CITIZEN SCIENCE: THEORY AND PRACTICE

iNaturalist Users Exhibit Distinct Spatiotemporal Sampling Preferences, with Implications for Biodiversity Science and Project Planning

RESEARCH ARTICLE

]u[ubiquity press

ERIN L. GRADY
CAITLIN J. CAMPBELL**
COREY T. CALLAGHAN
ROBERT P. GURALNICK**

*Author affiliations can be found in the back matter of this article

**co-senior authors

ABSTRACT

Biodiversity-focused contributory science platforms generate massive quantities of opportunistic records for research, but data are spatially, temporally, and taxonomically biased. While research attempting to quantify these biases abounds, less is known about how varied user motivations and behavior shapes how data accrue. Here, we compare how different iNaturalist user groups prioritize where and when they sample in the southeastern United States. We categorized users by participation level and traveler status, and examined how these groups differentially sample across land cover categories, urban and rural areas, protected land, urban parks, low-income urban neighborhoods, and weekends versus weekdays. We found that highly active users prioritize sampling in biodiversity-rich locations, filling data gaps in natural green spaces and rural areas while perpetuating biases toward protected areas and parks within urban areas. In contrast, casual users tend to primarily incorporate sampling into their daily lives, filling gaps within urban neighborhoods and on non-protected land while perpetuating biases toward developed areas. Local iNaturalist users, especially casual users, were the most likely to sample in low-income census tracts compared with travelers and are important for gap-filling in these underrepresented areas. Understanding how participants with different motivations shape opportunistic biodiversity data can inform contributory project planning and downstream data use. Our results emphasize the importance of recruiting new participants, retaining current participants, and engaging locals in contributory science programs. Further efforts to derive insight from opportunistic biodiversity data may benefit from accounting for variation in motivations of participants and resulting heterogeneity in biases across space and time.

CORRESPONDING AUTHOR:
Erin L. Grady
Florida Museum of Natural History, US
erinlgrady@gmail.com

KEYWORDS:
biodiversity citizen science; iNaturalist; participant behavior; opportunistic sampling; sampling bias; spatial bias

TO CITE THIS ARTICLE:
Grady, E.L., Campbell, C.J., Callaghan, C.T. and Guralnick, R.P. 2026. iNaturalist Users Exhibit Distinct Spatiotemporal Sampling Preferences, with Implications for Biodiversity Science and Project Planning. *Citizen Science: Theory and Practice,* 11(1): 3, pp. 1–15. DOI: https://doi.org/10.5334/cstp.868

INTRODUCTION

Digital biodiversity-focused contributory science platforms—projects within the broader field of citizen science in which participants primarily contribute to data collection—contribute vast quantities of data, enabling novel research at broad spatial, temporal, and taxonomic scales. Such platforms encourage volunteer participants to share observations and engage with a larger community, incentivizing data collection by providing information about the natural world (Campbell et al. 2023). Initiatives vary in structure, ranging from projects with predefined protocols, target taxa, and specific site locations, to more-flexible, opportunistic models that allow contribution with fewer constraints. While flexible approaches broaden participation, they also shape the distribution of observations, which may consequently reflect both social as well as ecological processes (Carlen et al. 2024). Observers upload records in accessible areas, at convenient times, and of taxa of personal interest. Thus, observations often exhibit biases such as a disproportionate focus on developed areas (Di Cecco et al. 2021), protected land (Botts et al. 2011), higher income areas (Estien et al. 2024), and weekends (Courter et al. 2013). These biases are important for both researchers—who must define and account for them to ensure sound ecological inferences—and project planners, who can strategically work to increase data coverage and close gaps in underrepresented areas.

iNaturalist (www.inaturalist.org), one of the most widely used and flexible platforms, relies on opportunistic sampling, allowing participants to make observations anytime, anywhere, and of any taxon. Identification support, through computer vision and volunteer curation, enables participation independent of previous biological training or background. By allowing flexibility in both observation and identification, iNaturalist supports large-scale data collection and broad participation, amassing more than 150 million research-grade observations to date, along with a rapidly growing observer base of more than 3.5 million (iNaturalist 2025). Scientists leverage these records for a wide range of applications, unlocking insights into species interactions (Pernat et al. 2024), the timing of key biological events (Barve et al. 2020), range shifts (Fourcade 2016), phenotypic variation (Davis et al. 2022), and response to environmental change (Callaghan et al. 2020). Simultaneously, community-led data collection fosters increased participation in policy decisions (Callaghan et al. 2025; Overdevest et al. 2004), connection with the natural world (Pocock et al. 2023a), and trust between community members and scientists (Bedessem et al. 2021).

Where, when, and how often a participant makes observations are likely shaped by their motivations (e.g., conservation, personal species lists, learning, coursework), abilities (e.g., financial resources, travel, time), and background (e.g., where they live, education). Likely due to these diverse motivations and factors (Rotman et al. 2014; West et al. 2021), individual observers may exhibit vastly different sampling patterns, differentially contribute to biases, and fill distinct data gaps. While general biases in the structure of observations have been described (Courter et al. 2013; Estien et al. 2024; Di Cecco et al. 2021), much less is known about how these biases are produced by the underlying activity of different users. Understanding the processes that govern which data are generated where and by whom is imperative for encouraging increased engagement, identifying and compensating for underlying biases, and filling gaps in under-sampled areas.

A core aspect of user activity is participation level, which ranges from users who submit a handful of observations to those who contribute hundreds of thousands. As in many contributory science initiatives, a small group of highly-dedicated users produce the majority of observations and generate a large amount of data disproportionate to their number (Di Cecco et al. 2021; Rowley et al. 2019; Wood et al. 2011). While these users are credited with generating the majority of contributory science data, users who make lower-volume contributions represent a far larger number of individuals and collectively contribute considerable data (Boakes et al. 2016). Previous work has found that increased participation levels are associated with greater motivation to contribute to conservation and research (Larson et al. 2020; Lowe et al. 2025). The distinction between highly active and casual users is an important behavioral axis that differs based on motivations, abilities, and backgrounds. These differences provide a useful contrast to test how intensity of engagement shapes where and when biodiversity is recorded, with important implications for downstream data use.

Users also vary in where they make observations. While some primarily observe close to home, others contribute while traveling or even travel with the specific goal of observing. In Hawaii, a location with unique tourism dynamics, residents have very different observation patterns than do visitors: Residents tend to be short-term observers and make more observations in developed areas, non-protected areas, and near roads (Dimson and Gillespie 2023). While we expect these sampling dynamics likely differ across regions with different social and land contexts, these questions remain untested. This distinction between locals and travelers represents a second key behavioral axis, reflecting differences in familiarity with the environment (Moon et al. 2024) and the purposes of observation. These differences provide a useful contrast to test how familiarity with the local environment versus tourism-oriented sampling shapes where and when biodiversity is recorded, with important implications for downstream data use.

Here, we examine how spatial and temporal sampling patterns vary across iNaturalist users in the southeastern United States. As iNaturalist does not collect social information from participants, we infer insights into behavior and motivation from their contribution patterns. We categorized users along two dimensions: participation level (highly active versus casual) and traveler status (local versus traveler). We examined how these groups differentially sample spatially, including across land cover categories, urban and rural areas, protected land, urban parks, and low-income neighborhoods; and temporally, focusing on weekends versus weekdays (Supplemental file 1: Table 1). Directly linking user dimensions to sampling patterns and biases will help inform efforts to improve data collection coverage and better quantify the processes that underlie sampling.

METHODS

DOWNLOADING AND FILTERING OBSERVATION DATA

Using custom code derived from the R package rinat (Barve and Hart 2022), we downloaded all verifiable iNaturalist observations (observed by December 31st, 2023 and uploaded by October 12th, 2024) in the focal region and removed those with obscured coordinates (Figure 1a). We focused on the southeastern USA, a biodiversity hotspot (Noss et al. 2015) that draws over 140 million tourists annually (Visit Florida Research 2025), contains areas with some of the nation's highest poverty rates (Baker 2020), and has extensive private land ownership (Butler and Wear 2013). Core analyses were conducted in R version 4.2.3 (R Core Team 2023), and we used the following R packages: tidyverse (Wickham et al. 2019), sf (Pebesma and Bivand 2023), terra (Hijmans 2024), nnet (Venables and Ripley 2002), and data.table (Barrett et al. 2025).

ASSOCIATING OBSERVATIONS WITH LAND CONTEXT

We associated each observation from the focal region with land context categories: land cover, protected areas, urban areas, urban parks, and low-income urban neighborhoods. We established land cover categories following methods described in Callaghan et al. (2019), aggregating land cover classes from the National Land Cover Database (USGS 2023) into urban green area, natural green area, agriculture, open-urban, low-intensity developed, and medium/high-intensity developed. Urban green area and natural green area were differentiated using the 2020 TIGER/Line Urban Areas boundaries (USCB 2020).

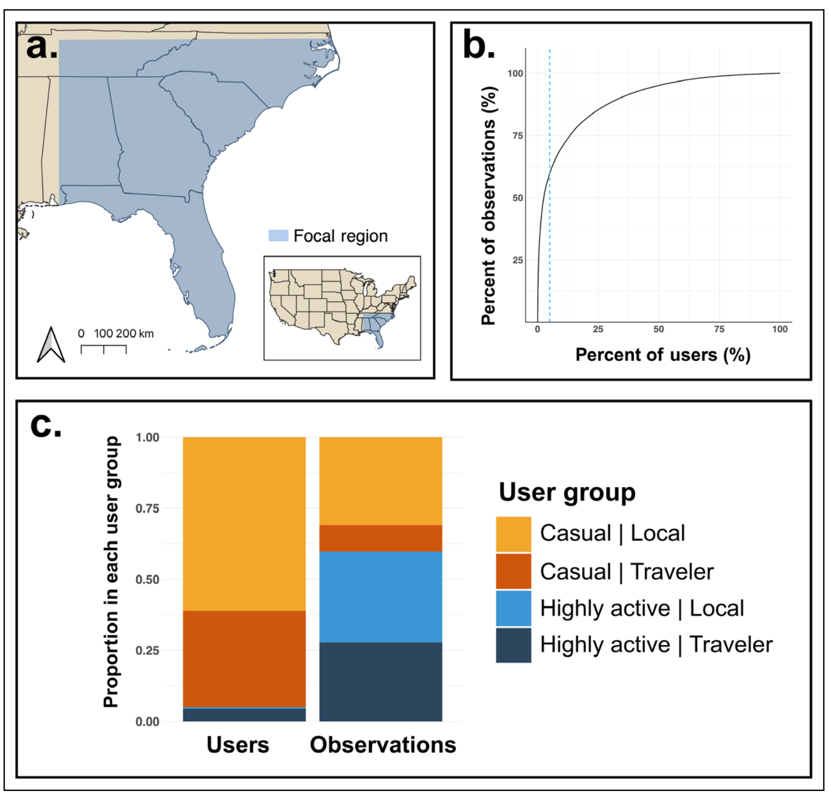

Figure 1 a) Map of southeastern USA focal region. **b)** The cumulative percent of all focal observations by percent of users contributing these observations. **c)** Proportion of users in each of the defined user groups, and proportion of observations made by each group.

We designated land protection status using the "Fee" feature class of the Protected Areas Database (USGS 2022). Urban areas were designated using 2020 TIGER/Line Urban Areas boundaries (USCB 2020). We used the ParkServe dataset to designate which urban observations were made in parks versus neighborhoods (TPL 2024). Finally, we used low-income census tract polygons from the American Community Survey (USCB 2022) to specify urban observations made in low-income areas.

GENERAL SAMPLING BIASES IN THE FOCAL REGION

To quantify overall spatial sampling biases, we first defined the proportion of observations expected in each land class based on area. We calculated the proportion of land within the focal region (for land cover, protected areas, and urban areas) and within focal urban areas (for urban parks and low-income neighborhoods) that met each land context categorization. We then calculated the actual proportion of observations made within each land class and compared these values with the expected proportions.

To quantify weekend versus weekday bias, we calculated the expected proportion of observations on weekends versus weekdays and determined whether each observation in the focal region was made on a weekend or weekday using the wday() function in the R package lubridate (Grolemund and Wickham 2011). We calculated the proportion of observations made on weekends versus weekdays and compared these values with the expected proportions. Weekend versus weekday bias was included here because it can strongly impact phenological analyses, which are often conducted using contributory science data (Courter et al. 2013).

ASSIGNING USER CATEGORIES

We compiled a list of users whose observations were included in the primary dataset. To assemble a complete dataset of global observations made by these users, we combined previously downloaded observations from Campbell et al. (2023) with additional data directly downloaded from iNaturalist, again using custom code based on the R package rinat (Barve and Hart 2022). We then counted each user's total number of verifiable global observations as of October 12, 2024 and assigned each user a percentile relative to others. The top 5% of observers by number of observations were classified as highly active and all others were classified as casual. We determined traveler status by calculating the proportion of each user's observations made in the southeastern USA relative to their global observation count. We classified users who had made half or more observations in the focal region as locals and those who made less than half as travelers.

This method relies on the assumption that observers make the majority of their observations in the immediate area in which they reside. Although there may be edge-cases in which observers live near the study region boundary or moved their primary residence during the study period, the large number of active observers included (283,392) ensures that such cases are unlikely to influence overall patterns. Misclassifications would be most likely to reduce the observed differences between groups, making our results somewhat conservative.

ASSESSING HOW PARTICIPATION LEVEL AND TRAVELER STATUS SHAPE SAMPLING

Quality grade

We calculated the proportion of observations in each quality grade (casual, needs ID, research grade) for casual locals, casual travelers, highly active locals, and highly active travelers and compared these values with the expected proportions. We then conducted a multinomial logistic regression to estimate the likelihood of an observation belonging to one of three quality grades based on user participation group, traveler status, and their interaction. Our aim was to generate exploratory models that examined potentially interactive relationships between user activity patterns and quality grade, without explicit *a priori* hypotheses (Tredennick et al. 2021). We fit four models, the first including participation group, traveler status, and their interaction; the second including participation group and traveler status; the third including just participation group; and the fourth including just traveler status. We then compared models and selected the top model using the Akaike Information Criterion (AIC).

Land context

We calculated the proportion of observations made within each land context class for casual locals, casual travelers, highly active locals, and highly active travelers and compared these values with the expected proportions based on land area. We then fit a set of logistic regression models predicting the likelihood that an observation was made in a given land category with user participation group, traveler status, and their interactions as predictors. We fit four competing models for each spatial variable, and selected the top model using the exploratory modeling process above. We used a multinomial logistic regression model to predict land cover class, and binomial logistic regression models to predict protected land status, urban versus rural areas, urban parks versus urban neighborhoods, and low- or not low-income urban areas. Odds ratios reported in Results reflect estimates derived from models, holding one variable constant to isolate the effect of the other.

Weekends versus weekdays

We calculated the proportion of observations made on weekends versus weekdays for casual locals, casual travelers, highly active locals, and highly active travelers and compared these values with the expected proportions. We then fit a binomial logistic regression model, using the same exploratory model selection process described above, to test whether the likelihood of an observation occurring on a weekend or weekday is influenced by user participation group, traveler status, and/or their interaction.

RESULTS

INATURALIST RECORDS

We downloaded a total of 8,897,124 observations. After removing records with obscured coordinates, 7,533,946 remained in the focal region, contributed by 283,392 unique users. We downloaded and compiled 58,435,335 observations made globally by these users prior to October 12, 2024.

GENERAL SAMPLING BIASES IN THE FOCAL REGION

We found that observations in five land cover classes were overrepresented in the focal region: low-intensity developed areas (20.7% observed, 4.6% expected), medium/high-intensity developed areas (16.4% observed, 2.3% expected), open urban areas (16.3% observed, 7.1% expected), and urban green spaces (9.2% observed, 2.2% expected) (Supplemental file 2: Table 2). Agricultural areas (5.5% observed, 20.2% expected) and natural green areas (31.9% observed, 63.6% expected) were underrepresented.

Protected land (39.4% observed, 14.4% expected) and urban areas (46.8% observed, 8.9% expected) were overrepresented, while unprotected land (60.6% observed, 85.6% expected) and rural areas (53.2% observed, 91.1% expected) were underrepresented. Within urban areas, urban parks (19.3% observed, 2.5% expected) were overrepresented, while urban neighborhood areas (80.7% observed, 97.5% expected) were underrepresented. Higher-income census tracts (68.3% observed, 67.3% expected) within urban areas were slightly overrepresented, and low-income census tracts (31.7% observed, 32.7% expected) slightly underrepresented. Weekends (35% observed, 28.6% expected) were overrepresented and weekdays (65% observed, 71.4% expected) underrepresented.

ASSIGNING USER CATEGORIES

Of the 283,392 users, we defined the most active 5% as highly active and the remaining 95% as casual based on their number of global observations (Figure 1c). Highly active users made an average of 3,419 total observations globally (median: 1,223, min: 494, max: 276,674, sd: 7,855.2), while casual users made an average of 37 total observations globally (median: 9, min: 1, max: 493, sd: 73.5). Highly active users were responsible for 59.7% of observations in the focal region and casual users 40.3% (Figure 1b). 61.6% of users were categorized as locals and 38.4% as travelers. Locals made 62.9% of all observations in the focal region and travelers made 37.1%. At the intersection of participation level and traveler status, 61.1% users were classified as casual locals, 33.9% as casual travelers, 0.5% as highly active locals, and 4.5% as highly active travelers. Highly active locals made the most observations (31.9%), followed by casual locals (31%), highly active travelers (27.8%) and casual travelers (9.3%) (Figure 1c).

ASSESSING HOW PARTICIPATION LEVEL AND TRAVELER STATUS SHAPE SAMPLING

Quality grade

The best-supported model of observation quality grade included participation group, traveler status, and their interaction as predictors (Supplemental file 3: Table 4). We found that highly active users were more likely to make observations that reach research grade, and casual users were more likely to make observations that remain as needs ID or are designated as casual grade (Figure 2; Supplemental file 3: Table 5). Travelers were more likely to make research-grade observations than residents, and less likely to make casual or needs ID observations.

Land cover

The best-supported land cover model contained participation group, traveler status, and their interaction as predictors (Supplemental file 3: Table 4, 7). Highly active users, regardless of traveler status, were less likely to sample in developed landscapes and more likely to sample in natural green areas compared with casual users (Figure 3a). Travelers, regardless of participation level, were more likely to sample in natural green areas and less likely to sample in areas with low development compared with locals. In developed areas, highly active travelers observed more than expected based on their participation and traveler status group effects alone. The category with the most variation in observation behavior was natural green areas, where highly active travelers observed the most and casual locals the least. With increasing human development, the difference between casual and highly active users generally widened, with these groups making similar proportions of observations in urban green and open urban areas, but casual users making higher proportions in developed areas (Figure 3a).

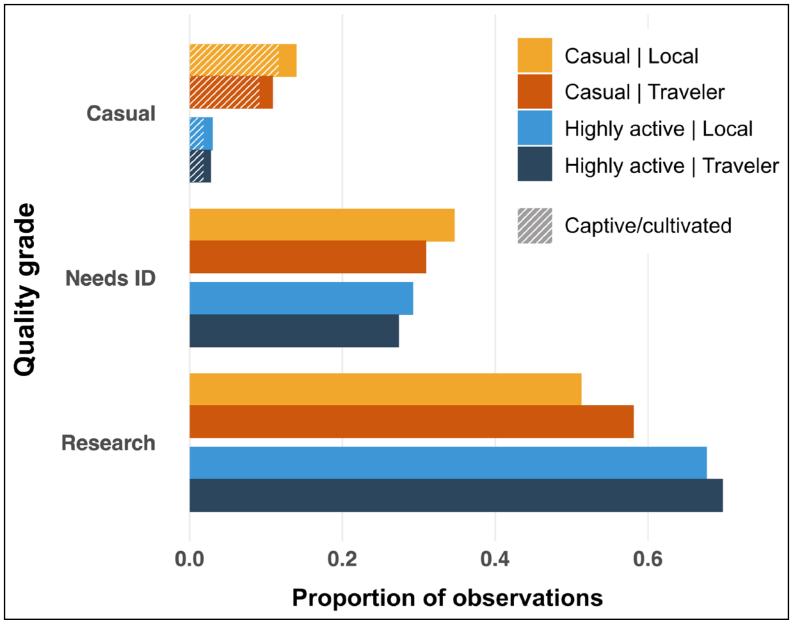

Figure 2 iNaturalist observation quality grade proportions made by each of the four defined user groups: casual locals, casual travelers, highly active locals, and highly active travelers.

Protected land

The best-supported protected land model included participation group, traveler status, and their interaction as predictors (Supplemental file 3: Table 4). Highly active users had 2.24 times higher odds of observing on protected land than casual users ($p < 0.0001$), while travelers had 1.29 times higher odds compared with locals ($p < 0.0001$; Figure 3b; Supplemental file 3: Table 7). Highly active travelers were slightly less likely to observe in protected areas than expected from the combined effects of participation level and traveler status ($p < 0.0001$; Supplemental file 3: Table 7). All four user groups observed more than expected on protected land. Highly active travelers were the most biased toward protected land, observing 36.2% more than expected, followed by highly active locals (+30.3%), casual travelers (+17.4%), and casual locals (+11.7%) (Figure 4).

Urban areas

The best-supported urban areas model included participation group, traveler status, and their interaction as predictors (Supplemental file 3: Table 4). Casual users had 2.08 times higher odds of observing in urban areas than highly active users ($p < 0.0001$), and locals had 1.33 times higher odds than travelers ($p < 0.0001$; Figure 3c; Supplemental file 3: Table 7). Highly active travelers were slightly more likely to observe in urban areas than expected from the combined effects of being highly active and a traveler ($p < 0.0001$; Supplemental file 3: Table 7). All four user groups observed more than expected in urban areas. Casual locals were the most biased toward urban areas, observing 52.3% more than expected, followed by casual travelers (+42.6%), highly active locals (+31.6%), and highly active travelers (+27.6%) (Figure 4).

Urban parks and neighborhoods

The best-supported urban parks model included participation group and traveler status without their interaction as predictors (Supplemental file 3: Table 4). However, there was equivocal support for the second-ranked model, which included the interaction term and is presented in the supplemental materials (Supplemental file 3: Table 7). Highly active users had 2.02 times higher odds of observing in parks compared with casual users ($p < 0.0001$), and travelers had 1.1 times higher odds compared with locals ($p < 0.0001$; Figure 3d; Supplemental file 3: Table 7). All four user groups observed more than expected in urban parks relative to neighborhoods. Highly active travelers were the most biased toward parks, observing 20.3% more in these areas than expected, followed by highly active locals (+18.8%), casual travelers (+12.8%), and casual locals (+12.6%) (Figure 4).

Low-income areas

The best-supported income model included participation group, traveler status, and their interaction as predictors (Supplemental file 3: Table 4). Locals had 1.33 times higher odds of observing in low-income areas than travelers ($p < 0.0001$), and casual users had 1.16 times higher odds than highly active ($p < 0.0001$; Figure 3e; Supplemental file 3: Table 7). Highly active travelers were slightly more likely to observe in low-income areas than explained by

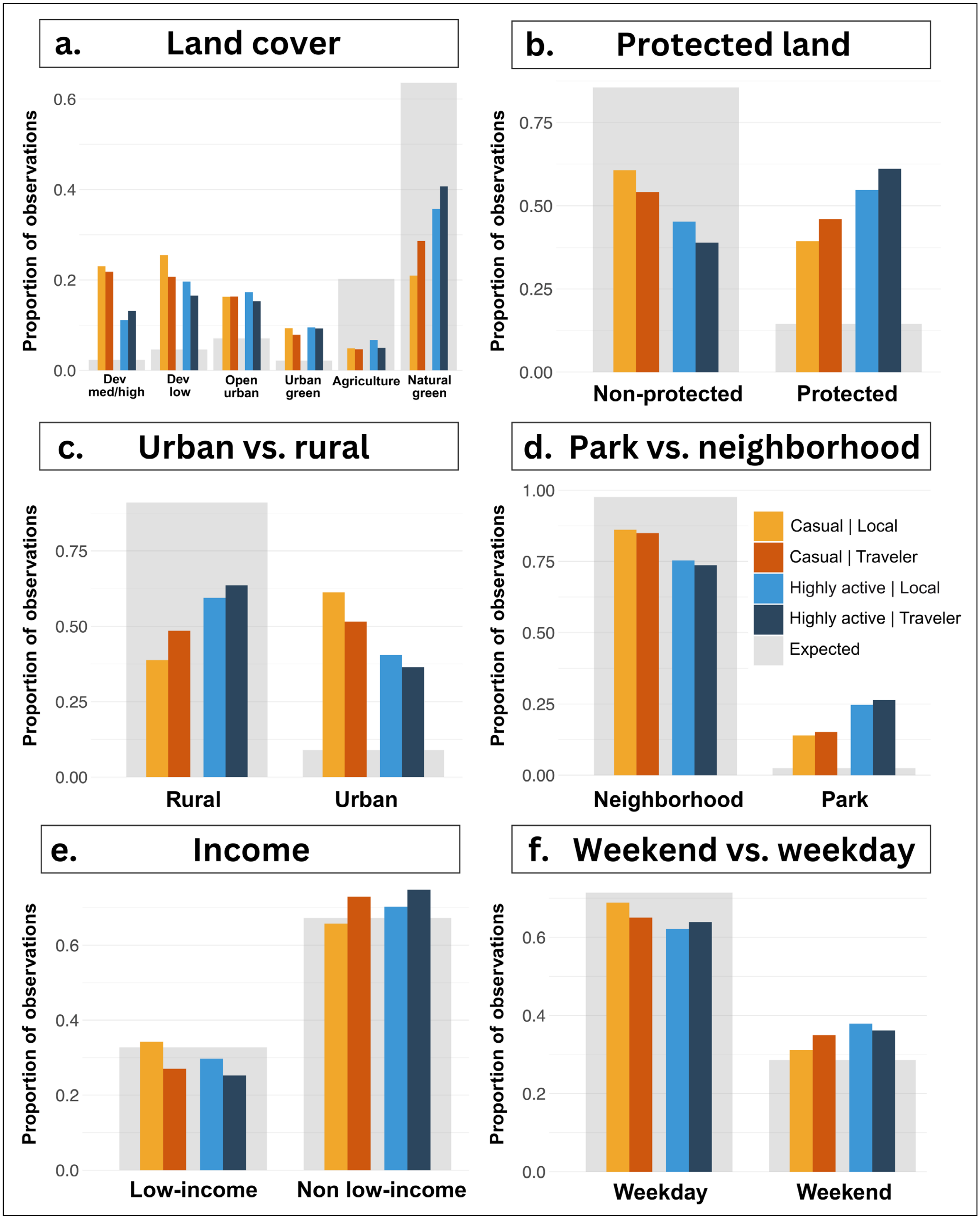

Figure 3 Proportion of observations made by each of the four defined user groups across spatial and temporal variables. Grey bars represent expected proportion based on land area for spatial variables and day ratios for the temporal variable.

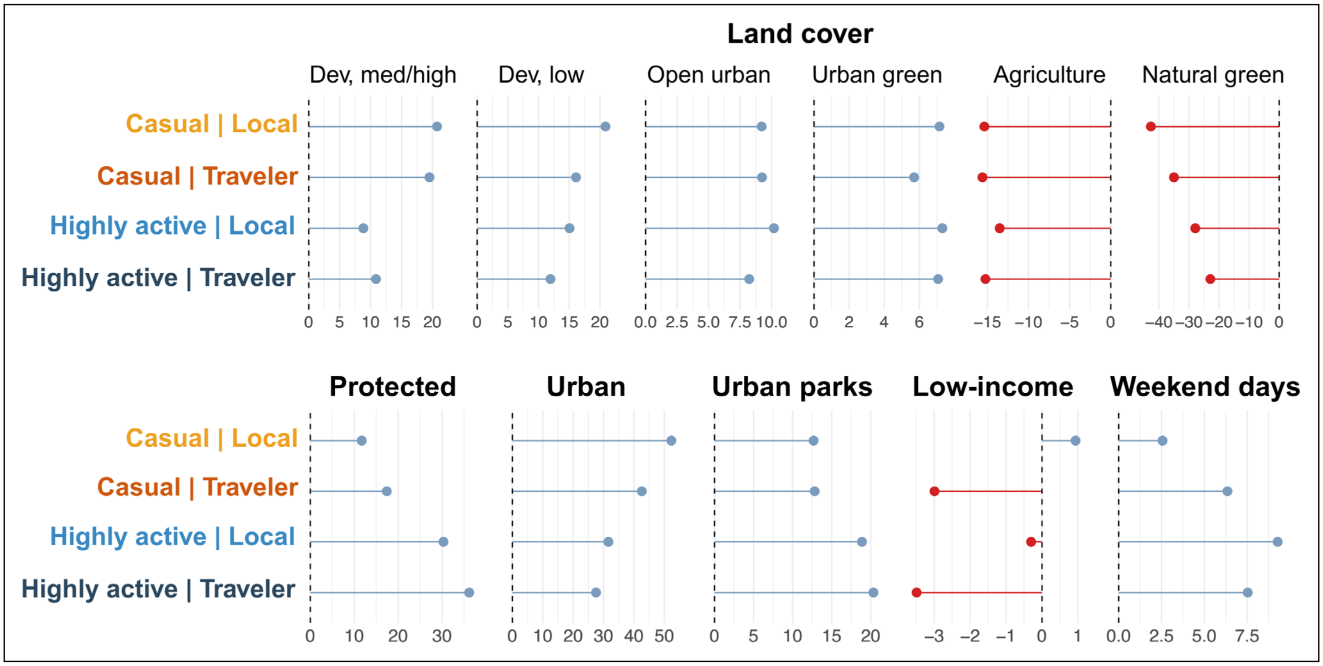

Figure 4 Percent difference between expected and realized sampling across land cover, protected land, urban areas, urban parks, low-income urban areas, and weekends for each of the four defined user groups. Blue lines right of zero indicate overrepresentation and red lines left of zero indicate underrepresentation.

the combined effects of being highly active and a traveler ($p < 0.0001$; Supplemental file 3: Table 7). One user group, casual locals, observed more than expected in low-income areas (+1%) (Figure 4). All other user groups—casual travelers, highly active locals, and highly active travelers—observed slightly less than expected in these areas. Highly active travelers under-sampled most in non-low-income areas, observing 3.5% less than expected, followed closely by casual travelers (–3%), and then highly active locals (–0.3%).

Weekends versus weekdays

The best-supported weekend versus weekday model included participation group, traveler status, and their interaction as predictors (Supplemental file 3: Table 4). Highly active users had 1.19 times higher odds of observing on weekends than casual users ($p < 0.0001$), and travelers had 1.05 times higher odds than locals ($p < 0.0001$; Figure 3f; Supplemental file 3: Table 7). There was a significant interaction, indicating the tendency to observe on weekends is weaker for traveling highly active users compared with traveling casual users ($p < 0.0001$; Supplemental file 3: Table 7). Of casual users, travelers were more likely to observe on weekends than locals, but in highly active users this trend flipped and locals were more likely to observe on weekends than travelers. All four user groups disproportionately observed more on weekend days than weekdays. Highly active locals were the most biased toward weekend days, observing 9.3% more than expected, followed by highly active travelers (+7.5%), casual travelers (+6.3%), and casual locals (+2.6%) (Figure 4).

DISCUSSION

Spatial and temporal biases in data contributed by volunteer participants have been well-documented (Di Cecco et al. 2021; Ellis-Soto et al. 2023), but without clear connection to how different users may perpetuate or reduce those biases. We established two key ways to distinguish users, those who participate more (highly active) or less (casual), and those local to the region (local) versus those visiting (traveler). We then asked how different user groups observe biodiversity across land contexts and days of week. We explicitly chose these metrics because we know, based on previous work (Di Cecco et al. 2021; Dimson and Gillespie 2023), observation effort is biased across these variables, and we expect that user groups have different behaviors and preferences impacting how observations accrue. A key result we explore herein is that highly active users tend to seek out biodiversity-rich areas, while casual users primarily incorporate iNaturalist into their day-to-day. We also found that locals likely fill gaps in low-income urban areas that travelers often miss. We present evidence supporting these insights, with implications for contributory program planning and downstream data use. We note that without participant surveys, it is possible to only indirectly infer user motivations, preferences, and abilities from their observation patterns alone.

A main finding of this work is that observer participation level more strongly shaped how observations were structured across space and time than traveler status. Within participation groups, whether a user was a local or traveler was secondary in structuring observations, with travelers often showing similar directional tendencies to highly active users, and locals similar to casual users. However, observation patterns in urban neighborhood income categories were shaped more by traveler status than participation group.

HIGHLY ACTIVE USERS SEEK OUT BIODIVERSITY-RICH AREAS, WHILE CASUAL USERS PRIMARILY INCORPORATE SAMPLING INTO DAILY LIFE

We found that casual and highly active users have different observational habits and likelihoods of making observations that reach research grade. In particular, highly active observers generally go out of their way to sample in natural and protected areas, both within and outside cities, and are more likely to add observations on weekends than casual users. Such areas are likely to harbor higher, unique diversity given that developed areas tend to act as strong filters for such diversity (Aronson et al. 2014). To be clear, highly active users also contribute numerous records in developed areas and during the week, but what sets them apart from casual users is their high proportion of observations in biodiverse, natural areas.

The preference of highly active observers toward these natural locations, presumably often during leisure time, aligns with their increased motivation to contribute to conservation research (Larson et al. 2020; Lowe et al. 2025), and with previous work focused on other contributory science initiatives. For example, Rosenblatt et al. (2022) found that specialist birders, who have stronger skills and devote more time to birding, travel farther from home to observe. Similarly, Bowler et al. (2022) observed that participants with more experience were more likely to conduct planned searches, and that these searches were more likely to occur in natural and protected areas than urban areas. Our findings, in combination with these works, suggest highly active users make intentional and focused efforts to collect biodiversity data.

Highly active users fill critical gaps in areas broadly under-sampled on iNaturalist, such as rural areas and natural green spaces, but also perpetuate biases toward protected land and urban parks. Still, observations from these biodiverse areas are particularly valuable for research on rare or threatened species, range shifts, ecosystem response to environmental change, and urban-natural comparisons. Consistent with previous work (Dimson and Gillespie 2023), we found observations made by highly active users were more likely to reach research grade than those by casual users. This may be because highly active users include more detailed images or metadata with their observations, or might initially provide more specific identifications (e.g., genus rather than family or order). As the primary source of research-grade records, highly active users play a key role in generating high-quality biodiversity data for research. However, these users also tend to neglect non-park urban areas and unprotected rural lands, which are most likely privately owned. These areas may host lower overall biodiversity, reducing their sampling potential and attractiveness to observers, but they also might simply be places highly active users can't access or don't frequent.

Our results suggest that observers who use iNaturalist more casually tend to primarily incorporate sampling into their daily lives. These casual users sample predominantly in urban areas, strongly perpetuating biases toward developed land that are well-documented in community-collected biodiversity data (Di Cecco et al. 2021). These findings align with those in Dimson and Gillespie (2023), who found that short-term observers who were residents of Hawaii were the least likely to sample outside developed areas. This is likely because casual users sample primarily close to home or during their routines and are less likely to go on nature-specific excursions, a conclusion further strengthened with the result that these users, especially locals, are less biased toward weekends than highly active users, and are more likely to make casual observations that reflect cultivated organisms. We note, however, the lack of direct information about where observers reside, and that these conclusions are inferences based on patterns in their sampling behavior.

Although casual users perpetuate data biases toward developed areas, they critically fill gaps in areas less served by highly active users. Within cities, casual users sample proportionally more than highly active users in non-park neighborhood areas. As observations in urban parks are generally overrepresented on iNaturalist, these non-park observations are particularly valuable for sampling broadly across cities and can help researchers more effectively understand how biodiversity responds across the broadest urban gradients (Callaghan et al. 2020). Some of these non-park observations are cultivated plants on private property based on a spot-check of records to determine cultivation status of casual-grade records. While these may be considered less valuable, records of cultivated species can offer valuable insight into the interaction between cultivated and natural biodiversity, the resiliency of urban green areas to environmental change, and environmental equity across cities (Leong et al. 2018). Still, the primary goal of iNaturalist is to collect biodiversity information on wild organisms, and cultivated observations can sometimes pose challenges for ecological analyses, particularly when the "cultivated" tag is not properly selected (López-Guillén et al. 2024).

In addition to filling data gaps within urban environments, casual users fill gaps in non-protected rural areas. In the southeastern USA, the majority of forested land is privately owned (Butler and Wear 2013) and heavily underrepresented on iNaturalist. Contributory biodiversity monitoring is especially critical in these areas, as they are generally not covered by traditional ecological monitoring. Casual users, perhaps because they represent a broader pool of participants who live in, know about, or have access to these areas, are helping fill these data gaps.

LOCALS FILL GAPS IN LOW-INCOME URBAN AREAS REGARDLESS OF PARTICIPATION GROUP

Regardless of participation group, local iNaturalist users were more likely to observe in low-income urban areas than travelers. Casual locals observed in these areas slightly more than expected by land area, representing the only case in our analyses in which a user group actively sampled against the overall data bias (Figure 4).

It is well-documented that contributory science platforms are impacted by socioeconomics, with historically redlined and lower-income areas underrepresented and yielding a less complete picture of biodiversity (Ellis-Soto et al. 2023; Estien et al. 2024). We did not find large differences in representation across income classes, likely in part due to the broad classifications of low-income versus higher-income areas in our analyses, but more importantly because iNaturalist users local to the southeastern USA helped mitigate biases toward higher income-areas. Filling gaps in underrepresented areas not only provides valuable data for research but also strengthens the capacity of communities in these areas to advocate for better environmental protections (Ellis-Soto et al. 2023). Here, we focused broadly on locals across the southeastern USA, but our work provides preliminary evidence that better engaging residents may be key to improving data availability and knowledge. Additionally, while this was not our focus here, facilitating participation from locals might reduce not only spatial but also taxonomic biases because locals, particularly those who are highly active, may be more attuned to regional biodiversity (Dimson and Gillespie 2023).

IMPLICATIONS FOR CONTRIBUTORY PROJECT PLANNING

Our results emphasize that a broader pool of contributors, varying in location, preferences, motivations, and abilities, enhances the scope of data collected and supports iNaturalist's mission to "connect people worldwide with nature while advancing biodiversity science" (iNaturalist 2025). While highly active users are often prioritized in contributory science projects, our findings highlight the importance of recruiting new participants and residents of under-sampled areas, regardless of whether they will eventually become highly active. Strategies focused solely on cultivating highly active users may risk overlooking other contributors who fill critical data gaps.

Our work offers insights into which user groups are likely, willing, or able to observe in certain environments, and can be used to target specific audiences depending on project goals. Previous research has demonstrated that contributory project participants can be influenced to observe in under-sampled areas or areas of conservation concern thorough behavioral nudging, an intervention with the goal of behavioral changes (Callaghan et al. 2023; Thompson et al. 2023). Our results can help augment these efforts by implementing targeted nudges based on behavioral attributes of participants (Hart et al. 2022). For example, casual users may be more likely to respond to nudges asking them to sample near their neighborhood, while highly active users may be more willing or able to travel to rural areas of conservation concern. It is unclear whether the effectiveness of behavioral nudging varies by user group, and this presents a valuable question to explore in future work.

IMPLICATIONS FOR THE FIELD OF CITIZEN SCIENCE

Our results illustrate how considering multiple behavioral axes and their relation to each other can disentangle participation patterns when assessing how volunteers contribute to citizen science. We found differences in sampling patterns across both the participation level and traveler status behavioral axes, generally supporting the notion that motivations of participants are complex and multifaceted (Dowthwaite et al. 2025; Robinson et al. 2021; West et al. 2021). As mentioned above, because different groups have different motivations and contextual conditions, project design needs to consider how and when to appeal to the different groups (Bowser et al. 2014; Lee et al. 2018). As an example, different maps could be provided to the different user types, highlighting specific areas to sample (Skarlatidou et al. 2024). This user-focused design concept is relevant not only to biodiversity-focused contributory science programs, but also citizen science programs more broadly (Fogg-Rogers et al. 2024). Understanding how different user groups contribute, and what motivates or enables their participation, provides a pathway to refine both analyses and project design, forming an important component of future research. When conducting these multi-axes analyses, axes may vary based on the size, complexity, goals, and subject matter of the citizen science project, participant information available to the researcher, or specific hypotheses or questions held by the researcher or project organizers.

IMPLICATIONS FOR BIODIVERSITY RESEARCH

Understanding that different kinds of observers are more or less likely to observe in various environments and at different times is key to understanding the processes which underlie opportunistic spatial and temporal data biases. Our work suggests that spatial and temporal biases(e.g., weekends versus weekdays) may be intimately linked, which is valuable to consider when accounting for oversampling in phenology analyses, an area of research rapidly expanding using opportunistic data (Li et al. 2021). Previous work has shown that different biodiversity trend analyses vary in robustness to variation in user sampling behavior (Pocock et al. 2023b).

These same user-structured spatial biases in sampling also likely impact region-specific taxonomic coverage. Previous literature suggests highly active and casual users also differ in their taxonomic preferences. Deitsch et al. (2024), for example, found less-experienced iNaturalist users were more likely to observe large, brightly colored, invasive spiders compared with more-active users. In sum, our work implies that taxonomic biases, in addition to temporal biases, may not be consistent across space, which is relevant for researchers aiming to draw comparisons across land contexts or gradients.

GENERALIZABILITY AND FUTURE DIRECTIONS

While our work encompasses more than seven million observations and a broad geographic area, our findings describe patterns and processes within the context of the southeastern USA. We expect many of our findings (i.e., highly active users preferentially targeting biodiverse and protected areas and casual users incorporating observations into daily routines) to be broadly transferable to other regions. This is because behaviors stem from general motivational and logistical constraints (e.g., time availability, travel capacity, proximity to home) that shape opportunistic biodiversity recording regardless of geography (Bowler et al. 2022). While the particular land-use configurations of the southeastern USA are unique, the underlying behavioral drivers are likely common across contexts. However, future studies, building upon the work of Dimson and Gillespie (2023) and our analyses, are still needed to explore whether user groups maintain distinct sampling patterns across different land, cultural, and socioeconomic contexts.

Although we think it likely that many of these conclusions are relevant to other contributory science platforms, previous work suggests differences in participant behavior, motivation, and preferences across platforms (Boakes et al. 2016; Crimmins et al. 2021). Further work to capture dynamics on other platforms would help extend these conclusions to the global citizen science field more broadly and clarify which are unique to iNaturalist.

Here, we focused on two dimensions of user behavior and broadly categorized users. While this was appropriate to answer our questions, future analyses could be extended to include additional and continuous behavioral axes (August et al. 2020). An additional next step to more clearly link motivation to sampling behavior is to survey participants and analyze how their motivations, abilities, and background predict sampling patterns. Finally, it is unknown whether users maintain their sampling preferences over time or shift their observation patterns as they transition to being more highly active. Our data summarizes over those differences, but individual user traces could be used to examine this question more directly.

CONCLUSIONS

Sampling patterns and biases in opportunistic biodiversity data reflect the varied preferences of iNaturalist users. We show that by classifying users based on simple behavioral characteristics, we can predict where and when they are likely to sample and better understand how biases accrue and critical data gaps are filled. These results highlight the importance of retaining highly dedicated users and recruiting new participants, especially residents of underrepresented areas. When researchers use these data to answer ecological questions, especially when interested in certain environments or comparisons across environments, it is useful to consider who might be making observations in different areas, their motivations or expertise, and how these might vary.

DATA ACCESSIBILITY STATEMENT

iNaturalist records are archived on Zenodo (DOI:10.5281/zenodo.15278505) and associated code is available on GitHub (https://github.com/eringrady/iNaturalist-users-exhibit-distinct-spatiotemporal-sampling-preferences.git).

SUPPLEMENTARY FILES

The Supplementary files for this article can be found as follows:

- **Supplemental File 1: Table 1.** Key variables considered in this work, their source, and related references. DOI: https://doi.org/10.5334/cstp.868.s1
- **Supplemental File 2: Tables 2–3.** Expected versus observed observation proportions. DOI: https://doi.org/10.5334/cstp.868.s2
- **Supplemental File 3: Tables 4–7.** Model selection and results. DOI: https://doi.org/10.5334/cstp.868.s3

ACKNOWLEDGEMENTS

We extend our gratitude to iNaturalist users who contributed records in the southeastern USA, making this work relevant and possible. We thank Dr. David Blackburn and Dr. Vaughn Shirey for providing valuable feedback. We acknowledge UFIT Research Computing for providing resources and support.

FUNDING INFORMATION

ELG was supported by NSF DBI-2223512. CTC acknowledges the intramural research program of the USDA, Hatch, FLA-FTL-006297.

COMPETING INTERESTS

The authors have no competing interests to declare.

AUTHOR CONTRIBUTIONS

ELG, RPG, CJC, and CTC developed the ideas; CJC downloaded and compiled the data; ELG analyzed the data; ELG led the writing of the manuscript. All authors contributed substantially to drafts and gave final approval.

AUTHOR AFFILIATIONS

Erin L. Grady orcid.org/0009-0001-5928-7515
Florida Museum of Natural History, US; Florida Museum of Natural History, University of Florida, Gainesville, Florida, 1659 Museum Rd, Gainesville, FL 32611, US

Caitlin J. Campbell orcid.org/0000-0002-8199-7775
Bat Conservation International, 500 N Capital of TX Hwy Bldg 8, Suite 225 Austin, TX 78746, US

Corey T. Callaghan orcid.org/0000-0003-0415-2709
Department of Wildlife Ecology and Conservation, Fort Lauderdale Research and Education Center, University of Florida, 3205 College Ave, Davie, FL 33314, US

Robert P. Guralnick orcid.org/0000-0001-6682-1504
Florida Museum of Natural History, University of Florida, Gainesville, Florida, 1659 Museum Rd, Gainesville, FL 32611, US

REFERENCES

Aronson, M.F.J., La Sorte, F.A., Nilon, C.H., Katti, M., Goddard, M.A., Lepczyk, C.A., Warren, P.S. et al. (2014) A global analysis of the impacts of urbanization on bird and plant diversity reveals key anthropogenic drivers. *Proceedings of the Royal Society B: Biological Sciences*, 281(1780), 20133330. https://doi.org/10.1098/rspb.2013.3330

August, T., Fox, R., Roy, D.B., and **Pocock, M.J.O.** (2020) Data-derived metrics describing the behaviour of field-based citizen scientists provide insights for project design and modelling bias. *Scientific Reports*, 10(1), Article 1. https://doi.org/10.1038/s41598-020-67658-3

Baker, R.S. (2020) Why is the American South Poorer? *Social Forces*, Volume 99, Issue 1, Pages 126–154, https://doi.org/10.1093/sf/soz149

Barrett, T., Dowle, M., Srinivasan, A., Gorecki, J., Chirico, M., Hocking, T., Schwendinger, B. et al. (2025) data.table: Extension of 'data.frame'. R package version 1.17.0, <https://CRAN.R-project.org/package=data.table>

Barve, V.V., Brenskelle, L., Li, D., Stucky, B.J., Barve, N.V., Hantak, M.M., McLean, B.S. et al. (2020) Methods for broad-scale plant phenology assessments using citizen scientists' photographs. *Applications in Plant Sciences*, *8*(1). https://doi.org/10.1002/aps3.11315

Barve, V. and **Hart, E.** (2022). rinat: Access 'iNaturalist' Data Through APIs. R package version 0.1.9, <https://CRAN.R-project.org/package=rinat>

Bedessem, B., Gawrońska-Nowak, B., and **Lis, P.** (2021) Can citizen science increase trust in research? A case study of delineating Polish metropolitan areas. *Journal of Contemporary European Research*, 17(2). https://doi.org/10.30950/jcer.v17i2.1185

Boakes, E.H., Gliozzo, G., Seymour, V., Harvey, M., Smith, C., Roy, D.B., and **Hakley, M.** (2016) Patterns of contribution to citizen science biodiversity projects increase understanding of volunteers' recording behaviour. *Scientific Reports* 6, 33051 https://doi.org/10.1038/srep33051

Botts, E.A., Erasmus, B.F.N., and **Alexander, G.J.** (2011) Geographic sampling bias in the South African Frog Atlas Project: Implications for conservation planning. *Biodiversity and Conservation*, 20(1), 119–139. https://doi.org/10.1007/s10531-010-9950-6

Bowler, D.E., Bhandari, N., Repke, L., Beuthner, C., Callaghan, C.T., Eichenberg, D., Henle, K. et al. (2022) Decision-making of citizen scientists when recording species observations. *Scientific Reports*, *12*(1), Article 1. https://doi.org/10.1038/s41598-022-15218-2

Bowser, A., Hansen, D., Preece, J., He, Y., Boston, C., and **Hammock, J.** (2014) Gamifying Citizen Science: A Study of Two User Groups. *In Proceedings of the Companion Publication of the 17th ACM Conference on Computer Supported Cooperative Work & Social Computing, Baltimore, MD, USA,* Association for Computing Machinery: New York, NY, USA, 2014; pp. 137–140. https://doi.org/10.1145/2556420.2556502

Butler, B.J. and **Wear, D.N.** (2013). Forest ownership dynamics of southern forests. In D.N. Wear and J.G. Greis (Eds.), *The Southern Forest Futures Project: Technical report* (pp. 103–121). U.S. Department of Agriculture, Forest Service, Southern Research Station.

Callaghan, C.T., Bino, G., Major, R.E., Martin, J.M., Lyons, M.B., and **Kingsford, R.T.** (2019) Heterogeneous urban green areas are bird diversity hotspots: Insights using continental-scale citizen science data. *Landscape Ecology*, *34*(6), 1231–1246. https://doi.org/10.1007/s10980-019-00851-6

Callaghan, C.T., Ozeroff, I., Hitchcock, C., and **Chandler, M.** (2020) Capitalizing on opportunistic citizen science data to monitor urban biodiversity: A multi-taxa framework. *Biological Conservation*, *251*, 108753. https://doi.org/10.1016/j.biocon.2020.108753

Callaghan, C.T., Thompson, M., Woods, A., Poore, A.G.B., Bowler, D.E., Samonte, F., Rowley, J.J.L. et al. (2023) Experimental evidence that behavioral nudges in citizen science projects can improve biodiversity data. *BioScience*, *73*(4), 302–313. https://doi.org/10.1093/biosci/biad012

Callaghan, C.T., Winnebald, C., Smith, B., Mason, B.M., and **López-Hoffman, L.** (2025) Citizen science as a valuable tool for environmental review. *Frontiers in Ecology and the Environment,* 23(1), e2808. https://doi.org/10.1002/fee.2808

Campbell, C.J., Barve, V., Belitz, M.W., Doby, J.R., White, E., Seltzer, C., Di Cecco, G. et al. (2023) Identifying the identifiers: How iNaturalist facilitates collaborative, research-relevant data generation and why it matters for biodiversity science. *BioScience*, *73*(7), 533–541. https://doi.org/10.1093/biosci/biad051

Carlen, E.J., Estien, C.O., Caspi, T., Perkins, D., Goldstein, B.R., Kreling, S.E.S., Hentati, Y. et al. (2024) A framework for contextualizing social-ecological biases in contributory science data. *People and Nature*, *6*(2), 377–390. https://doi.org/10.1002/pan3.10592

Courter, J.R., Johnson, R.J., Stuyck, C.M., Lang, B.A., and **Kaiser, E.W.** (2013) Weekend bias in Citizen Science data reporting: implications for phenology studies. *International Journal of Biometeorology,* 57(5), 715–20. doi: https://doi.org/10.1007/s00484-012-0598-7. Epub 2012

Crimmins, T.M., Posthumus, E., Schaffer, S., and **Prudic, K.L.** (2021) COVID-19 impacts on participation in large scale biodiversity-themed community science projects in the United States. *ScienceDirect,* 256, 109017. https://doi.org/10.1016/j.biocon.2021.109017

Davis, A.K., Nibbelink, N., and **Deneka, C.J.** (2022). Revisiting geographic variation in melanism of monarch butterfly larvae in North America using iNaturalist photos. *Journal of Thermal Biology*, *110*, 103374. https://doi.org/10.1016/j.jtherbio.2022.103374

Deitsch, J., Chuang, A., Nelsen, D., Sitvarin, M., and **Coyle, D.** (2024) Quantifying how natural history traits contribute to bias in community science engagement: A case study using orbweaver spiders. *Citizen Science: Theory and Practice*, *9*(1). https://doi.org/10.5334/cstp.690

Di Cecco, G.J., Barve, V., Belitz, M.W., Stucky, B.J., Guralnick, R.P. and **Hurlbert, A.H.** (2021) Observing the observers: How participants contribute data to iNaturalist and implications for biodiversity science. *BioScience*, *71*(11), 1179–1188. https://doi.org/10.1093/biosci/biab093

Dimson, M. and **Gillespie, T.W.** (2023) Who, where, when: Observer behavior influences spatial and temporal patterns of iNaturalist participation. *Applied Geography*, *153*, 102916. https://doi.org/10.1016/j.apgeog.2023.102916

Dowthwaite, L., Spence, A., Lintott, C., Miller, G., Sprinks, J., Blickhan, S., and **Houghton, R.** (2025) Exploring the relationship between basic psychological needs and motivation in online citizen science. *Transactions on Social Computing*, 8, 1–2, Article 4. https://doi.org/10.1145/3702210

Ellis-Soto, D., Chapman, M., and **Locke, D.H.** (2023) Historical redlining is associated with increasing geographical disparities in bird biodiversity sampling in the United States. *Nature Human Behaviour*, *7*(11), 1869–1877. https://doi.org/10.1038/s41562-023-01688-5

Estien, C.O., Carlen, E.J., and **Schell, C.J.** (2024) Examining the influence of sociodemographics, residential segregation, and historical redlining on eBird and iNaturalist data disparities in three U.S. cities. *Ecology and Society*, 29(3), 16. https://doi.org/10.5751/ES-15263-290316

Fogg-Rogers, L., Sardo, A.M., Csobod, E., Boushel, C., Laggan, S., and **Hayes, E.** (2024) Citizen-led emissions reduction: Enhancing enjoyment and understanding for diverse citizen engagement with air pollution and climate change decision making. *Environmental Science & Policy*, 154, 103692. https://doi.org/10.1016/j.envsci.2024.103692

Fourcade, Y. (2016) Comparing species distributions modelled from occurrence data and from expert-based range maps. Implication for predicting range shifts with climate change. *Ecological Informatics*, *36*, 8–14. https://doi.org/10.1016/j.ecoinf.2016.09.002

Grolemund, G. and **Wickham, H.** (2011) Dates and Times Made Easy with lubridate. Journal of Statistical Software, 40(3), 1–25. URL https://www.jstatsoft.org/v40/i03/.

Hart, A., Adcock, D., Barr, M., Church, S., Clegg, T., Copland, S., De Meyer, K., et al. (2022) Understanding engagement, marketing, and motivation to benefit recruitment and retention in citizen science. *Citizen Science: Theory and Practice*, 7(1). Available at: https://doi.org/10.5334/cstp.436

Hijmans, R. (2024) _terra: Spatial Data Analysis_. R package version 1.7–78, <https://CRAN.R-project.org/package=terra>.

iNaturalist. (2025) *Observations*. https://www.inaturalist.org/observations. Accessed: April 23, 2025

Larson, L.R., Cooper, C.B., Futch, S., Singh, D., Shipley, N.J., Dale, K., LeBaron, G.S. et al. (2020) The diverse motivations of citizen scientists: Does conservation emphasis grow as volunteer participation progresses? *Biological Conservation*, *242*, 108428. https://doi.org/10.1016/j.biocon.2020.108428

Lee, T.K., Crowston, K., Harandi, M., Østerlund, C., and **Miller, G.** (2018) Appealing to different motivations in a message to recruit citizen scientists: Results of a field experiment. *Journal of Science Communication,* 17(01), A02. https://doi.org/10.22323/2.17010202

Leong, M., Dunn, R.R., and **Trautwein, M.D.** (2018) Biodiversity and socioeconomics in the city: a review of the luxury effect. *Biology Letters*, 14(5). https://doi.org/10.1098/rsbl.2018.0082

Li, D., Barve, N., Brenskelle, L., Earl, K., Barve, V., Belitz, M.W., and **Doby, J.** et al. (2021) Climate, urbanization, and species traits interactively drive flowering duration. *Global Change Biology,* 27: 892–903. https://doi.org/10.1111/gcb.15461

López-Guillén, E., Herrera, I., Bensid, B., Gómez-Bellver, C., Ibáñez, N., Jiménez-Mejías, P., Mairal, M. et al. (2024). Strengths and challenges of using iNaturalist in plant research with focus on data quality. *Diversity*, *16*(1), 42. https://doi.org/10.3390/d16010042

Lowe, K.L., Mason, B.M., Guralnick, R., Morales, N.A., and **Callaghan, C.T.** (2025) Participant intensity influences motivations for contributing to iNaturalist. *Citizen Science Theory and Practice,* 10(1), p.25. https://doi.org/10.5334/cstp.823.

Moon, K., Yates, S., Callaghan, C.T., and **Thompson, M.** (2024). The relational nature of citizen science. *People and Nature*, 6, 2060–2076. https://doi.org/10.1002/pan3.10709

Noss, R.F., Platt, W.J., Sorrie, B.A., Weakley, A.S., Means, D.B., Costanza, J., and **Peet, R.K.** (2015) How global biodiversity hotspots may go unrecognized: lessons from the North American Coastal Plain. *Diversity and Distributions*, 21: 236–244. https://doi.org/10.1111/ddi.12278

Overdevest, C., Orr, C.H., and **Stepenuck, K.** (2004) Volunteer stream monitoring and local participation in natural resource issues. *Human Ecology Review*, *11*(2), 177–185.

Pebesma, E. and **Bivand, R.** (2023) Spatial Data Science: With Applications in R. Chapman and Hall/CRC. https://doi.org/10.1201/9780429459016

Pernat, N., Memedemin, D., August, T., Preda, C., Reyserhove, L., Schirmel, J., and **Groom, Q.** (2024) Extracting secondary data from citizen science images reveals host flower preferences of the Mexican grass-carrying wasp Isodontia mexicana in its native and introduced ranges. *Ecology and Evolution*, *14*, e11537. https://doi.org/10.1002/ece3.11537

Pocock, M.J.O., Hamlin, I., Christelow, J., Passmore, H.A., and **Richardson, M.** (2023a) The benefits of citizen science and nature-noticing activities for well-being, nature connectedness and pro-nature conservation behaviours. *People and Nature*, 5, 591–606. https://doi.org/10.1002/pan3.10432

Pocock, M.J.O., Logie, M., Isaac, N.J.B., Fox, R., and **August, T.** (2023b) The recording behaviour of field-based citizen scientists and its impact on biodiversity trend analysis. *Ecological Indicators,* 151, 110276. https://doi.org/10.1016/j.ecolind.2023.110276

R Core Team. (2023) *R: A language and environment for statistical computing*. R Foundation for Statistical Computing. https://www.R-project.org/

Robinson, J.A., Kocman, D., Speyer, O., and **Gerasopoulos, E.** (2021) Meeting volunteer expectations — a review of volunteer motivations in citizen science and best practices for their retention through implementation of functional features in CS tools. *Journal of Environmental Planning and Management,* 64(12). https://doi.org/10.1080/09640568.2020.1853507

Rosenblatt, C.J., Dayer, A.A., Duberstein, J.N., Phillips, T.B., Harshaw, H.W., Fulton, D.C., Cole, N.W. et al. (2022) Highly specialized recreationists contribute the most to the citizen science project eBird. *Ornithological Applications*, *124*(2), duac008. https://doi.org/10.1093/ornithapp/duac008

Rotman, D., Hammock, J., Preece, J., Hansen, D., Boston, C., Bowser, A. and **He, Y.** (2014) Motivations Affecting Initial and Long-Term Participation in Citizen Science Projects in Three Countries. *iConference 2014 Proceedings*. https://doi.org/10.9776/14054

Rowley, J.J.L., Callaghan, C.T., Cutajar, T., Portway, C., Potter, K., Mahony, S., Trembath, D.F., et al. (2019). FrogID: Citizen scientists provide validated biodiversity data on frogs of Australia. *Herpetological Conservation and Biology, 14:1,* 155–170.

Skarlatidou, A., Moreu, M., and **Haklay, M.** (2024) The utilization of maps in geographic citizen science: A preliminary analysis of usability and user experience issues and opportunities. *Annals of the American Association of Geographers*, *115*(2), 316–333. https://doi.org/10.1080/24694452.2024.2426714

Thompson, M.M., Moon, K., Woods, A., Rowley, J.J.L., Poore, A.G.B., Kingsford, R.T. and **Callaghan, C.T.** (2023) Citizen science participant motivations and behaviour: Implications for biodiversity data coverage. *Biological Conservation*, *282*, 110079. https://doi.org/10.1016/j.biocon.2023.110079

Tredennick, A.T., Hooker, G., Ellner, S.P., and **Adler, P.B.** (2021) A practical guide to selecting models for exploration, inference, and prediction in ecology. *Ecology* 102(6):e03336. https://doi.org/10.1002/ecy.3336

Trust for Public Land. (2024) U.S. ParkServe Dataset. https://www.tpl.org/park-data-downloads

U.S. Census Bureau. (2020) *TIGER/Line Shapefiles*, Nation, U.S., 2020 Census Urban Area. https://www.census.gov/geographies/mapping-files/time-series/geo/tiger-line-file.html.

U.S. Census Bureau. (2022) *American Community Survey (ACS) 5-Year Estimates, 2016–2020: Tables B17020 and B19113*.

U.S. Geological Survey (USGS). (2022) Protected Areas Database of the United States (PAD-US) 3.0. https://doi.org/10.5066/P9Q9LQ4B.

U.S. Geological Survey (USGS). (2023) Annual NLCD Collection 1 Science Products. https://doi.org/10.5066/P94UXNTS

Venables, W.N. and **Ripley, B.D.** (2002) Modern Applied Statistics with S. Fourth Edition. Springer, New York. ISBN 0–387–95457-0. https://doi.org/10.1007/978-0-387-21706-2

Visit Florida Research, https://www.visitflorida.org/resources/research/. Accessed Sept. 2025

West, S.E., Pateman, R.M., and **Dyke, A.** (2021) Variations in the motivations of environmental citizen scientists. *Citizen Science: Theory and Practice*, 6(1), p.14. https://doi.org/10.5334/cstp.370

Wickham, H., Averick, M., Bryan, J., Chang, W., McGowan, L.D., François, R., Grolemund, G. et al. (2019) Welcome to the tidyverse. *Journal of Open Source Software*, 4(43), 1686. doi: https://doi.org/10.21105/joss.01686

Wood, C., Sullivan, B., Iliff, M., Fink, D., and **Kelling, S.** (2011) eBird: Engaging birders in science and conservation. *PLOS Biology*, *9*(12), e1001220. https://doi.org/10.1371/journal.pbio.1001220

TO CITE THIS ARTICLE:

Grady, E.L., Campbell, C.J., Callaghan, C.T. and Guralnick, R.P. 2026. iNaturalist Users Exhibit Distinct Spatiotemporal Sampling Preferences, with Implications for Biodiversity Science and Project Planning. *Citizen Science: Theory and Practice,* 11(1): 3, pp. 1–15. DOI: https://doi.org/10.5334/cstp.868

Submitted: 01 May 2025 **Accepted:** 01 January 2026 **Published:** 29 January 2026