ABSTRACT

PERKINS, DEJA J. The Geography of Participation: A Geospatial Analysis of Socio-Spatial Gaps in US Participatory Science (Under the direction of Dr. Caren Cooper).

Popular participatory science projects generate big data that advances scientific research, informs natural resource management and policy, and produces outcomes benefiting participants. Hundreds of thousands of volunteers share geo-referenced observations near their homes and frequented locations. The geographic information attached to every observation reveals patterns of participation —where and how often people collect environmental data. However, by allowing volunteers to choose when and where to collect data, large-scale projects can introduce spatial and temporal biases. This dissertation assesses demographics, place, and location to emphasize the importance of representation for geographic evenness in data produced through volunteer monitoring. In chapter one, I assess nationwide spatial gaps in two large-scale biodiversity projects. I found that eBird and iNaturalist data gaps can be predicted by income and race across urban and rural areas. In chapter two, I use Exploratory Factor Analysis to group Qualtrics responses into structural and personal-cultural barriers. I used a linear regression to test for a significant difference in the perception of barriers across demographic groups (age, race, gender, education, citizenship, and prior experience. In chapter three, I assess if populations are over or represented in Audubon's Christmas Bird Count across the southeast. By identifying predictors of spatial gaps and barriers to participation, this dissertation produces insights to enhance data collection, broaden environmental knowledge, and democratize science.

The Geography of Participation: A Geospatial Analysis of Socio-Spatial Gaps in US Participatory Science

by
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DEDICATION

This dissertation is dedicated to my community. We fly further with the support of those who uplift us. This dissertation is a labor of determination and perseverance. Lastly, this dissertation is dedicated to all the little Black girls who have ever been told “they can’t”. Keep soaring.

BIOGRAPHY

Deja Perkins was born and raised in Chicago Illinois. She attended Tuskegee University in Tuskegee, Alabama, for her Bachelor of Science in Environmental, Plant Science, and Natural Resources 3+1 program. After taking wildlife classes in Mississippi at Mississippi State University. She came to NC State to get her Master's in Wildlife Fisheries and Conservation Biology. She graduated during COVID-19 and started her nature education company Naturally Wild LLC. With this company, Deja built a community in North Carolina educating people virtually and in person about their neighborhood nature and the importance of community environmental monitoring with participatory science. In 2021 she joined NC State's Center for Geospatial Analytics to pursue her doctorate. While earning her degree, Deja simultaneously ran Naturally Wild LLC and co-organized Black Birders Week 2020-2025. During her time at NC State, Deja was an active part of the campus community, serving as the President of the Black Graduate Student Association and collaborating with the libraries to run the 2023 Pack Science Challenge.

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Introduction

The history of imperialism, colonialism, and white supremacy has been a driving force in the geographic distribution of Black and Brown bodies around the world. Naturalists and the "exploration" and study of new places were funded by colonial endeavors in the 1600s (Miriti et al 2022). The role of the naturalist was to map, explore, and observe the "new" lands that British, Spanish, Danish, and French ships sailed to. This was the beginning of the exploitation of Indigenous knowledge, resources, and a lack of reciprocity in natural science, as these early naturalists made way for the control and extraction of natural resources and, eventually, bodies (Miriti et al 2022). The United States has a dark history where many people have been forcibly displaced, impacting the distribution of people for generations. From 1526 to 1867, people from Africa were kidnapped, enslaved, and transported across continents, resulting in a Black diaspora reaching from the United States, the Caribbean, and South America (Bertocchi, G. 2016).

Even after the importation of Black bodies became illegal in the US, Black people were transported across the Southeast, resulting in the large population of Black individuals that exist across the Southeast today. Between 1910 and 1970, millions of Black Americans fled the rural south to more northern states and cities to escape persecution and in search of a better life. This event contributed to the high numbers of Black Americans seen in cities like Chicago, New York, Detroit, Philadelphia, Los Angeles, St Louis, and more. Across many Northern and Western cities, redlining practices between 1930 and 1960 prevented Black Americans from obtaining housing loans in areas with quality environments, trees, and parks. This practice, while short-lived, left a lasting legacy of how Black and other melanated ethnic minorities are physically concentrated in urban areas. While these policies don't exist today, practices like

political gerrymandering (the redrawing of political voter maps) are used for control and to maintain an unfair balance of power at local levels.

Indigenous Americans have a similar story where they were forced to resettle in western states under the threat of violence between 1830 and 1850, after their land was stolen and food sources depleted by Europeans. This displacement resulted in a large number of tribal lands in western states, but also the detachment from their ancestral spaces. A third wave of migrations are happening now in the 21st century, where people from around the world are attempting to immigrate to the US, many to flee persecution, war, or other destruction in their home countries. However, the United States' closed border policies and mass deportation campaigns in 2025 are resulting in another wave of geographic distribution where people are being exported to other countries like Panama, Costa Rica, and Mexico (NYT The Daily: Exporting America's Immigration Problem).

US Census data can help us map these patterns of migration, and when paired with other environmental data (urban heat, tree cover, air pollution, precipitation), it can help us make powerful predictions about how environmental conditions impact people and help determine who will be the most impacted. Another potentially powerful dataset is the volunteered geographic information attached to participatory science observations. Participatory science is an umbrella term for various methodologies engaging the public in scientific research (Perkins, Dunn, and Nichols 2023). Participatory science is somewhat rooted in the understanding that everyone holds knowledge. Post World War II, science in the West was seen as an "Ivory Tower" (Shapin 2012), an elitist circle closed off from the community it is supposed to benefit (Strasser et al 2019). However, science did not always exist in this structure. The professionalization of science in the nineteenth century turned something that was once seen as a hobby into a career field that

requires multiple years of training through expensive institutions, and something that is often not accessible for those of lower socio-economic classes or to ethnic minorities. Historically, "Western natural science" was completed by lay observers, individuals with free time (usually those of higher economic classes, typically white and male) (Vetter 2011). However, knowledge production does not always need to be attached to a title. It has been done through the tending of the land and monitoring of the seasons by many Indigenous populations around the world (Finn et al 2017). Traditional ecological knowledge (TEK) and traditional ways of knowing (TWK) are often passed down orally compared to the way Western knowledge is "verified" through written publications. Compared to TEK, western scientific knowledge is often locked behind the Ivory Tower of academia in the form of paywalls through a predatory journal system. The participatory sciences however, have the opportunity to question "who" gets to produce science. It has the potential to push against the system of academia and the ivory tower by challenging how science is produced, who gets to steer the research direction, challenging how, where and why science is done (Strasser et al 2019) by putting science back into the hands of the people.

The current system of knowledge production in academia exists as a system of checks and balances created to produce "rigorous data." The system relies on distributed labor to ensure the entire process of knowledge production is validated through fact-checking, citations, and peer review (Freakonomics 572). Scholars are expected to keep this cycle of knowledge flowing by paying for "publication" once papers are accepted into this reviewed system of journals, but they are also expected to review submitted journal articles for free with the idea that future scholar(s) will return the favor to keep the cycle of knowledge flowing. This is a lose-lose situation for the public and other academics, who then have to pay for access to read the journals. Many scientists have turned to using "Open Science," and "Open Access," terms and concepts that prioritize

broadening access to the knowledge produced by the academic "ivory tower" by prioritizing reproducibility and access to data, journals, and software (Ramanchadon et al 2021). "Open science" aims to increase accessibility to knowledge and the scientific process, creating a collaborative culture by making sharing more efficient, providing transparency on the process of science, and improving scientific impact metrics (Ramanchadon et al 2021). The idea of Open Access is to ideally remove the barrier between academics and the public, allowing the public to read the data that is funded through their tax dollars (Watson 2015). Open science requires academics to provide data, code, and use open-source software, while open access removes paywalls for journals, data sources (i.e. satellite data), and software (ESRI, etc), increasing the capacity for diversity of thought by allowing those who were previously restricted by paywalls a seat at the table. These practices have proven useful in a community context for trail mapping (Gire et al 2022), displaying environmental hazards (Fuller 2011), urban planning, and classroom learning (Schlemper et al 2018), among other uses. Open-access datasets have been especially useful for research on biodiversity and other types of environmental monitoring using big data (Sullivan et al 2017; Mahr and Dickle).

Some scholars have questioned when we will move beyond the idea of choosing to provide "open access" to data, journals, and software and move towards making open science the standard (Watson 2015). The participatory sciences and its promise of "democratizing science" is one additional way to make the production and sharing of science accessible to the general public. Participatory practices promotes the idea that "anyone can be a scientist" (Gonforth 2016). It broadens the capacity for monitoring and, as such, introduces a variety of perspectives on where to monitor. The unstructured and semi-structured projects potentially allow for massive amounts of widespread participation, generating and including knowledge on places that would

be hard for scientists to capture alone (Dickinson 2010). More collaborative and co-created methodologies create the potential for expanding the types of topics undertaken by including a wider variety of backgrounds, experiences, and world views in the process of knowledge production (Wylie & Sismondo 2015).

Participatory science encompasses a variety of projects that can be characterized by their level of involvement, types of tasks and actions undertaken by participants, and project goals (Bonney et al 2009; Wiggins and Crosten 2011; Perkins, Dunn, and Nichols 2023). Participatory projects can have many goals ranging from education and increased science literacy, action and advocacy, knowledge production and data processing, as well as research or publications (Wiggins and Crowston 2011; Perkins, Nichols, Dunn 2023). Project tasks can be conducted in person or virtually (Wiggins and Crowston 2011) involving elements like sensing, computing, analyzing, creating, and self-reporting (Strasser et al., 2019). The actions and tasks can stretch across a variety of typologies regardless of the project's level of collaboration.

The main difference between various types of participatory science research lies in their level of collaboration with the public (Shirk et al 2012). These collaboration levels range from projects that fully engage the public at every stage of the project to those that only require minimal participation in the form of data contribution. These collaboration levels include projects that are co-created, collaborative, contributory, contractual, and collegial (Shirk et al 2012). Co-created and Collaborative style projects involve high amounts of participation from the public through most, if not all, stages of the scientific process (Shirk et al 2012). Projects that fall under the co-creation category aim to have research agendas that benefit both the researchers and the community of participants. Projects that fall under this categorization include paradigms like community-based participatory research, some forms of community science, and

participatory action research. These projects are usually "grassroots" or driven by the research interest of the community of participants. They are usually action-oriented with a goal of action and advocacy. Collaborative projects also have high levels of public involvement, but the research question and aims may still be driven by the institution. Projects that fall under the collaborative style of participation include projects that involve participatory mapping (Kloetzer et al 2017), and crowdsourcing. Additional projects under this category are Photovoice (the public shares images and stories of relevant places to the research project) and GitHub (an online platform for collaborative science and sharing code).

While co-created and collaborative-style projects are usually grassroots-driven and have maximum public involvement in the construction of the research question, protocols, or analysis, on the other end of the spectrum are contributory projects. Many researchers are familiar with the contributory style of public participation, which may be more commonly known in the literature and in practice as "citizen science." Projects that fall under the typology of "citizen science" are usually institution-driven, meaning that some larger organization or research entity is in control of the direction of the research question and the project goals. Citizen science as a term, refers to a type of participatory science that is usually contributory, where participants primarily aid in data collection and sensing or monitoring of their environment (Bonney et al 2019; Wiggins & Crowston 2011; Cooper 2021). These types of projects tend to be broadly focused and large in scale, making it uncommon for participants to have engagement with project management. Contributory projects can be small or large in scale, for example, large-scale projects like Globe at Night or iNaturalist for learning and identification, or small-scale projects like Illinois River Monitors curated in a locally relevant context for monitoring local waterways (Blake et al 2018). However, projects that are larger in scale have the potential for more widespread geographic

contribution, expanding the capacity for knowledge production and holding a promise of new discoveries (Strasser et al 2019). Projects range across disciplines from virtual gamified Alzheimer's research (Stall Catchers), to in-person precipitation reporting (CoCoRHaS), and even home-based investigations of tap water quality (Crowd the Tap) and insect diversity (Never Home Alone).

Participatory projects follow three main data collection structures: unstructured, semi-structured, and structured (Kelling et al 2019). Unstructured projects are characterized by open and flexible participation, making them highly accessible. Semi-structured projects also have open and flexible participation but include specific procedures for recording effort (i.e. time of day, number of observers, hours, and distance traveled), clear objectives, and variation that can be accounted for by statistical techniques. Structured projects are the most rigorous because they have clear objectives and plans for data analysis, in addition to strict survey/project design and data collection protocols to control for variation. Unlike unstructured and semi-structured projects, structured projects do not have open and flexible recruitment allowing just anyone to sign up to participate. Projects with the primary goal of learning and increased science literacy are often more unstructured to allow room for a wide variety of participants and choice in where and how they participate (Smith et al 2021). The primary goal of these styles of projects is to learn about the natural world around them through inquiry and observation, thereby exposing participants to two steps in the scientific process. Projects with the goal of education may also have curricula or adaptations designed for students in middle, high, or collegiate-level classes (Aristeidou et al 2021). Projects with multiple goals, however, occasionally conflict. For example, if a project has goals of knowledge production and education, these goals can potentially conflict due to projects with the goal of knowledge production requiring more

structured protocols than projects with general goals of education and increasing science literacy (McKinley 2018).

The variety of typologies means that participatory projects can have benefits across wide-reaching areas for science, society, and participants (Receveur et al 2022). As such, participatory science has a variety of stakeholders outside of researchers and participants including educators, community members, and natural resource or other scientific managers. For example, participatory science can be used to teach social justice concepts (Vance-Chalcraft et al 2024) or collect data for environmental justice initiatives (Davis and Ramierez 2021).

While the participatory sciences have value for science, society, and individuals, it is a free-choice activity, similar to recreation. People have different motivations for engaging in extra-curricular science, and motivations may differ between scientists (whose goals are to advance knowledge) and volunteers due to the differences in goals and outcomes (Shirk et al 2012). From the scientific perspective, a successful project equates to project success means being able to publish papers and answer larger research questions. However, from the participants' perspective, successful projects help them satisfy their needs and interests and further their education goals (Rotman et al 2012). Both scientist and participant motivations for participating change and evolve throughout a project, cycling through intrinsic and extrinsic motivations based on egoism (improving self and personal welfare), principlism (upholding personal values), collectivism (for the good of the community/increasing welfare of the group), and altruism (increasing the welfare of someone else) (Rotman et al. 2012; Larson et al 2020). Many papers have studied motivations across a variety of forms of project engagement, including gamified citizen science and mobile participation (Ertiö et al 2016), as well as various disciplines, including ecological projects (Kaplan Mintz et al. 2023), climate projects

(Gharesifard and Wehn 2016), biodiversity projects (Hobbs and White 2012), marine projects (Martin et al. 2016), and air quality projects (McCrory et al. 2017).

Many studies focus on the barriers to scientists' engagement in and use of participatory science methods in their research (Wehn & Almomani 2019; Burgess et al 2017), but very few focus on the volunteer perspective of this lack of engagement (Asingizwe et al 2020). Scientists have reported a lack of awareness, preference for specific datasets, lack of project alignment, and inconsistent data quality, which prevent their engagement in and use of participatory science methods in their research practice (Burgess 2016). Other studies have investigated the barriers to participation in crowdsourcing projects (Baruch et al. 2016), and organizer perspectives on participant lack of engagement (Hobbs and White 2012).

One potential barrier for some groups in the US is the term “citizen science” itself which has undergone debate due to the exclusionary and charged nature of the term “citizen” in the United States and its political repercussions for some ethnic minority groups (Cooper 2021). While the term carries harmful underlying connotations in the US, citizen science as a field is international in scope, with associations in Europe, North America, and Australia (Cooper et al. 2021). Some scholars in the US have turned to the term “contributory projects” to define traditional citizen science projects and describe this category of projects by their participation style and level of involvement rather than maintaining the exclusive term “citizen science” (Perkins, Nichols and Dunn. 2023; Cooper et al 2021). The variety of terms used to describe the practice and its volunteers (Eitzel et al 2017) can present a challenge when trying to understand the discipline as a whole and how people engage with the practice and the term itself. Citizen science can apply to international projects, but contributory science offers a more inclusive term when referring to large-scale projects where the public serves as human sensors, data collectors,

and monitors. This dissertation focuses on large-scale contributory style projects and refers to "participatory science" when speaking more broadly about the discipline and the wide variety of projects.

Many academics originally questioned the credibility of citizen science data because it was "untrained amateurs" doing science (Greenwood 2007). There were concerns about volunteers submitting "poor quality, misleading, malicious or biased" data due to their lack of training and understanding of the scientific process and connections to actual scientific studies (Hunter et al 2012; Dickinson 2010). However, other studies have shown that the quality of participatory science data is of similar accuracy to trained professionals (Kosmala et al 2016). The potential for poor quality, misleading or biased data collection is a flaw of humanity, whether amateur scientists or not. Freakonomics episode 572, entitled "Why is There So Much Fraud in Academia", explores instances of cheating and fraudulent behavior in the Ivory Tower and its impacts on society. Brian Nosak, a Psychology Professor at the University of Virginia, states that "sometimes people are so motivated to advance that they are willing to change the evidence fraudulently," calling into question "trustworthiness" in science and academia. If academics cannot be trusted with science because they can be "motivated to change evidence fraudulently under pressure for career advancement," and scientists do not trust volunteers to assist with science, who is to be trusted with producing scientific knowledge? This mistrust between scientists and the public is not new, but extremely heightened in 21st century, now deemed the "Age of Misinformation" (Lupia et al 2024; National Academies of Sciences 2024). While many studies have emerged showing that citizen science data can be equal to the quality of technician-collected data (Galvan et al 2022), there are still a variety of challenges that users must be aware of, including spatial (Callaghan 2021; Chandler et al 2017;), temporal (Dimeson

et al 2023), sampling (Isaac et al. 2014), demographic (Waugh et al 2023) and statistical (Grade et al 2023).

A secondary aim of open science is to exist as a system of checks and balances. Brian Nosak claims that "Fraud has existed in science since science has existed, and that is because it is people doing the science (Freakonomics episode 572). People come with ideas, beliefs, motivations, and reasons they are doing what they do." Scientists, whether formally trained or amateur, have the capacity to show geographic biases in where they study based on areas and topics of interest and importance to them and, more broadly, funders. While we are taught to believe that science is unbiased, studies have shown that our cultural identity and perspective influence our science (Tackas 2003; Muhammad et al 2015). This is the idea of "positionality" that "an individual's worldview, and thus perceptions and research activities, is shaped by the frameworks, social identities, lived experiences, and sociopolitical context within which they live" (Cooper et al 2024). Our "positionality" is displayed geographically when mapping VGI data showcasing where we choose to conduct science. For academics, this results in conducting research and publishing papers near your home institution or hometown. Chandler (2017) shows that most academic publications are focused on studies done in the Global North. Due to the reliance on volunteers, participatory projects can have a spatial bias based on infrastructure and population density (Geldmann et al 2016); therefore, most observations occur where people are. This creates what we know as the urban-rural bias (Di Ceccco et al). Carlen et al (2024) found that observations of two biodiversity projects predominantly sample areas with predominantly white residents and high canopy cover in St Louis, Missouri. Participatory science volunteers have also been found to demonstrate a spatial and temporal bias in where they participate, choosing to observe in locations close to home and on weekends (Arazy and Malkinson 2021;

Dimson and Gillespie 2023; Courter et al 2024). In unstructured and semi-structured projects, the participants' viewpoints and aspects of their positionality can be displayed when using GIS techniques to map observation data. This can impact the actual species pool reported in biodiversity monitoring projects because participant choice creates a variety of filters that influence what species are likely to be reported (Carlen et al 2024). This can be seen globally in the locations and taxa that volunteers choose to take observations on where participation primarily occurs in Europe and North America globally, and the majority of data is collected on birds, mammals, and insects (Chandler et al 2017).

Aside from a geographic bias in participation, in the United States, it has been found that people who participate in citizen science tend to be overwhelmingly white (Blake et al 2020; Allf et al 2022, Pateman et al), older (Rutter et al 2021; others), and more educated than the general population (Blake et al 2020). Blake et al (2020) documented how majority white participation leads to a mismatch in the quality of waterways being monitored in a river monitoring citizen science project. Allf et al (2022) discovered through surveys that bird monitoring citizen science initiatives like the Christmas Bird Count, which has over 100 years of data, also lacks diversity, with surveyed participants being 96% white. Many initiatives do not collect biodiversity data upon sign-up, so some projects partner with researchers to survey participant demographics. Rutter et al (2021) found that eBird, a popular bird-based observation and recording platform, also primarily consisted of participants that were majority White (94.8%), and that social connection and demographic characteristics play an important role in building a culture of community and inclusion in bird-related citizen science, alluding to the importance of representation (having others who look like you in spaces where you engage) and mentorship when engaging in these activities.

If participation in contributory projects is majority white, it creates a white lens on where and what to monitor, which serves as an injustice to Black and other ethnic minorities who have not only been historically excluded from participating in science but have also been the topic of scientific exploitation throughout history (Miriti et al 2023). A fundamental paper by Shirk et al (2012) shows that citizen science as it currently stands does a disservice to minority communities because if deliberate project design helps achieve procedural justice (or equitable voice), but participants are mostly white, who broadly as a group has representation or a seat at the decision-making table, it does not provide an equitable voice. This current lens of research agendas leaves a gap of "undone science" — science that is unfunded, incomplete, or ignored but holds value to many social justice initiatives (Scott et al 2010).

Throughout this dissertation, each chapter aims to contribute to the understanding of whether large-scale contributory style projects are representative of the various identities that make up the US (race/ethnicity, age, gender, education) and truly achieve a democratized science from a geographic perspective. In chapter one, I expand on these ideas by assessing the geographic evenness in eBird and iNaturalist participation across census tracts in the United States. In chapter two, I investigate if there is a difference in the perception of barriers to engagement of science across demographic groups. In chapter three, I asses the demographic evenness across survey areas of Audubon's Christmas Bird Count in the Southeast.

CHAPTER 1

Geography of Race and Income Shape Spatial Data Gaps In Two National Participatory Science Projects

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Abstract

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. We used hurdle models to analyze 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 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.

The geography of race and income were significant predictors 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 or 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. The geography of race and income likely shape the spatial distribution of participatory data due to persistent racial

segregation in urban spaces and income-based segregation that is widespread in the US. In addition, areas with less data may have lower attraction for participants, and/or project structures may (inadvertently) exclude people of color 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. 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. We recommend future studies disaggregate participation data by specific racial communities because solutions may not be one-size-fits-all.

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 can't access (e.g., backyards). These forms of institution-driven projects, hereafter called contributory projects (see Cooper et al., 2021 for the usage of terms), number in the thousands, and a single project can be popular enough to engage millions (Waldispühl et al., 2020).

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). There is uncertainty about whether contributory projects are truly egalitarian and accessible to all members of society. Growing evidence in the US suggests that contributory projects are not often engaging non-white participants with higher than average income and education levels (Allf et al., 2022; Blake et al., 2020; Pateman et al., 2021; Rutter et al., 2021 National Academies of Sciences 2018). 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's 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 semi-structured 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 behavior (Callaghan et al., 2019). Additional sources of human-related biases can include population density, socioeconomic 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 patterns often appear on a finer scale—such as separations by railroads or streets—reflecting a legacy of white intolerance toward large Black communities or racially mixed neighborhoods (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 BIPOC people (Black, Indigenous, or People of Color) in cities across the US (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) have 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).

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 nationwide within two large-scale contributory projects. In this paper, we investigated the extent to which race and income explain the geographical unevenness in the distribution of participatory science data using two popular tools for collecting and analyzing biodiversity data: eBird (bird-centric) and iNaturalist (all taxa).

Data and Methods

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

eBird:

The eBird platform now includes data from over 796,000 people in 250 sub-regions, 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 amongst bird watchers, global reach, and ability to download large amounts of data at any time (Kelling et al., 2019). Data from eBird is 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 has been used for studies of avian ecology, to inform conservation and policy, and to support student education initiatives (Sullivan et al., 2014). However, despite its broad reach, eBird contributors are predominantly white (94.8%) (Rutter et al., 2021).

Observers can contribute to eBird anytime and anywhere. However, of the 96.3 million bird watchers, 95% observe near home, while 44% travel away from home to observe (*2022 National Survey of Fishing, Hunting, and Wildlife-Associated Recreation | FWS.Gov*, 2023). eBird's platform encourages participation through birding "hotspots," encouraging birders new and experienced 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 create lists (checklists) and, therefore, requires a certain level of knowledge to participate, creating a higher barrier to entry.

iNaturalist:

iNaturalist is a platform crowdsourcing 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). iNaturalist contains over 192 million observations with over 3 million observers and over 360 thousand identifiers globally. 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 don't need the ability to identify an organism to submit an observation. 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 photo, 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 behavior 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 four days each year. These millions of observations are submitted in 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.

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 Global Biodiversity Information Facility (GBIF) for the year 2018. All data included latitude and longitude coordinates, totaling approximately 1.7 million iNaturalist observations and 66 million eBird observations. We retained eBird data from all three observation types (stationary, traveling, and incidental), including complete and incomplete 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). This dataset included boundaries for the 73,056 Census Tracts (Walker & Herman, 2024).

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 approximately 4,000 to 6,000 residents and are the preferred analytical geography for approximating neighborhood analysis (c.f., (Spielman & Logan, 2013). For each Census Tract, we calculated the percentage of residents who identified as non-Hispanic white and calculated the inverse as BIPOC (Black, Indigenous, or People of Color), which included residents who identified as Black, Hispanic, Asian, Indigenous, or Mixed. Citizen science observation data was spatially joined to the Census geographies to summarize the total number of iNaturalist and eBird point observations in each polygon. The final dataset included the following for each Census Tract: median household income (from ACS), percent 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, similar to the way the Census Bureau designated urbanized areas. In this analysis, “urban” Census Tracts meet or exceed a density of 1 person per acre or 640 people per square mile (247.105 people per square kilometer). All other Census Tracts are designated as “rural.”

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 modeling 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 percent BIPOC (0-1) and median household income (25,000 - 250,000) as predictor variables. Since hurdle models can be 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. We ran all models in R using the `pscl` package (Jackman, 2005; Zeileis et al., 2008).

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).

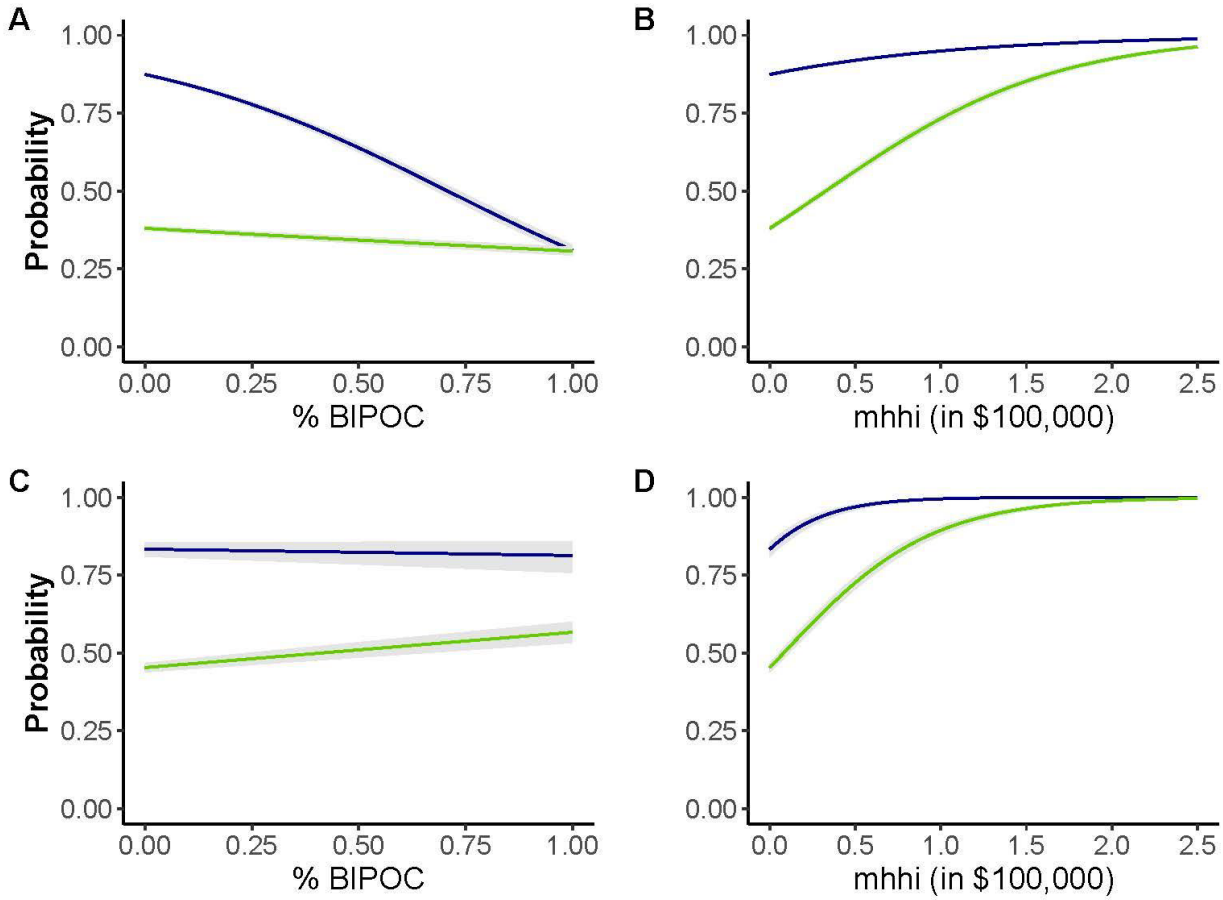

Figure 1. Showcases urban (A & B) and rural (C & D) zero-count hurdle model predictions for eBird (blue) and iNaturalist (green) observation presence with increasing percent BIPOC and median household income (mhhi).

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 percent of US eBird observations were in urban Census Tracts, specifically in 75% of urban tracts (Table 1). Thirty-

nine percent of US iNaturalist observations were in urban Census Tracts, specifically in 58% of urban tracts (Table 1).

Table 1. Comparison of urban and rural statistics for the number of Census Tracts, total population, number of eBird and iNaturalist observations, and percentage of tracts with eBird and iNaturalist observations.

	Urban (%)	Rural (%)	Total
Census tracts	50,096 (0.69)	22,960 (0.31)	73,056
Population	227,290,100 (0.70)	95,612,930 (0.3)	322,903,030
Total eBird observations	23,565,097 (0.35)	42,921,139 (0.65)	66,486,236
% tracts with eBird	0.75	0.96	
Total iNaturalist observations	667,684 (0.39)	1,058,138 (0.61)	1,725,882
% tracts with iNaturalist	0.58	0.76	

In the urban eBird zero hurdle model, %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 %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 with 100% BIPOC had a 28% probability of containing at least one eBird observation, whereas, at the other extreme, tracts estimated to be 100 % 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 higher %BIPOC, but when observations did occur in those tracts, they were fewer. In the count model (urban Census Tracts with at least one observation), %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).

Table 2 eBird and Hurdle Model results

eBird Rural

Count Model				
Variable	Estimate	Standard Error	Z	p
Intercept	6.34	0.042	150.308	<0.0001
%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
Zero Hurdle Model				
Intercept	1.61	0.16	9.90	<0.0001
%BIPOC	-1.40	0.17	-0.82	0.41
Income	3.69	0.29	12.87	<0.0001

eBird Urban

Count Model				
Variable	Estimate	Standard Error	Z	p
Intercept	5.54	0.05	115.05	<0.0001
%BIPOC	-1.00	0.05	-19.02	<0.0001
Income	0.73	0.04	17.40	<0.0001
log	-2.48	0.03	-83.54	<0.0001
Zero Hurdle Model				
Intercept	1.94	0.04	46.84	<0.0001
%BIPOC	-2.74	0.04	-65.83	<0.0001
Income	1.00	0.04	23.37	<0.0001

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).

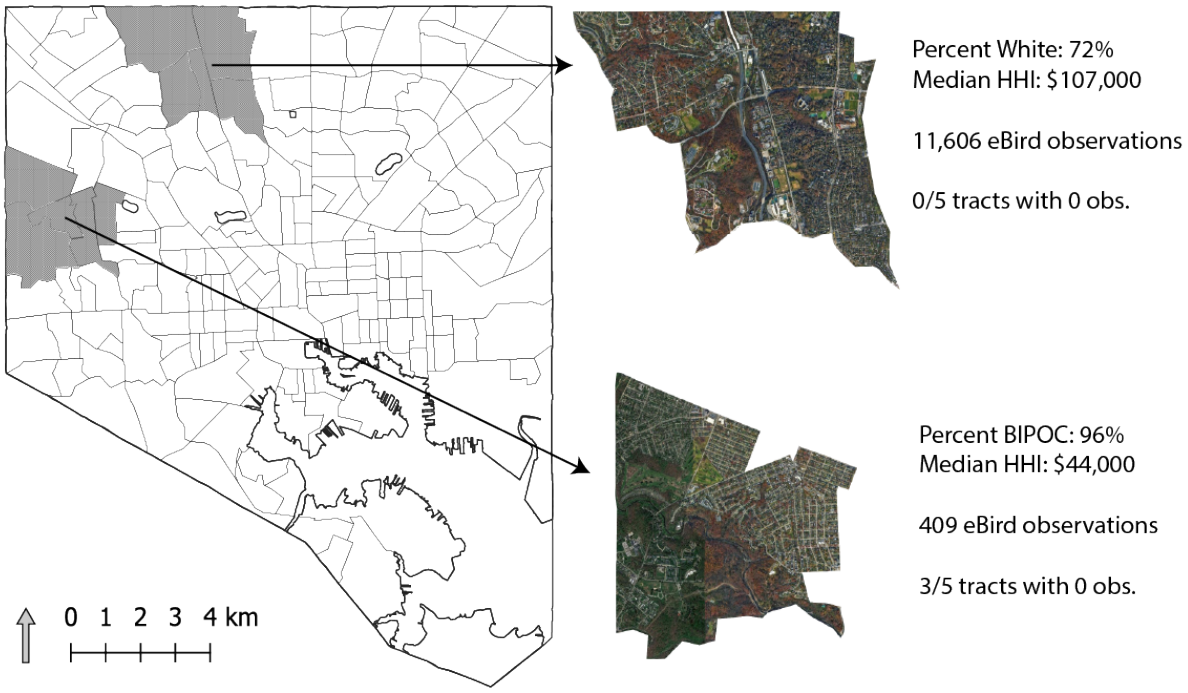

Figure 2. This map showcases the median household income, percent BIPOC, number of eBird observations, and number of tracts with 0 observations in Baltimore County, Maryland. Two areas in the county are highlighted to demonstrate the differences in the number of observations and income between predominantly white and predominantly BIPOC-occupied areas.

To summarize, urban Census Tracts that were predominantly BIPOC populations with many eBird observations were the least common (the smallest block, L-H, in Figure 3), while the most common urban Census Tracts were those that were predominantly BIPOC and few or no eBird observations (the largest block, L-L, in Figure 3).

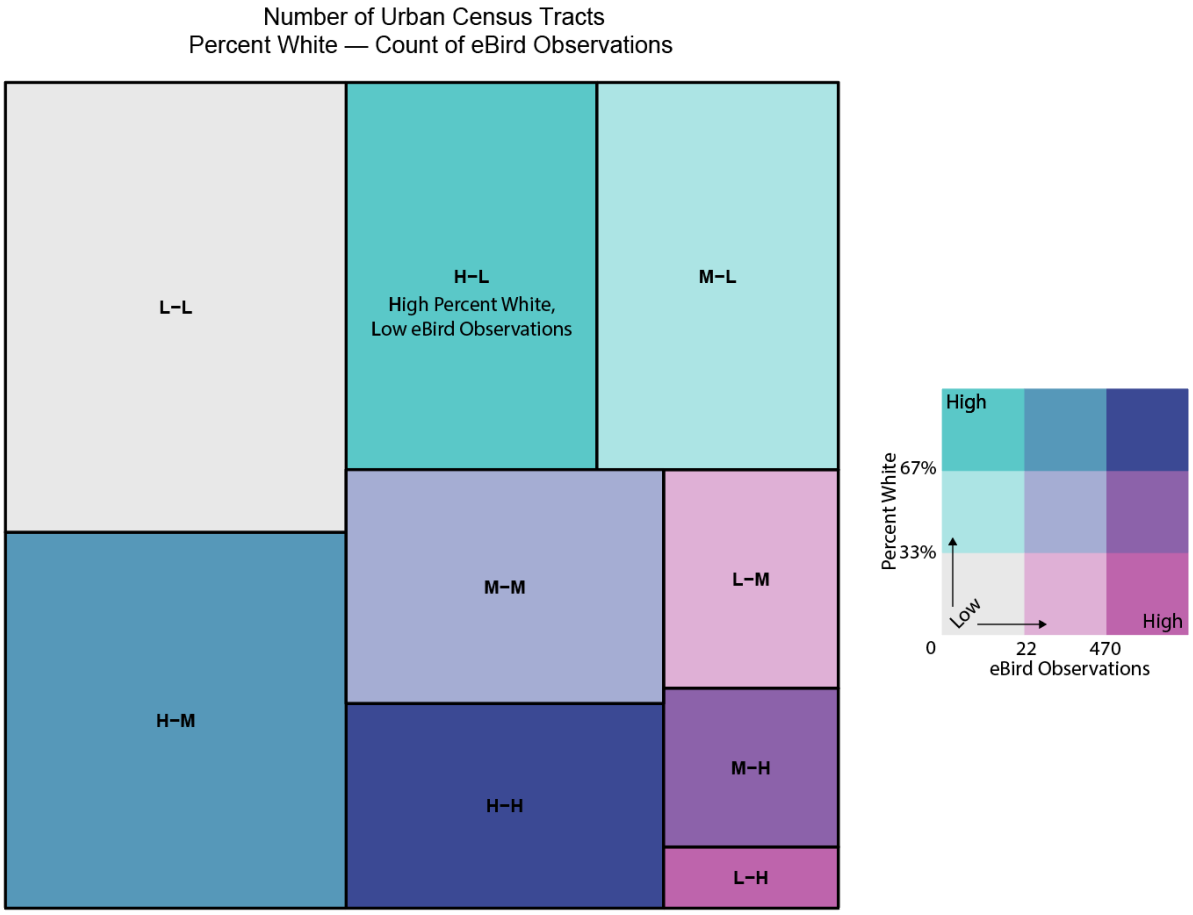

Figure 3. This bivariate treemap diagram shows the number of high, medium, and low values for eBird observations and the percentage of white residents in urban Census Tracts across the continental US. L-H references a **L**ow percentage of whiteness (high BIPOC) and a **H**igh number of eBird Observations. H-L references a **H**igh percentage of whiteness (low BIPOC) and a **L**ow number of eBird Observations.

In the urban iNaturalist zero hurdle model, %BIPOC was a significant and negative predictor of the likelihood of having at least one iNaturalist observation (Estimate =-.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 %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.

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, %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 3). However, income 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 3). 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 3), indicating that wealthier rural tracts have more eBird observations.

Table 3 iNaturalist Hurdle Model

iNaturalist Rural

Count Model				
Variable	Estimate	Standard Error	Z	p
Intercept	-1.39	1.97	-0.71	0.48
%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
Zero Hurdle Model				
Intercept	-0.19	0.06	-3.15	0.001
%BIPOC	0.46	0.08	5.87	<0.0001
Income	2.32	0.09	24.84	<0.0001

iNaturalist Urban

Count Model				
Variable	Estimate	Standard Error	Z	p
Intercept	-9.25	6.65	-1.39	0.16
%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
Zero Hurdle Model				
Intercept	-0.49	0.03	-15.40	<0.0001
%BIPOC	-0.33	0.03	-9.78	<0.0001
Income	1.50	0.03	44.35	<0.0001

In the rural iNaturalist zero hurdle model, %BIPOC was a weak positive predictor of the likelihood of having at least one observation (Estimate=0.46, +/- 0.08SE, p <0.001; Table 3). Income, however, was a strong positive predictor (Estimate=2.32, +/- 0.09SE, p<0.0001; Table 3), significantly increasing the likelihood of the occurrence of iNaturalist observations. For rural tracts containing iNaturalist observations (count model), both %BIPOC (Estimate=1.89, +/- 0.11SE, p<0.0001; Table 3) and income (Estimate=1.26, +/- 0.09SE, p<0.0001; Table 3) 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).

Discussion

The influence of Census Tract composition on the distribution of volunteer-generated data is an important consideration when using these data to model solutions for the future. Our results indicate that the geography of race and income influences nationwide spatial patterns of where nature observations are submitted by volunteers to eBird and iNaturalist. Large-scale participatory science projects can accommodate massive amounts of engagement with no cap on the number of people who can potentially engage (e.g., over one million in three months, (Waldispühl et al., 2020). There are several possible explanations for the under-sampling of predominantly BIPOC and lower-income areas in the US in these two popular projects. We'll review two sets of explanations that 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 are geographically concentrated within rural and urban 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. There is a lower likelihood of greenspaces, parks, and street trees in neighborhoods 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 neighborhoods, which can harm people and reduce biodiversity (Jbaily et al., 2022; Liu et al., 2021). Furthermore, ecological studies have noted the luxury effect, where biodiversity is associated with affluent neighborhoods (Leong et al., 2018). One flaw that makes the low attraction hypothesis insufficient explanation is that those viewing biodiversity are often attracted to areas that are far from pristine, such as sewage treatment facilities, superfund sites, and landfills (Murray & Hamilton, 2010; Schaffner, 2009; Svensson, 2018).

The second explanation, we call the project exclusion hypothesis, which is based on the lower participation of BIPOC and lower-income individuals in submitting observations. Lower 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, 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. For example, 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.

Residential segregation and skewed demographics in contributory projects alone do not *necessarily* bias the spatial distribution of wildlife observations (Carlen et al., 2024). The low attraction hypothesis assumes high mobility among participants, suggesting participants (of any demographic category) intentionally choose and travel to places of greater biodiversity. The project exclusion hypothesis assumes participants collect data at or near where they live. Evidence is equivocal. Some studies find that participants tend to contribute observations at and around their homes (Thompson et al., 2023), and other studies find that participants travel (Di Cecco et al., 2021). According to the USFWS Survey of Outdoor Recreationists (2022), more people watched wildlife at home. Yet, many still traveled to view wildlife, and Black, Asian and other non-white individuals accounted for 36% of away-from-home wildlife watchers.

Support for the low attraction and/or project exclusion hypotheses, which are not mutually exclusive, could each lead projects to incentivize participants to collect data in under-sampled areas (e.g Callaghan et al., 2023). The incentive approach, like the low attraction hypothesis itself, ignores known racial and economic disparities in participation. A more robust solution would involve projects adopting inclusive practices and engaging new audiences so that they become more diverse. To be clear, we are not suggesting that projects encourage their existing, predominantly white volunteer base to observe in Black and Brown communities. Instead, we believe projects should work towards engaging potential volunteers in 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.

The type of solution employed is crucial because geographic unevenness in volunteer-generated observation locations creates significant implications for ornithology and biodiversity research, management, education, and learning. Further, it affects the distribution of benefits for people not living near observation locations whether participants or not. 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. If low attraction due to the luxury effect contributes to patterns of white individuals staying within white and/or high-income spaces to sample biodiversity, the implications are that estimates of biodiversity are overly optimistic with the underrepresentation of data from lower biodiversity areas.

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" (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).

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 some 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 of large-scale participatory science include participants engaging in local action (Kloetzer et al., 2017), improving other aspects of their lives through their perceptions of science (Land-Zandstra et al., 2016), and valuing the importance of scientific debate (Aristeidou & Herodotou, 2020). More intensive forms of participatory science can produce an even wider array of learning outcomes, such as greater 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). In addition to producing learning outcomes in their own right, contributory projects like eBird and iNaturalist, which have a lower bar of commitment and entry for participation, can function as a gateway for deeper engagement in co-created projects (Cornwell & Campbell, 2012).

The patterns and implications uncovered in this study would not exist without white supremacy culture, and the policies and practices creating 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 entrenched persistent residential racial 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. Given the history and impact of white supremacy culture and colonialism around the world, similar gaps could exist in other countries based on each country's history and community practices and norms.

Given that eBird and iNaturalist are examples for thousands of other contributory projects across disciplines and sectors, the likelihood that other projects also show similar racial and economic patterns means that the compounded effect itself is an environmental justice issue: cumulatively, contributory projects may create data-rich areas and data-poor areas. Data are 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 participatory science projects are not collectively creating an equitable distribution of data, then they are exacerbating environmental injustice. Additionally, if tools like eBird have features that are marketed as a tool to inform where people should go to see "cool" birds (hotspots), and participation and data collection are over-representing wealthy white areas, it perpetuates a vicious cycle based on misconceptions of what areas are best able to support biodiversity, which misinforms decisions about what areas need funding for restoration and preservation. In this scenario, projects may

reinforce the problematic patterns of what areas matter geographically and which racial and economic groups receive benefits from ecosystem services.

Since the rise of the modern mainstream environmental movement in the US, there have been alternative environmental concerns and movements led by BIPOC. There have been many efforts, such as #BlackBirdersWeek and many groups such as Latino Outdoors, Outdoor Afro Black In Marine Science (BlMS), and others which highlight and uplift the voices of Black and other historically excluded populations' participation in birdwatching and other forms of nature-based recreation and science. Our findings suggest an urgent need to increase participation in nature-based contributory projects. In this paper, we use the term BIPOC, which was created to highlight the unique violence experienced by Black and Indigenous peoples separate from other people of color in the United States. We chose to use the term BIPOC over POC to emphasize the anti-Black history and policies contributing to the geographic distribution of people in the United States — “a country founded on the enslavement of Black people and the genocide of Indigenous peoples” (Grady, 2020). While this paper groups everyone “non-white” under the term “BIPOC,” it is important that future research investigates spatial 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.

Chapter 2:

Structural and Cultural Barriers to Engagement in Participatory Science

Introduction

Science occurs in a variety of contexts, in both formal and informal settings. Participatory science is one way of conducting science by engaging the public and using collective input to solve problems. Public engagement in science expands the capacity for data collection and the collective knowledge we have about different geographic areas around the world, creating a more comprehensive understanding of potential issues and solutions in areas that are under-resourced and under-monitored (Dickinson et al. 2010). Participatory science can take a variety of forms, including contributory science (better known as citizen science), community science, public science, civic science, crowdsourcing, and participatory research. Each of these forms of participatory science is unique in how they collect data and engage with the public. Across the variety of forms of engagement, each has potential to provide benefits to participants through increased science literacy and benefits to the broader field of science through increased data collection and knowledge production (Bonney et al 2009).

Despite its benefits, a lack of participant diversity creates and reinforces disparities in who generates knowledge and receives benefits. Currently, participatory projects engage overwhelmingly white, higher-earning, and highly educated populations (Blake et al. 2021, Rutter et al. 2021, Allf et al. 2022). Contributory projects sometimes come at a monetary "cost" to volunteering (i.e., Project Feederwatch, CoCoRHaS), which can be a barrier to participation for individuals who do not have the monetary freedom or social capital to engage. Other barriers include lack of time to participate, caregiving, lacking transportation, and more (Pateman et al. 2021). There have been several papers that have documented a lack of diversity across a variety

of environmental citizen science through an analysis of participant diversity. Pateman et al (2021) documented patterns of participant characteristics and the likelihood of participation across age, gender, age, and social grade. They found that marginalized groups are underrepresented in citizen science and that people aged 25-34 were less likely to have participated. As a result, the current structure of some forms of participatory science perpetuates a cycle of engagement producing information on how majority white, middle to high-income ecosystems function. For example, in water monitoring projects, waterways in proximity to predominantly white neighborhoods are more likely to be designated as impaired and receive funding for remediation than waterways near communities of color simply because there's more volunteer water monitoring data near white neighborhoods (Blake et al., 2021). This is concerning because participatory projects are viewed as a way to democratize science (Strasser et al. 2018) and collect data from a broader range of areas (Dickinson et al 2010). Yet, when participation is not diverse, these goals are not achieved.

Engagement in participatory science is a free choice activity, where participation in this extra-curricular science is like a hobby, something participants opt in to do in their free time. As such, barriers to participatory science can be similar to constraints in outdoor recreation. In the field of leisure studies, constraints are defined as factors limiting participation in activities, services, or inhibiting joy and satisfaction (Jackson & Scott 1999; Shores 2007). In recreation, constraints to participation are experienced based on ethnicity and race, class, and immigration status (Stoldoskka, Shinew, Acevedo & Izenstark, 2011; Stoldoska, Shinew & Camarillo 2018). Constraints can be experienced differently within racial/ethnic groups where gender, age, and education become compounding constraints (Bustam 2011; Shores et al 2007). Those of lower socio-economic status experience constraints related to cost and time (Stoldoska 2020; Shores et

al 2007). Immigrants can experience constraints due to a lack of programming material and facilitation in their native language. Those who are undocumented often experience even more barriers, for example, needing to secure spots with cash over credit card or having hesitancies over engaging government entities due to fear of deportation (Stoldoska 2020).

Crawford, Jackson, and Godbey (1991) define constraints as existing in a hierarchy consisting of structural, interpersonal, and intrapersonal constraints. Structural constraints relate to limiting elements within the environment of the participant, while interpersonal constraints are based on the individual's relationship with others. They suggest that intrapersonal constraints (related to the characteristics and beliefs of the individual) are the most limiting. Stoldoska, Shinew, and Camarillo (2020) redefine these into four main themes, which impact people of color directly, including individual, interpersonal, context, and systems. Individual constraints are most related to intrapersonal constraints, which are constraints specific to a person (i.e. lack of time, lack of money, language, etc). Interpersonal constraints are define as things like interracial tensions, lack of familial or peer support, and lack of co-participants (constraints based on relationships between people). Context and systems constraints are most related to structural constraints, where context refers to the environment where an individual exists (safety issues, neighborhood or home environment), and systems refer to larger systemic constraints (societal beliefs, laws/policies, systemic racism) (Stodolska et al 2018; Stodolska et al 2020). Many of these constraints can be classified as “static” or “dynamic”, highlighting how some categories (i.e., discrimination) are stable, whereas others may change over time (i.e., language, childcare) (Stodolska 1998) We believe similar classifications could prove useful for assessing constraints to contributory science projects.

Within the realm of citizen and participatory science, existing studies primarily focus on the motivations and barriers to engagement, volunteerism, and its impact on recruitment (Rotman et al 2014; West and Pateman 2016;), but few studies have focused on barriers to volunteer engagement explicitly. In geoscience, a lack of diverse volunteer engagement is attributed to factors such as lack of time and interest, responsibilities to other tasks, misalignment with community values, unfamiliarity, discomfort, and financial obligations (Levine 2009), which align well with individual and interpersonal constraints. Age, gender, education, and disability have all been found to impact volunteer participation, recruitment, and motivation (Behrens and Colombelli-Negrel 2024; West and Pateman 2016). In recreation, participation from older individuals (over 65) is limited by health and income (Shores, Scott and Floyd 2006). However, this constraint contrasts directly with what is seen in the citizen science literature, where participation is overrepresented by individuals over the age of 65 (Allf et al 2020; Larson et al 2020). Older volunteers have been found to contribute more effort due to higher time availability (retirees) than younger volunteers (establishing family and career) (Choi and Chou 2010). Participant barriers have been found to change throughout the project and among demographics, like gender (Asinizwe et al. 2020). For women, fear can be a barrier to participation in both urban and forested environments (Virden & Walker 1999; Riger and Gordan 1981; Shoals et al 2007). In weather monitoring participatory projects, this can mean hesitancy around sharing geolocated data (e.g., weather information) (Gharesifard and When 2016), due to fear of safety.

Understanding motivations may be key to promoting engagement and understanding recruitment strategies in participatory science projects, but it doesn't address why people aren't participating. Many studies focus on existing participants (Pateman, Dyke and West 2021) in

UK, Allf et al (2020) in US, etc.), but very few examine barriers explicitly or consider the perspective of prospective participants, and even fewer have intentionally focused on marginalized demographics. Race/ethnicity, age, gender, and socioeconomic status (income/class) are the four broad variables in leisure studies that impact an individual's "status" or "social position" (Shores et al 2007). This paper investigates barriers to engagement in science across race/ethnicity, age, gender, and citizenship status, including the perspective of participants who have not previously engaged. We incorporated the perspective of citizens vs non-citizens in an attempt to capture the immigrant's perspective adding to the low number of studies about immigrant barriers in the US (). Our main goals are to 1) identify perceived barriers to engagement in participatory science and 2) understand the difference between race, citizenship, age, gender, education, and prior experience on perceived barriers to engagement in participatory science.

Methods

Data Collection

Survey responses were obtained through a Qualtrics XM panel composed of respondents who signed up to earn money by participating in online surveys through the Qualtrics website. Similar panel survey methods have become quite common in the social science literature and can effectively deliver large, representative samples (Boas et al., 2019). We set criteria for the sample (i.e., nationally representative sample across the United States, but with quotes for race/ethnicity), and Qualtrics invited respondents to participate who met the criteria. Qualtrics continued to collect data until set quotas were filled. The same survey instrument was used to obtain data in two waves with slightly different sampling criteria. In the first wave, from February 19-26, 2021, criteria were set for respondents over 18 years of age in the United States

(all 50 states) and the United Kingdom. In the second wave, from October 19-23, 2021, criteria were set for respondents over 18 years of age in the United States with quota sampling for roughly equal distribution across the four largest racial/ethnic groups (White, Hispanic, Black, Asian) as well as a targeted sampling of people without citizenship status. The dataset was merged in Microsoft Excel to combine the two sampling waves prior to data analysis. The North Carolina State University Institutional Review Board approved the data collection protocol (IRB #16606).

Survey Instrument

The instrument began by framing public engagement in science broadly: "Below you will see several phrases that might be used to describe the process of people, including those without scientific credentials, contributing to science. These contributions might include activities such as: "Identifying issues for study, Designing experiments, Collecting information or data, Conducting analyses, Interpreting study results, Communicating those results to others." We then asked respondents to rate their familiarity with and perceptions of different phrases that might be used to describe participatory science activities (e.g., citizen science, community science, public science, participatory research). Comparing public perceptions of these different phrases was the goal of a separate study. Here, we used the terms to paint a broad picture of what science engagement might look like.

To characterize past participation in science, each respondent was asked to "Select ONE response that best described their involvement in the activities described earlier in the survey (citizen science, civic science, community science, crowdsourcing, participatory research, public science, and/or volunteer science)?" Response options for this item were: "I have NOT engaged in these types of activities," "I am NOT SURE if I have engaged in these types of activities," "I

have engaged as a leader or coordinator of participants in these activities," "I have engaged as a participant in these activities," and "I have both led/coordinated AND participated in these activities." Participants were then asked about the types of scientific research projects they had been involved in across the following disciplinary themes: Behavioral and social science projects, Environmental and life science projects, Engineering and earth/physical science projects, Health and medical science projects, and Other types of projects.

Another section of the survey included 21 items about potential barriers to engagement in science (Table 1). These included questions like "Participating in science activities is not fun for me" and "I lack the technological resources needed to do science activities". Because little previous research has focused on barriers to citizen science participation (Shinbrot et al 2023), our barriers were adapted from papers that focus on a range of constraints to leisure activities (White 2008; Shores et al. 2007; Ghimire et al. 2014; Stodolska et al. 2020). Items were selected to capture different dimensions of constraints, including individual/intrapersonal, interpersonal and cultural, and structural/contextual (Stodolska et al., 2020). The final section of the survey included demographic questions. The first questions focused on country of residence (United States or United Kingdom) and citizenship status. For United States respondents, we asked if they were a citizen of the United States (citizen born in the US, born abroad to United States citizen parents, or citizen by naturalization) or not. For UK respondents, we asked if they were a British citizen or not and, if a citizen, we asked about their country of birth (England, Northern Ireland, Republic of Ireland, Scotland, Wales, Elsewhere). Other demographic items asked respondents to self-report their racial/ethnic background (White, Hispanic/Latino, Black or African American, Asian, American Indian or Alaska Native, Middle Eastern or North African, Native Hawaiian or Pacific Islander, Mixed Race, Other), gender (man, woman, non-binary,

other), age (year of birth), highest level of education achieved (high school or secondary school diploma or GED or less, Associate's or Bachelor's degree, Graduate or professional degree), and primary occupation (STEM field or profession involving science, technology, engineering or math, Other non-STEM field or profession).

Data Analysis

We used descriptive statistics to characterize the demographic attributes of respondents and their previous experience with public participation in scientific activities. We aggregated responses to the "past experience" question into two categories: individuals who had participated in such activities in the past (either as a participant or leader/coordinator) and those who had not. We further divided past participants into two categories based on the disciplinary types of projects they had engaged in: either a single type of project (single) or multiple projects spanning multiple disciplines (multi). This distinction was derived from Allf et al.'s (2022) typology of citizen science volunteers based on multi-project participation and the fact that some respondents might consider their participation in the Qualtrics survey itself as a form of public participation in scientific activities (i.e., their single project), which could skew results and mask true participation rates.

We used an Exploratory Factor Analysis to examine the factor structure of the 21 items measuring barriers to participation. Exploratory Factor Analyses are used to identify the underlying structure between a set of variables and examine their convergent and discriminant validity across different dimensions. We ran the factor analysis in R using the 'psych' package with two factors and principal axis factoring as well as a "varimax rotation" with a maximum of 100 iterations to facilitate interpretation. Once factors were identified, we calculated a mean

score for each index based on the items within the factor. We also assessed the internal consistency of items within each factor using Cronbach's alpha (Cronbach's alpha = .94).

We determined the number of factors based on a scree plot showing minimal change after two factors and an increase in cross-loading in items at three factors. After determining the number of factors, we averaged the variables based on their loadings for each factor and used these values in two separate linear regression models. We used linear regression models to test the difference between the effects of race, citizenship status, previous experience, gender, age, and education categories on the means of the structural and cultural models. The reference levels for the model were set to the values representing the average participatory science volunteer: white, college-educated, citizen, age 50-64, men, and "yes" the participant had previous experience in participating in science.

Results

Summary statistics

Data for this paper was collected through a Qualtrics survey distributed in two waves. In the first wave, we received 1300 responses from the US and UK; however, the present analysis was restricted to US respondents, which was a sample of 519. The second wave yielded 1,335 responses in the US. Individuals indicating "other" or "NA" (n = 23) were removed from the sample. The final sample used in the analysis, therefore, consisted of 1,832 completed surveys in the United States (with quota sampling yielding near-equal distribution across the four racial/ethnic groups).

Science Engagement

Of the 1,823 respondents, 35.38% reported prior experience, and 64.62% did not have experience. Participation rates were highest among individuals who were men (63.91%), high-school educated (45.36%), aged 35-49 (31.27%), citizens (86.78%), and white (25.78%).

Table 1. Distribution of respondent demographics.

Factor	Category	n	Percent
age_5cat	18-24	396	21.72
	25-34	491	26.93
	35-49	570	31.27
	50-64	246	13.49
	65 +	120	6.58
cit_sci_participation_combined2cat	yes	645	35.38
	no	1,178	64.62
citizen_us	yes	1,582	86.78
	no	240	13.17
	other	1	0.05
education_level_3cat	college	722	39.61
	high school	827	45.36
	grad school	274	15.03
gender_2cat	men	1,165	63.91
	women	658	36.09
race_categories6	White	470	25.78
	Hispanic	364	19.97
	Black	375	20.57
	Asian	413	22.65
	Indigenous	90	4.94
	Multiracial	111	6.09

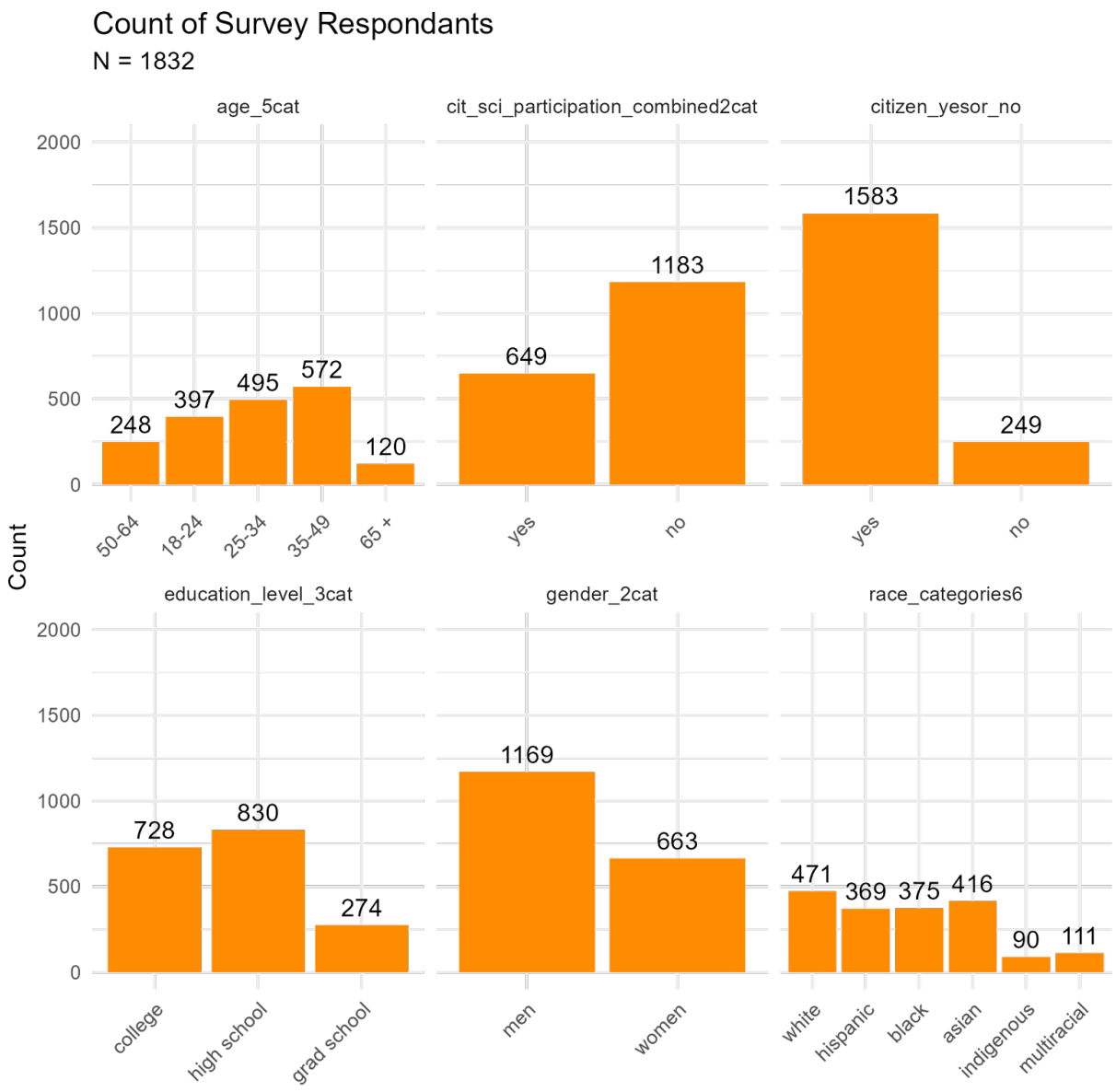

Figure 1. Distribution of respondent demographics.

Type of Barriers

The Exploratory Factor Analysis found the components loaded onto two factors explaining 53% of the variation. Based on item content, we described one group of items as "structural barriers" and the other as "personal and cultural barriers."

Factor 1 (Project Structural Barriers)

Factor 1 (M = 1.23, SD = 0.82) contained 7 items (items 7, 8, 9, 10, 11, and 12), which appeared to measure structural barriers to engagement (e.g. high cost, lack training, lack of resources, never invited)). All of these barriers are logistical challenges associated with citizen science projects that hinder participation rates. A follow-up reliability analysis found factor 1 to have high internal consistency (Cronbach's alpha = .88).

Factor 2 (Personal and Cultural Barriers)

Factor 2 (M = 0.94, SD = 0.77) contained 12 items (items 2, 3, 5, 6, 14, 15, 16, 17, 18, 19, 20, and 21), which appeared to measure personal barriers to engagement (e.g., lack of interest, not fun for me, doesn't align with values) and cultural reasons for not engaging (e.g., not in my primary language, don't feel welcome). All of these barriers relate to the nature of the individual or the cultural context of the project. A follow-up reliability analysis found factor 2 to have excellent internal consistency (Cronbach's alpha = .94).

Crossloaded Items

Two of the items: "I lack free time to participate" and "I don't have anyone to participate with me", did not load explicitly onto one factor over the other and were removed from further analysis.

Table 2. Mean, Standard Deviation, and Factor loadings for (A) Structural Barriers and (B) Personal and Cultural Barriers based on Factor Analysis with Varimax rotation for barrier items. We extracted only factors with eigenvalues > 1; The 2-factor model accounts for 53% of the total variance.

Item	Item text	Mean*	SD	A	B
7	I am not aware of opportunities to participate	1.39	1.10	**0.74**	0.13
8	I do not have access to these opportunities	1.27	1.05	**0.70**	0.27
9	I was never invited to engage in science activities	1.34	1.09	**0.69**	0.22
11	I lack the training needed to do science activities	1.21	1.05	**0.62**	0.40
12	I lack the technological resources needed to do science activities	1.14	1.03	**0.57**	0.46
4	I don't have the skills or abilities to do science activities well	1.12	1.03	**0.55**	0.48
10	The cost of science activities is too high	1.21	1.03	**0.55**	0.41
15	Science activities don't align with my values	0.894	0.988	0.21	**0.75**
6	Science activities aren't available in my primary language	0.839	1.00	0.21	**0.72**
5	Science activities don't accommodate my disability	0.853	1.01	0.21	**0.71**
14	I lack support from family and/or peers	0.912	1.02	0.28	**0.68**
18	I don't feel comfortable due to a lack of diversity in science activities	0.987	1.01	0.33	**0.68**
19	I fear negative consequences from my participation in science activities	0.975	1.00	0.29	**0.67**
16	Science activities aren't designed for people like me	0.990	1.00	0.39	**0.66**
20	Science activities won't help me address problems I care about	0.985	0.986	0.33	**0.66**
17	I don't feel welcome in science activities	1.01	1.01	0.37	**0.65**
3	Participating in science activities is not fun for me	1.01	1.02	0.33	**0.65**
2	I am not interested in doing science activities	1.04	1.04	0.35	**0.61**

Table 2 continued. Mean, Standard Deviation, and Factor loadings for (A) Structural Barriers and (B) Personal and Cultural Barriers based on Factor Analysis with Varimax rotation for barrier items. We extracted only factors with eigenvalues > 1; The 2-factor model accounts for 53% of the total variance.

21	My participation won't make a difference	0.996	0.993	0.40	**0.62**
1	I lack free time to participate	1.18	1.04	0.44	0.41
13	I don't have people to participate with me	1.11	1.02	0.49	0.50
	Eigenvalues			6.76	4.48
	Proportion Variation			0.32	0.21

*Survey Likert scale: 0-Not a barrier;1-Minor barrier; 2-Moderate barrier; 3- Major barrier

Sociodemographic Correlates of Science Engagement Barriers

Structural Barriers Linear Model results

The value of the reference groups for the structural model was highly significant (B = 1.23, p = 2e-16). In the structural barrier linear model, Asian (B = 0.164, p = 0.004), Hispanic (B = 0.135, p = 0.021), and Black (B = 0.126, p = 0.030) identifying individuals perceived structural barriers significantly higher than white-identifying individuals. Non-citizens significantly perceived higher structural barriers than citizens (B = 0.137, p = 0.018). Indigenous respondents perceived higher structural barriers than white-identifying individuals, but not significantly. Multiracial individuals perceived fewer structural barriers than white individuals, but it was not significant. Not having previous experience or participation caused individuals to perceive higher barriers, but not significantly. While education did not produce significant results, high and graduate school-educated individuals perceived fewer structural barriers than college-educated individuals. Gender and age were not significantly different than men, and those 50-64 years old. The adjusted r-squared value was 0.01491, indicating the demographic variables had a weak predictive capacity for perceived structural barriers.

Table 3. Structural Linear Model

	Structural Barrier Linear Regression Model			
	Variable	Estimate	Std. Error	P-value
Race	Black	0.126	0.058	**0.030**
	Hispanic	0.135	0.058	**0.021**
	Asian	**0.164**	**0.057**	**0.004**
	Indigenous	0.108	0.095	0.256
	Multiracial	-0.076	0.087	0.382
Gender	Women	-0.037	0.040	0.355
Citizenship Status	Non- Citizen	**0.137**	**0.058**	**0.018**
Experience	No Experience	0.037	0.041	0.374
Education	High School	-0.064	0.043	0.137
	Graduate School	-0.052	0.058	0.375
Age	18 - 24	-0.123	0.068	0.071
	25 - 34	-0.108	0.064	0.092
	35 - 49	-0.106	0.062	0.088
	65+	0.120	0.092	0.129
	Intercept/Reference Group	**1.23**	**0.073**	**<2e-16**

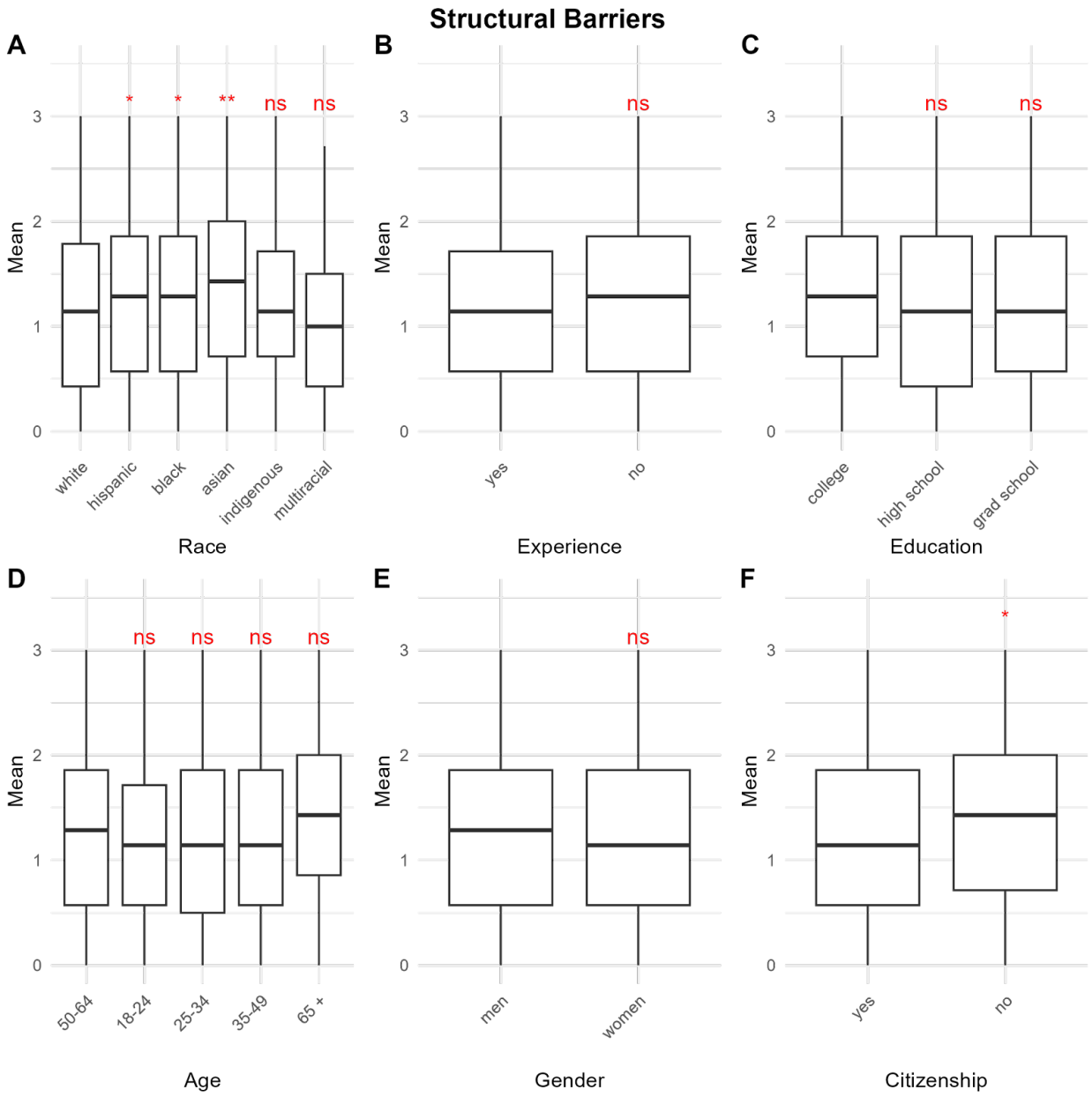

Figure 2. Mean of Structural Barriers (Factor 1 (M = 1.23, SD = 0.82)) across the race, citizenship, experience, and education categories. A star indicates a significance level of .05, two stars indicate a significance level of 0.01, three stars indicate 0.001, and "ns" indicates not significant. The first plot is the comparison group.

Cultural Barriers results

The cultural barriers model reference group was highly significant (Estimate 12.3, p-value = 2e-16). In the linear regression model, Hispanic (B = 0.139, p = 0.011) and Black (B = 0.233, p = 1.86e-05) individuals perceived significantly higher cultural barriers than white individuals. Non-citizens perceived significantly more cultural barriers than citizens (B = 0.156, p = 0.004), and those without experience (B = -0.152, p = 9.63e-05) perceived significantly fewer cultural barriers than those with experience. and Indigenous individuals perceived more cultural barriers than white individuals, but it was not significant. Multiracial individuals perceived fewer cultural barriers than white individuals, but it was not significant. High school and graduate school-educated individuals perceived fewer cultural barriers than college-educated individuals, but not significantly. Women perceived slightly more cultural barriers than men but not significantly. Across age groups, 18-24-year-olds significantly perceived more cultural barriers than those 50-64 in age, while all other age groups did not have a significant difference. The adjusted r-squared value was 0.02601, indicating a weak predictive capability between the demographic variables and cultural barriers.

Table 2.4 Cultural Barrier Linear Regression Model Stats

	Personal and Cultural Barrier Linear Regression Model			
	Variable	Estimate	Std. Error	P-value
Race	Black	**0.233**	**0.054**	**1.86e-05**
	Hispanic	**0.139**	**0.055**	**0.011**
	Asian	0.071	0.054	0.185
	Indigenous	0.074	0.089	0.405
	Multiracial	-0.034	0.081	0.678
Gender	Women	0.003	0.038	0.942
Citizenship	Non- Citizen	**0.156**	**0.054**	**0.004**
Experience	No Experience	**-0.152**	**0.039**	**9.63e-05**
Education Level	High School	-0.044	0.040	0.280
	Graduate School	-0.031	0.055	0.565
Age	18 - 24	**0.138**	**0.064**	**0.032**
	25 - 34	0.102	0.060	0.088
	35 - 49	0.067	0.058	0.253
	65 +	0.043	0.086	0.617
	Intercept/Reference Group	**0.865**	**0.068**	**<2e-16**

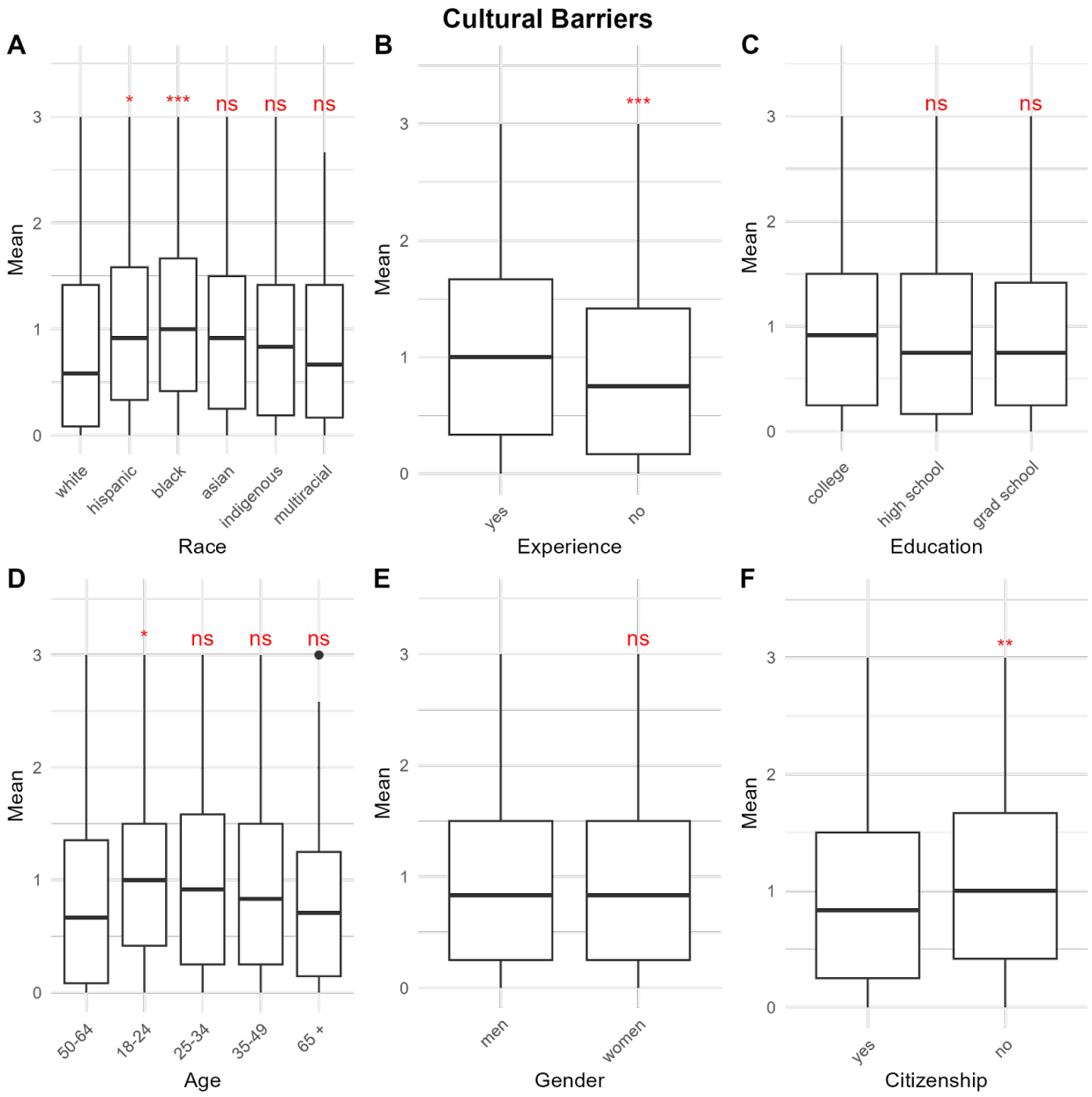

Figure 3. The mean of cultural barriers (Factor 2 (M = 0.94, SD = 0.77)) across the race, citizenship, experience, and education categories. A single star indicates a significance level of .05, and a triple star indicates a significance of .001 and "ns" indicates not significant.

Discussion

Despite the increase in the diversity of the STEM workforce between 2011 and 2021, those holding Black, Asian, Hispanic, or Indigenous identities only make up about 35% of the STEM workforce (National Science Foundation 2023). In the participatory sciences, participation has been found to be lowest amongst African Americans, Hispanics and Indigenous

Americans (Pandya 2012). Very little research has examined barriers to contributory science to date, but understanding the barriers to participation will aid in planning strategies for more inclusive engagement to diversify participants and increase the capacity for geographic evenness in data collection. This study used exploratory factor analysis to determine primary groups of barriers to engagement in participatory science and linear regression to test the difference between demographic groups (race, citizenship, age, gender, education) and prior experience on perceived barriers to engagement in science. Barriers were found to fall into two categories, structural and personal-cultural. Our findings align well with the recreational constraints literature, including items relating to structural (external factors/systems*),* interpersonal *(*interactions with others/peers/etc*)*, and intrapersonal *(*personal characteristics beliefs etc*)* *(*Crawford & Goodey 1978; Kavasoglu et al 2023). However, the adjusted R-squared values indicated that the demographic variables did not possess strong predictive power over the perception of structural or personal and cultural barriers.

Structural Barriers

Structural barriers were characterized by barriers that were related to the structure of the project. The factor analysis classified items like "cost of projects being too expensive," "not being invited to engage," "not having access to or awareness of opportunities." and "lacking training and technological resources." Much of the current literature focuses on barriers related to project structure. Our findings that race and citizenship are the most significant factors differentiating the perception of structural barriers align with previous literature indicating that race, gender, and immigration status can compound structural barriers like cost, lacking access, and lacking knowledge of opportunities (Stodolska et al 2020, Shinew et al 2004).

Items like not being invited to engage or not having access to and awareness of opportunities point to an issue within how projects market to and recruit volunteers. These types of barriers indicate that project recruitment materials may not reach a wide audience. There are a variety of strategies that can be employed to recruit and retain volunteers through the several stages of the participant journey, from project awareness to initial, sustained, and final participation (West and Pateman 2016). Understanding and advertising to a variety of motivations and including diverse representation in recruitment media are two important strategies in making potential participants aware of the project (awareness stage) (West and Pateman 2016). Limiting logistical barriers such as time, money, and ability aids in successfully recruiting and retaining volunteers (Behrens and Colombelli-Negrel 2024). Marginality theory, suggests that Black individuals are too impoverished to participate and therefore lack the time and money to engage is not an absolute indicator of the lack of participation. However, all "races" are not a monolith and while some are constrained by economic status, it is not the whole race/ethnicity's primary reason for lack of participation (Washburn 1978).

Many of the structural items relate to a project's investment in volunteers and their implementation of intentional recruitment strategies. Inclusive engagement can aid in big data collection (Dalby et al 2021). Technology like machine learning can reduce barriers to projects with high barriers to entry (Wood et al. 2022). However, our findings indicate that a lack of training on how to use these resources or a lack of access to these resources can constrain participation. Projects that invest in volunteer training and engagement throughout the different phases of volunteer participation have higher retention rates (West & Pateman 2016). Providing training, technical resources, and lowering project costs are common strategies shown to increase participation (West & Pateman 2016). Successful large-scale projects that reach the goals of

publishing papers and answering large research questions employ strategies such as engaging existing communities of interest, creating user-friendly platforms, planning simple participant tasks, building community with scientists, and making project data available (Golumbic et al. 2020).

Cultural Barriers

Cultural barriers included items related to the culture of the project or the individual. Barriers within this category were items such as lacking interest (the topic or projects not fun), lack of community (no familial or peer support or diversity) and belonging (activities not designed for them, not feeling welcome), lack of alignment with principals (not feeling included based on values, won't address problems they care about), lack of inclusion (disability or language), and feelings related to project contribution (fearing negative consequences from their participation and feeling like their participation won't make a difference).

Our findings indicate that race, citizenship, and lacking prior experience categories significantly differ in the perception of cultural barriers. Since participation in citizen and the participatory sciences are extracurricular science activities, or science hobbies, leisure studies help highlight the differences in engagement between ethnic and racial minorities in recreational activities. Someone's race or ethnicity can influence how they choose to partake in recreational activities and which activities they choose to engage in (Shores et al 2007). A participant's race, ethnicity, or even citizenship status can influence their willingness to engage in a project, especially if it does not align with culturally relevant topics or their cultural norms (Gomez & Malega 2007). Ethnicity theory hypothesizes that patterns of Black leisure are based on subculture identity (Washburn 1978). People are also influenced by their social networks (Hibbler & Shinew 2002; Stokowski & Lee 1991), and who we choose to surround ourselves

with intentionally or unintentionally impacts what we choose to do (Baybeck (n.d)). Shores and colleagues (2007) found race to be significantly related to a constraint categorized as "disapproval of others", meaning the disapproval of their peers and the desire for social acceptance can prevent Black individuals from participating because it is not an "ethnically sanctioned activity" (Phillip 1999; Dowat 2022). In other words, the cultural idea that an activity is "white people shit" and not something that Black folks partake in.

The neighborhoods in which we reside can act as geographic and social boundaries (Baybeck (n.d.) that structure what activities, interests, places, and values we hold. For example, in the segregated city of Chicago, different neighborhoods offer culturally relevant restaurants, grocery stores, and recreational activities (e.g., soccer fields vs football fields). This is an example of "ethnic enclosure," where a geographic area has a high population of one particular ethnic group, which influences community resources and access (Stoldoska, 2007). These demographically homogeneous neighborhoods can promote psychological and emotional comfort (Stoldoska, 2007), but they can also prevent exposure to other people, cultures, lifestyles, perspectives, pastime activities, etc (Gomez & Malega, 2007). Subculture identity can dictate what type of activities are socially acceptable (Gomez & Malega, 2007), so the culture of the community or the neighborhood could prevent participation in science if science projects are not culturally relevant or popular.

Cultural barriers related to community include a lack of diversity or familial and peer support, which prevent participants from engaging. In leisure activities, people typically engage with members of their own ethnic group due to comfort level, common culture, and similar experiences, while language barriers, discrimination, and lack of common ground for conversation topics can be barriers to engagement (Stodolska, 2007). Familial support or

participation can be important for some ethnic groups. For example, members of the Latinx community commonly visit parks in familial groups due to their strong family values (Gibster 2002), while family and companionship have been found to be important for Black American participation (Dowart 2022). In contrast, non-Hispanic whites tend to participate in less social outdoor activities (Tinsley, Tinsley & Croskeys 2002). Recreational activities can be important because they build social capital and community, but the capital lacks transferability (Horolets, Stoldoska & Peters 2019), and creates difficulty when changing geographic locations, like through immigration (Bourdieu 1984).

A sense of belonging in science or the outdoors is related to identity, which can be influenced by internal and external factors (Sandrone 2022). Some of the cultural barriers related to belonging include participants feeling like activities were not designed for them or not feeling welcome. For example, Stoldoska (2018; 2020) found that some adults refrained from participating in activities at their local park districts due to marketing materials and programming focusing on children or families, giving the impression that the activities were "not designed for them." Lack of awareness of cultural norms and practices can result in a lack of adequate facilities appropriate for cultures like those of the Muslim faith who require space for daily prayer, and single-sex facilities which can send a message that a facility or place where an activity is held is "not designed for them" (Livengood & Stoldoska 2004). Language barriers, can also add to feeling like projects are "not designed for them," compounding the cultural barriers that non-citizens may experience. A sense of belonging and identity in science is important because it allows participants to see themselves as a success and part of the community helping with retention (Chen et al 2020).

Science, participatory science, and the outdoors traditionally center around a white cultural frame, which may not be relevant to people of other races and ethnicities, contributing to a lack of belonging. The perception of "whiteness" and white spaces with certain outdoor activities can prevent those from other ethnic backgrounds from participating due to fear of not belonging (Dowat 2022), which can be a powerful motivator. According to context and structural constraint theories, issues of the environment like safety or neighborhood crime can prevent participation in activities, especially if the neighborhood identity becomes known as an area that is not safe, or where certain activities are not done, for example due to gang culture (Stoldoska 2011) or even sundown towns. Interpersonal constraints like discriminatory, cold, rude, and abusive behavior from locals can prevent immigrants and communities of color from engaging (Li 2006; Stoldoska et al 2011). Fear of discrimination and racial prejudice also applies to Black Americans and may prevent them from participating in outdoor leisure activities (Woodard 1988/ Shinew et al 2006). Subculture identity has a direct effect on recreation participation through experiences of discrimination (Gomez 2006). Phillip (1999) examined perceived welcomeness within leisure activities between African Americans and European Americans and found that European Americans did not recognize the unwelcomeness in their behavior that African Americans perceived and likely other minoritized racial/ethnic groups as well. Unwelcomeness can include "bad looks, verbal abuse, and social isolation," which was experienced by many American Muslims after 9/11, and during 2016 when facing religious persecution during Trump's first term which constrained their willingness to participate in leisure activities due to discrimination (Livengood and Stodolska 2004).

Participant's motivations can be based in ego and altruism (Rotman et al 2012). Both scientist and participant motivations for participating change and evolve throughout a project,

cycling through intrinsic and extrinsic motivations based on egoism (improving self and personal welfare), principlism (upholding personal values), collectivism (for the good of the community/increasing welfare of the group), and altruism (increasing the welfare of someone else) (Rotman et al. 2012; Larson et al 2020). Cultural barriers like a "fear of consequences" could also be based in altruism. Martin et al (2016) found that in marine science projects, a lack of knowledge of marine species was the biggest barrier to participation. A "fear of consequences" could originate from an altruistic desire to not create bad science by contributing to a project when the participant has a lack of knowledge. While education as a whole did not significantly increase the perception of cultural barriers, those in high school and graduate school experienced fewer barriers than those in college. This could be because the unstructured format of some projects are commonly used for engaging middle and high school students and, therefore have curriculums with language catered to those with less than a high school education (Williams, Hall, & O'Connell 2021). Those with a graduate-level education have more experience with research (following protocols, basic research skills etc), and therefore, the barrier to engagement is lower, especially if the participant has an existing interest and experience in the project topic area (Darby et al 2020). From the participants' perspective, successful projects help them satisfy their needs, interests, and further their education goals (Rotman et al 2012). Successful large-scale projects that achieve the goal of publishing papers and answering large questions employ strategies like engaging existing communities of interest, building community with scientists, creating user-friendly platforms, planning simple participant tasks, and making project data available (Golumbic et al. 2020). These strategies rely on engaging those with similar interests (existing community), and having low structural barriers to interest, but even so, don't help expand to other communities and those who may need training

Cross-loaded Constraints

Lacking free time to participate and not having anyone to participate with were cross-loaded in our analysis. These two items relate to intrapersonal and interpersonal constraints in the recreation literature. If not for cross-loading, “not having anyone to participate with” aligns with literature relating to lacking community and peer support, two items listed within our cultural barriers. Lacking free time is often a constraint experienced by women and those who are younger/mid-life stage (age group) (Bustam 2011). In our study, we interpret this cross-loading to mean it could be a structural constraint where the project could reduce the amount of time it takes to participate, or it could be a cultural constraint that the project can’t assist with changing.

Conclusion

We find that engagement in science can have barriers related to the project's structure, the culture of the project. We hypothesize that elements related to the project structure can be changed to reduce barriers through intentional recruitment strategies and investment in volunteers. While eliminating structural barriers is the lowest hurdle to address, our results indicate that addressing these items alone is insufficient given cultural barriers. Barriers related to the culture of the project can be reduced by adopting additional cultural frames to allow for more racial and ethnic identities to build connection and identity/belonging through relevant cultural values. Investing in diversity overall has the potential to reduce both structural and personal cultural barriers by disrupting the feedback loop, while investing in volunteers as a whole has the potential to lower structural barriers. Intentional recruitment and volunteer engagement through increased training, lower costs, and providing technology when needed will aid in reducing structural barriers.

The volunteer's racial identity and citizenship status are two parts of their identity that influence experiences of discrimination, exclusion, community, and belonging. We propose that the factors of both the structural and cultural barriers exist in a feedback loop, compounding the number of barriers volunteers must overcome in order to engage in and sustain their participation. If a project lacks diversity, the few individuals who do choose to participate don't see themselves reflected in the project, aren't able to build community, and don't feel included based on their personal and cultural values, disability, or language. Therefore diverse individuals aren't able to build a sense of belonging with the project or its community of participants, contributing to a lack of retention among diverse participants. Our findings provide further evidence that ethnicity theory over marginality theory constrains participation. Washburn (1978) concluded that leisure differences are a reflection of participant choice, and our findings reinforce that participation can be constrained by projects lacking the appropriate cultural frame or relevance.

Overcoming these barriers to engage more diverse volunteers is essential to achieving the true potential of participatory science: democratizing science (Roszczyńska-Kurasińska et al 2023). With diverse participation, projects will be able to gain additional data about the lived experiences and environmental conditions in areas historically underserved by science, potentially helping to fill the data gap within racially diverse and low-income neighborhoods. In chapter one we found that sociocultural factors like historical and present-day policies influence the geographic structure of participants' homes and how race and income can predict observation presence in two large-scale contributory-style projects. This paper re-emphasizes how sociocultural factors of those conducting research influence and shape research directions (Schell et al., 2021). It considers the barriers and constraints of diverse participation to better address

diversifying where monitoring and data collection occur. Addressing these barriers and constraints to participation will be crucial for understanding why people may not participate and increasing engagement.

Chapter 3:

An Assessment of Christmas Bird Count Surveys in the Southeast

Introduction

The Christmas Bird Count is the National Audubon Society's longest-running annual community engagement project that involves the public in conservation through bird monitoring. This project, which began in 1900, is one of the first examples of conservationists beginning to take advantage of participatory methods when ornithologist Frank M. Chapman suggested counting birds during the holiday season rather than hunting them (*History of the Christmas Bird Count Audubon*, n.d.). This large-scale project taps into the network and popularity of birdwatching, relying on the commitment of annual volunteer contributions. What started with 27 birders counting birds in 25 locations has transformed into thousands of volunteers counting birds from December 14th through January 5th every year. During the 122nd count during the 2021-2022 period (December 14th, 2021 - January 5th, 2022), the CBC had a total of 2621 count circles with 76,880 participants (64,882 field observers and 11,998 feeder watchers) observing 42,876,395 birds across the US, Canada, Latin America, the Caribbean, and the Pacific Islands (audubon.org).

Volunteer collected data in participatory projects are helpful beyond engaging the public, and providing exposure to the scientific process, as this data is often used for scientific research and generating new knowledge about the natural world (Bonney et al 2009). Data collected from the CBC over the past century have helped contribute to several environmental reports, including Audubon's 2014 Climate Change Report (National Audubon Society 2014), Common Birds in Decline Report (Rosenberg et al., 2019), and the US Fish and Wildlife Service 2009 State of the Birds Report (North American Bird Conservation Initiative, U.S. Committee, 2009). Internally,

this data is analyzed bi-annually and visualized for the public to compare to historical CBC data. This data is also used to inform Audubon's other pillars, including management, policy, and advocacy. Externally, CBC data has contributed to academic research, contributing to the understanding of species-specific trends and migration patterns(Butcher, 1986; Butcher et al., 1990; Hussell & Risely, 1978; La Sorte et al., 2009).

Participatory projects have different levels of public involvement, but its core feature is that they rely on the contributions and perspectives of the public, who can help identify questions, places, and issues that are important for science. One unique aspect of projects like the CBC is the flexibility in volunteer contribution to and control of site selection. Due to the participatory nature of site selection, participants can have a heavy influence on the lens through which observations are made, and how science is done through the concept of place and place attachment. "Place" is defined as a concrete location where natural, cultural, sociopolitical, and ontological processes overlap (Scannell & Gifford 2010; Karrow & Fazio 2010). "Place attachment" is how we create connections to our environment through our identity, emotional connection, and physical/social dependence (Altman & Low 1992; Haywood 2013).

Volunteer contributions to site selection can influence the robustness of data because different sampling schemes impact the distribution of participant data. The three-tiered structure of sampling schemes determines the robustness of data collection and the flexibility through which volunteers can collect data. Projects fall within three main sampling schemes: structured (effort metrics collected and participants told where to collect information), unstructured (no effort metrics collected, participants choose when and where to collect information), and semi-structured (effort metrics collected but participants choose when and where to collect data) (Kelling et al., 2019). Unstructured and semi-structured models are the most common to allow

greater project accessibility, allowing volunteers freedom in when, where, and sometimes how to collect data. The volunteer-led nature of unstructured and semi-structured sampling schemes allows participants to select monitoring sites of importance or interest to them, allowing them to control the spatial aspect of data collection. For example, volunteers are more likely to observe in places they are familiar with or places close to home (Di Cecco et al., 2021). This is likely due to place attachment and aspects like place identity, place dependence, and place meaning (Haywood 2013). In addition to spatial and geographic control, volunteers can also influence the temporal aspects of data collection through the time of day and day of the week they tend to monitor. For example, many volunteers tend to monitor on the weekends (Adrien Guetté et al., 2022; Dimson & Gillespie, 2023). The National Audubon Society's Christmas Bird Count (CBC) is one example of a semi-structured project that taps into place attachment in conservation monitoring.

Much of the Christmas Bird Count's success can be attributed to its broad participant community. In many aspects, the CBC works because participatory science is a place-based scholarship that relies on the concept of "massive engagement" and engaging bird lovers to establish circles and monitor bird habitat in areas accessible and important to them. Similarly to many other contributory projects, the locations of CBC monitoring are determined by the volunteers. It allows participants the freedom to select the circle sites based on where they believe are the most important places to survey, and locations where they have the capacity for long term monitoring. New circles are created based on areas that volunteers are willing to manage long-term. To establish a new circle, the applicant or "party leader" submits an application with the latitude and longitude of the center point of their 15-mile circle and an explanation of why it is an important area to monitor. While this method allows easy access to

the creation of new locations, it can also potentially skew data collection and the understanding of important bird areas if a project's participant base is not diverse. For example, Carlen and colleagues (2024), as well as Mahmoudi and colleagues (2022), found that large-scale projects can have geographic sampling biases related to participant demographics. While Christmas Bird Count observations have contributed to a robust body of research (over 300 publications), recent studies have shown that its volunteer base is not very diverse 96% white, older (over the age of 65), and STEM-educated (Allf 2021) potentially leading to geographic biases within the data and the understanding and management of birds and their habitat.

The CBC's semi-structured sampling scheme tracks annual monitoring efforts (number of observers, number of hours spent observing per participant, total number of hours spent at feeders) through local compilers, but it does not track the geographic location (latitude and longitude) of every participant's route within the CBC circle. Based on previous literature, the lack of knowledge of where participants are monitoring within the 15-mile study area opens questions to the potential of geographic bias and what quality of habitats are being surveyed in the Christmas Bird Count. Add comment about the luxury effect and redlining and the potential difference in the quality of habitat. While many participants use the traditional paper recording and submission method, volunteers also have the option to use the recording app eBird to track and submit data. The geospatial nature of eBird observations opens the potential for new understandings of the geographic coverage of CBC survey areas.

This paper will assess the geographic representation of different race/ethnic groups in the Christmas Bird Count, and volunteer use of eBird during Christmas Bird Count surveys. This paper will achieve these goals by 1) assessing the degree to which demographic groups are over- or under-represented in the census tracts of sampling sites in the Christmas Bird Count within six

Southeast states (Alabama, Georgia, Mississippi, North Carolina, South Carolina, and Tennessee); 2) assessing if Christmas Bird Count circles are clustered near areas with similar demographics; and 3) assessing if CBC circles with a high use of eBird data are clustered near other CBC circles with a high use of eBird.

Methods

The analysis for this chapter assessed demographic variables and sampling locations via eBird. Demographic data was downloaded from the US Census Bureau using `censusapi` and `tidycensus` packages (Recht 2022). Race/ethnicity and total population estimates were downloaded for the year 2022 for six EPA Region 4 States (Alabama, Georgia, Mississippi, North Carolina, South Carolina, and Tennessee) at the census tract level. At the state level, I summarized the total population percentage for each state, including percent Asian, Black, Hispanic, Indigenous, and White.

To assess the demographics of Christmas Bird Count Survey locations, I used CBC locations from the 2021-2022 survey year and 2022 US Census demographic data (race/ethnicity population estimates and community resilience estimates) from the American Community Survey using the `censusapi` package in R (Recht 2022). I used the Summarize Within tool in ArcGIS Pro version 3.0 to summarize the population values of the race/ethnicity demographic values and the total population for census tracts that fall within the 15-mile area of the CBC circles which often overlapped multiple census tracts. The Summarize Within tool calculates population summaries based on areal proportions of the overlapping census tracts (https://pro.arcgis.com/en/pro-app/latest/tool-reference/analysis/summarize-within.htm). The dataset was exported into R Studio to calculate the areal-weighted population values for each state and the areal population-weighted averages of the circles for each state. I divided the total

study area hectares by the state total area hectares, and multiplied this proportion by the expected counts to get a proportional population count for the state comparison to ensure the expected and observed values were at the same geographic extent. I calculated the population-weighted average of the race/ethnicity percent for the observed (circle) data to account for circles being distributed in unequally populated areas. Some circles were located in densely populated cities, while others were located in rural census tracts. I used a Chi-Square Goodness of Fit Test to test for a significant difference between the circle population demographics (observed values) and the total state population demographics (expected values). Both of the raw observed and expected values were divided by the number of circles in the state prior to the Chi-Square Test to ensure estimated values were distributed across same geographic extent. The Chi-Square Test identified which demographics were over and under-sampled in each state.

In the second part of the analysis, I ran a Local Moran's I Cluster Outlier Analysis in ArcGIS Pro Version 3.0 to test the demographic consistency of Christmas Bird Count Circles. This analysis used the summarized values from the first analysis to test if circles are clustered in regions of similar demographics. The Local Moran's I Cluster Outlier Analysis in ArcGIS Pro identifies statistically significant "hot spots" (similar high values), "cold spots" (similar low values), and outliers (dissimilar values, i.e., high values surrounded by low values or low values surrounded by high values) than expected in a random distribution. I used K-Nearest Neighbors set to 10 neighbors to define clusters and 499 permutations to simulate a pseudo p-value and z-score to simulate a randomized computation. Features with p-values less than 0.05 are considered statistically significant.

In the third part of the analysis, I assess eBird data use across Christmas Bird Count Survey areas. I downloaded eBird data for the six states in the study area (North Carolina, South

Carolina, Tennessee, Georgia, Mississippi, and Alabama) from eBird.org. The data was filtered to the dates of the 122nd Christmas Bird Count, which ran from December 14th, 2021- January 5th, 2022 using the `lubridate` package (Grolemund and Wickham 2011). Any data lacking a latitude and longitude and NA's were removed using `na.omit`. The geometry was added to the data using the `sf` package to allow for spatial analysis. I clipped the data to the area of the Christmas Bird Count surveys across the study area (six southeast states) using st_intersection from the `sf` package (Pebesma 2018). I used eBird's `auk` package to obtain the unique checklist entries, as checklists are often shared when bird-watching within groups, resulting in multiple entries for a location (Strimas-Mackey et al 2023). Unique checklists are identified by the "sampling_event_identifier." I calculated the total number of unique eBird observation locations (locality_ID) per circle. I calculated the total number of unique eBird observations based on a count of the unique geometries per circle. The eBird data was exported into ArcGIS Pro Version 3.0 for a cluster outlier analysis using Local Moran's I Cluster Outlier Analysis to test for clusters of circles with similar high or low observation locations to find high or low clusters of eBird participation in the CBC.

Results

The six southeast states had a population ranging from 2,958,846 to 10,722,325. The Christmas Bird Count survey covered a general area of 8,130,158.7 hectares and a total of 189 circles across the six states. Alabama had the least amount of survey circles (n = 14) with North Carolina having the most amount of survey circles (n = 63). Alabama had a total of 575,561.7 hectares monitored, and an estimated area covering 38% of its total population. Georgia had a total of 1,328,814 hectares monitored, and an estimated area covering 72% of its total population. Mississippi had a total of 874,368 hectares monitored, covering an estimated area

encompassing 24% of its population. North Carolina had the highest estimations with a total of 2,523,486 hectares monitored, covering an area with 83% of the state's population. South Carolina had a total of 1,257,094 hectares monitored, an area covering 65% of its population. Tennessee had a total of 1,570,835 hectares monitored, encompassing 64% of the state's population. Some circles overlapped multiple states (n = 19) and some circles were found along coastal areas (n= 33).

Table 1. State and Christmas Bird Count circle demographic comparison.

State Name	State Total Population Estimate	Percent of Expected Population Sampled	Percent of Actual Population Sampled	Race	State Population Percent	Average Circle Population Percent
Alabama	5,028,092	37.95	7.26	Asian	1.39	2.25
				Black	26.38	28.37
				Hispanic	4.62	5.41
				Native	0.42	0.28
				White	66.21	63.15
Georgia	10,722,325	72.09	20.94	Asian	4.34	4.78
				Black	31.47	28.65
				Hispanic	10.06	9.12
				Native	0.35	0.39
				White	54.28	57.06
Mississippi	2,958,846	24.07	12.96	Asian	0.98	1.28
				Black	37.24	33.90
				Hispanic	3.28	3.34
				Native	0.43	0.20
				White	56.95	60.08
North Carolina	10,470,214	83.21	65.56	Asian	3.11	3.14
				Black	20.94	21.22
				Hispanic	10.04	9.72
				Native	1.05	0.43
				White	64.95	65.46

Table 1 continued. State and Christmas Bird Count circle demographic comparison.

			Asian	1.67	2.55
			Black	25.79	27.39
South Carolina	5,142,750	65.36 67.41	Hispanic	6.20	7.73
			Native	0.30	0.26
			White	65.00	61.37
			Asian	1.86	1.64
			Black	16.27	19.21
Tennessee	6,923,772	64.28 46.52	Hispanic	5.96	6.17
			Native	0.20	0.22
			White	74.85	71.90

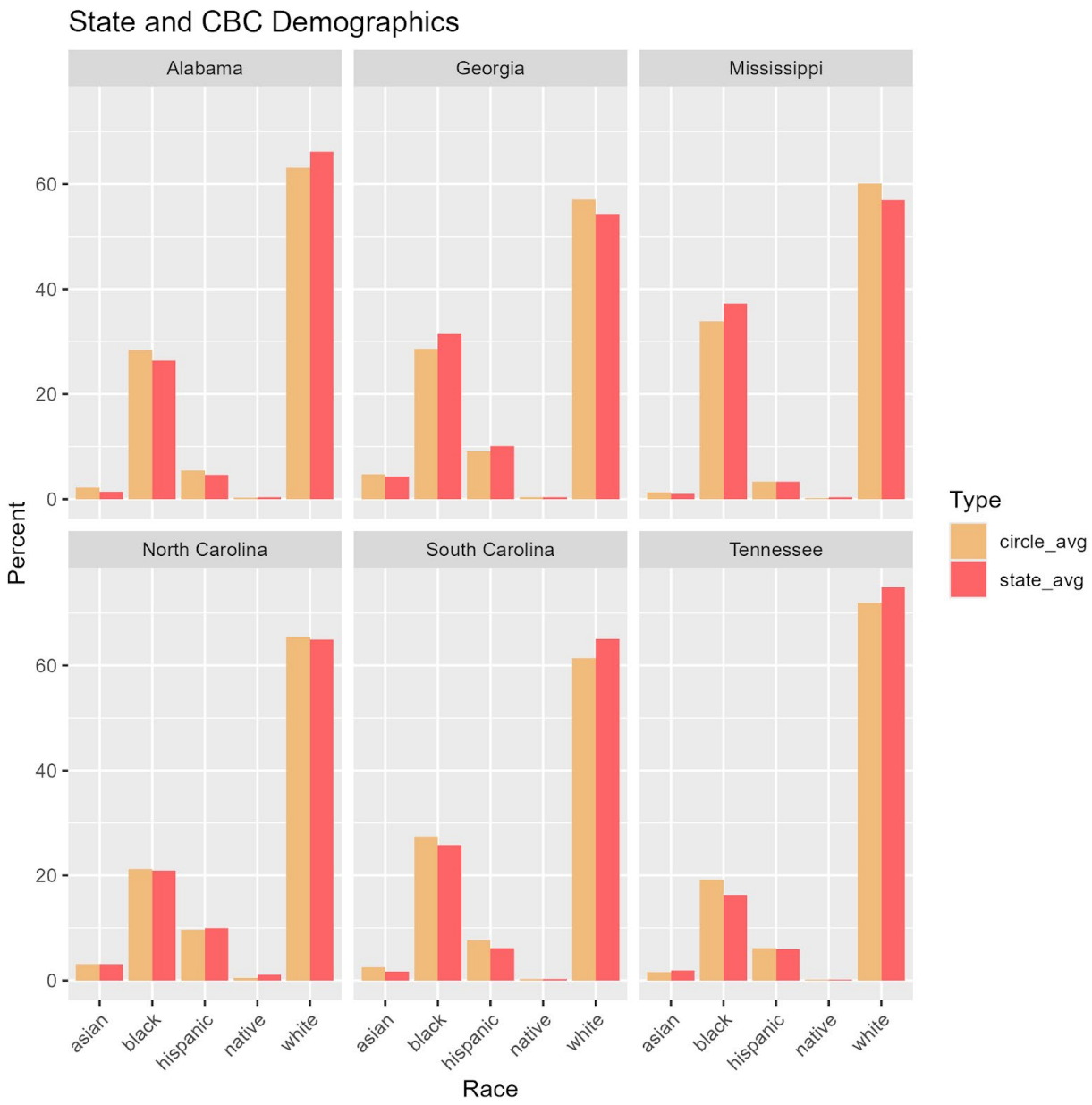

Figure 1. Comparison of the average percent demographics (circle_avg) for Christmas Bird Count Circles compared to the percent demographic for the state (state_avg).

Chi Square Analysis

Table 3.2 Results of chi-square analysis between the areal weighted state demographics (expected values) and the areal weighted average of the CBC survey areas (observed values).

	Alabama	Georgia	Mississippi	North Carolina	South Carolina	Tennessee
Chi Square	24558	14674	6357.6	8421.7	26534	13274
P-value	2.2e-16	2.2e-16	2.2e-16	2.2e-16	2.2e-16	2.2e-16
	Residuals					
Asian	113.4	36.9	28.9	2.41	102.8	**-22.1**
Black	57.0	**-79.0**	**-52.3**	10.0	45.3	101.7
Hispanic	55.8	**-46.8**	3.20	**-14.8**	92.0	12.1
Native	**-34.3**	11.4	**-33.4**	**-89.4**	**-12.8**	5.20
White	**-64.5**	68.9	40.7	10.8	**-72.6**	**-47.6**

All of the statewide chi-square tests were significant (p= 2.2e-16, Table 3.2). Minority populations were underrepresented across all six states. However, Native populations were the least represented, being underrepresented in all states except Georgia (11.4). Asian populations were only underrepresented in and Tennessee (-22.1). White identifying demographics were underrepresented in Alabama (-64.5), South Carolina (-72.6) and Tennessee (-47.6) compared to what was expected for a statewide sample representing a similar geographic extent. The Black population was underrepresented in Georgia (-79.0) and Mississippi (-52.3) from what was expected. Hispanic populations were underrepresented across Georgia (-46.8) and North Carolina (-14.8).

Local Moran's I Cluster Outlier Analysis

The Local Moran's I found mostly insignificant clusters in the survey region. However, there were significant clusters within Georgia, North Carolina, South Carolina, and Mississippi. In North Carolina, seven circles indicated clustering of HH (high white demographics surrounded by circles with other high white percentage). Six and a partial circle indicated LH

values indicating circles that had lower percent white population surrounded by circles that were higher in white demographic (Figure 3.3). South Carolina had about 5 significant clusters with two having partial overlaps into other states. Georgia, had the second highest amount of significant clusters, with seven HH clusters, one HL cluster, one LL cluster, and six LH clusters. Mississippi had six significant clusters, where all but one were LL clusters. The one that was not, was a significant outlier indicating high white population surrounded by circles that had a low total population of white individuals. Tennessee had one significant cluster which was an outlier of high white surrounded by low white demographic circles.

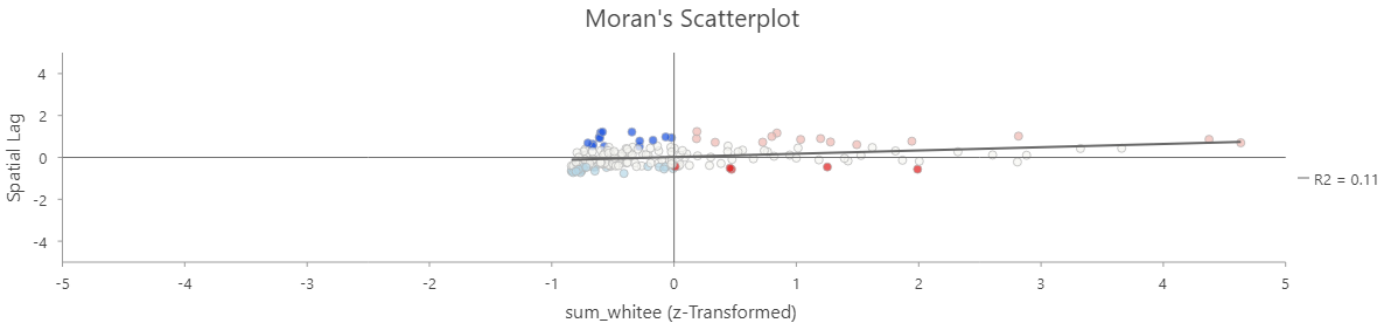

Figure 3.2. Local Moran's I Scatterplot of the summarized White population totals within the southeast Christmas Bird Count Circles.

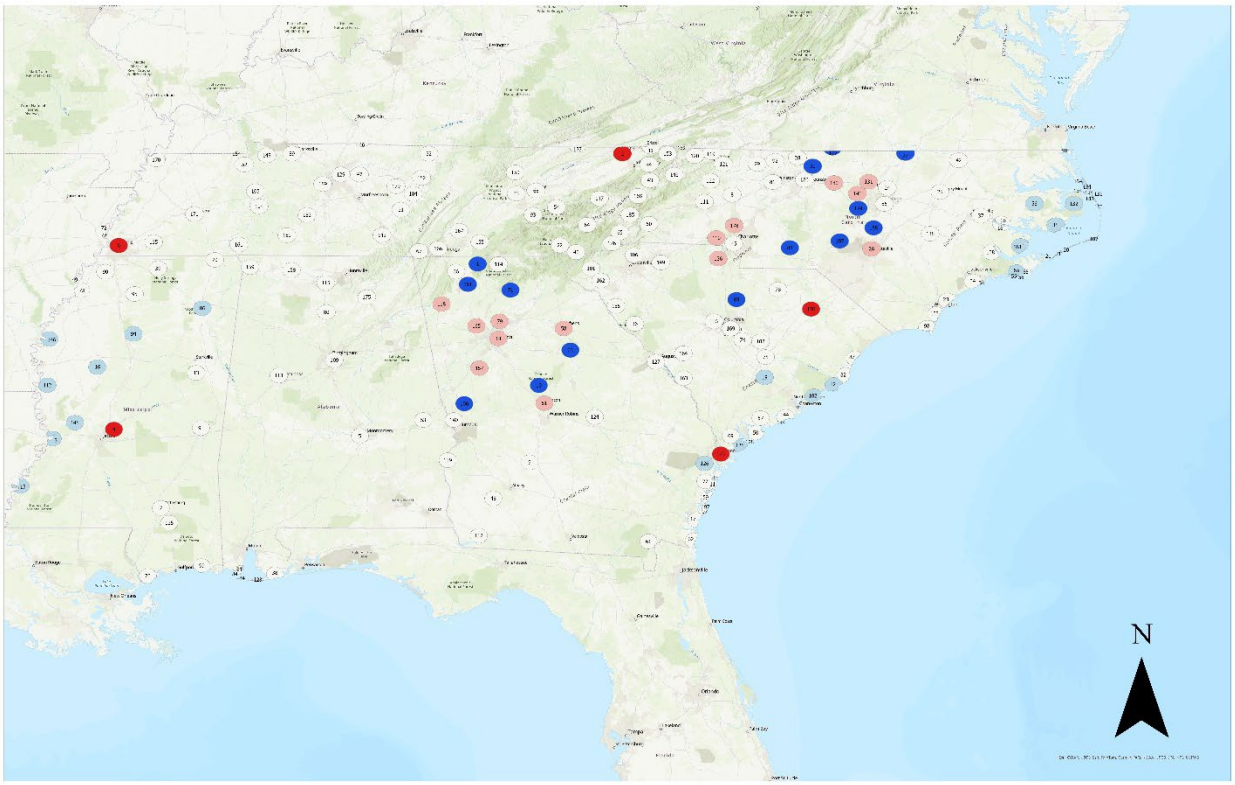

Figure 3.3 Map of Local Moran's I Clusters and Outliers of white identifying individuals in the region (North Carolina, South Carolina, Georgia, Alabama, Mississippi, and Tennessee). HH clusters are light red, LL clusters are light blue, LH clusters are dark blue, and HL clusters are dark red. Circles with insignificant clusters are white.

Table 3.3. Spread of eBird Variables in Each State

State Name	N CBC Circles	N eBird Locations	N eBird Checklists
Alabama	13	540	956
Georgia	32	1819	3234
Mississippi	19	248	374
North Carolina	57	2347	5194
South Carolina	30	1041	2372
Tennessee	26	745	1460

* The number of circles differs between the demographic analysis and the spatial regression analysis due to dropping partial circles to validate the geometries for the spatial regression models.

The Local Moran's I Analysis displayed similar regions of clustering with eBird data as with the demographic data (Figure 3.4). There were significant clusters of participation in Georgia, Mississippi, the coastal areas of South Carolina, and the mountains of North Carolina/Tennessee. In Georgia, there were nine circles with significantly high number of eBird locations surrounded by circles with similar values (Appendix B). There were also 4 circles that were Low-high outliers. Alabama had two circles that were outliers of low participation in comparison to the high participation in Georgia. Most of Mississippi's circles were LL clusters while one circle had a significantly high amount of participation. In Tennessee, two circles were outliers of high participation while other circles were primarily insignificant or circles with low participation. In North Carolina, most circles were insignificant, but there were three circles that were outliers of high participation clustered near circles of low participation. In South Carolina, there were significant clusters of high participation on the coast and three outliers of low participation.

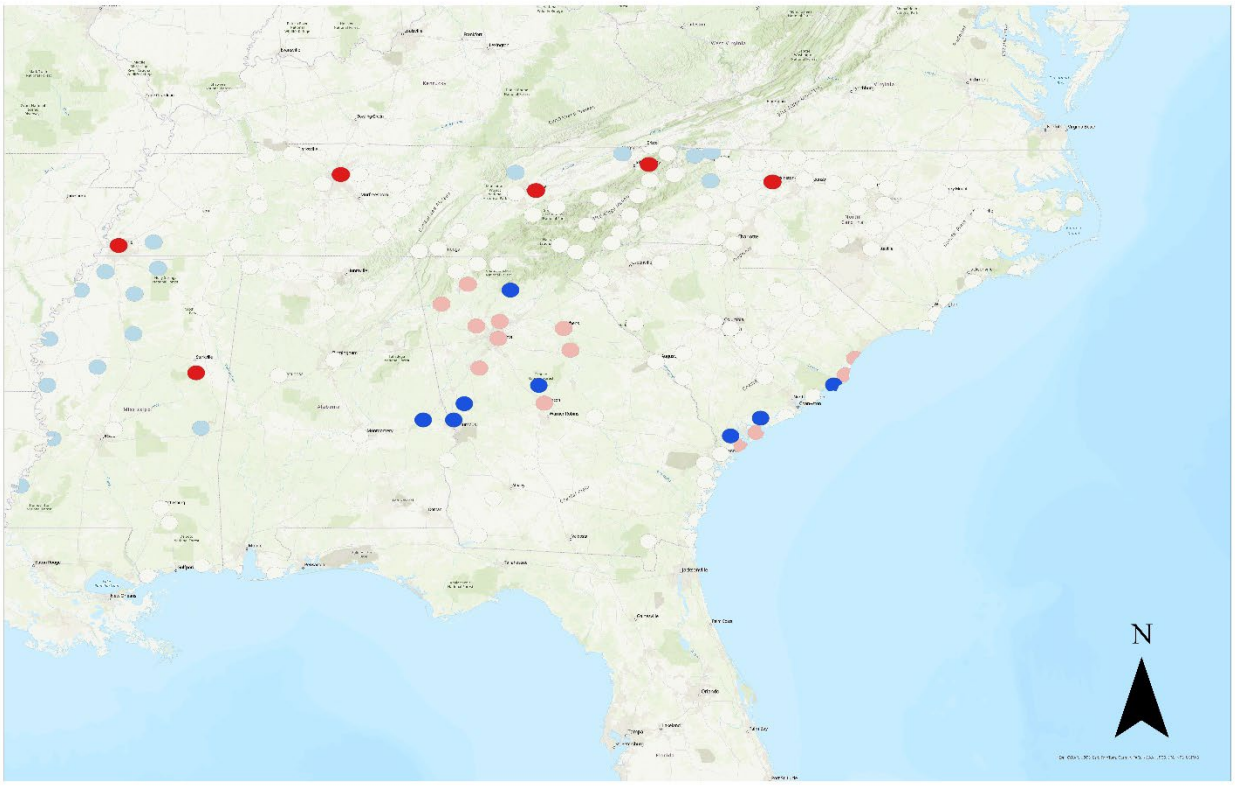

Figure 3.4. Map of Local Moran's I Clusters and Outliers for eBird Locations. This map showcases clusters of similar rates of eBird submission locations within Christmas Bird Count Circles in the region (North Carolina, South Carolina, Georgia, Alabama, Mississippi, and Tennessee). HH clusters are light red, LL clusters are light blue, LH clusters are dark blue, and HL clusters are dark red. Circles with insignificant clusters are white.

Discussion

Across all six states, the proportion of the state's population sampled by the CBC circles was not proportional to the areal weighted values from the state. The demographic comparison showed that CBC circles in Alabama, Mississippi and Georgia, are likely in more rural locations as their populations did not sample demographics or total population as would be expected for the statewide demographics of a similar geographic extent. While the population averages of the CBC circles in North Carolina, South Carolina and Tennessee were not equal to what is expected of the statewide demographics in areas of a similar geographic extent, they were very close to

proportional. Circles in these three states were likely located in more urban or highly populated areas in general.

The white identifying population was under-sampled in Alabama, South Carolina, and Tennessee, indicating that circles in these states were in more geographically diverse areas (Table 3.2). Native/Indigenous populations were the least represented in Christmas Bird Count Circles, being under-represented in 4 out of 6 states. The low representation of Indigenous populations indicates that the project should aim to engage tribal members in different states to establish circles on reservations. The Black population was under-represented in Georgia and Mississippi, two states which sampled more rural populations, whereas Hispanic populations were under-sampled in North Carolina and Georgia.

While the demographic analysis indicated that the circles in Alabama, South Carolina and Tennessee were in more geographically diverse areas, the Local Moran's I indicated that Alabama and Tennessee did not have significant demographic clusters, while South Carolina had a few significant clusters of LH (outliers of low white population surrounded by circles with higher white demographic) and HL (outliers of high white population surrounded by circles with lower white demographic). The results of the Local Moran's I Analysis also indicates that CBC circles in Georgia and North Carolina are likely located in less geographically diverse areas as many circles were HH indicating significant clusters of high white population surround by similar areas, and LH (outliers of low white population surrounded by circles with higher white demographic). The circles in Mississippi were in more geographically diverse areas as most of the significant clusters in the state were either clusters of LL (low White population surrounded by other circles with a low white demographic) or HL (high white demographic population surrounded by areas of low). LL clusters (such as in Mississippi) represent circles in more

diverse areas, and LH clusters (such as in Georgia and North Carolina) represent circles of more diverse areas surrounded by circles that were not diverse.

While race was not a significant predictor of circle clustering in Tennessee and Alabama, the spatial error model results indicate that other factors may be better predictors. For example, population density might have been a better variable for analysis, since most observations occur in developed land uses (i.e. where people are (Di Cecco 2019). Based on research by Schell (2021) and others, urban forests and greenspaces in urban areas are clustered in neighborhoods, where due to social structures like redlining or development practices like fragmentation, habitat may be concentrated into clusters. However, in this analysis, the clustering was not consistent across all six states, likely due to the differences in the distribution of demographics in each state and the large difference in the number of CBC circles across the six states (min = 13, max = 57).

My results further indicate that volunteer site selection can cause biases in participatory data if site selection is skewed towards areas of importance for one particular demographic. In addition to demographic and selection biases, participation in participatory projects generally skews toward areas with higher population densities, leading to an urban-rural bias, where we see higher participation in urban areas (Di Cecco 2019). Our comparison of the population percent sampled by the Christmas Bird Count in comparison to the population percent of the state suggests that this pattern likely exists in participation of the CBC in some of the states as well.

My results indicate that understanding geographic patterns in participation may require analysis at different spatial scales. The regional analysis allowed for an understanding of how CBC circles are clustered across multiple states. This can be important since multiple circles overlapped state boundaries (n= 19). Analyzing the data on a state-by-state basis can be

important for comparison, but breaking apart survey areas to respect state boundaries can cause values to be over represented due to partial geographies. The Local Moran's I analysis indicated that many CBC circle areas seemed more clustered on the landscape and occurring in places with less diversity. However, analysis at a more local scale (within an individual CBC circle) using Moran's I on eBird points, could help determine if CBC participation is dispersed or clustered within the 15 mile survey. These results show that in states like Mississippi and Georgia, low and high values of eBird participation align with circles that have more and less diversity respectively. The geography of eBird participation within the CBC is important to understand as eBird participation is generally clustered due to the encouragement of participation at birding "hot spots" (eBird.org). Incorporating eBird data at a local scale can show if those points exist within spaces that are clustered on the landscape in areas that our results indicate predominantly oversample white spaces. However, my results show that many CBC circles across the region did not have significant use of eBird to indicate clustering across most states. States that predominantly did not have significant eBird participation, had a few circles that were outliers of high participation surrounded by circles of low participation (North Carolina and Tennessee). One caveat to the local scale (within circle) analysis is that not all Christmas Bird Count data is submitted via eBird. If Audubon tracked the location of all monitoring efforts within the CBC, it would provide a better understanding of the spatial distribution of points and if there is any under or oversampling based on demographic predictor variables.

Understanding the geography of participation can be important for Audubon to understand how to target areas for future sampling. For example, understanding that Georgia under-samples in areas with Hispanic and Black populations or that North Carolina under-samples Hispanic and Native populations can inform Audubon of what groups should be targeted

for recruitment and engagement for participation in the CBC. Since Audubon uses this data to inform other studies, it will be especially important to have increased participation and data from under-monitored areas.

Biases can cause problems in the interpretation of the Christmas Bird Count data and any future analysis or management outcomes. Geographic unevenness created through biases (over-or-under-representation of certain groups) and volunteer biases (site selection preference) can be problematic in participatory research because they lead to oversampling (continued monitoring of areas that are frequently monitored) and missing areas of importance (areas of higher vulnerability). The flexibility for participant contribution in unstructured and semi-structured projects is beneficial in many ways, including that it allows researchers to map and better understand landscapes important for the public. However, without diversity, these locations will only reflect certain segments of society, and the corresponding places and issues of that culture.

Conclusion

Many environmental and nature-based participatory science projects occur outdoors, at specific sites, and places that hold different socio-ecological contexts (Goodchild 2007) that may prevent or encourage monitoring at different locations. This dissertation used geospatial techniques to assess the geography of participation in large-scale contributory style participatory science. In chapter one, we find that demographic variables like race and income are predictors of geographic unevenness in eBird and iNaturalist (two biodiversity projects) across urban and rural areas. In my second chapter, I find that people experience barriers to participation in science differently based on aspects of their demographic identity like race/ethnicity, citizenship status, age, education, and previous experience. People can experience barriers to engagement related to the project's structure and personal-cultural barriers. In my third chapter, I found that the Christmas Bird Count, an annual winter bird count, predominantly oversamples geographic areas overrepresented by the white ethnic identity, and that circles are clustered across the state. While race was generally not a predictor of circle clustering outside of the Black Belt region, the spatial error model results indicate that other factors may be better predictors causing the over-dispersion of participation. However, at a more local scale (within an individual CBC circle) using Moran's I with K-Nearest Neighbors on eBird points, we can see that CBC participation is dispersed across the landscape.

One caveat to the study in chapter one and many studies investigating the difference between the experience of different race and ethnicity groups are the way we categorize people based on race in the United States. Race and racism are social constructs rather than facts of biology (Sasidharan 2002). They were created to establish a hierarchical system, to keep one group of people (initially enslaved Africans turned Black Americans in the US) oppressed. These

groupings have created a society where people have shared experiences based on physical and biological criteria. This social construct remains in US society and has impacted every aspect of life, including data analysis. Many research papers use race and ethnicity interchangeably, and this method of categorization is at the basis of many types of analysis. While this grouping has proven useful for large-scale analysis and visualizations (like mapping), it does a disservice to understanding how various systems impact different ethnic groups.

The US Census Bureau dataset is a core dataset for many demographic analyses. However, historically, the Census has only offered four racial groups and one ethnic group: Black, White, Asian, Native American/Native Indian/Pacific Islander, and Hispanic/Not Hispanic or Latino. The US is an increasingly diverse place, and many ethnic groups exist but do not receive representation in the Census. For example, Haitian Americans are expected to select "Black," but the Haitian American culture is different than the Black American culture. Similarly, for different Asian ethnicities, Korean, Chinese, Filipino, Bangladeshi, Indian, etc., yet the only ethnicity represented on the Census is Hispanic/Latino or not Hispanic/Latino. The American experience is very nuanced, but due to racism and white supremacy ideology, communities of color are forced into a box. Many people do not know where they fit within these groupings, for example, people of Moroccan or Egyptian descent may not identify as African American despite both countries being located on the continent of Africa. Indeed there are cultural differences, especially if the term "Black/African American" is supposed to represent those who share the experience of being descendants of enslaved peoples from Africa. Yet still, these groupings are the best system we have to be able to compare the very real differences between the dominant White American experience and the "othered" experience of melanated minorities based on white hegemony, power, and privilege.

The dominance of "whiteness" as a racial identity within the US, can make it difficult for those without a racial minority identity to recognize the predominant culture of "whiteness" (Willis 1997). However, communities of color are constantly forced to see it due to their experience with racism (Willis 1997). This may be why many White Americans do not associate the outdoors or participatory projects as having a culture and may not see the need for cultural additions to the outdoors and participatory science. However, as they have the predominant position of power in the United States, they are not often forced to see the system upon which many of those with minoritized identities are forced to live within. Washburn (1987) questions if those from an ethnic minority should be encouraged to take on the values and ethics of white users. This, however, is assimilation or acculturation. Some may equate assimilation to inclusion, but forcing diverse participants to assimilate into a culture that they do not identify with does not achieve the underlying issue of fostering a sense of belonging.

If citizen science were to be more diverse, ideally, it would create a more representative knowledge base about the way our world works across all communities. It would provide a diversity of perspectives and lenses through which to view the data. Ideally, a world of open science practices, including data sharing, open source software, open access journals, community-guided research agendas, and publicly generated data, would allow for the equitable production of knowledge (Ramanchadon et al 2021) and a more holistic view of the world according to the diversity of its population. Additionally, these practices, if done in an equitable and inclusive way, could begin to heal the mistrust between science and society. Contributory projects may bring science outside of the ivory tower, but they still primarily operate under the same norms, traditions, and values (Strasser et al 2019).

However, the idea of open science may not be a one size fits all solution. Despite the well-meaning intentions of the push for open science by scholars in the Global North, the hegemonic system of checks and balances created through open science does not work for the Global South (Dutta 2021). Scholars of the Global South do not have the same view of open data as scholars in the North, because their science has always been rooted in community and community issues (Dutta 2021). Instead, they challenge the idea of hegemonic open data and push to decolonize the idea of what open data, open access, and open science means in a global context. Dutta and colleagues (2021) believe that the idea of "open data" and open science from a hegemonic Global North perspective perpetuates a cycle of exploitation of indigenous and marginalized individuals and communities in the Global South. They provide examples of how data and knowledge are extracted from individuals and communities of the Global South and published in the North, where the community of study or "participation" is no longer able to access the information (Dutta et al 2021). Publishing open access is more expensive than traditional publishing, which in itself makes the idea of open access exclusively for the scholars who can afford it. Not only is the system flawed because it takes advantage of academics by requesting free labor, but according to Freakonomics episode 572, because this system is flawed, it occasionally allows bad science to slip through the cracks.

Scholars in the Global South raise important topics for consideration. Not only for how we think of participatory science and open science globally, but also about how it impacts marginalized and Indigenous populations here in the US. Open data and open science approaches alike can leave room for exploitation with their lack of reciprocity (Christine and Thinyane 2021), non-diverse engagement, and geographic unevenness emphasized in this dissertation. Observation, monitoring, land management, and other forms of manipulation common within

environmental, ecological, and agricultural science did not start in and are not restricted to the ivory tower. Indigenous populations all over the world have passed down knowledge of how to care for, maintain, and otherwise live harmoniously with the natural world (Miriti et al., 2023). This is why the idea of "Participatory Science" has the potential to democratize science. It relies on the knowledge systems of the public: the best places to view/monitor birds; the places with the most plastic pollution; the areas where flooding and environmental change are occurring the most. If project managers create more inclusive practices then the participatory sciences, specifically contributory science, will increase the potential of achieving the goal of democratizing science and creating knowledge about all areas of society.

In chapter three, I investigate using geospatial techniques to assess participation in a large-scale contributory project. While geospatial techniques could prove useful for understanding existing participation and where to target for future participation, conducting these analysis at different scales will be important to avoid misrepresentation in the data. At larger scales, like a regional analysis, demographic patterns of participation may seem clustered due to additional variables like population density. At more local scales these patterns appear differently (potentially more dispersed) and demographics may play more of a role due to volunteer choice in site selection and differences in place attachment. However, with these caveats in mind, geospatial techniques can be useful tools for assessing project participation and supplement more traditional survey techniques. As participatory science and contributory style projects become more popular, geospatial techniques could be helpful for assessing geographic coverage and understanding whose environmental stories are being left out.

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APPENDICES

Appendix A

Table3.3 Local Moran's I Results for eBird Locations per circle

State Name	Circle ID	LM Index	LM Z Score	LMI P Value	CO Type	Spatial Lag
Tennessee	54265	3.01	1.41	0.05	LL	-4.19
	56124	-1.03	-1.47	0.03	HL	-4.84
	58645	-0.09	-1.97	0.00	HL	-5.84
	60080	-2.99	-1.58	0.02	HL	-5.16
	55942	3.09	1.46	0.04	LL	-4.30
	55938	-5.52	-1.51	0.04	HL	-4.70
	56259	1.89	1.51	0.02	LL	-4.62
	58844	3.95	1.84	0.01	LL	-5.50
	54587	2.77	1.30	0.05	LL	-3.85
Mississippi	59227	3.44	1.48	0.02	LL	-4.79
	54917	3.00	1.50	0.03	LL	-4.96
	59943	3.42	1.75	0.02	LL	-5.16
	59069	3.46	1.56	0.03	LL	-4.82
	54738	-1.48	-1.62	0.03	HL	-4.96
	54956	3.44	1.69	0.02	LL	-4.99
	59420	3.56	1.62	0.02	LL	-4.96
	55440	2.75	1.72	0.01	LL	-5.27
	56261	0.52	1.33	0.05	LL	-4.11
	55732	1.73	1.70	0.01	LL	-5.35
	54651	1.78	1.76	0.01	LL	-5.50
	59092	3.93	1.84	0.01	LL	-5.70

Table 3.3 Continued. Local Moran's I Results for eBird Locations per circle

State Name	Circle ID	LM Index	LM Z Score	LMI P Value	CO Type	Spatial Lag
Mississippi	59333	4.07	1.95	0.00	LL	-5.89
South Carolina	59366	4.08	3.28	0.01	HH	9.30
	54457	1.03	1.89	0.05	HH	5.55
	59239	1.03	1.89	0.05	HH	5.55
	55259	1.08	2.00	0.04	HH	5.86
	55516	0.66	2.33	0.02	HH	6.54
	58090	0.66	2.33	0.02	HH	6.54
	54457	-2.00	-2.14	0.03	LH	6.77
	59239	-2.00	-2.14	0.03	LH	6.77
Georgia	58090	-2.19	-2.49	0.02	LH	7.42
	54955	-0.69	-5.55	0.00	LH	16.80
	56309	3.28	5.06	0.00	HH	15.41
	54462	-8.53	-5.66	0.00	LH	18.36
	59656	83.32	4.81	0.00	HH	13.02
	56178	28.81	4.29	0.00	HH	12.82
	56307	-0.62	-4.58	0.00	LH	15.06
	58394	0.67	4.85	0.00	HH	15.38
	56287	-1.53	-2.68	0.02	LH	8.39
	58802	11.60	2.03	0.04	HH	6.46
	54916	26.30	4.69	0.00	HH	13.39
	56181	36.08	5.65	0.00	HH	17.36
North Carolina	59301	7.58	3.94	0.01	HH	13.73
	54262	1.32	1.98	0.00	LL	-6.26

Table 3.3 Continued. Local Moran's I Results for eBird Locations per circle

State Name	Circle ID	LM Index	LM Z Score	LMI P Value	CO Type	Spatial Lag
North Carolina	54269	1.32	1.98	0.00	LL	-6.26
	54262	0.92	1.40	0.05	LL	-4.36
	54269	0.92	1.40	0.05	LL	-4.36
	59625	2.78	1.58	0.03	LL	-4.82
	54587	2.77	1.30	0.05	LL	-3.85
Alabama	59536	-0.84	-3.29	0.01	LH	8.59
	56287	-1.53	-2.68	0.02	LH	8.39

Appendix B

Table 3.4 Local Moran's I Results of White Demographic Cluster Analysis

State Name	Circle ID	LM Index	LM Z Score	LMI P Value	CO Type	Spatial Lag
Georgia	54462	-0.70	-4.05	0.00	LH	1.18
	55755	-0.30	-1.74	0.05	LH	0.53
	59656	3.22	2.29	0.03	HH	0.70
	56309	0.16	2.97	0.00	HH	0.89
	58241	-0.23	-1.75	0.01	HL	-0.52
	56307	-0.71	-3.63	0.00	LH	1.21
	58394	0.23	3.87	0.00	HH	1.24
	60041	0.03	1.50	0.04	LL	-0.44
	58802	-0.22	-2.48	0.02	LH	0.78
	54916	0.97	3.98	0.00	HH	1.16
	56181	2.85	3.40	0.00	HH	1.02
	56178	1.07	2.75	0.02	HH	0.90
	59301	-0.58	-3.03	0.01	LH	0.96
	54955	-0.42	-3.63	0.01	LH	1.21
	59624	3.75	2.91	0.01	HH	0.86
Mississippi	59227	0.30	1.50	0.04	LL	-0.46
	54917	0.47	1.95	0.00	LL	-0.60
	59136	0.34	1.46	0.04	LL	-0.46
	59092	0.45	1.94	0.00	LL	-0.58
	59069	0.26	1.56	0.04	LL	-0.47
	55853	-0.27	-1.90	0.00	HL	-0.57
	59057	0.00	1.76	0.01	LL	-0.54

Table 3.4 Continued. Local Moran's I Results of White Demographic Cluster Analysis

State Name	Circle ID	LM Index	LM Z Score	LMI P Value	CO Type	Spatial Lag
Mississippi	59333	0.46	1.77	0.00	LL	-0.60
	55732	0.42	2.04	0.00	LL	-0.65
Tennessee	58645	-1.12	-1.86	0.01	HL	-0.57
	54265	-0.57	-1.54	0.03	HL	-0.46
South Carolina	54457	0.38	1.52	0.04	LL	-0.47
	59239	0.38	1.52	0.04	LL	-0.47
	55516	0.06	1.51	0.04	LL	-0.46
	58090	0.06	1.51	0.04	LL	-0.46
	54501	0.00	-1.48	0.05	HL	-0.43
	59398	0.29	1.45	0.05	LL	-0.45
	55445	0.88	2.87	0.01	HH	0.86
	58241	-0.23	-1.75	0.01	HL	-0.52
	54446	0.04	1.91	0.01	LL	-0.55
	58091	-0.36	-1.83	0.05	LH	0.54
	59380	0.90	2.05	0.03	HH	0.61
North Carolina	56213	0.55	2.15	0.00	LL	-0.67
	55766	0.52	2.06	0.00	LL	-0.63
	58775	0.24	2.22	0.03	HH	0.72
	58991	-0.42	-2.05	0.03	LH	0.63
	60035	-0.15	-1.81	0.05	LH	0.52
	54701	0.54	2.24	0.00	LL	-0.67
	56210	-0.56	-2.95	0.01	LH	0.92
	55315	0.09	1.61	0.03	LL	-0.43

Table 3.4 Continued. Local Moran's I Results of White Demographic Cluster Analysis

State Name	Circle ID	LM Index	LM Z Score	LMI P Value	CO Type	Spatial Lag
	56808	0.48	2.11	0.00	LL	-0.64
	58845	0.47	2.02	0.00	LL	-0.62
	59068	-0.02	-2.88	0.01	LH	0.94
	59380	0.90	2.05	0.03	HH	0.61
	55930	0.52	2.31	0.03	HH	0.73
	58393	0.59	2.36	0.00	LL	-0.72
	55174	0.55	2.34	0.00	LL	-0.73
	54739	0.31	2.36	0.00	LL	-0.76
	55445	0.88	2.87	0.01	HH	0.86
	55186	0.94	2.47	0.03	HH	0.74
North Carolina	56444	-0.07	-3.13	0.00	LH	0.98
	54273	-0.48	-2.24	0.03	LH	0.69
	54698	1.49	2.87	0.01	HH	0.77
	55955	0.80	3.17	0.01	HH	1.00
	56214	0.34	1.53	0.04	LL	-0.47
	59224	0.53	2.07	0.00	LL	-0.67
	57343	-0.14	-2.62	0.01	LH	0.82

Appendix C

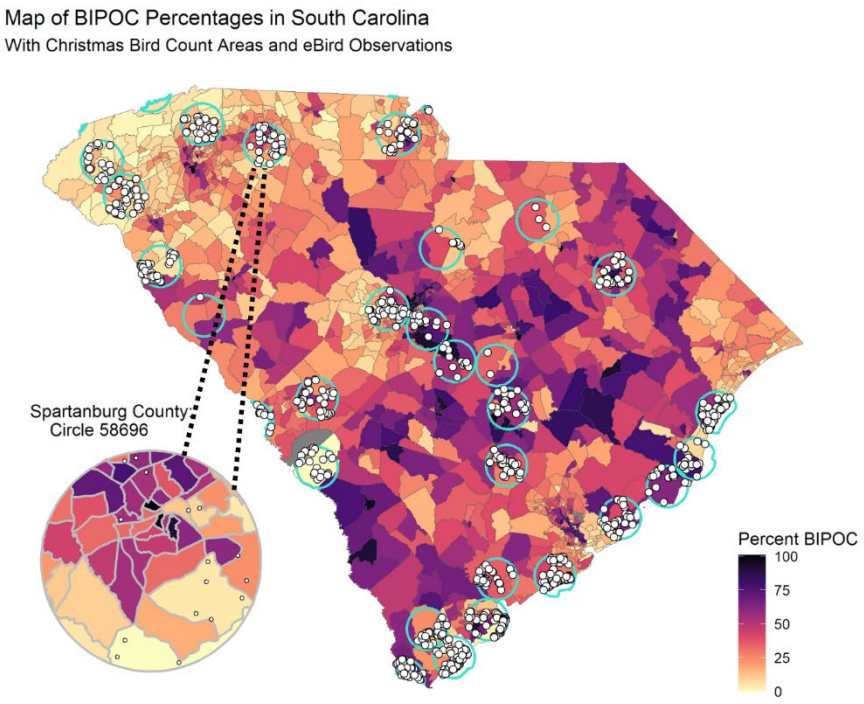

Figure 3.5. Map of BIPOC (Black, Indigenous and People of Color) percentage in South Carolina with Christmas Bird Count Survey Circles and eBird observation locations. This map includes an inset of eBird points within Spartanburg County.

Appendix D

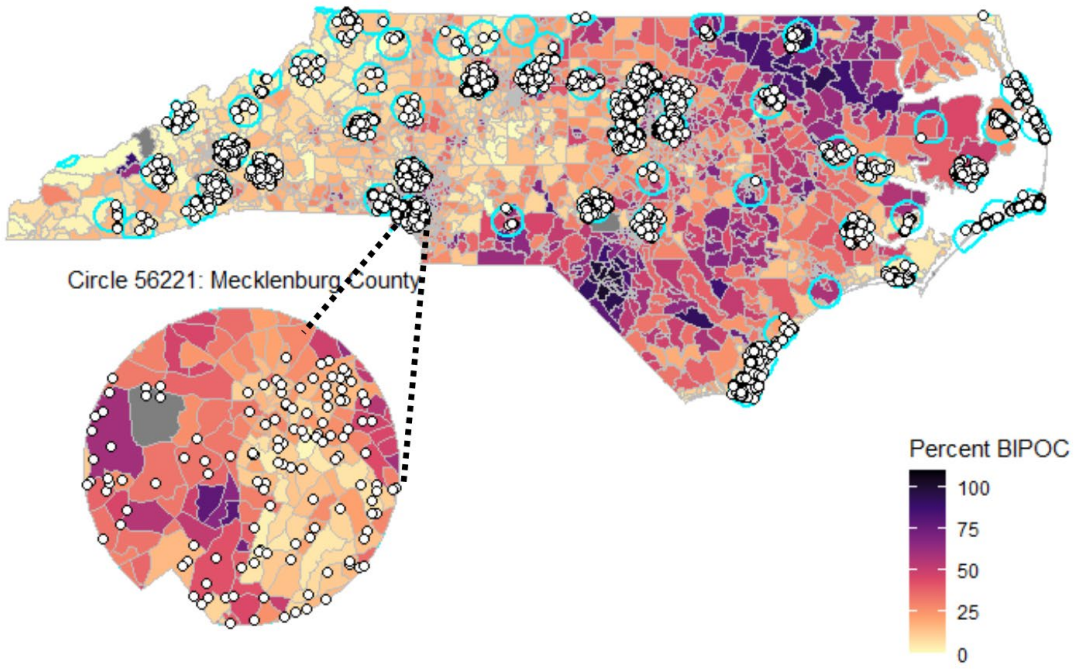

Figure 3.6. Map of BIPOC (Black, Indigenous and People of Color) percentage in North Carolina with Christmas Bird Count Survey Circles and eBird observation locations. This map includes an inset of eBird points within Mecklenburg County.

Appendix E

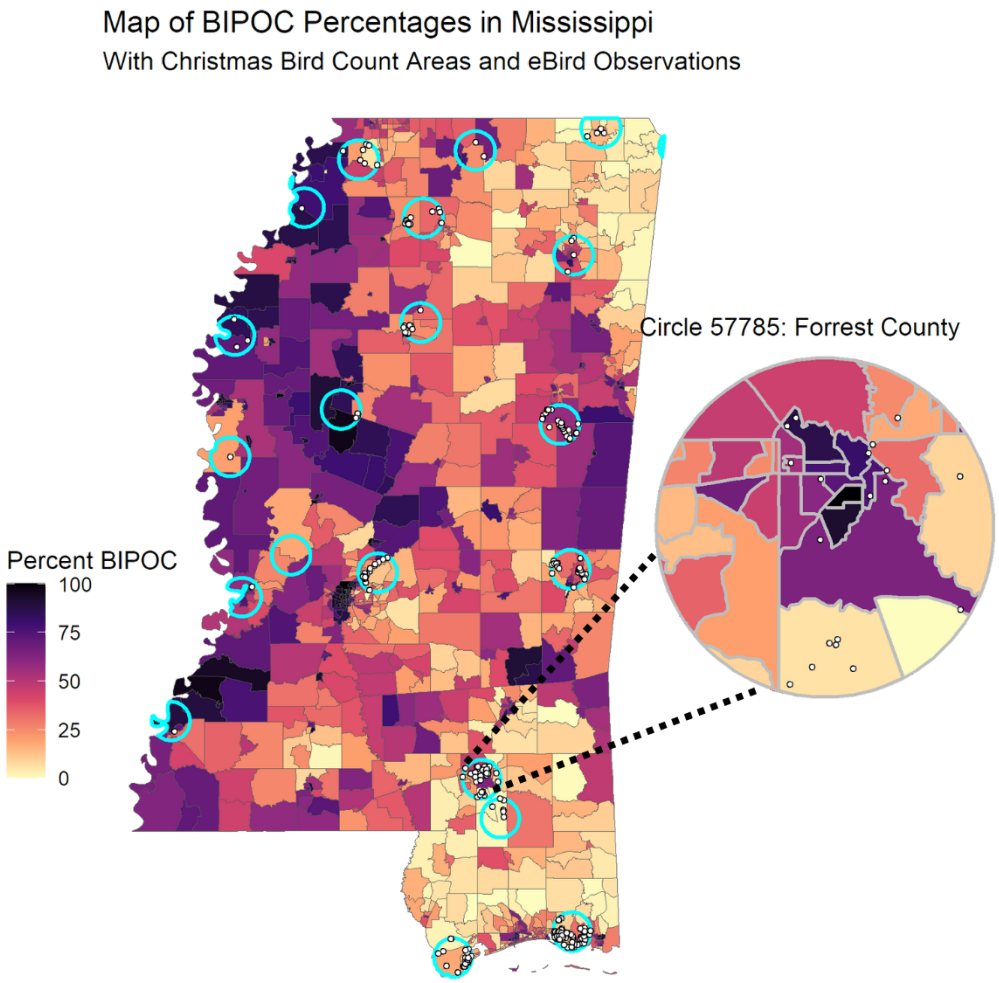

Figure 3.7. Map of BIPOC (Black, Indigenous and People of Color) percentage in Mississippi with Christmas Bird Count Survey Circles and eBird observation locations. This map includes an inset of eBird points within Forrest County.

Appendix F

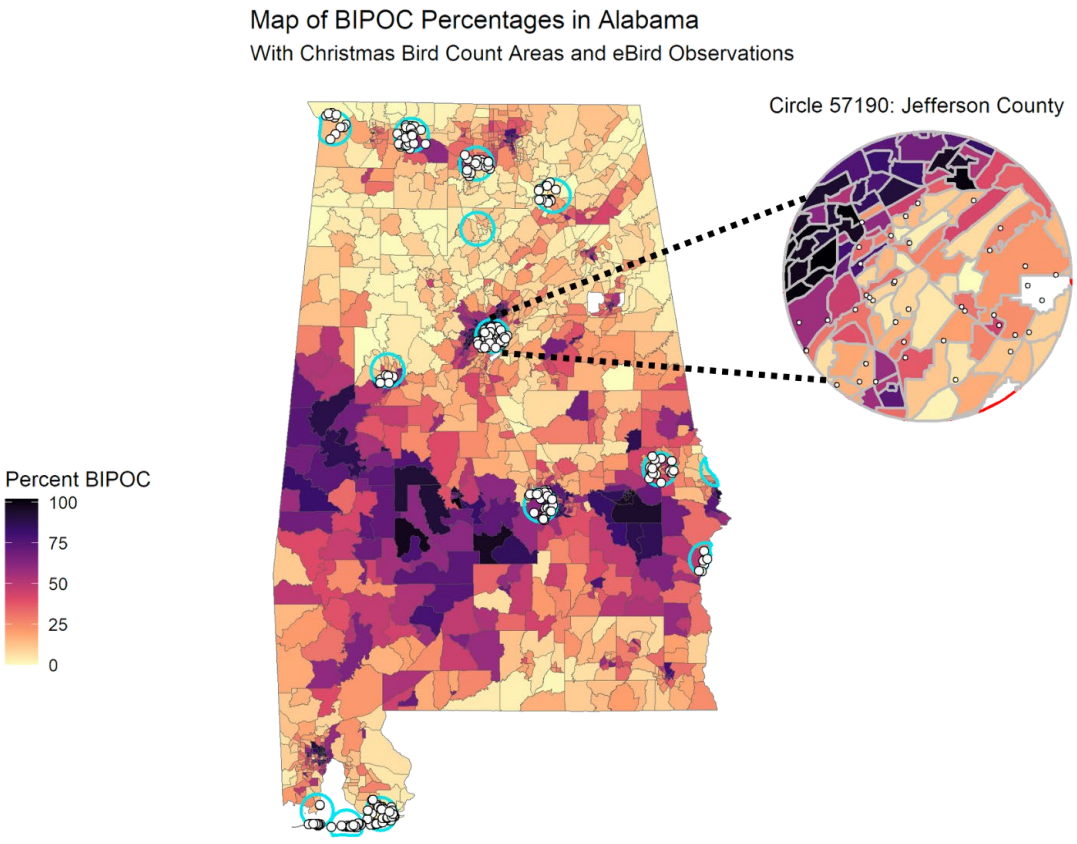

Figure 3.8. Map of BIPOC (Black, Indigenous and People of Color) percentage in Alabama with Christmas Bird Count Survey Circles and eBird observation locations. This map includes an inset of eBird points within Jefferson County.

Appendix G

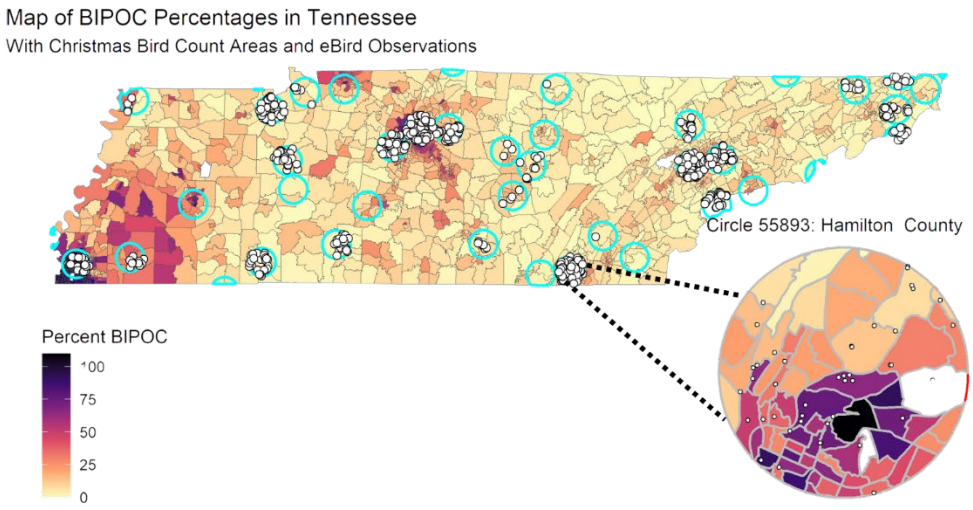

Figure 3.9. Map of BIPOC (Black, Indigenous and People of Color) percentage in Tennessee with Christmas Bird Count Survey Circles and eBird observation locations. This map includes an inset of eBird points within Hamilton County.

Appendix H

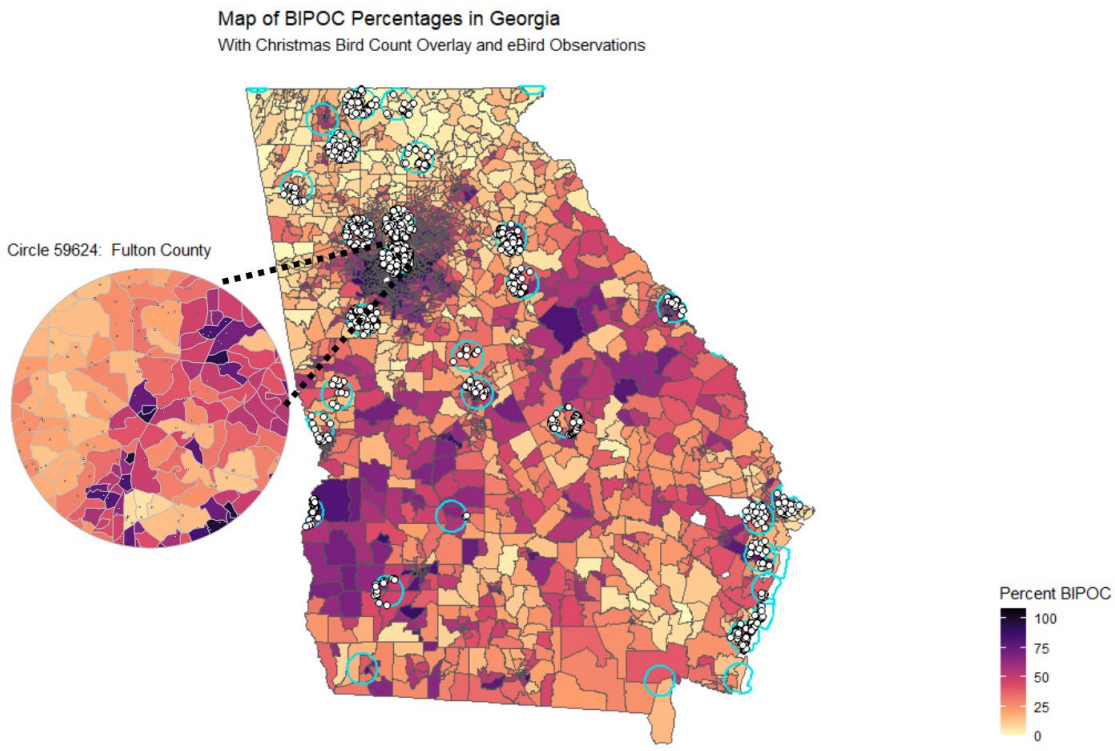

Figure 3.10. Map of BIPOC (Black, Indigenous and People of Color) percentage in Georgia with Christmas Bird Count Survey Circles and eBird observation locations. This map includes an inset of eBird points within Fulton County.