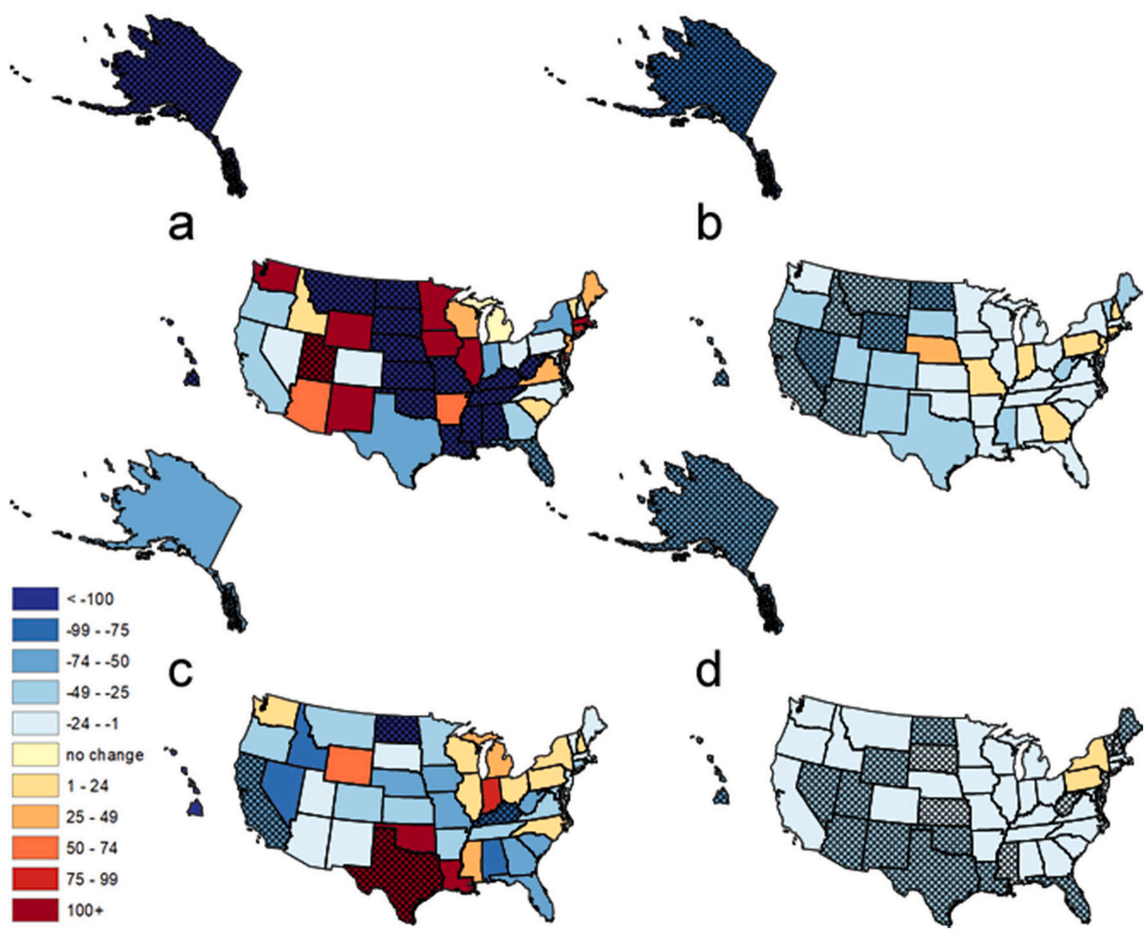

Fig. 3. Percent difference in the observed number of participants in March–June 2020 from the expected number of participants in March–June 2020 based on participation patterns in March–June 2015–2019 in four biodiversity community science programs: a) eButterfly, b) iNaturalist, c) *Nature's Notebook*, and d) eBird. Blue tones indicate fewer participants than expected in 2020; red tones indicate more participants than expected in 2020; hatching indicates a significant difference between predicted and observed number of participants in 2020 ($p < 0.05$). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

hundredth meridian tended to show increases in observations (Fig. 4b, d). Finally, most states exhibited a decrease in the number of observations reported to *Nature's Notebook* in 2020 (Fig. 4c).

3.3. Shift in geography of observations

When all states were combined, the percent of observations submitted from within urban areas significantly increased in 2020 over what was expected for both iNaturalist and eBird (Fig. 2c). In 2020, 45% of iNaturalist and 46% of eBird observations originated in urban areas (iNaturalist 95% prediction interval: 41–44%; eBird 95% prediction interval: 37–42%; Table A.3). The percentage of observations submitted from within urban areas decreased non-significantly in both eButterfly and *Nature's Notebook* over what was expected based on 2015–2019 patterns (Table A.3).

State-specific results varied appreciably by program in the shift of observations submitted from urban and non-urban areas. Across much of the western U.S. and the Ohio Valley, the proportion of observations submitted from within urban areas dropped sharply in 2020 in the eButterfly program, though none of these decreases were significant (Fig. 5a, Table A.4). In contrast, iNaturalist and eBird both exhibited increases in the proportion of observations reported from within urban areas in 2020 across the majority of states, and the shifts toward more urban observations were significant for many states in the eBird program (Fig. 5b, d). Patterns apparent in *Nature's Notebook* were mixed, with large increases in the proportion of observations reported from within urban areas increasing in states in the Southeast, Northeast, and West, and decreasing in many Great Plains states (Fig. 5c).

3.4. Influence of length of lockdown on participants, observations, and percent urban observations

There was a suggestive but inconclusive positive relationship between the number of days states were in lockdown and the number of participants contributing data to eButterfly by state ($p = 0.103$, adj $r^2 = 0.03$; Table A.5), such that the longer a state was in lockdown, the greater the number of participants contributing in 2020. There were similarly significantly positive relationships between the number of days in lockdown and the percentage of observations submitted from urban areas to both eButterfly ($p = 0.032$, adj $r^2 = 0.07$) and *Nature's Notebook* ($p = 0.066$, adj $r^2 = 0.05$), such that states experiencing longer periods of lockdown were associated with a higher proportion of observations submitted from urban areas. The number of days in lockdown did not show a relationship with the number of participants in iNaturalist, *Nature's Notebook*, or eBird; in the proportion of observations submitted from within urban areas to iNaturalist or eBird; or with the number of observations contributed to any of the programs (Table A.5).

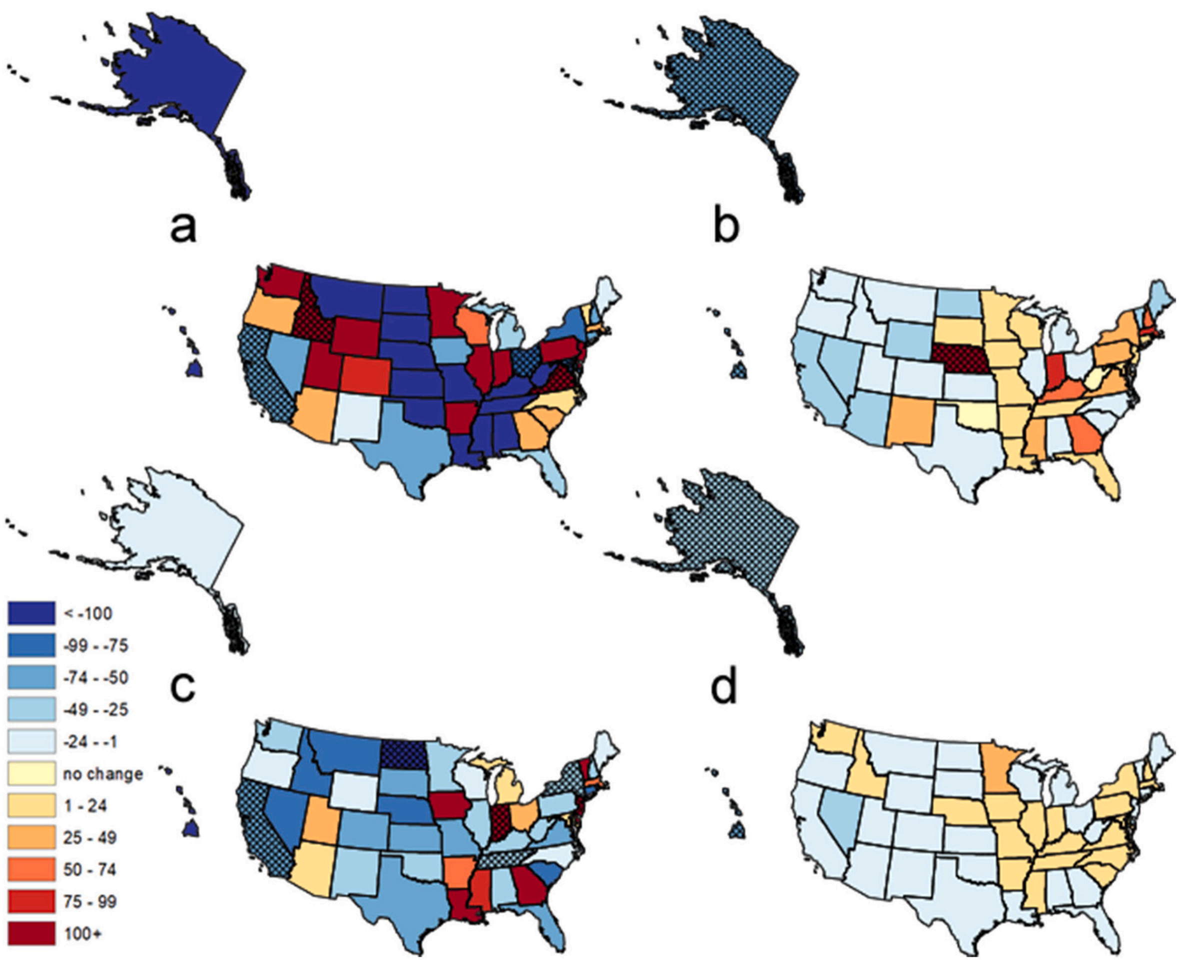

Fig. 4. Percent difference in observed observations submitted in March–June 2020 from the expected number of observations in March–June 2020 based on participation patterns in March–June 2015–2019 in four biodiversity community science programs: a) eButterfly, b) iNaturalist, c) *Nature's Notebook*, and d) eBird. Blue tones indicate fewer observations than expected in 2020; red tones indicate more observations than expected in 2020; hatching indicates a significant difference between predicted and observed number of observations submitted in 2020 ($p < 0.05$). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

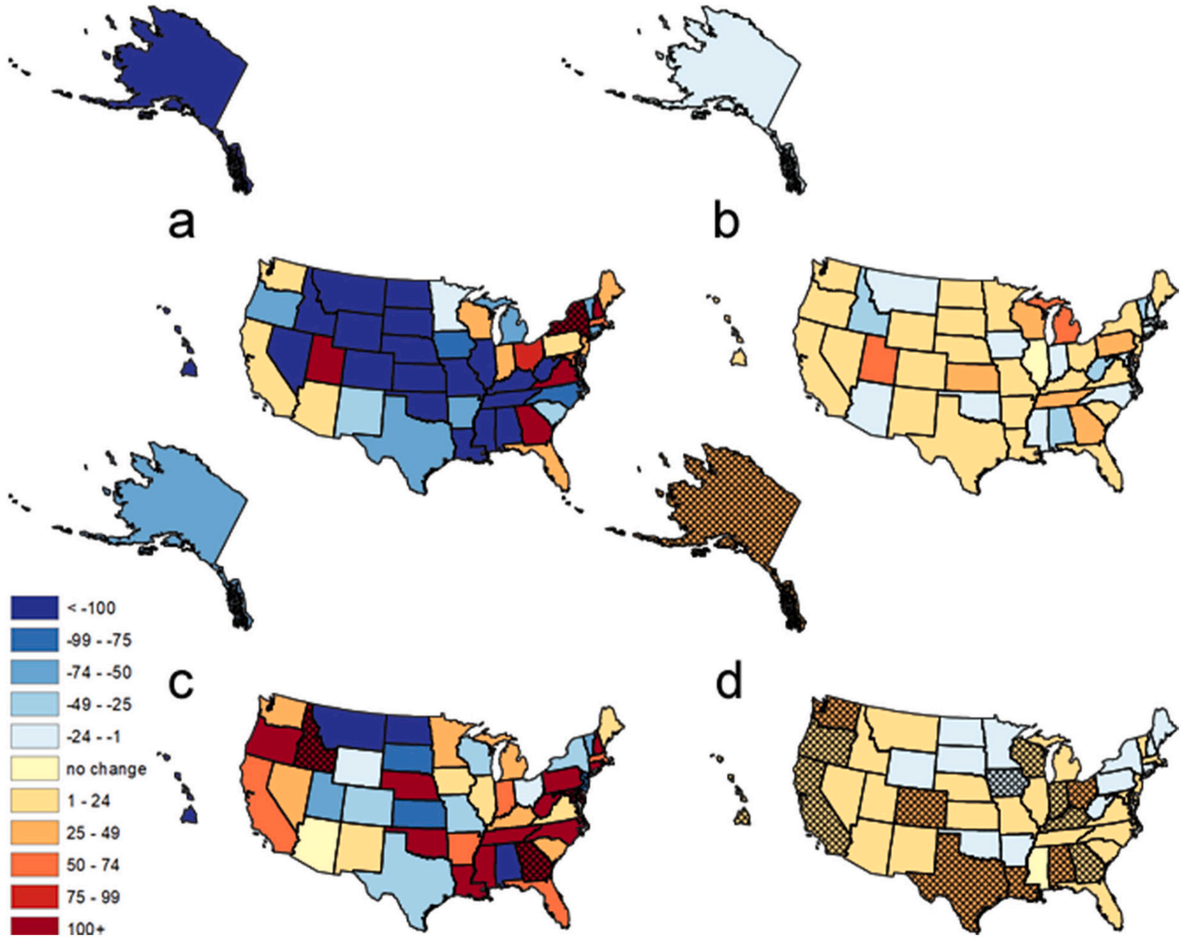

Fig. 5. Percent difference in the proportion of observations submitted from within an urban area in March–June 2020 from the expected proportion of observations submitted from within an urban area in March–June 2020 based on participation patterns in March–June 2015–2019 in four biodiversity community science programs: a) eBButterfly, b) iNaturalist, c) *Nature's Notebook*, and d) eBird. Blue tones indicate a smaller proportion of observations submitted from within urban areas than expected in 2020; red tones indicate a larger proportion of observations submitted from within urban areas than expected in 2020; hatching indicates a significant difference between predicted and observed percent of records submitted from within urban areas in 2020 ($p < 0.05$). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

4. Discussion

This study evaluated impacts of COVID-related stay-at-home orders and widespread closures on the participation and activity level in four biodiversity-themed community science programs in the United States. The four studies evaluated here vary by orders of magnitude in terms of the numbers of participants and observations submitted (Fig. 1). Further, within programs, data contributions vary by geography, with certain states accounting for a large proportion of the participation. This is important because even small changes in participation in states that account for a large proportion of participation can translate to substantial impacts to overall participation numbers for a program.

Overall, the results of this evaluation revealed variable patterns in activity among the programs and across geography - inconsistent with our expectations that all programs would show uniform drops in participation as a consequence of the pandemic. The two programs exhibiting the greatest participation, iNaturalist and eBird, showed similarities in their patterns of change.

4.1. Changes in participant activity varied by program and geography

We had predicted that both the number of participants and the amount of observations submitted across the U.S. in spring 2020 would be fewer than what would have been expected had COVID not occurred. Though we see a clear overall decrease in participants and observations submitted to *Nature's Notebook*, these patterns did not hold for the other three programs. Further, patterns of change varied dramatically among states and programs.

The patterns exhibited in participants and incoming observations across the U.S. in iNaturalist and eBird follow an interesting pattern oriented along a longitudinal gradient. The largest decreases in both metrics were observed in western states and increases were generally observed in eastern states, and a more in-depth assessment should be undertaken to fully evaluate the reasons for this pattern. One explanation for the increases documented in iNaturalist, especially in the Northeast, may be that iNaturalist continued to encourage participation in local and regional BioBlitz events and other community biodiversity projects throughout spring 2020 (City Nature Challenge, 2020). The City Nature Challenge, an event that takes place in cities worldwide and utilizes the iNaturalist platform, occurred late in April in 2020 (City Nature Challenge, 2020). In 2020, 244 cities participated in the City Nature Challenge, a substantial increase over 2019, when 159 cities participated (Young, 2020). Many of the U.S. in the City Nature Challenge in 2020 were concentrated in the eastern portion of the country. In addition, iNaturalist featured instructions on how to participate in the program safely during the pandemic on their homepage from April to June of 2020 (Iwane, 2020); this may also account for increased participation in the program. eBird similarly experienced intense activity in May because of an annual springtime event. Global Big Day, occurring annually in the spring, engages birders worldwide in documenting and celebrating birds. Global Big Day took place on May 9, 2020 and broke records for participation, yielding a larger than 30% increase in participants over 2019 (Team eBird, 2020). Finally, social justice movements such as #BlackBirdersWeek and #BlackInNature that took place in the spring 2020 (Mock, 2020) may also account for the upticks observed in these two programs.

The patterns we see in eButterfly participation for 2020 across states and for the U.S. as a whole is complicated by two factors outside of COVID. First, the program released a new version of the web platform with associated messaging to the community in mid-May; the need to adjust to a new interface may have slowed users' contributions to some extent. Second, reports of butterflies are typically low in spring (March–June) in the U.S. due to their phenology. Patterns in eButterfly participation may be driven by the comparatively low sample sizes in this program.

Nature's Notebook exhibited highly variable patterns of increases and decreases in participants and incoming observations in 2020. The dramatic increases in participation seen in several states, including Indiana, Oklahoma, Louisiana, and Colorado are likely due to the establishment of several new groups of individuals tracking phenology in these states. A unique aspect of *Nature's Notebook* is that monitoring can be undertaken by individuals as well as by community or regionally-organized groups referred to as Local Phenology Programs (LPPs). Organizations such as nature centers, arboreta, land conservancies, and National Wildlife Refuges use *Nature's Notebook* to meet a diversity of outcomes, including asking and answering scientific questions about the impact of environmental change, informing natural resource management and decision-making, and educating and engaging the public. Several new LPPs were established in early 2020 in the states depicting the largest increases in participants; one of these states was the focus of a data collection campaign in late 2019 and early 2020. Newly established LPPs are also the likely reason for the increase in observations seen in several states in 2020, including Indiana and New Jersey. The large increase in participants in Texas is likely the result of the launch of a new campaign focused on tracking juniper pollen in this state in late 2019. The clear decrease in participation and incoming observations observed in California, Tennessee, New York, and other states are likely attributable to closures of public spaces such as parks, nature centers, natural areas, and schools where many active *Nature's Notebook* LPP sites exist.

The mixed patterns we see in participation and incoming data in these four programs in the spring of 2020 are partially in conflict with the reports of record-breaking participation in other community science projects (Bowser et al., 2020; Kubis, 2020; Dinneen, 2020). One reason for such differences may be the way in which volunteers participate: in many of the programs boasting large increases, volunteers participate completely online using a computer or other device. In contrast, the programs evaluated in this study focus on outdoor phenomena, and participants typically step outside to identify or evaluate individual organisms. Many parts of the country were still experiencing inclement weather in March, April, and even into May, which may have encouraged participation in computer-based programs and discouraged participation in programs requiring time spent outside.

We expect that we also see decreases in participation in *Nature's Notebook* and eButterfly because many formerly active participants no longer had time available to dedicate to the efforts during a period characterized by major upheaval and change in both personal and professional lives. Click rates reported by Constant Contact for *Nature's Notebook* newsletters - which remained constant from 2019 to 2020 - support the notion that participants continued to care for the program despite a decline in their participation during spring of 2020. This bodes well for the future of these community science programs, suggesting that once participants feel settled in their lives again, they may reengage.

4.2. Shift toward urban observation locations in more popular programs

We had predicted that participants would log a larger proportion of observations from urban locations in 2020 as a result of the stay-at-home orders issued across the country over the spring period. eBird and iNaturalist exhibited the clearest and most widespread shifts toward increased urban-based observations contributed in 2020. iNaturalist exhibited a clear increase in all three measures, suggesting enthusiastic involvement in this program in urban areas, likely resulting at least in part from major growth in City Nature Challenge events. eBird also showed growth the number of incoming observations, though not in the number of participants, suggesting increased participation, especially in urban areas, by approximately the same number of participants as in spring 2019. A shift toward urban participation during COVID lockdown has been reported for iNaturalist in Europe as well BIOCON-20-00460, this issue.

Findings for eButterfly and *Nature's Notebook* were more mixed. We observed a significant increase in the percent urban observations in New York. We suspect many participants who live in urban areas such as New York City and travel to more butterfly biodiversity spring locations such as the southwest and California switched their behavior to local environs, but more in- depth analysis is needed. Many other states show drops in the proportion of observations submitted from within urban areas in eButterfly; the states showing shifts away from urban areas are also those exhibiting decreases in overall participation (Figs. 3a and 5a).

Patterns of shifts in *Nature's Notebook* show large increases in urban participation in many states, which is likely the result of the USA-NPN's concerted efforts to encourage participants to register new sites and continue monitoring close to home if the facilities where they had previously been collecting observations were closed. Recognizing the potential for significant drops in *Nature's Notebook* activity due to such closures, USA-NPN staff sent email newsletters and social media messages throughout spring 2020 encouraging participants to establish new sites in their yards or nearby, accessible locations to offset the loss of incoming data from sites no longer accessible. The positive relationship between the proportion of observations originating from urban areas and the length of lockdown in both eButterfly and *Nature's Notebook* suggests that participants responded and reoriented their activities to locations closer to their homes. Incidentally, visitation to urban, peri-urban, and other natural areas dramatically increased during stay-at-home lockdowns (Fisher et al., 2020; Goodier and Rayman, 2020), consistent with the large-scale shift toward urban observations in the community science programs evaluated in this study. The increases in urban observations might reflect either increased usage of urban greenspaces or a shift to greater observation activity closer to urban dwellings, or both.

4.3. Conservation implications

Several federal and state agencies and other conservation organizations rely on data from programs such as those evaluated in this study to inform management decision making. For example, data contributed to *Nature's Notebook* have been used to develop phenological indicators of wildfire danger (Nathan et al., 2019); a sudden drop in incoming observations on these indicator species could negatively impact managers assessing wildfire danger in public lands. Similarly, the California Department of Fish and Wildlife leveraged iNaturalist and eBird observations to develop a connectivity plan and identify key land acquisitions to grow and maintain corridors (Jennings et al., 2019). The results of this study demonstrate that pandemic-related shutdowns can have serious consequences on the availability of volunteer-contributed data necessary to support these sorts of management and planning activities. This is especially true for states where community science is more widely adopted and data contribution is high, such as California, which experienced a drop in incoming data in spring 2020 over what was expected based on previous years in all four programs evaluated.

A long-recognized benefit of community science programs is that they contribute valuable insights that are otherwise not possible to achieve. That community science programs fill in gaps in knowledge and understanding is particularly true during pandemic-related closures, when many other forms of monitoring have been shuttered (Pennisi, 2020). One way in which observations contributed through community science programs might prove especially useful is in documenting the changes in wildlife, such as increases in species richness, higher breeding success, and reduced road-killing that have occurred as a result of reduced traffic and other changes associated with pandemic-related closures (Manenti et al., 2020). The results of this study indicate that participation in these volunteer programs have been affected as well; even so, the incoming data stand to provide one of the best approaches for documenting wildlife responses to COVID-related shutdowns. The findings specific to the four programs evaluated here may point to what might be expected regarding patterns in participation and consequent impacts on resultant data in other community science programs and in other countries.

The results of this study also underscore the value of greenspaces and urban and peri-urban parks. The importance of urban greenspaces to support biodiversity as well as mental health during lockdown and closures has rapidly been documented (Kleinschroth and Kowarik, 2020; Slater et al., 2020). We see clear evidence that people appreciate these spaces as opportunities to document wildlife, plants, progression of phenological events like leaf-out and flowering over the course of the season. The closure of many parks and public facilities where participants in *Nature's Notebook* in particular had regularly observed prior to the COVID shutdowns resulted in a clear drop in incoming data in the spring of 2020. Second, it seems highly likely that the greater proportion of observations originating from urban locales during shutdowns is being collected at greenspaces that have remained open, including city parks or open lots. An increased understanding of the importance of greenspaces for the biodiversity they support as well as in maintaining mental health will help city planners manage them as ecosystems (Plummer et al., 2020).

The findings of this analysis offer insights for staff managing biodiversity-themed community science programs. Program staff may use the changes documented here to encourage adaptations to participation that better suit participants' limited options during closures or to emphasize particular activities that better match their current tendencies in participation. For example, the Maryland Department of Natural Resources invited participants to create their own 'State Park' in their local private backyards and share their creations and wildlife observations with others on social media and iNaturalist. Similarly, the California Academy of Sciences, the home of iNaturalist, modified their City Nature Challenge in San Francisco during spring 2020 to accommodate social distancing and travel restrictions (California Academy of Sciences, 2020). The findings of this study may also provide insight for staff to most effectively reinvigorate participants once it is possible to return to pre-shutdown levels of activity.

As well, the pandemic-related changes in program participation documented in this study are important for data users to consider. The clear geographic shifts documented here may result in otherwise inexplicable changes in the composition, abundance, or range of species reported. Likewise, decreases in species reports during the spring of 2020 may be directly traceable to declines in participation in these programs and therefore may necessitate careful use of statistical techniques BIOCON-20-00460, this issue.

5. Conclusions

In this study, we evaluated the impact of the shutdown on participation patterns and rates in four national-scale biodiversity-themed community science programs: eBird, eButterfly, iNaturalist, and *Nature's Notebook*. We had predicted a decline in the number of participants and observations contributed to the four programs as a result of COVID-related lockdowns, but found that patterns were not as clear or stark as we had feared. Overall, *Nature's Notebook* exhibited the largest declines in participants and observations compared to what was expected for spring 2020, and iNaturalist showed large increases over what was expected in both metrics. Further, as predicted, both iNaturalist and eBird experienced significant increases in the proportion of records coming from urban areas. Patterns varied by state and by program. Finally, we anticipated changes in participation to be driven by the length of lockdown; these patterns were weak.

Our findings suggest that participation in the community science programs evaluated had adapted as a result of lifestyle changes imposed by pandemic-related closures. Participants have generally continued their activity, albeit in different locations than previously. Though the numbers of participants generally decreased in some programs compared to what was expected for 2020, the amount of incoming data appears to be impacted to a lesser degree, offering a sense of hope for the future of these programs and the incoming data. That participants in these programs are persevering is encouraging, as the rich and geographically extensive volunteer-contributed reports of plants and animals originating from these programs have the potential to provide important insight into wildlife responses to pandemic-related closures and yield data to offset losses due to the shuttering of formal plant and animal monitoring efforts.

Declaration of competing interest

The authors declare no conflicts of interest.

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Data statement

The data and code used in this analysis are available at https://zenodo.org/record/4430966#.X_uQmlNKiV4.

Appendix A

Table A.1
Total number of participants, observations submitted, and percentage of observations originating from urban areas contributed to eButterfly, iNaturalist, *Nature's Notebook*, and eBird in the U.S., March–June 2015–2020.

Program	Year	Participants	Observations	%Urban observations
eButterfly	2015	318	10,373	28%
	2016	299	8066	22%
	2017	281	10,391	23%
	2018	223	6361	20%
	2019	204	5722	23%
	2020	184	5547	19%
iNaturalist	2015	9963	185,519	36%
	2016	17,745	351,788	37%
	2017	21,242	589,864	38%
	2018	32,876	902,758	40%
	2019	75,578	1,441,358	41%
	2020	110,023	1,945,420	45%
Nature's Notebook	2015	1411	107,850	30%
	2016	1582	106,068	44%
	2017	1922	123,691	46%
	2018	2188	132,627	44%
	2019	1937	126,387	47%
	2020	1744	98,256	51%
eBird	2015	66,846	1265,152	38%
	2016	79,622	1,464,060	37%
	2017	91,016	1744,873	38%
	2018	107,925	2,144,422	39%
	2019	130,385	2,486,899	39%
	2020	128,225	2,948,944	46%

Table A.2
Model selection.

Program	y	Model selected
eButterfly	Observations	Linear
	Participants	Linear
	%Urban	Linear
iNaturalist	Observations	Polynomial
	Participants	Polynomial
	%Urban	Linear
Nature's Notebook	Observations	Linear
	Participants	Linear
	%Urban	Polynomial
eBird	Observations	Linear
	Participants	Linear
	%Urban	Polynomial

Table A.3
Predicted 2020 counts, observed 2020 counts, 95% predicted 2020 interval, and percent change between predicted and observed participants, contributed observations, and percent of observations originating from within urban areas, March–June 2020, for four community science programs. *Denotes 2020 actual value falls outside of 95% prediction interval.

Program	Observed 2020 participants	Predicted 2020 participants	95% prediction interval	Percent change (observed vs. predicted 2020 participants)
Nature's Notebook	1744	2328	1460–3195	−25
eButterfly	184	174	116–231	6
iNaturalist	110,023	75,389	12,331–138,448	46
eBird	128,225	141,773	123,001–160,545	−10

Program	Observed 2020 observations	Predicted 2020 observations	95% prediction interval	Percent change (observed vs. predicted 2020 observations)
Nature's Notebook	98,256	138,415	105,980–170,849	−29*
eButterfly	5547	4880	0–11,898	13
iNaturalist	1,945,420	1,613,212	1014,473–2,211,951	21
eBird	2,948,944	2,758,238	2,439,344–3,077,132	7

Program	Observed 2020 %urban observations	Predicted 2020 %urban observations	95% prediction interval	Percent change (observed vs. predicted 2020 %urban observations)
	51%	56%	30–75%	−3%

(continued on next page)

Table A.3 (*continued*)

Program	Observed 2020 %urban observations	Predicted 2020 %urban observations	95% prediction interval	Percent change (observed vs. predicted 2020 %urban observations)
Nature's Notebook				
eButterfly	19%	20%	8–32%	−5%
iNaturalist	45%	43%	41–44%	6%*
eBird	46%	40%	37–42%	16%*

Table A.4

Predicted 2020 counts, observed 2020 counts, 95% predicted 2020 interval, and percent change between predicted and observed participants, contributed observations, and percent of observations originating from within urban areas by state, March–June 2020, for four community science programs. *Denotes 2020 actual value falls outside of 95% prediction interval. Tables are sorted by number of observations, participants, or %urban observations reported in 2020.

Table A.4.a. eButterfly predicted and observed counts of observations.

State	2020 observations	Predicted 2020 observations	95% prediction interval	Percent difference
South Carolina	1108	748	336–1305	48
Virginia	646	303	71–643	113*
Vermont	637	567	230–1062	12
Arizona	396	317	77–682	25
Massachusetts	294	223	42–553	32
Texas	254	579	240–1045	−56
North Carolina	246	230	50–596	7
California	242	624	267–1158	−61*
Arkansas	219	85	0–311	158
Idaho	196	2	0–89	11278*
New Jersey	191	64	0–270	200
Florida	183	295	69–689	−38
Michigan	140	227	35–513	−38
Georgia	112	84	0–329	34
Rhode Island	83	46	0–228	79
Maryland	73	308	79–684	−76*
Pennsylvania	72	12	0–142	504
Maine	70	76	0–319	−8
Indiana	67	22	0–161	201
New Mexico	58	72	0–290	−19
Washington	51	9	0–123	443
Utah	34	1	0–56	6445
Oregon	33	23	0–176	41
Wisconsin	30	19	0–168	60
Iowa	23	63	0–288	−63
Colorado	21	11	0–137	83
Minnesota	18	1	0–90	1135
Connecticut	12	47	0–241	−74
New York	12	74	0–298	−84
New Hampshire	11	30	0–196	−63
Ohio	8	189	31–471	−96*
Delaware	2	0	0–61	2413
Illinois	2	0	0–70	7111
Nevada	2	6	0–131	−67
Wyoming	1	0	0–83	223
Alabama	0	7	0–125	−100
Alaska	0	5	0–128	−100
District of Columbia	0	0	0–67	−100
Hawaii	0	0	0–89	−100
Kansas	0	1	0–83	−100
Kentucky	0	0	0–65	−100
Louisiana	0	1	0–88	−100
Mississippi	0	2	0–46	−100
Missouri	0	18	0–178	−100
Montana	0	1	0–89	−100
Nebraska	0	1	0–55	−100
North Dakota	0	4	0–43	−100
Oklahoma	0	0	0–89	−100
South Dakota	0	3	0–49	−100
Tennessee	0	2	0–106	−100
West Virginia	0	8	0–131	−100

Table A.4.b. eButterfly predicted and observed counts of participants.

State	2020 participants	Predicted 2020 participants	95% prediction interval	Percent difference
Vermont	20	18	9–30	14
Virginia	19	14	5–25	40

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Table A.4 (*continued*)

Table A.4.b. eButterfly predicted and observed counts of participants.

State	2020 participants	Predicted 2020 participants	95% prediction interval	Percent difference
Arizona	12	8	2–18	56
Massachusetts	12	5	1–13	143
California	11	17	7–29	−35
South Carolina	10	8	2–18	23
Michigan	9	9	3–19	0
North Carolina	9	12	4–23	−22
Washington	7	3	0–10	130
Florida	5	13	5–25	−62*
Maine	5	4	0–11	35
Maryland	5	6	1–15	−16
New Jersey	5	4	0–10	39
New Mexico	5	2	0–8	108
Ohio	5	5	1–13	−1
Connecticut	4	2	0–8	80
Pennsylvania	4	4	1–11	−8
Texas	4	11	4–22	−64
Georgia	3	6	1–14	−46
Iowa	3	1	0–6	114
New Hampshire	3	4	0–11	−19
Rhode Island	3	1	0–6	213
Utah	3	0	1–3	2373*
Arkansas	2	1	0–7	52
Colorado	2	2	0–8	−12
Minnesota	2	1	0–5	203
New York	2	6	1–15	−67
Oregon	2	3	0–10	−40
Wisconsin	2	2	0–7	32
Delaware	1	0	1–4	175
Idaho	1	1	0–6	1
Illinois	1	0	0–4	109
Indiana	1	2	0–8	−55
Nevada	1	1	0–5	−6
Wyoming	1	0	1–3	925
Alabama	0	1	0–6	−100*
Alaska	0	3	0–9	−100*
District of Columbia	0	0	0–4	−100*
Hawaii	0	0	1–2	−100*
Kansas	0	0	1–3	−100*
Kentucky	0	0	1–3	−100*
Louisiana	0	1	0–5	−100*
Mississippi	0	0	1–2	−100*
Missouri	0	2	0–7	−100*
Montana	0	0	0–4	−100*
Nebraska	0	0	1–2	−100*
North Dakota	0	0	2–1	−100*
Oklahoma	0	0	0–4	−100*
South Dakota	0	0	1–2	−100*
Tennessee	0	1	0–6	−100*
West Virginia	0	1	0–5	−100*

Table A.4.c. eButterfly predicted and observed percent of observations originating from urban areas. Prediction intervals >100% are reported to indicate the size of the interval, even though >100% is not possible.

State	2020 %urban observations	Predicted 2020 %urban observations	95% prediction interval	Percent difference 2020
New York	67	13	−36–63	394*
Ohio	63	32	−20–80	95
Georgia	62	24	−24–75	156
New Hampshire	55	7	−42–58	640
Arizona	45	38	−23–77	17
Maryland	45	26	−7–88	71
Massachusetts	45	27	−20–78	68
Indiana	43	32	−19–85	37
Florida	37	27	−20–78	38
Wisconsin	37	29	−21–78	28
New Jersey	36	25	−21–78	43
Virginia	33	16	−35–65	108
Washington	18	17	−33–65	3
California	17	16	−33–66	9
Pennsylvania	14	12	−39–61	19
Maine	13	9	−40–59	36
Utah	12	5	−47–53	144
Rhode Island	11	31	−15–83	−66
Texas	10	23	−26–74	−55
Iowa	9	44	−19–81	−80

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Table A.4 (*continued*)

Table A.4.c. eButterfly predicted and observed percent of observations originating from urban areas. Prediction intervals >100% are reported to indicate the size of the interval, even though >100% is not possible.

State	2020 %urban observations	Predicted 2020 %urban observations	95% prediction interval	Percent difference 2020
New Mexico	9	16	−5–90	−47
Oregon	9	30	−34–68	−70
Connecticut	8	19	−32–68	−55
Vermont	7	15	−34–65	−54
Minnesota	6	6	−24–76	−7
North Carolina	6	27	−44–54	−79
South Carolina	5	9	−40–59	−44
Michigan	4	14	−34–64	−69
Arkansas	2	4	−45–53	−51
Alabama	0	6	−42–56	−100
Alaska	0	19	−29–68	−100
Colorado	0	8	−40–59	−100
Delaware	0	23	−23–73	−100
District of Columbia	0	57	7–104	−100*
Hawaii	0	20	−27–72	−100
Idaho	0	16	−32–67	−100
Illinois	0	28	−21–80	−100
Kansas	0	6	−44–59	−100
Kentucky	0	17	−31–64	−100
Louisiana	0	35	−14–82	−100
Mississippi	0	17	−29–61	−100
Missouri	0	2	−50–51	−100
Montana	0	4	−48–57	−100
Nebraska	0	4	−46–51	−100
Nevada	0	9	−38–56	−100
North Dakota	0	4	−48–55	−100
Oklahoma	0	11	−40–64	−100
South Dakota	0	4	−47–51	−100
Tennessee	0	4	−43–54	−100
West Virginia	0	3	−44–57	−100
Wyoming	0	3	−43–54	−100

Table A.4.d. iNaturalist predicted and observed counts of observations.

State	2020 observations	Predicted 2020 observations	95% prediction interval	Percent difference
California	421,217	646,163	298,846–1,371,409	−35
Texas	324,382	417,169	191,859–847,278	−22
Florida	102,353	89,616	38,673–196,973	14
New York	69,034	55,263	24,233–125,965	25
Virginia	64,914	48,953	21,810–111,707	33
Massachusetts	62,134	34,308	15,718–79,581	81
North Carolina	57,913	54,998	23,821–128,904	5
Ohio	56,446	63,488	28,495–148,840	−11
Pennsylvania	53,803	39,138	18,068–90,312	37
New Jersey	51,865	45,634	20,711–102,604	14
Maryland	48,320	44,035	19,535–99,190	10
Illinois	46,632	51,279	22,674–121,561	−9
Washington	34,030	39,698	18,419–91,715	−14
Oregon	33,731	37,700	16,826–83,479	−11
Arizona	32,992	60,004	26,386–135,104	−45
Vermont	31,067	62,015	27,096–140,588	−50
Minnesota	30,584	25,307	10,970–57,865	21
Wisconsin	27,845	26,248	12,412–59,896	6
Tennessee	27,436	24,027	10,716–54,993	14
Georgia	25,908	15,146	6783–34,783	71
Alabama	25,809	27,035	12,479–57,656	−5
Michigan	25,430	27,326	11,988–63,880	−7
Colorado	23,825	25,432	11,158–58,757	−6
Louisiana	21,120	16,983	7511–40,129	24
New Mexico	20,597	15,388	6991–33,828	34
Arkansas	18,297	15,936	7017–34,138	15
Oklahoma	17,626	17,294	7542–38,104	2
Indiana	14,546	7444	3376–17,452	95
Missouri	13,430	11,929	5068–26,152	13
South Carolina	13,363	16,100	6898–35,862	−17
Connecticut	13,021	12,398	5551–25,433	5
Utah	12,369	12,579	5704–29,990	−2
New Hampshire	11,881	7538	3498–16,869	58
Mississippi	11,638	7725	3365–18,211	51
Nevada	11,224	16,394	7787–40,065	−32
Kentucky	10,675	6795	3021–15,530	57
Idaho	8260	9394	4382–20,943	−12
Nebraska	8220	3214	1359–7286	156*

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Table A.4 (*continued*)

Table A.4.d. iNaturalist predicted and observed counts of observations.

State	2020 observations	Predicted 2020 observations	95% prediction interval	Percent difference
Maine	7877	11,197	4725–26,598	−30
Kansas	7470	8675	3833–18,720	−14
Alaska	7418	16,885	6830–36,057	−56
West Virginia	5925	5862	2613–13,397	1
Hawaii	5594	17,054	7854–38,337	−67*
Iowa	4845	4106	1760–9393	18
Rhode Island	4416	1667	701–3778	165*
Montana	4204	4268	1824–9863	−1
District of Columbia	3897	7608	3223–17,827	−49
Delaware	3573	4704	2054–10,395	−24
South Dakota	2879	2690	1207–6258	7
Wyoming	2573	3980	1830–8782	−35
North Dakota	812	1338	592–2835	−39

Table A.4.e. iNaturalist predicted and observed counts of participants.

State	2020 participants	Predicted 2020 participants	95% prediction interval	Percent difference
California	17,307	30,102	17,997–51,653	−43*
Texas	11,120	16,064	9115–27,829	−31
Florida	7534	8086	4815–14,115	−7
New York	4437	4953	2772–8669	−10
North Carolina	4371	4547	2657–7939	−4
Pennsylvania	3882	3467	2037–5890	12
Virginia	3755	4587	2715–8345	−18
Massachusetts	3653	3846	2239–6782	−5
Ohio	3195	4254	2525–7687	−25
Maryland	2865	3020	1665–5466	−5
Washington	2864	3528	2126–6215	−19
Georgia	2628	2128	1280–3624	24
Illinois	2375	2815	1656–4924	−16
New Jersey	2173	2136	1226–3626	2
Oregon	2166	3486	2030–6194	−38
Minnesota	2110	2197	1306–3891	−4
Tennessee	2102	2216	1332–3886	−5
Arizona	2087	3898	2178–6472	−46*
Colorado	1984	3243	1853–5443	−39
Michigan	1971	2044	1238–3664	−4
Wisconsin	1670	1904	1079–3178	−12
Missouri	1612	1393	843–2416	16
Connecticut	1456	1265	730–2201	15
Alabama	1407	1667	947–2963	−16
Vermont	1372	2366	1389–4116	−42*
Utah	1342	1836	1099–3300	−27
Indiana	1335	1201	701–2060	11
South Carolina	1300	1615	917–2826	−19
Louisiana	1149	1431	836–2488	−20
New Hampshire	1054	1013	594–1726	4
Oklahoma	1030	1138	666–1980	−10
New Mexico	963	1527	874–2658	−37
Arkansas	929	1082	641–1941	−14
Kentucky	884	1113	634–1874	−21
Maine	818	1131	664–1999	−28
Nebraska	788	594	336–1014	33
Hawaii	592	1727	1022–2941	−66*
Nevada	580	1355	820–2313	−57*
Idaho	579	1017	579–1796	−43
Iowa	555	645	385–1112	−14
Kansas	524	649	390–1240	−19
Mississippi	519	756	420–1291	−31
West Virginia	495	690	401–1206	−28
District of Columbia	467	1079	619–1868	−57*
Montana	448	845	465–1428	−47*
Rhode Island	399	320	180–547	24
Delaware	344	493	285–862	−30
Wyoming	304	752	421–1318	−60*
Alaska	242	1084	617–1870	−78*
South Dakota	213	363	215–621	−41*
North Dakota	74	196	112–343	−62*

Table A.4.f. iNaturalist predicted and observed percent of observations originating from urban areas. Prediction intervals >100% are reported to indicate the size of the interval, even though >100% is not possible.

State	2020 %urban observations	Predicted 2020 %urban observations	95% prediction interval	Percent difference

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Table A.4 (*continued*)

Table A.4.f. iNaturalist predicted and observed percent of observations originating from urban areas. Prediction intervals >100% are reported to indicate the size of the interval, even though >100% is not possible.

State	2020 %urban observations	Predicted 2020 %urban observations	95% prediction interval	Percent difference
District of Columbia	100	102	88–117	−2
New Jersey	64	63	47–78	2
New York	62	57	43–72	8
Illinois	58	58	42–73	0
Massachusetts	57	73	57–87	−21
Virginia	57	55	40–70	4
Georgia	55	41	41–70	33
Maryland	55	56	25–56	−2
Pennsylvania	55	41	28–56	32
Connecticut	54	60	34–65	−10
Rhode Island	54	49	45–75	9
Texas	51	48	34–63	5
Florida	48	44	29–58	9
Louisiana	46	44	24–53	4
Missouri	46	39	29–60	20
Washington	46	40	25–55	15
Indiana	45	54	38–69	−16
North Carolina	45	52	24–53	−14
South Carolina	45	39	35–65	16
Minnesota	44	40	25–55	11
Tennessee	44	31	17–46	44
California	43	42	27–57	4
Nebraska	42	40	26–56	5
Michigan	41	26	11–41	57*
Ohio	41	40	26–55	2
Kansas	39	27	12–42	43
Utah	38	25	10–39	53
Oklahoma	37	37	21–52	−1
Colorado	35	32	11–41	12
Delaware	35	26	17–47	38
Hawaii	34	34	18–49	1
Oregon	34	31	17–48	9
Wisconsin	34	24	10–39	40
Iowa	33	34	19–49	−4
Alabama	30	45	30–59	−33
Arizona	26	27	8–37	−2
Arkansas	26	23	12–42	13
Nevada	26	26	9–41	0
Maine	23	19	4–34	23
Mississippi	23	29	14–44	−21
New Mexico	22	20	7–36	10
Kentucky	21	20	4–35	7
West Virginia	21	31	17–47	−32
Alaska	20	20	5–36	−2
Idaho	18	23	1–32	−23
North Dakota	18	16	8–39	10
Montana	17	19	5–34	−12
New Hampshire	16	19	3–33	−17
South Dakota	15	13	6–34	13
Vermont	15	20	−1–28	−26
Wyoming	10	8	−7–22	27

Table A.4.g. *Nature's Notebook* predicted and observed counts of observations.

State	2020 observations	Predicted 2020 observations	95% prediction interval	Percent difference
Massachusetts	12,238	8075	4687–12,627	52
New York	9712	15,005	9730–20,572	−35*
Minnesota	9385	13,879	8997–19,570	−32
Arizona	7720	6290	3218–10,248	23
Michigan	7137	6783	3616–11,565	5
Tennessee	6072	11,694	7169–17,093	−48*
California	5699	15,462	10,506–21,709	−63*
Maine	4565	4633	2157–8290	−1
Indiana	3515	802	37–2522	338*
North Carolina	3463	4214	1895–7625	−18
New Hampshire	2722	4223	1747–7424	−36
Colorado	2209	4520	1864–7998	−51
Ohio	2161	1454	260–3463	49
Oregon	1842	1980	449–4466	−7
Illinois	1800	2580	808–5483	−30
Pennsylvania	1726	2401	689–4940	−28
New Jersey	1665	144	0–1146	1053*
Louisiana	1477	492	0–1951	200

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Table A.4 (*continued*)

Table A.4.g. *Nature's Notebook* predicted and observed counts of observations.

State	2020 observations	Predicted 2020 observations	95% prediction interval	Percent difference
Maryland	1452	1348	200–3448	8
New Mexico	1085	1865	413–4157	−42
Texas	1030	2311	536–4942	−55
Washington	856	1559	304–3729	−45
Wisconsin	834	915	67–2789	−9
Georgia	795	368	0–1859	116
Virginia	790	2424	723–5119	−67
Florida	709	1906	493–4379	−63
Mississippi	707	392	0–1786	80
Iowa	599	256	0–1453	134
Utah	483	386	0–1746	25
Kentucky	436	678	16–2286	−36
West Virginia	381	740	40–2548	−48
Arkansas	372	230	0–1397	62
Kansas	356	708	17–2319	−50
South Dakota	343	901	57–2884	−62
Vermont	325	155	0–1248	109
Wyoming	320	358	0–1727	−11
Alabama	277	503	0–2061	−45
Alaska	222	226	0–1503	−2
Missouri	205	794	27–2689	−74
District of Columbia	138	246	0–1478	−44
Delaware	130	50	0–814	158
South Carolina	99	970	71–2746	−90
Oklahoma	65	105	0–1085	−38
Connecticut	54	403	0–1843	−87
Montana	47	584	1–2090	−92
Rhode Island	20	66	0–982	−70
Idaho	13	355	0–1666	−96
Nebraska	4	95	0–1148	−96
Nevada	1	154	0–1218	−99
Hawaii	0	56	0–1009	−100
North Dakota	0	543	7–1953	−100*

Table A.4.h. *Nature's Notebook* predicted and observed counts of participants.

State	2020 participants	Predicted 2020 participants	95% prediction interval	Percent difference
New York	231	190	114–303	22
Texas	179	30	6–77	491*
Massachusetts	130	132	62–220	−1
California	88	250	160–364	−65*
Arizona	81	104	48–186	−22
North Carolina	76	73	25–138	4
Minnesota	66	97	39–174	−32
Colorado	65	118	56–207	−45
Michigan	64	50	13–105	28
Pennsylvania	63	53	15–113	19
Illinois	62	53	17–116	16
Maine	61	79	32–148	−22
Oregon	45	61	20–121	−27
Tennessee	35	60	21–125	−41
Washington	34	31	5–76	11
Indiana	33	18	1–56	85
Maryland	31	51	15–106	−39
New Hampshire	31	30	4–74	4
Wisconsin	31	30	5–73	4
New Mexico	30	35	8–88	−15
Ohio	30	25	2–70	22
Virginia	30	49	14–106	−39
Oklahoma	27	6	0–34	362
Louisiana	24	11	0–43	110
Wyoming	19	11	0–45	66
Kentucky	18	112	53–193	−84*
South Dakota	15	17	0–57	−10
Utah	15	15	0–52	−2
District of Columbia	13	16	0–51	−18
New Jersey	12	13	0–47	−6
Kansas	11	21	2–59	−47
Mississippi	11	8	0–38	30
Florida	10	31	5–82	−68
Missouri	10	21	1–63	−52
West Virginia	9	24	3–68	−62
Vermont	8	10	0–42	−17
Connecticut	7	10	0–44	−31

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Table A.4 (*continued*)

Table A.4.h. *Nature's Notebook* predicted and observed counts of participants.

State	2020 participants	Predicted 2020 participants	95% prediction interval	Percent difference
Georgia	7	15	0–51	−54
Iowa	6	12	0–45	−51
Montana	5	9	0–39	−41
Arkansas	4	8	0–36	−49
Alaska	3	7	0–34	−59
Idaho	3	23	2–73	−87
Nebraska	3	6	0–35	−52
Delaware	2	3	0–26	−22
Rhode Island	2	4	0–27	−45
South Carolina	2	7	0–34	−69
Alabama	1	9	0–39	−89
Nevada	1	6	0–34	−85
Hawaii	0	6	0–32	−100
North Dakota	0	16	0–55	−100*

Table A.4.i. *Nature's Notebook* predicted and observed percent of observations originating from urban areas. Prediction intervals >100% are reported to indicate the size of the interval, even though >100% is not possible.

State	2020 %urban observations	Predicted 2020 %urban observations	95% prediction interval	Percent difference
District of Columbia	100	86	29–141	17
Nevada	100	74	19–129	35
South Carolina	100	69	15–127	44
Rhode Island	100	50	−7–105	99
Idaho	100	44	−10–98	127*
Delaware	100	17	−34–71	483*
Kentucky	100	80	24–134	25
Georgia	99	29	−26–85	240*
Florida	99	58	5–113	70
Oklahoma	95	47	−8–104	103
Michigan	95	66	13–128	44
Arkansas	92	61	9–116	50
Maryland	91	34	−18–87	168*
Indiana	84	51	−3–107	64
Illinois	79	66	10–124	20
Oregon	78	27	−27–83	190
West Virginia	72	33	−21–90	117
Washington	71	55	2–110	30
Massachusetts	71	47	−4–99	50
Connecticut	70	28	−23–84	152
Virginia	67	57	2–110	18
Iowa	59	51	−4–102	15
Texas	59	81	29–132	−27
Mississippi	58	17	−40–73	234
North Carolina	56	22	−30–74	157
Wyoming	51	56	4–111	−9
Pennsylvania	50	25	−28–83	104
Ohio	50	63	2–119	−20
Nebraska	50	20	−38–72	148
Minnesota	45	31	−27–89	45
Arizona	43	43	−10–96	0
New Mexico	43	36	−20–92	20
Wisconsin	42	62	6–116	−33
Maine	39	32	−23–85	22
Louisiana	36	5	−55–61	638
New York	34	46	−5–101	−25
California	32	21	−39–81	54
Colorado	28	49	−7–100	−43
Utah	26	56	−1–110	−54
Missouri	21	31	−25–81	−32
New Hampshire	17	1	−53–58	1508
Tennessee	12	4	−53–58	213
Vermont	10	27	−26–84	−63
Alaska	8	24	−35–76	−68
South Dakota	7	59	6–112	−89
New Jersey	5	71	19–127	−93*
Kansas	2	12	−40–67	−84
Alabama	0	36	−19–92	−100
Hawaii	0	19	−32–77	−100
Montana	0	11	−44–68	−100
North Dakota	0	35	−21–88	−100

Table A.4.j. eBird predicted and observed counts of observations.

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Table A.4 (*continued*)

Table A.4.j. eBird predicted and observed counts of observations.

State	2020 observations	Predicted 2020 observations	95% prediction interval	Percent difference
State	2020 observations	Predicted 2020 observations	95% prediction interval	Percent difference
New York	218,659	193,087	138,498–263,557	13
California	213,295	242,914	170,640–340,753	−12
Pennsylvania	150,625	141,104	98,730–199,461	7
Texas	142,329	183,661	131,394–254,042	−23
Florida	124,574	144,507	103,823–199,484	−14
Michigan	121,443	128,107	93,063–177,884	−5
Ohio	113,267	119,427	85,514–166,551	−5
Washington	104,635	99,251	70,081–140,343	5
Massachusetts	102,812	95,707	69,494–136,349	7
Wisconsin	100,974	120,192	86,576–168,677	−16
Virginia	97,540	90,976	64,118–129,777	7
Colorado	96,765	102,331	74,187–144,880	−5
Illinois	96,251	96,219	70,344–134,582	0
Oregon	93,816	106,668	75,532–151,217	−12
Maryland	90,380	73,715	52,453–105,951	23
Minnesota	86,422	69,095	49,730–95,886	25
Arizona	71,975	95,744	67,924–133,395	−25
North Carolina	71,618	60,374	42,985–84,597	19
New Jersey	65,790	74,360	52,729–104,084	−12
Indiana	53,294	47,535	33,904–66,255	12
Maine	51,133	58,214	40,629–80,450	−12
Georgia	46,017	52,421	36,887–71,876	−12
Connecticut	45,663	48,831	36,021–68,532	−6
Tennessee	40,169	38,444	27,639–55,040	4
Missouri	39,218	33,731	23,977–46,735	16
Vermont	38,630	42,852	30,649–61,221	−10
New Mexico	32,585	34,544	24,331–49,447	−6
Montana	32,076	40,364	28,503–55,613	−21
South Carolina	30,587	29,147	20,263–40,799	5
New Hampshire	30,463	28,789	20,374–40,543	6
Kansas	29,057	34,048	24,441–48,024	−15
Utah	28,953	34,712	24,509–50,626	−17
Idaho	28,661	25,750	18,519–36,328	11
Alaska	22,279	39,909	28,803–55,014	−44*
Kentucky	21,007	18,452	12,969–25,513	14
Iowa	20,324	20,069	14,159–28,504	1
Louisiana	18,950	21,666	15,859–30,553	−13
Alabama	18,849	19,737	14,349–27,406	−5
Nebraska	17,612	16,371	11,662–22,938	8
Wyoming	15,586	16,382	11,709–23,148	−5
Oklahoma	15,286	18,772	13,428–26,233	−19
North Dakota	14,601	15,578	11,287–21,891	−6
Arkansas	14,477	13,724	9760–19,093	5
West Virginia	12,870	14,848	10,603–21,057	−13
Delaware	12,505	16,711	11,794–23,176	−25
Mississippi	10,798	10,663	7745–14,983	1
Rhode Island	10,436	9299	6558–13,094	12
South Dakota	10,324	11,724	8293–16,479	−12
Nevada	9945	13,610	9758–19,056	−27
District of Columbia	8446	7376	5246–10,219	15
Hawaii	4973	10,543	7518–14,804	−53*

Table A.4.k. eBird predicted and observed counts of participants.

State	2020 participants	Predicted 2020 participants	95% prediction interval	Percent difference
California	9385	12,104	9355–15,317	−22
New York	8039	7965	6227–10,180	1
Texas	6012	8267	6580–10,418	−27*
Florida	5879	8233	6567–10,253	−29*
Pennsylvania	5872	5871	4602–7406	0
Ohio	4559	5817	4558–7320	−22*
Virginia	4456	4796	3734–6148	−7
Massachusetts	4391	4703	3687–5968	−7
Washington	4376	4754	3763–6079	−8
Michigan	4369	5039	4019–6369	−13
Illinois	4004	4326	3389–5533	−7
North Carolina	3935	4101	3232–5258	−4
Wisconsin	3842	4539	3561–5677	−15
Colorado	3777	4439	3497–5632	−15
Maryland	3470	3641	2854–4589	−5
Arizona	3204	5087	3969–6421	−37*
New Jersey	3188	4126	3267–5162	−23*

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Table A.4 (*continued*)

Table A.4.k. eBird predicted and observed counts of participants.

State	2020 participants	Predicted 2020 participants	95% prediction interval	Percent difference
Oregon	3097	3637	2858–4619	−15
Minnesota	2793	3141	2510–3937	−11
Georgia	2705	3157	2447–4036	−14
Indiana	2551	2598	2058–3293	−2
Tennessee	2085	2378	1880–3041	−12
Connecticut	2015	2139	1695–2674	−6
Missouri	2007	2153	1718–2744	−7
South Carolina	1999	2542	1996–3174	−21
Maine	1878	2814	2237–3525	−33*
Utah	1654	2281	1798–2875	−27*
New Mexico	1511	2276	1786–2896	−34*
New Hampshire	1416	1830	1449–2301	−23*
Vermont	1374	1779	1387–2258	−23*
Montana	1344	1644	1289–2098	−18
Idaho	1314	1397	1090–1765	−6
Kentucky	1139	1361	1055–1733	−16
Iowa	1130	1259	987–1600	−10
Kansas	1123	1463	1156–1880	−23*
Alabama	1114	1402	1090–1761	−21
Louisiana	1033	1537	1222–1953	−33*
Oklahoma	934	1300	1019–1639	−28*
Delaware	924	1513	1196–1915	−39*
West Virginia	920	1204	925–1541	−24*
Wyoming	903	1348	1065–1706	−33*
Nebraska	895	1060	841–1339	−16
Arkansas	857	1041	819–1315	−18
Rhode Island	740	712	560–904	4
Nevada	735	1356	1078–1711	−46*
Alaska	725	1694	1328–2162	−57*
District of Columbia	651	951	741–1213	−32*
Mississippi	634	842	661–1075	−25*
South Dakota	510	655	521–823	−22*
North Dakota	413	597	460–761	−31*
Hawaii	344	847	669–1073	−59*

Table A.4.l. eBird predicted and observed percent of observations originating from urban areas. Prediction intervals >100% are reported to indicate the size of the interval, even though >100% is not possible.

State	Observed 2020 %urban observations	Predicted 2020 %urban observations	95% prediction interval	Percent difference 2020 observations (observed – predicted / predicted * 100)
District of Columbia	100	103	97–110	−3
Illinois	63	63	57–68	1
New Jersey	61	56	50–62	8
Florida	60	55	49–61	8
Massachusetts	60	60	54–65	0
Connecticut	59	64	58–70	−8
Georgia	58	52	46–58	11*
California	57	48	43–54	18*
Rhode Island	54	49	43–54	11
Washington	53	40	35–46	33*
Louisiana	51	37	31–42	40*
Maryland	50	49	43–55	3
Kentucky	49	43	38–49	13*
North Carolina	49	46	40–52	6
Texas	49	39	34–45	24*
Virginia	49	46	40–52	5
Ohio	47	38	32–44	25*
Colorado	46	36	30–42	26*
Tennessee	46	41	35–47	11
Minnesota	45	46	40–52	−3
South Carolina	45	41	35–47	9
Alabama	44	35	29–41	27*
Pennsylvania	44	45	39–50	−3
Indiana	43	37	32–43	17*
New York	43	46	40–52	−8
Oregon	42	36	30–41	18*
Hawaii	41	35	29–41	17*
Mississippi	41	41	36–47	0
Missouri	41	40	34–47	3
Nevada	40	38	32–44	5
New Mexico	40	35	30–41	14
Michigan	37	36	31–42	1
Wisconsin	37	31	25–36	20*

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Table A.4 (*continued*)

Table A.4.l. eBird predicted and observed percent of observations originating from urban areas. Prediction intervals >100% are reported to indicate the size of the interval, even though >100% is not possible.

State	Observed 2020 %urban observations	Predicted 2020 %urban observations	95% prediction interval	Percent difference 2020 observations (observed – predicted / predicted * 100)
Oklahoma	35	40	34–46	−13
Utah	35	31	25–37	15
Delaware	34	34	28–39	1
Kansas	33	28	22–34	18
New Hampshire	33	34	29–40	−4
Arizona	32	29	24–35	10
Arkansas	32	34	28–40	−6
Alaska	30	23	18–29	29*
Nebraska	29	26	20–31	15
Idaho	26	25	19–31	5
Iowa	26	34	28–39	−21*
Maine	24	25	20–31	−7
West Virginia	22	25	19–31	−13
Montana	21	18	12–24	14
North Dakota	19	20	15–26	−5
Wyoming	19	20	14–26	−8
Vermont	18	17	11–23	8
South Dakota	13	16	10–22	−16

Table A.5

Correlation between the length of stay-at-home orders (days) and counts of 2020 participants 2020 observations, and 2020 percent of observations originating from within urban areas, March–June 2020, for four community science programs.

Program	y	x	Adj r squared	F1,49 statistic	p value	Estimate	Standard error
Nature's Notebook	2020 observations	Length stay at home (days)	−0.01973	0.0327	0.8571		
eButterfly	2020 observations	Length stay at home (days)	−0.01963	0.03732	0.8476		
iNaturalist	2020 observations	Length stay at home (days)	−0.01954	0.04176	0.8389		
eBird	2020 observations	Length stay at home (days)	−0.02041	0.0000615	0.9934		
Nature's Notebook	2020 participants	Length stay at home (days)	−0.01969	0.03467	0.8531		
eButterfly	2020 participants	Length stay at home (days)	0.03397	2.758	0.1031	−3.305	1.99
iNaturalist	2020 participants	Length stay at home (days)	−0.01711	0.159	0.6918		
eBird	2020 participants	Length stay at home (days)	−0.0007943	0.9603	0.3319		
Nature's Notebook	2020 %urban observations	Length stay at home (days)	0.04846	3.547	0.06561	2.788	1.48
eButterfly	2020 %urban observations	Length stay at home (days)	0.07229	4.896	0.03161	1.5966	0.7216
iNaturalist	2020 %urban observations	Length stay at home (days)	−0.01922	0.05694	0.8124		
eBird	2020 %urban observations	Length stay at home (days)	−0.008157	0.5955	0.444		

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