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RESEARCH ARTICLE

Geography of race and income shape spatial data gaps in two national participatory science projects

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Abstract

1. *Context and Need*: Participatory projects where people contribute geo-referenced biodiversity data, like eBird and iNaturalist, are commonly used tools to enhance the data collection capacity for research, management, and environmental learning. Despite their utility, demographic disparities in participation, demographic patterns of residential segregation, and individual choice of participation may skew data, influencing research outcomes, management decisions, and the distribution of project benefits.
2. *Approach and Methods*: We used hurdle models to analyse the occurrence and abundance of volunteer observations from 2018 to eBird and iNaturalist across the United States ($n = 90$ million) in relation to the racial composition and median household income levels of Census Tracts (approximately 1200–8000 residents per tract) in 2018. We ran models separately for urban and rural areas to account for different patterns of residential demographic segregation and the geographic concentration of racial and income groups relative to tract size.
3. *Main Results*: The geography of race and income was a significant predictor of eBird and iNaturalist locations, respectively. In urban areas, the eBird locations were significantly less likely to occur and less abundant in tracts that were predominantly Black Indigenous and People of Color (BIPOC). In urban and rural areas, iNaturalist locations were significantly less likely to occur and less abundant in tracts that were predominantly low-income residents.
4. *Synthesis and Applications*: Our analysis explicitly examined whether the geography of people aligns with the geography of contributory science participation, highlighting how socio-spatial processes shape both demographic patterns and data coverage. This unevenness can distort scientific inferences, limit the effectiveness of participatory science in addressing local ecological and environmental management needs and lead to the inequitable distribution of benefits. In addition, areas with less data may have lower attraction for participants, and/or project structures may (inadvertently) exclude people of colour and those with lower income. If these patterns occur in similar participatory projects, which number in the thousands in the US, then contributory projects may inadvertently

be creating data-rich and data-poor areas. We recommend future studies disaggregate participation data by specific racial communities because solutions may not be one-size-fits-all.

KEYWORDS
BIPOC communities, citizen science, data gaps, large-scale, participatory science, urban–rural

1 | INTRODUCTION

Across many disciplines, there are varied participatory approaches for generating new knowledge. In one approach, professionals at scientific institutions engage lay publics to share local knowledge in ways that generate geo-referenced datasets across many locations (large extents and fine grain) and over long-time scales, including rare events/observations, and areas that scientists cannot access (e.g. backyards). These forms of institution-driven projects, most often referred to as 'citizen science', number in the thousands, and a single project can be popular enough to engage millions (Waldispühl et al., 2020). In this paper, we refer to them as contributory projects due to the exclusionary nature of the term 'citizen science' in the United States (Cooper et al., 2021).

Scholars debate how and to what extent the varied suite of participatory sciences can democratize knowledge production (Ottinger, 2010; Strasser et al., 2018). Contributory projects attempt to be an inclusive variant within the scientific enterprise, enabling those without formal scientific credentials to engage in authoritative knowledge production (Bonney et al., 2009). However, there is uncertainty about whether contributory projects are truly egalitarian and accessible to all members of society. For example, in the United Kingdom, participation has been found to be the lowest among women, those from minority ethnic groups, and the unemployed (Pateman et al., 2021). Similarly, in the United States, growing evidence suggests that contributory projects are not often engaging non-white participants, those with lower-than-average income and lower education levels (Allf et al., 2022; Blake et al., 2020; National Academies of Sciences, Engineering, and Medicine et al., 2018; Rutter et al., 2021). In light of the skewed participant demographics, the achievements of contributory projects in advancing science, informing policy and generating diverse learning outcomes (McKinley et al., 2017) may be only a fraction of what is possible.

While contributory projects have many benefits to science and the public, those that engage participants in sharing geo-referenced data are especially valuable to disciplines like conservation (Belitz et al., 2021; Ramesh et al., 2022; Saunders et al., 2022), public health (Den Broeder et al., 2016; King et al., 2016) and urban planning (Mueller et al., 2018). Many contributory projects collect data using unstructured and semistructured methods to reduce participant commitment requirements (increasing the potential for participation; Perkins et al., 2023). However, these flexible project structures make the location data vulnerable to spatial biases, shaped by the demographic characteristics of the participants (Geldmann et al., 2016) and their behaviour (Callaghan et al., 2019; Callaghan et al., 2023; Thompson et al., 2023). Additional sources of human-related biases can include population density, socio-economic status, gender, language and community practices and norms (Johnson & Hecht, 2015).

In the United States, racial segregation remains a deeply embedded community practice with a distinct geographic legacy. This history is visible in the spatial concentration of racial groups across both urban and rural areas. In urban spaces, these spatial patterns often appear on a finer scale—such as separations by railroads or streets—reflecting a legacy of white intolerance towards large Black communities or racially mixed neighbourhoods (Massey, 2020). Digitized maps of redlining practices visually demonstrate how the historical intolerance of melanated racial minorities resulted in the geographic concentration and spatial isolation of Black Indigenous and People of Color (BIPOC) in cities across the United States (Nelson et al., 2023). In rural areas, these patterns are a legacy of chattel slavery, concentrating large populations of Black individuals in the fertile crescent or 'Black Belt counties' of the agricultural south (Rebbeck, 2022). Work by Schell et al. (2021) and others (Hoover & Scarlett, 2023; Locke et al., 2024) has demonstrated the influence of sociodemographic drivers on the composition of the landscape, concentration of resources and research priorities. Discriminatory zoning practices in urban and rural areas aid in the concentration of people, pollution and resources historically and in the present day (Hoover & Scarlett, 2023). These combined forces result in minoritized areas experiencing greater burdens of pollution (Motairek et al., 2022), urban heat (Hoffman et al., 2020; Wilson, 2020), decreased tree canopy cover, biodiversity and access to green spaces, as well as gaps in biodiversity (Ellis-Soto et al., 2023) and precipitation data (Mahmoudi et al., 2022).

Similarly to race, neighbourhoods of similar economic composition may be clustered together due to top-down higher-order structures (political, institutional and economic forces) and bottom-up (individual) forces (Sampson, 2018). Rural areas are generally poorer than urban areas, but urban areas have a wider divergence of areas that are richer and poorer than the rest of the United States (Manduca, 2019). After 1980, cities became increasingly stratified by education and income, resulting in a skewed distribution of economic resources (Manduca, 2019). Incarceration (Sampson & Loeffler, 2010) and deindustrialization (Autor et al., 2013) also contributed to these income and wealth gaps. Wealth in the United States is often measured by home value (Suss et al., 2024), but this measure also ignores the growing population of renters. The history of these combined social processes in the US creates homogeneous clusters of people across the landscape, along with their resulting race and income characteristics.

Contributory science data, like other types of data, can be a form of social capital used to inform decisions and provide the basis for policy changes. Environmental data can justify additional financial resources and infrastructure, attract investments in communities and support compliance with regulations. If contributory science projects are not collectively creating an equitable distribution of data, then they are exacerbating environmental injustice. In this paper, we investigated the extent to which race and income align with the geographical unevenness in the distribution of contributory project data using two popular tools for collecting and analysing biodiversity data: eBird (bird-centric) and iNaturalist (all taxa).

We hypothesized that, given residential segregation in the United States and the lack of racial diversity in contributory projects, an area's racial and income characteristics would shape spatial patterns of project data gaps across the United States within large-scale contributory projects. Following a relational approach (West et al., 2020), we argue that by concentrating birding activity and data production in whiter, more affluent areas, the platforms amplify their perceived value while relationally diminishing attention to, and investment in, birding in less privileged spaces. Given that eBird and iNaturalist are examples for thousands of other contributory projects across disciplines and sectors, the likelihood that other projects would show similar racial and economic patterns means that the compounded effect itself would be an environmental justice issue: cumulatively, contributory projects may create data-rich and data-poor areas.

2 | DATA AND METHODS

This study accessed data from two widely used contributory projects for biodiversity observations, eBird and iNaturalist.

2.1 | eBird

The eBird platform now includes data from over 796,000 people in 250 sub-regions (States/provinces), recording over 10,000 bird species, with over 69 million checklists from around the world (https://ebird.org/home). eBird has become a popular data source for bird-related analysis because of its popularity among bird watchers, global reach and ability to download large amounts of data at any time (Kelling et al., 2019). Data from eBird are publicly accessible via the website's science portal and through the Global Biodiversity Information Facility (GBIF). Data quality is controlled through a two-part system, consisting of (1) automated filters to flag unlikely records based on observation date and geographic location, and (2) regional volunteer reviewers with 'expert' bird knowledge who review the flagged entry and follow up with the observer (Sullivan et al., 2014). Through this open-data platform, data from eBird have been used globally for studies of avian ecology, to inform conservation and policy and to support student education initiatives (Sullivan et al., 2014). However, despite its global usage, eBird contributions mostly occur in the US (Sullivan et al., 2014), and in the United States, eBird contributors are predominantly white (94.8%) (Rutter et al., 2021).

Bird watchers (observers) can contribute to eBird anytime and anywhere. However, of the 96.3 million bird watchers in the United States, 95% observe near home, while 44% travel away from home to observe (FWS, 2023). eBird's platform encourages participation through birding 'hotspots', encouraging new and experienced birders to report in locations where high concentrations of birds are known, such as parks with pristine habitats. eBird is a tool made specifically for bird watchers to track their bird observations (checklists) and therefore requires a certain level of knowledge to participate, creating a higher barrier to entry.

2.2 | iNaturalist

iNaturalist is an international platform for users to upload nature observations of any taxonomic group, with many sub-projects focused on either individual taxa or habitats. iNaturalist exists to 'connect people to nature while advancing biodiversity science and conservation' (inaturalist.org). The platform is supported by a community of observers (data reporters) and a community of identifiers (taxonomic experts). This two-tiered participation system creates a lower barrier to entry because participants do not need the ability to identify an organism to submit an observation. As a result, iNaturalist contains over 192 million observations with over 3 million observers and over 360,000 identifiers globally. Data from iNaturalist can be accessed via the iNaturalist website and through GBIF. While anyone can share observations, iNaturalist only shares 'research-grade' observations to GBIF (data with an accompanying photograph, date, coordinates and taxonomic identification verified through its online community of experts). iNaturalist data has been used in over 100 publications, contributing to knowledge about mammal behaviour during the COVID-19 pandemic (Vardi et al., 2021), fire impacts on biodiversity (Kirchhoff et al., 2021) and suitable habitat predictions for invasive species (Serniak et al., 2023).

While iNaturalist is used for science, it is more often used as an educational tool, adapted for middle (Aristeidou et al., 2021; Eden, 2023), high school (Echeverria et al., 2021) and college classroom use (Niemiller et al., 2021). Aristeidou et al. (2021) found that youth (participants aged 16–19) contribute a large number of research-grade observations to the platform. iNaturalist is marketed as a tool for learning, tracking and hosting projects, but it is also commonly used for local bioblitzes (inaturalist.org), the largest being the annual community science initiative, the City Nature Challenge. The City Nature Challenge helps provide millions of observations in cities around the world across 4 days each year. These millions of observations are submitted to iNaturalist and stored in GBIF alongside non-City Nature Challenge data. Current literature suggests that iNaturalist observers tend to monitor close to home (Di Cecco et al., 2021), assisting scientists in collecting biodiversity data in hard to access places like backyards and on a geographic scale larger than technicians can accomplish alone.

To understand the geography of iNaturalist and eBird observations and their relationship to social and economic factors, we downloaded all iNaturalist and eBird observations from the GBIF in the United States for the year 2018. All data included latitude and longitude coordinates, totalling approximately 1.7 million iNaturalist observations and 66 million eBird observations across the United States. We retained eBird data from all three observation types: stationary (birding in a single location without travelling more than 30 m in any direction); travelling (birding as if on a trail moving more than 30 m); and incidental (finding a bird while doing something other than intentionally birding) and included both complete (contained all the birds the observer was able to identify) and incomplete (did not contain all the birds, species and number, that the observer could identify) checklists. We retained all research-grade observations from iNaturalist, and we did not cull any data by species or taxa. In addition to nature observations, we also downloaded race, ethnicity, and income data from the 2018 5-year American Community Survey (ACS) at the Census Tract level using the tidycensus package in R (Walker & Herman, 2024). The ACS is an ongoing, nationally representative survey administered by the U.S. Census Bureau that provides annually updated demographic, social, economic and housing data for communities across the United States. The ACS samples approximately 3.5 million addresses each year using a combination of mail, telephone, internet and in-person interviews, resulting in robust, high-resolution estimates with a response rate typically exceeding 95% (US Census Bureau, 2024). Data from the ACS are reported at a variety of geographic scales, with the census tract serving as the primary unit of analysis for this study. Census tracts are small, relatively permanent subdivisions of a county, generally designed to contain between 1200 and 8000 people (with an average of about 4000) (US Census Bureau, 2018), and are intended to approximate neighbourhoods or other meaningful community boundaries while remaining stable over time to facilitate longitudinal research. In total, our dataset included boundaries for 73,056 Census Tracts.

iNaturalist, eBird and ACS data were summarized at the Census Tract level to test for patterns of geographic unevenness. We chose Census Tract geographies for analyses because tracts are roughly standardized to include an average of 4000–6000 residents and are the preferred analytical geography in the United States for approximating neighbourhood analysis (Spielman & Logan, 2013). For each Census Tract, we used ACS Table B03002 ('Hispanic or Latino Origin by Race') to calculate the percentage of residents who identified as non-Hispanic white (i.e. individuals who selected 'white alone' and reported not being of Hispanic or Latino origin); the complement of this group, which we refer to as BIPOC (Black Indigenous and People of Color), includes all residents who identified as Black or African American, Hispanic or Latino (of any race), Asian, Indigenous or as more than one race. This approach ensures that race and ethnicity are treated as distinct but intersecting categories and that our white/BIPOC classification is mutually exclusive and collectively exhaustive, consistent with standard demographic practices. Citizen science observation data were spatially joined to the Census geographies to summarize the total number of iNaturalist and eBird point observations in each polygon. Median household income, from ACS Table B19013 ('Median Household Income in the Past 12 Months'), was selected as our primary economic indicator because it is the most widely used and robust measure of current economic status available. Although the Census does not collect direct measures of household wealth, median household income provides the best available proxy for current material resources and is a standard metric for assessing economic well-being in demographic and geographic research. The final dataset included the following for each Census Tract: median household income (from ACS), per cent BIPOC residents, count of iNaturalist observations, and count of eBird observations.

The geographies of urban and rural spaces vary dramatically. Rural Census Tracts cover large land areas with low and/or clustered distributions of residents, whereas residents in suburban and urban tracts are more evenly distributed in space. To accommodate the spatial differences between rural and urban places, the Census Tracts were split into urban and rural based on the density of residents. We used a density-based approach but applied a threshold of one person per acre at the Census Tract level to classify tracts as urban. This provides a straightforward, tract-level proxy for urbanization based on population density, analogous to—but not identical with—the Census Bureau's more granular, block-level criteria. All other Census Tracts are designated as 'rural'. As expected, there is positive spatial autocorrelation of our variables before and after splitting into urban and rural datasets. Spatial autocorrelation measures how observations located near each other tend to have more similar values than those farther apart. This spatial autocorrelation reflects socio-economic processes that spatially sort populations by race and income. Rather than treating this as a nuisance, our analysis explicitly examines whether the resulting geography of people aligns with the geography of citizen science participation, highlighting how socio-spatial processes shape both demographic patterns and data coverage.

To test the relationship between observations, race/ethnicity and household income, we fit a two-stage hurdle model for each combination of urban or rural Census Tracts and eBird and iNaturalist observations. Two-stage hurdle models are particularly useful for cases when the response variable exhibits overdispersion and excess zeros (Zuur et al., 2009), qualities that exist in our dataset. For example, of the 73,056 Census Tracts, 13,496 had zero eBird observations, and the remaining 59,560 tracts contained 66 million observations. In essence, the modelling approach is to fit a binomial GLM to presence-absence data and a zero-truncated GLM to the count data. We used the same model structure for each of our models, with observation count (either eBird or iNaturalist) as the response variable and proportion BIPOC (0–1) and median household income (25,000–250,000) as predictor variables. Since hurdle models can be

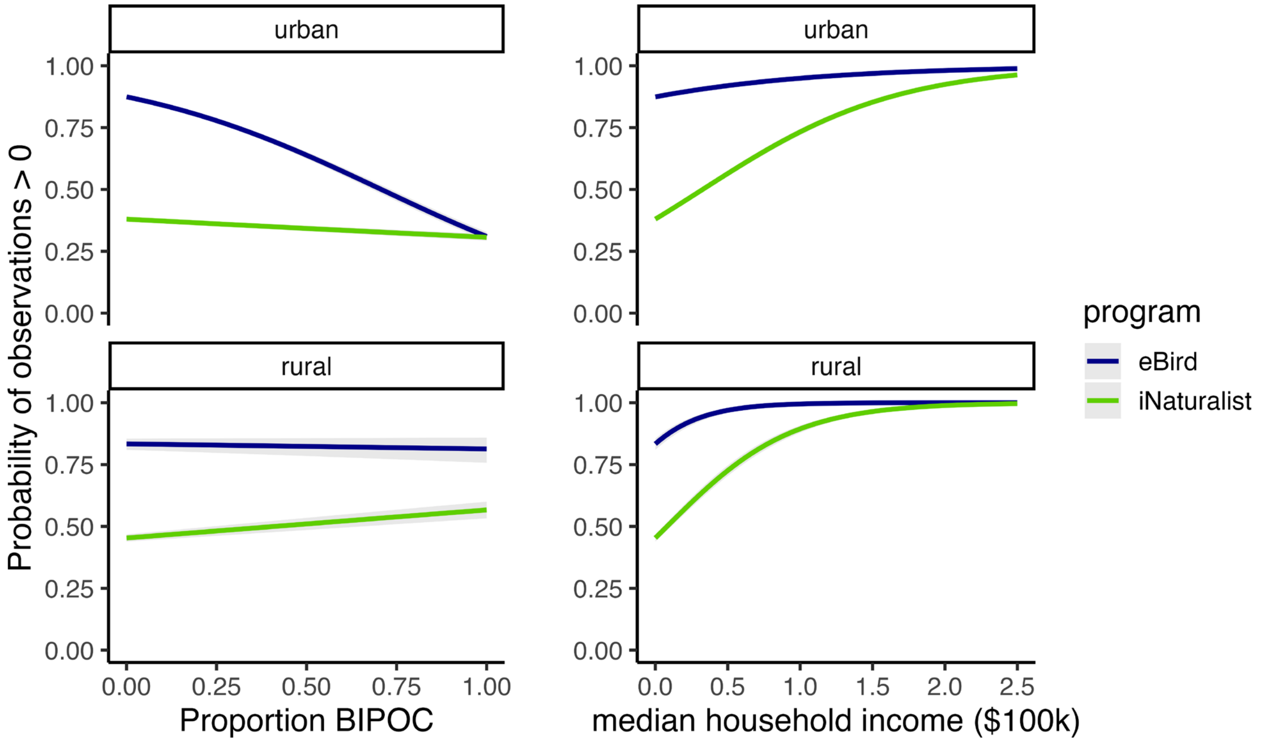

FIGURE 1 Urban and rural zero-count hurdle model predictions for eBird (blue) and iNaturalist (green). The graphs show the probability of observations being greater than 0 as the proportion of Black Indigenous and People of Color (BIPOC) and median household income increases.

sensitive to the size of the predictor variables if they are on different scales, we scaled median household income to be 1/100,000th of its original value. These scalings do not impact model coefficients or model significance (Zuur et al., 2009). For the first stage in our two-stage hurdle model, we fit a binomial model with a logit link to predict the probability of a non-zero value or the presence of an observation in a tract. For the second stage, we used a zero-truncated negative binomial model with a log link to predict the count or the number of observations in a tract. We fit separate models for urban and rural Census Tracts to accommodate the differences in segregation patterns in these two geographies. Prior to analysis, we calculated the Pearson correlation coefficient between the two predictor variables; they were not highly correlated in either urban ($r = -0.37$) or rural ($r = -0.21$) geographies. We ran all models in R using the 'pscl' package (Jackman, 2005; Zeileis et al., 2008).

3 | RESULTS

We found that race and income were significant predictors of the distribution of eBird and iNaturalist observations, respectively. However, the strength of their predictive capacity varied between urban and rural geographies (Figure 1). Each model contains results for both stages of the hurdle model: the zero hurdle model, or the probability of having at least one observation, and the count model, the predicted number of observations in Census Tracts that have observations (non-zero tracts).

3.1 | Urban models

We classified about two-thirds of all Census Tracts as urban (more than one person per acre), comprising about two-thirds of the US population. Thirty-five per cent of US eBird observations were in urban Census Tracts, specifically in 75% of urban tracts (Table 1). Thirty-nine per cent of US iNaturalist observations were in urban Census Tracts, specifically in 58% of urban tracts (Table 1).

In the urban eBird zero hurdle model, the proportion of BIPOC was a significant and strong negative predictor of having at least one observation (Estimate = −2.74, ±0.04SE, $p < 0.0001$; Table 2), indicating that as the proportion of BIPOC increased, the likelihood of having at least one eBird observation decreased in urban Census Tracts (Figure 1). In contrast, income was a significant and moderate positive predictor (Estimate = 1.00, ±0.04SE, $p < 0.0001$; Table 2), indicating that as the scaled income of a tract increased, the likelihood of having at least one eBird observation in that tract also increased (Figure 1). For example, the zero hurdle model predicted that urban Census Tracts that were fully BIPOC had a 28% probability of containing at least one eBird observation, whereas, at the other extreme, tracts estimated to be fully white had nearly three times higher (83%) probability of containing at least one eBird observation.

Not only was the occurrence of eBird observations less likely in tracts with a higher proportion of BIPOC, but when observations did occur in those tracts, they were fewer. In the count model (urban Census Tracts with at least one observation), the

TABLE 1 Comparison of urban and rural statistics for the number of Census Tracts, total, mean and median population, total, mean and median census tract land area, tract population density, Black Indigenous and People of Color (BIPOC) percentages, number of eBird and iNaturalist observations, and the percentage of tracts with eBird and iNaturalist observations.

	Urban	Rural
Census Tracts	50,096	22,960
Population (Tract Mean)	4537	4164
Population (Tract Median)	4219	3892
Population (Total)	227,290,100	95,612,930
Land Area (Tract Mean)	1.71 square miles	151.62 square miles
Land Area (Tract Median)	1.00 square miles	41.90 square miles
Land Area (Total)	86,042 square miles	3,447,002 square miles
Density (Tract Mean)	7786 people per square mile	168 people per square mile
Density (Tract Median)	3966 people per square mile	93 people per square mile
Density (Total)	2642 people per square mile	28 people per square mile
BIPOC (Tract Mean)	20.4%	46.3%
BIPOC (Tract Median)	40.1%	11.6%
BIPOC (Total)	20.8%	46.6%
Median Household Income (Tract Mean)	$66,289	$59,970
Median Household Income (Tract Median)	$58,722	$55,023
Total eBird observations	23,565,097 (0.35)	42,921,139 (0.65)
% tracts with eBird	0.75	0.96
Total iNaturalist observations	667,684 (0.39)	1,058,138 (0.61)
% tracts with iNaturalist	0.58	0.76

proportion of BIPOC was a significant and moderate negative predictor of the number of eBird observations (Estimate = −1.00, ±0.05SE, $p < 0.0001$; Table 2), while income was a significant moderate positive predictor (Estimate = 0.73, ±0.04SE, $p < 0.0001$; Table 2). To put this in context, we pulled out data in Baltimore, a city highly segregated by race and income. In Baltimore, an area of five Census Tracts that was 72% white with a median household annual income of $107,000, had over 11,000 eBird observations spread across all five tracts. In contrast, a five-tract area with 96% BIPOC and a median household annual income of $44,000 had about 400 eBird observations spread across only two of the five tracts (Figure 2). To summarize, urban Census Tracts that were predominantly BIPOC populations with many eBird observations were the least common (the smallest block, High-High, in Figure 3), while the most common urban Census Tracts were those that were predominantly BIPOC and had few or no eBird observations (the largest block, High-Low, in Figure 3).

In the urban iNaturalist zero hurdle model, proportion BIPOC was a significant and negative predictor of the likelihood of having at least one iNaturalist observation (Estimate = −0.33, ±0.03SE, $p < 0.0001$; Table 2), and income was a significant and positive predictor (Estimate = 1.50, ±0.03SE, $p < 0.0001$; Table 2). For example, urban Census Tracts with a median income of 50,000 or less had a 50% probability of having at least one iNaturalist observation. In contrast, tracts with a median income over $250,000 had over a 90% likelihood of containing at least one observation. For urban Census Tracts with at least one iNaturalist observation (count model), both proportion BIPOC (Estimate = 0.22, ±0.06SE, $p < 0.0001$; Table 2) and income (Estimate = 0.94, ±0.04SE, $p < 0.0001$; Table 2) were significant and positive predictors, although the effects were moderate.

3.2 | Rural models

We classified about one-third of the US population as residing in rural Census Tracts, which contained 65% of US eBird observations and 61% of US iNaturalist observations (Table 1). Almost all rural tracts (96%) had eBird observations, and many rural tracts (76%) had iNaturalist observations (Table 1).

In the rural zero hurdle model for eBird, proportion BIPOC was not a significant predictor of the likelihood of having at least one observation in a rural tract (Estimate = −0.140, ±0.170SE, $p = 0.41$; Table 2). Despite not being statistically significant, the highest number of eBird observations in rural tracts occurred in predominantly white tracts (Figure 3 Low per cent BIPOC). Income, however, was a significant and strong positive predictor of the presence of at least one eBird observation in rural tracts (Estimate = 3.69, ±0.286SE, $p < 0.0001$; Table 2). For rural tracts that contained at least one observation (count model), income continued to be a significant and positive predictor of the number of observations (Estimate = 1.64, ±0.06SE, $p < 0.0001$; Table 2), indicating that wealthier rural tracts have more eBird observations.

In the rural iNaturalist zero hurdle model, proportion BIPOC was a weak positive predictor of the likelihood of having at least one observation (Estimate = 0.46, ±0.08SE, $p < 0.001$; Table 2). Income, however, was a strong positive predictor (Estimate = 2.32, ±0.09SE, $p < 0.0001$; Table 2), significantly increasing the likelihood of the occurrence of iNaturalist observations. For rural tracts containing iNaturalist observations (count model), both proportion BIPOC (Estimate = 1.89, ±0.11SE, $p < 0.0001$; Table 2) and income (Estimate = 1.26, ±0.09SE, $p < 0.0001$; Table 2) were significant and positive predictors of the number of observations, indicating that tracts with higher populations of BIPOC and tracts with higher income have more iNaturalist observations (Figure 1).

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TABLE 2 (a) eBird hurdle model and (b) iNaturalist hurdle model results.

Variable	Estimate	Standard error	Z	p
eBird urban				
Zero hurdle model				
Intercept	1.94	0.04	46.84	<0.0001
Proportion BIPOC	−2.74	0.04	−65.83	<0.0001
Income	1.00	0.04	23.37	<0.0001
Count model				
Intercept	5.54	0.05	9.90	<0.0001
Proportion BIPOC	−1.40	0.05	−0.82	0.41
Income	3.69	0.04	12.87	<0.0001
Log	−2.48	0.03	−83.54	<0.0001
eBird rural				
Zero hurdle model				
Intercept	1.61	0.16	9.90	<0.0001
Proportion BIPOC	−1.40	0.17	−0.82	0.41
Income	3.69	0.29	12.87	<0.0001
Count model				
Intercept	6.34	0.042	150.308	<0.0001
Proportion BIPOC	0.49	0.057	8.51	<0.0001
Income	1.64	0.060	27.47	<0.0001
Log	−1.15	0.012	−96.05	<0.0001
iNaturalist urban				
Zero hurdle model				
Intercept	−0.49	0.03	−15.40	0.48
Proportion BIPOC	−0.33	0.03	9.78	<0.0001
Income	1.50	0.03	44.35	<0.0001
Count model				
Intercept	−9.25	6.65	−1.39	0.16
Proportion BIPOC	0.22	0.06	3.51	<0.0001
Income	0.94	0.04	22.27	<0.0001
Log	−13.08	6.65	−1.97	0.01
iNaturalist rural				
Zero hurdle model				
Intercept	−0.19	0.06	−3.15	0.001
Proportion BIPOC	0.46	0.08	5.87	<0.0001
Income	2.32	0.09	24.84	<0.0001
Count model				
Intercept	−1.39	1.97	−0.71	0.48
Proportion BIPOC	1.89	0.11	16.52	<0.0001
Income	1.26	0.09	14.0	<0.0001
Log	−5.98	1.99	−3.01	0.001

4 | DISCUSSION

The influence of Census Tract composition on the distribution of contributory project data is an important consideration when using these data to model solutions for the future. Our results indicate that nationwide spatial patterns of eBird and iNaturalist nature observations align with geographic patterns of race and income. In urban areas, census tract race and income are predictors of observation presence, but race is a stronger predictor. Urban census tracts are, on average, smaller in size (1.71 square miles; Table 1), with higher population densities (7786 people per square mile). Due to the influences of segregation, redlining and gerrymandering concentrating racial/ethnic groups in the same geographic area, the patterns between race, income and observations are detected across census tracts.

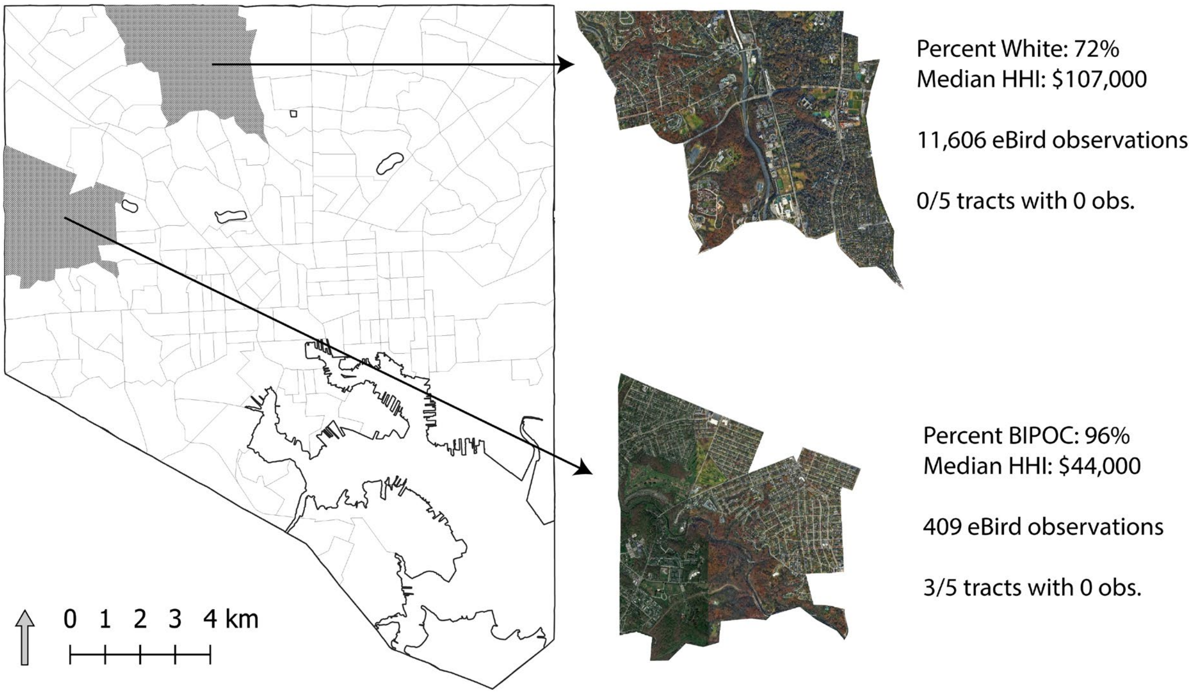

FIGURE 2 This map showcases the median household income (Median HHI), per cent BIPOC (Black Indigenous or Person of Color), number of eBird observations and number of tracts with 0 observations in Baltimore County, Maryland. Two areas in the county are highlighted to demonstrate the differences in the number of observations and income between predominantly white and predominantly BIPOC-occupied areas.

In rural areas, income was a strong predictor of observation presence for both eBird and iNaturalist, but race had a smaller effect. In rural tracts with observations, more observations were likely to occur in wealthier tracts regardless of the racial demographics of the tract. For example, rural tracts that had more than 0 eBird observations had at maximum 5000 observations regardless of the proportion of BIPOC residing in the tract (Figure 4). In contrast, as median household income increased, eBird observations reached up to 40,000 in some tracts that were whiter and wealthier. Unlike eBird, iNaturalist has fewer observations, so the change in the number of observations as income and race proportions increase is much more drastic, up to 250–300 iNaturalist observations in wealthier tracts with a higher proportion of BIPOC (Figure 4). In comparison, wealthier rural tracts (>150K), which tend to be whiter demographically, have higher iNaturalist observations (200–500) according to Figure 4. People in wealthier rural tracts likely have sufficient income to afford leisure time for observing and reporting wildlife. Additionally, observers may be travelling into wealthier rural tracts (which happen to have a lower proportion of BIPOC residents) to observe. Unlike in urban areas, race was not a strong indicator of observations in rural areas because census tracts are too large to see the nuances in the geographic patterns of race. In rural areas, census tracts are larger (151.62 square miles; Table 1) and people are more spatially dispersed (168 people per square mile; Table 1), so the racial patterns are within rather than across census tracts. The patterns likely still exist within rural areas, but are not detected at the census geography due to the large size of rural tracts. While using smaller geographies, like census blocks, may detect the racial differences in rural areas, we would lose the ability to compare income.

We provide two potential explanations for the undersampling in predominantly urban BIPOC as well as urban and rural lower-income areas, based on the current literature. These two hypotheses are not mutually exclusive, each starting with the fact that the United States has a history of racial segregation that is persistent and visible in the way racial groups and wealth/income are geographically concentrated within urban and rural areas. Due to the spatial scale of segregation, the influence of race and income among tracts was more detectable in urban census tracts than in rural tracts.

The first explanation we call the low attraction hypothesis, which is that predominantly BIPOC and lower-income tracts have fewer birds and other forms of biodiversity and therefore attract fewer volunteers to make observations. Numerous studies support the first part of the explanation, but not necessarily the second. In urban areas, there is a lower likelihood of greenspaces, parks and street trees in neighbourhoods that are predominantly BIPOC and less affluent (Dai, 2011; Wen et al., 2013). Many studies have also documented a higher likelihood of pollution and contamination in predominantly BIPOC and lower-income neighbourhoods across urban and rural areas, which can harm people and reduce biodiversity (Jbaily et al., 2022; Liu et al., 2021). Furthermore, ecological studies have noted a 'luxury effect', where biodiversity is associated with affluent neighbourhoods (Leong et al., 2018). One flaw that makes the low attraction hypothesis an insufficient explanation is that those viewing biodiversity are often attracted to areas that

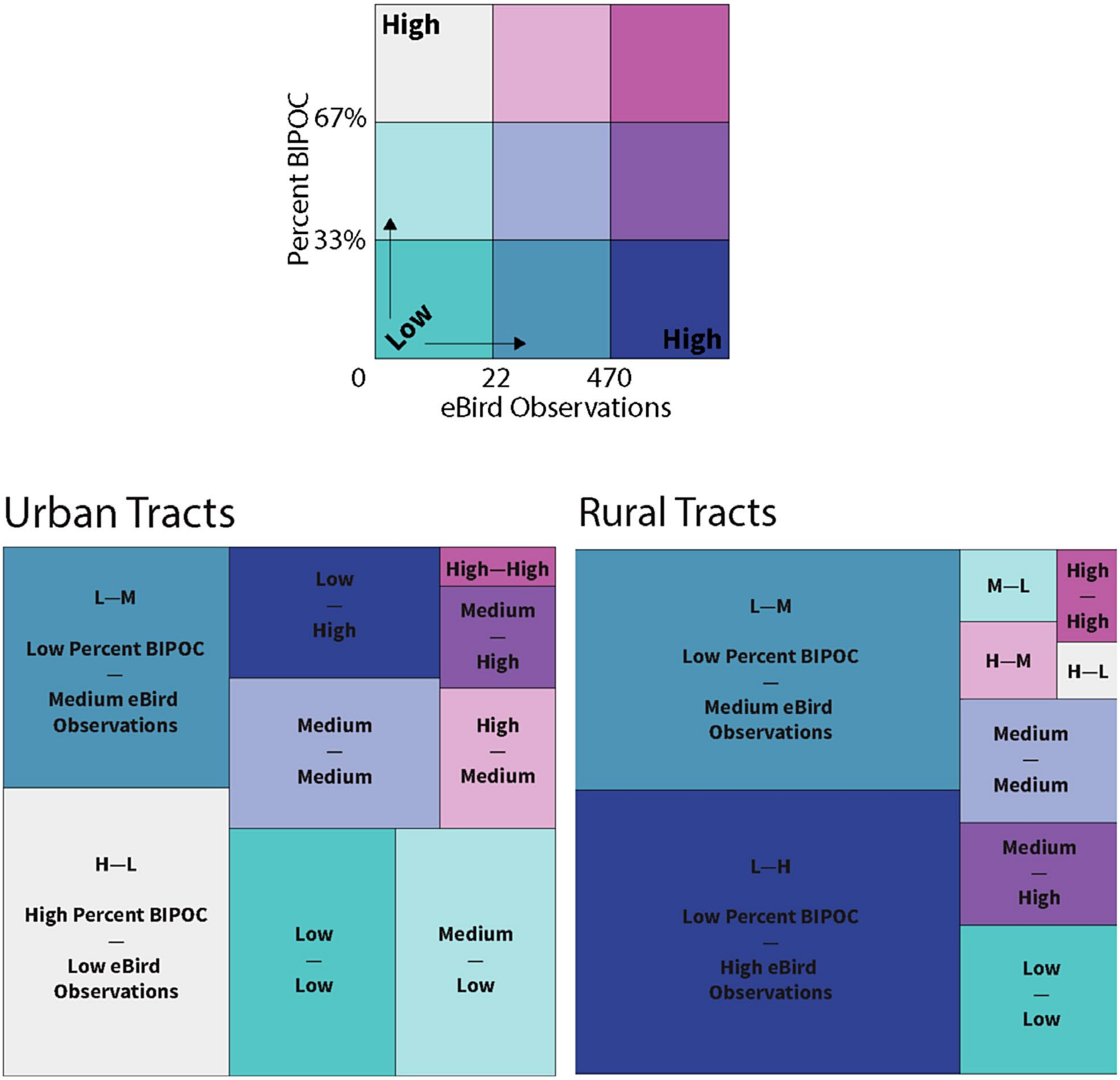

FIGURE 3 This bivariate treemap diagram shows the number of high, medium and low values for eBird observations and the percentage of BIPOC residents in urban and rural census tracts across the continental US. L-H or Low-High references a Low percentage of BIPOC—Black, Indigenous or Person of Colour (high whiteness) and a High number of eBird Observations. H-L or High-Low references a High percentage of BIPOC (low whiteness) and a Low number of eBird Observations. L-M represents a Low per cent BIPOC and Medium number of eBird Observations.

are far from pristine, such as sewage treatment facilities, superfund sites and landfills (Murray & Hamilton, 2010; Schaffner, 2009; Svensson, 2018). Additionally, this hypothesis may not hold in rural areas because while rural areas are typically poorer than many urban areas, they have larger unfragmented landscapes, allowing them to support a higher abundance and diversity of species (Estrada-Carmona et al., 2022; Gonçalves-Souza et al., 2025).

The second explanation, which we call the project exclusion hypothesis, is based on the lower participation of BIPOC and lower-income individuals in submitting observations. Low engagement of BIPOC and those with lower education (which can often be a predictor of lower income) appears to be a widespread phenomenon in contributory projects (Allf et al., 2022; Blake et al., 2020; National Academies of Sciences, Engineering, and Medicine et al., 2018; Pateman et al., 2021; Rutter et al., 2021). We want to emphasize that skewed participation in contributory projects does not necessarily result from skewed interest. Since the rise of the modern mainstream environmental movement in the United States, there have been numerous environmental concerns and movements led by Black Indigenous or People of Colour. There have been many efforts, such as #BlackBirdersWeek and many groups such as Latino Outdoors, Outdoor Afro Black In Marine Science (BIMS), and others, which highlight and uplift the voices of Black and other historically excluded populations' participation in birdwatching and other

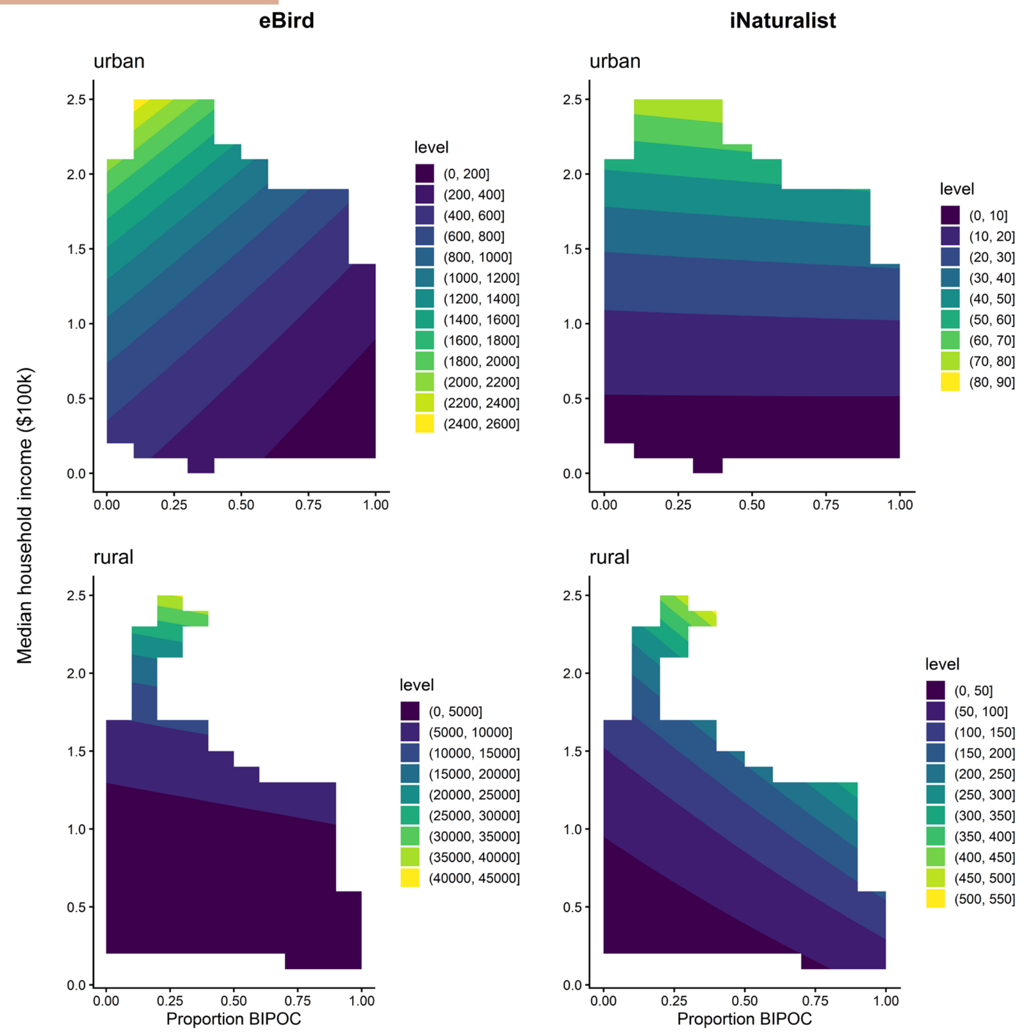

FIGURE 4 Hurdle model count predictions. This plot showcases the predicted intersections of proportion BIPOC and Median Household Income for the existing census tracts and their corresponding values. For census tracts with >0 observations, colours (and corresponding values along contour lines) illustrate the predicted number of observations as a function of a tract's proportion of BIPOC individuals and median household income. For urban tracts, tracts with higher proportions of BIPOC residents have fewer eBird observations, and tracts with lower income have lower observations. In rural tracts, the number of eBird observations is so high that it requires meeting a threshold of over $125k to see an increase in observations, whereas iNaturalist has much fewer observations (max 550), and income has a bigger effect on the number of observations compared to race.

forms of nature-based recreation and science, showcasing historical and present day interest in nature related science and recreation. BIPOC collectively account for 38.4% of the US population (2022 US Census), and according to the 2022 US Fish and Wildlife Service (USFWS) Survey of Outdoor Recreationists, Black, Asian, and other non-white individuals accounted for 34% of at-home wildlife watchers (watching wildlife, including birds, within 1 mile of home). Nevertheless, only 5.2% of eBirders identified as BIPOC (including Native American, Black, Asian, Pacific Islander, Hispanic/Latino or multiracial; Rutter et al., 2021). Thus, projects may have features and structures that (inadvertently) exclude certain minoritized demographics from participating, resulting in lower observation submissions in predominantly urban BIPOC and rural low-income areas.

Our findings suggest an urgent need to increase participation in nature-based contributory projects. Residential segregation and skewed demographics in contributory projects alone do not necessarily bias the spatial distribution of wildlife observations (Carlen et al., 2024). Projects may unintentionally reinforce problematic patterns about which areas matter geographically and which racial and economic groups receive benefits from ecosystem services. For example, eBird encourages the creation of and visitation to 'hotspots', or areas with high biodiversity, that inform where people should go to see 'cool' birds. If the luxury effect creates 'low attraction' to urban, low-income spaces and contributes to patterns of individuals travelling to or staying within white and/or high-income spaces to sample biodiversity, and 'hotspots' encourage more participation, sampling, and recording in those spaces, it results in overly optimistic estimates of biodiversity, with underrepresentation of data from lower-biodiversity areas. When participation and data collection predominantly reflect wealthy white areas, this reinforces a harmful cycle based on misconceptions about which areas support biodiversity best, misguiding decisions about where funding for restoration and preservation should go.

Unlike eBird, iNaturalist does not capitalize on a single audience (i.e. bird watchers); instead, they have a broader audience of general nature enthusiasts. iNaturalist has fewer data observations compared to eBird (Table 1), suggesting it has a less dedicated community of observers across both urban and rural regions. iNaturalist mainly operates with ‘subprojects’, which can be local or broader in scope and focus on specific taxa, likely leading to bias in species data over geographic areas.

5 | CONCLUSION

The uneven geographic patterns of race and income in the participation locations of contributory project data collection found in this study create significant implications for biodiversity research data quality, science advancement and science learning. First, race- and income-based spatial gaps in data lower data quality and limit its utility for intended uses by the project. While integrating complementary datasets and statistical techniques to account for sampling bias may lead to predictions of species distributions and estimates of biodiversity (Bird et al., 2014), increasing diverse representation among participants will improve the spatial distribution of the data, improving research capacity. To be clear, we are not suggesting that projects encourage their existing, predominantly white volunteer base to observe in Black and Brown communities. Instead, projects should work towards overcoming the project exclusion hypothesis by engaging potential volunteers who live within, or culturally identify with, the racially and economically diverse areas that lack participation, while being mindful not to place an undue burden on those communities, particularly those with the least capacity for additional responsibilities.

Second, contributory projects with uneven representation across tracts with varied race and income have limited ability to advance science in ways that benefit diverse segments of society (Blake et al., 2020; Mahmoudi et al., 2022). The research agendas of contributory projects like eBird and iNaturalist are more likely to benefit underrepresented groups if they engage them. Even though contributory projects can provide powerful insights and actionable findings to achieve significant scientific impact (Cooper et al., 2014), by failing to engage historically excluded segments of society, the projects are likely to only provide these scientific benefits in ways that align with dominant culture and priorities. They leave a gap of ‘undone science’ or unfunded and ignored research areas that social movements or community-based organizations identify as worthwhile research (Frickel et al., 2010). If underrepresented racial and economic groups were to be engaged in contributory projects, the research agendas and methodological approaches would likely be situated beyond the confines of the dominant culture (The ICBOs and Allies Workgroup et al., 2022), benefiting all people rather than a small segment of society.

Third, disparities in participation result in disparities in the benefits of informal science learning. eBird and iNaturalist are iconic contributory style participatory science projects that can produce learning outcomes for participants. For example, participants gain knowledge about the project topic (Jordan et al., 2011), an understanding of the scientific method (Kountoupes & Oberhauser, 2008), scientific thinking (Trumbull et al., 2000) and sense of place (Haywood, 2014; Haywood et al., 2021). Other learning outcomes include participants engaging in local action (Kloetzer et al., 2017), personal agency and political participation (Conrad & Hilchey, 2011; Overdevest & Mayer, 2008), access to civic and legal forums that provide legitimacy to public input (McCormick, 2012), advocacy for environmental action (Cornwell & Campbell, 2012) and increased accountability and industrial compliance with regulatory agencies (Overdevest & Mayer, 2008). Without widespread participation, all groups do not have the potential to experience these benefits, and in the case of advocacy and environmental action, this provides an additional disservice to communities who could use this data to advocate against environmental harms.

Lastly, the patterns and implications uncovered in this study would not exist without white supremacy culture and the policies and practices that created a legacy of racial segregation. Comparing our urban and rural model results showcases the nuances of the spatial scale of racial segregation. Massey (2020) explained how a legacy of intolerance has shaped the geographic distribution of Black, Hispanic and Asian individuals. Across the nation, a range of policies and practices have created persistent residential racial and economic segregation. Although the Fair Housing Act of 1968 aimed to address these issues, new and ongoing policies continue to perpetuate segregation today. Practices such as data-driven analytics are used in Market Value Analysis, targeting areas for investment, disinvestment and public service upgrades or disconnections (Safransky, 2020), furthering the racial wealth gap. Race and income are often intertwined, yet in this study we see clear patterns where race has more predictive power on the lack of observations in urban areas, whereas income is more influential on the prediction of data gaps in rural areas.

Given the history and impact of white supremacy culture and colonialism around the world, similar race or income gaps could exist in other countries based on each country's history and community practices and norms. While this paper groups everyone ‘non-white’ under the term ‘BIPOC’, it is important that future research investigates spatial data gaps by each minoritized community. Aggregating demographic data is a disservice to the individual communities because it contributes to the erasure of the unique histories and issues within each community (Deo, 2021). Furthermore, solutions to address race and income gaps in contributory projects will differ based on each community's needs.

AUTHOR CONTRIBUTIONS

Dillon Mahmoudi, Erica Henry and Caren Cooper conceived the ideas and designed the methodology. Erica Henry downloaded the data. Erica Henry, Dillon Mahmoudi and Deja Perkins analysed the data and created visualizations. Deja Perkins and Caren Cooper led the writing of the manuscript. All authors contributed critically to the drafts and gave final approval for publication.

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CONFLICT OF INTEREST STATEMENT

The authors state no conflict of interest.

DATA AVAILABILITY STATEMENT

All datasets used in this study are publicly available. eBird and iNaturalist data can be downloaded from gbif.org, and census data can be found at uscenus.gov.

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