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Mapping for Whom? Communities of Color and the Citizen Science Gap

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Abstract

Citizen science harnesses the power of nonscientist observations, often resulting in a vast network of data. Such projects have potential to democratize science by involving the public. Yet participants are mostly white, affluent, and well-educated, participants that contribute data from their residence or places they frequent. The geography of the United States is heavily segregated along lines of race and class. Using a Census Tract-level hurdle model, we test the relationship between the locations of the rain gauges from the citizen science project Community Collaborative Rain, Hail, and Snow Network (CoCoRaHS) with continuous variables for percent non-Hispanic white and median household income. We find whiter and more affluent Census Tracts are significantly more likely to have a rain gauge. The highly localized nature of precipitation combined with the uneven geography of storm-water infrastructure make data missing from citizen science projects like CoCoRaHS of vital importance to the project's goals. We warn that scientific knowledge created from citizen science projects may produce scientific knowledge in service of wealthy, whiter communities at the expense of both communities of color and low-income communities.

Keywords

Participatory science, racial justice, political ecology, volunteered geographic information, critical GIS

Introduction

The continued development of digital technologies to capture and disseminate data has significant by-products for scientific and social justice communities. Geospatially tagged images or content generated by non-scientists and voluntarily submitted to a centralized source, or volunteered geographic information (VGI), can be a rich source of data for citizen science projects (Haklay 2013). According to the PEW Research Center, 85% of the United States (US) population owns a smartphone (2021). Users submit VGI using their smartphone, including a range of applications such as participants requesting non-emergency municipal reporting through 311 applications (Goodchild 2007) to surveying (or listing) local bird populations while contributing to bird migration monitoring (Sullivan et al. 2009).

The latter is also an example of how VGI contributes to citizen science projects. Projects that deliberately engage the public to generate "reliable data and information usable by scientists, decisionmakers, or the public and that is open to the same system of peer review that applies to conventional science" (McKinley et al. 2017, 16). Despite the growing complexities of participation in VGI schemes and their location data (F. Harvey 2013; Verplanke et al. 2016), the potential for massive quantities of data to be collected over large coverage areas from diverse sets of participants and diverse geographies (Cooper, Shirk, and Zuckerberg 2014; Ries and Oberhauser 2015) as well as for sufficient sampling of rare phenomenon (Losey, Allee, and Smyth 2012; MacDonald et al. 2015). Citizen science projects have advanced research at broad temporal and spatial scales. For example, citizen science data was the basis of half of what's understood about migratory songbirds and climate change (Cooper, Shirk, and Zuckerberg 2014), and almost twenty percent of research on monarch butterflies was based on citizen science data (Ries and Oberhauser 2015). The limitations of citizen science are well-documented, however, including: 1) potential for data quality issues because of opportunistic sampling by participants (Kelling et al. 2009), 2) unequal participation within projects (Haklay 2016), 3) a lack of diversity in participants as most participants are white, affluent, and well-educated (Pateman, Dyke, and West 2021; Allf et al. 2022), and 4) exclusionary project design practices (Montanari et al. 2021).

In this paper, we explore and test how the pervasiveness of racial segregation across US Census Tracts affects the quality of data collected in a passive geographic citizen science project. We first discuss successful large-scale citizen science projects, detail the importance of representation and diversity in knowledge creation, and review ecological spatial patterns that are intimately connected to social geographies. We then introduce data on race/ethnicity and income in the US and a citizen science dataset of rain gauge locations. In the Results section, we detail the Census Tract-level hurdle regression model to evaluate the relationship between the locations of the citizen science rain gauge project and race/ethnicity and income. We find that whiter and more affluent tracts are significantly more likely to have a rain gauge in both urban and rural Census Tracts. Finally, we end with the implications of our findings on the development of scientific knowledge through citizen science for critical GIS.

Citizen Science and Space

Citizen Science, Ontology, and Epistemology

Citizen science data can be laden with spatial biases stemming from uneven sampling effort, clumpy distributions, spatially clustered distribution of collections, and unstructured sampling design (Mair and Ruete 2016) or semi-structured sampling design (Kelling et al. 2019). Spatial bias can arise from volunteer behaviors, such as spatial and temporal clustering of human activity. Geldmann et al. (2016) showed that built infrastructure and human population density were direct influences on the extent of spatial bias in citizen science data. Spatial bias occurs at multiple scales. For example, approximately one-third of bird species live in the neotropics, but most publicly archived data on bird occurrences were in North America, Europe, India, Australia, and New Zealand (La Sorte and Somveille 2020), reflecting the birding legacy of British colonization. Gaps in data on bird occurrences were most prevalent in northern and central Africa and northern Asia.

Statistical measures and modeling approaches that can alleviate some of these biases (Isaac et al. 2014; Bird et al. 2014; Geldmann et al. 2016; Robinson, Ruiz-Gutierrez, and Fink 2018). For example, Johnston et al. (2020) found that the accuracy of species distributions predicted by data from the opportunistic sampling of the United Kingdom (UK) citizen science project BirdTrack were equal to the uniform atlas bird sampling by weighting sampling density. Nonetheless, modeling the entire UK by spatially weighted observations made at popular locations visited by citizen science participants assumes that the environment where samples were collected reflect the broader geography of the UK. According to Montanari et al. (2021) this assumption would be an example of geographical discrimination. The spatially weighted opportunistic sampling model was less accurate and less precise in the Scottish Highlands where the environment is distinct from the rest of the UK and there were fewer observations. Spatial bias introduced by the overrepresentation of observations in one place or environment, and consequently the underrepresentation in another place, may reflect broader socio-spatial patterns. In the US, structural racism and uneven development manifest spatial segregation based on race, class, and other forms of difference (Lee et al. 2008). Schell et al. (2020) found measurable differences in environmental quality by race and class using a dataset collected from mostly white participants that were tasked with collecting information in particular locations. The lack of observations across space and the potential for differing environments leaves potential for issues in accuracy and precision.

In addition to statistical modeling methods, project design can limit the bias affecting the quality of data generated by citizen science. Project protocols can limit opportunistic sampling and unequal participation by either including estimates of volunteer effort and/or standardizing volunteer effort of time and space. For example, projects that use gridded atlas sampling create more homogenous structure across space, but might reduce both redundancies and gaps in opportunistic data collection that may lead to skewed data on spatial scales (Callaghan et al. 2019). Similarly, increasing sampling intervals allows for more representative data across temporal scales.

Difference in participation and spatial bias are connected to critiques that feminist geographers and critical GIS scholars have long warned about, especially as they pertain to map making. The earliest notion of critical GIS emerged in the 90s as scholars sought to understand the intersections of critical theory and GIScience (Pickles 1995; Sieber 2004). During the second and third wave of critical GIS (cf Sieber 2000; Schuurman 2009), scholars increasingly sought to address epistemological issues within GIS data as well as explore the social outcomes of GIS-based knowledge production. Their insights yield important implications for VGI and citizen science projects. One such insight stems from an important critique of the way GIS-based research epistemically privileges certain understandings of the world (Sheppard 1995), prioritizing the accuracy of data (for example, the *exact* GPS coordinates or the *exact* amount of rainfall captured) without addressing geography and relationship between missing and present data (Sieber and Haklay 2015; Mahmoudi and Shelton *this issue*). Another important insight was the development and use of Participatory GIS (PGIS) methods (Elwood 2008; Leszczynski 2009) that seek to empower participants and the public by creating new data (Elwood 2006). PGIS brings significant power in addressing the *method* of collecting data and the localness of that data, whereas VGI privileges the data itself and the use of vast quantities of data (Sieber and Haklay 2015; Verplanke et al. 2016). Sieber and Haklay (2015, 133) point out that the social context of VGI data collection is important and that misalignment could favor participation by certain groups, making small digital inequalities or social differences in participation result in significant representation issues.

Haklay (2016) summarizes the challenge for crowd-sourced citizen science projects and VGI projects alike: data collection is inherently a socio-technical process, especially if researchers do not pay attention to who or under what context data are collected. Elwood (2008) and Sieber and Haklay (2015) emphasize that VGI, crowdsourcing, and PGIS—potential forms of data collection in citizen science projects—are socio-technical processes that reproduce and embed social values in their process, data of collection, and data abstraction (Elwood 2008; Sieber and Haklay 2015). These warnings are often dismissed or minimized when researchers make the implicit assumption that the identity of the participant has little to no bearing on the quality of the data—a narrow conception of quality that is reduced to the accuracy and precision of the measurement or its geospatial location—if participants can follow standardized project protocols (Haklay 2016). Citizen science efforts often seek to expand the quantity of data collected at the expense of improving diversity of participants, sometimes ignoring available demographic data. As the dataset gets larger, outliers and issues of representation are assumed to be negligible in analyses. Following this logic, there is little incentive to alleviate the well-known, albeit complex, barriers that generally prevent the participation of people of color and low-income individuals (Pandya 2012). Physical scientists argue this disparity may stem from an assumption that other than moral obligations, the gender, race, and income level of the participant have no impact on the quality (see above) of the data (Pandya 2012). In one example, a survey of participants from online citizen science platform Zooniverse—which hosts citizen science projects—found that 87% of survey respondents were white (Masters et al. 2016).

In sum, participation in passive citizen science projects reflects broader societal inequities, heavily falling on lines of race/ethnicity and class, yet there are important co-created projects that hire and train people from affected communities. Such projects broaden science education while addressing the spatial inequalities that can arise from passive enrollment. Active engagement approaches have the potential to improve the spatial coverage of scientific observation, but they are difficult to scale toward, for example, national data collection. Instead, active engagement projects primarily focus on localized hazard mitigation—participation is sometimes necessary for the safety of their communities (Wilson 2009). Projects that recruit people based on the availability of outdoor leisure time present a class privilege that is a barrier to those that have neither time nor money for the activity. Conversely, projects with high numbers of participants of color are often participating out of necessity for their livelihood due to a localized crisis. These differences in participation are directly reflected in who participates in citizen science projects. Considering how social geography might be intertwined with ecological geography raises new questions about diversity of participants and the geography of participation, but this discussion is scarce.

Race, Space, and the Geography of Citizen Science

Many citizen science projects are inherently spatial and the phenomenon they capture is rooted in, at least in part, the socially-determined geography of its participants. The geography of people, as participants, and nature, as phenomena, are inextricably linked by racial capitalism. Racial capitalism is the relational process of value extraction and dispossession through the hierarchical fabrication, and assignment, of people along lines of race, gender, class, and other forms of difference (N. Leong 2012; Melamed 2015). As geographers have shown, racial capital accumulation is an inherently spatial process (D. Harvey 2007) whose logics order and segregate space in distinct and intimately intertwined geographies (Gilmore 2006). The transatlantic slave trade (Williams 1994), plantations (McKittrick 2011; Davis et al. 2019), prisons (Gilmore 2006), and inner city disinvestment (Rothstein 2018) are just some of the many examples of spatialized violence that expropriated profit through the devaluation of Black bodies and Black spaces (McKittrick 2011; Fraser 2018). The urban geography created through redlining and racial restrictions in homeownership are some of the most common forms of segregation whose resulting urban spatial ordering persists today (Aaronson, Hartley, and Mazumder 2017). Racial hierarchies, in concert with other hierarchies of difference, are necessary preconditions for the reification of differentiated, uneven space as part of the expansion of capital.

The stark topography produced through racial capitalism is not exclusive to social outcomes. The landmark study by the United Church of Christ (1987) showed the unmistakable relationship between toxic waste and Black and Hispanic populations in the US. A growing body of research shows that socio-economic segregation is connected to, and sometimes drives, socio-ecological heterogeneity which produces racialized spaces that are functionally different in socio-ecological terms (Schell et al. 2020). For example, Seamster and Purifoy (2020) found that neighboring white and Black towns had significantly different versions of waste and toxins because the white towns relocated all of their waste and toxins across the border to Black towns. They found that white spaces were cleaner because of regular waste removal and the displacement of dirty energy production to neighboring black spaces. This type of environmental racism combined with a reduction in infrastructure and investment from municipalities that could destabilize majority Black, Indigenous, and other people of color (BIPOC) spaces is commonplace in the US.

Similarly, Ueland and Warf (2006) demonstrated that altitudinal discrimination resulted in an altitudinal segregation of BIPOC neighborhoods at lower elevations, leading to greater exposure and impact to environmental hazards like flooding. Socio-ecological segregation was naturalized and inscribed on the topography of cities, constituting environmental injustice. Ueland and Warf call for social geographers to engage with the physical landscape, arguing that cities are landscapes "[in] which social structures and processes are entwined with local biophysical conditions in complex, contingent, and sometimes contradictory manners" (2006, 51). Leong et al. (2018) document the "luxury effect," describing how affluent neighborhoods worldwide have higher levels of biodiversity. Older neighborhoods and arid cities have greater divergence in biodiversity due to the luxury effect. Important to this study is the ways in which socioeconomic affluence results in greater plant diversity, canopy, vegetative cover, public and private land maintenance, and stewardship while simultaneously resulting in lower environmental hazards and burdens.

Citizen science projects, especially those whose data are based on the collection of geographic observations, produce data with a racial-based bias in situations where the identity of the participant may be very closely related to their location. In these geographic citizen science projects, how participants operate in space and what places they have access to, are just as critical as the nature they observe. For example, Blake et al. (2020) found that white participants represented almost 90% of their Illinois-based river monitoring project despite accounting for only 60% of the state population. This skew in representation also undermined the project goals: the streams monitored by the volunteers overrepresented streams that had the lowest environmental justice concerns. Callaghan et al. (2019) suggests the statistical information problems of spatial, temporal, and spatio-temporal bias that may occur in working with majority white communities. Both Callaghan et al. (2019) and Blake et al. (2020) stress the importance in working with communities of color in citizen science projects, especially in passive projects, to find greater spatial resolution, yet neither discuss the implications of racialized or class-based geographies of people and the data. Millar et al. (2019) found that participants in aquatic monitoring projects selected sites for recreational value and deemed it the "cottage effect" for the high number of samples clustering around summer homes. A major constraint for citizen science scholars is the difficulty in getting participants, let alone communities of color and low-income participants. Active, co-created projects may help alleviate some of these issues but are difficult to scale.

The issue of poor recruitment of people of color, and the related issue of lack of observations in majority-BIPOC places for large-scale citizen science projects depending on VGI, may mask and/or worsen existing spatial environmental disparities. The notable exceptions are small-scale citizen science projects which seek to counteract local environmental hazards in BIPOC communities. Both examples above show that if scientists were to address ecological or environmental concerns based on these large-scale projects, the scientific knowledge might be representative of wealthy and white places, white the phenomenon being measured might also be connected to race and class, as water is generally considered an amenity. That is, the spaces that are measured might already be biased toward those that can financially afford to be near water. Further, streams and aquatic monitoring are not everywhere because water is not everywhere.

Data and Methods

To examine the extent to which issues in the geography of citizen science observations might take on a spatial pattern that is connected to race and class, we examined the locations of rain gauges from a popular contributory citizen science project, the Community Collaborative Rain, Hail and Snow Network (CoCoRaHS). CoCoRaHS presents an ideal test for racial bias because, unlike stream or other aquatic monitoring, rain happens everywhere and CoCoRaHS has participants—and importantly, subsequent rain gauges—across the US. CoCoRaHS is a national project designed to enroll volunteers in a system for the standardized collection of precipitation data daily. Volunteers must purchase a standardized rain gauge, place it on their property according to specific parameters, record the quantity of captured precipitation daily, and report those amounts online, producing VGI. The resulting data on rainfall are both fine scale and over large spatial extents and used for a variety of purposes, including prediction of localized flooding. CoCoRaHS began in the aftermath of a major flash flood in Colorado, where meteorologists were not able to predict the degree of flood risk based on RADAR because precipitation is highly localized. The catastrophic storm highlighted the need for high densities of rain gauges providing data on the ground to complement RADAR.

Meteorologists across the country use CoCoRaHS data, which now includes more than 64,700 rain gauges, along with other data sources to create fine-scale weather forecasts. The finer detail data is essential to understanding, analyzing, and responding to complex weather events (Moon et al. 2009; Wesley et al. 2013; Poulos et al. 2014). Further, communities that have had flooding events have reached out to CoCoRaHS to try to increase their preparedness in future storms. Even though CoCoRaHS has expanded from Colorado to around the country, there are clear demographic patterns of the participants.

In 2009, CoCoRaHs initiated a survey to understand volunteer behavior and concerns and found that most participants were Caucasians of middle-to-retirement-age with advanced degrees (Reges 2016).

We used population data from the American Community Survey 2015-2019 (U.S. Census Bureau 2020) and the location of participant's rain gauges collected by the CoCoRaHS for 2017 (CoCoRaHS 2017). We sought to understand the distribution and potential impacts of uneven and unequal environments. We then spatially joined the count of rain gauges to 2010 Census Tract geographies. We used tract-level data from the American Community Survey on median household income and race/ethnicity to compute the percent of people of color (non-white) for individual tracts. When summarizing multiple tracts, we computed the average of median household income across tracts.

To provide summary statistics, we categorized Census Tracts in three ways. First, we categorized tracts into two categories: those with a rain gauge and those without a rain gauge. Second, to address the distinct spatial patterns of urban and rural segregation, we used the 2019 Census delineation of the 392 metro areas (Core Based Statistical Areas) as a simplistic measure to delineate "Sub/Urban" tracts (inside of metro areas) and "Rural" tracts (outside a metro). Most persons tabulated in the Census live in a metro area, representing approximately 279 million of the total US population of approximately 325 million people. Finally, we categorized tracts based on the median of share of Black, Indigenous, and other people of color (BIPOC) of populated tracts. Thus, those tracts over 30.4% BIPOC were designated as "More BIPOC" and inversely, those with less than 30.4% BIPOC (or over 69.6% non-Hispanic, White alone) were designated as "More White." The labels do not indicate whether a tract had a majority of people who identify as non-Hispanic white alone or a majority of people who identify as BIPOC. We chose to use the National tract median to account for skewing

We tested for a statistical relationship between the number of rain gauges in a Census Tract and the race/ethnicity and income of a tract's inhabitants. To do this, we fit a hurdle model, a best practice when the response variable exhibits overdispersion and excess zeros (Zuur et al. 2009). In our data, the count of rain gauges exhibits overdispersion and excess zeros; there are 72,410 Census Tracts, 27,218 of which had at least one rain gauge from a total of 62,539 rain gauges. Tract rain gauge counts range from 0 to 85, with a median of 0 and a mean of 0.86. The hurdle model presents findings in two-parts. The first part treats the data as zeros and non-zeros and uses a binomial model to predict the probability of a non-zero value. The second part of the model uses a truncated negative binomial model to predict the count in tracts containing rain gauges.

The model includes continuous variables of a tract's percent of non-Hispanic white and median household income as covariates in both parts of the model. Note that percent non-Hispanic white is the inverse of percent of a Census Tract that reports as BIPOC, with values ranging from 0 to 1. Because hurdle models can be sensitive to the size of the dependent variables if they are on different scales (UCLA: Statistical Consulting Group 2021), we linearly 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). 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 (Zeileis, Kleiber, and Jackman 2008; Jackman 2020).

Results and Discussion: The Spatial Gap is a Racial Gap

We found that the presence and number of rain gauges in a Census Tract is correlated with income and the race/ethnicity of a tract's residents, but the relative importance of these factors varies in

Count of Tracts by Metro and BIPOC

	More BIPOC (than National Tract Median)		More White (than National Tract Median)		Total	
	$ Avg MHHI	# Tracts	$ Avg MHHI	# Tracts	$ Avg MHHI	# Tracts
Rural	42,004	2,923	52,470	8,977	49,916	11,900
No gauge	39,211	1,396	49,996	3,285	46,815	4,681
≥1 gauge	44,511	1,527	53,893	5,692	51,910	7,219
Sub/Urban	61,969	33,282	80,782	27,228	70,459	60,510
No gauge	60,082	25,914	80,971	14,597	67,635	40,511
≥1 gauge	68,555	7,368	80,564	12,631	76,143	19,999
Total	60,360	36,205	73,755	36,205	67,077	72,410

Table 1. The distribution of volunteer sites for monitoring precipitation in the CoCoRaHS project varies with race, which results in reduced capacity for fine-scale forecasting in urban and suburban areas where people of color live.

Sub/Urban vs. Rural locations. Generally, as the percentage of white residents and median household income increase, so does the probability that a Census Tract contains at least one CoCoRaHs rain gauge. Below, we first detail three important findings from summary statistics, then discuss the illustrative maps of Baltimore, Maryland and Portland, Oregon in Figure 1 and Figure 2, respectively. Finally, the results from our hurdle model are presented in Table 2.

Rural tracts with at least one rain gauge had an approximately $5,000 higher median household income than those with no gauges. This pattern held for both More BIPOC and More White tracts. However, for Rural tracts, median household income in More White tracts was roughly $10,000 higher than in More BIPOC tracts, regardless of whether there was a rain gauge. Among Rural tracts, More BIPOC tracts with no gauge had the lowest median household income ($39,211) and More White tracts with at least one gauge had the highest median household income ($53,893).

For More White Sub/Urban tracts, the median household income did not differ between tracts with or without a rain gauge. However, for More BIPOC tracts, the tracts with a rain gauge had a median household income approximately $8,000 higher than tracts with no rain gauge. Among Sub/Urban tracts, more BIPOC tracts with no gauge had the lowest median household income ($60,082), which was approximately $20,000 less than More White tracts regardless of the presence of a rain gauge.

Lastly, tracts with higher incomes were more likely to have a gauge except for Sub/Urban More White tracts where their income was the highest across any group. In these exceedingly high- income areas, the presence of a rain gauge did not seem to be related to median household income—a result in stark contrast to the relationships between tracts in other groups across race/ethnicity, and Sub/Urban or rural.

Maps of Baltimore and Portland illustrate the key Sub/Urban findings. Baltimore is a majority Black city in the center of the Baltimore-Columbia-Towson, MD metro area that is just over half non-Hispanic white. In Figure 2, large swatches of residents in majority BIPOC tracts have no rain gauges, while there is fairly even coverage of white neighborhoods. North and west of the city is an area that has adjacent tracts that are majority BIPOC and contain no rain gauges. Portland is a majority non-Hispanic white city in the even whiter Portland-Vancouver-Hillsboro, OR-WA metro area. The inner eastside of the city is much whiter than the outer east neighborhoods and the inner suburbs to the west of the city. Not only is there more participation in CoCoRaHS but the outer east neighborhoods do not have the same coverage of rain gauges as their whiter counterparts. Interestingly, the inner suburbs to the west of the city—with higher numbers of wealthier non-Hispanic Asian residents—show rain gauge distribution comparable to the rest of the region. The entire Portland region is much whiter than Baltimore city and surrounding areas. Even so, the five tracts in Figure 2 that are 60-80% BIPOC do not contain rain gauges.

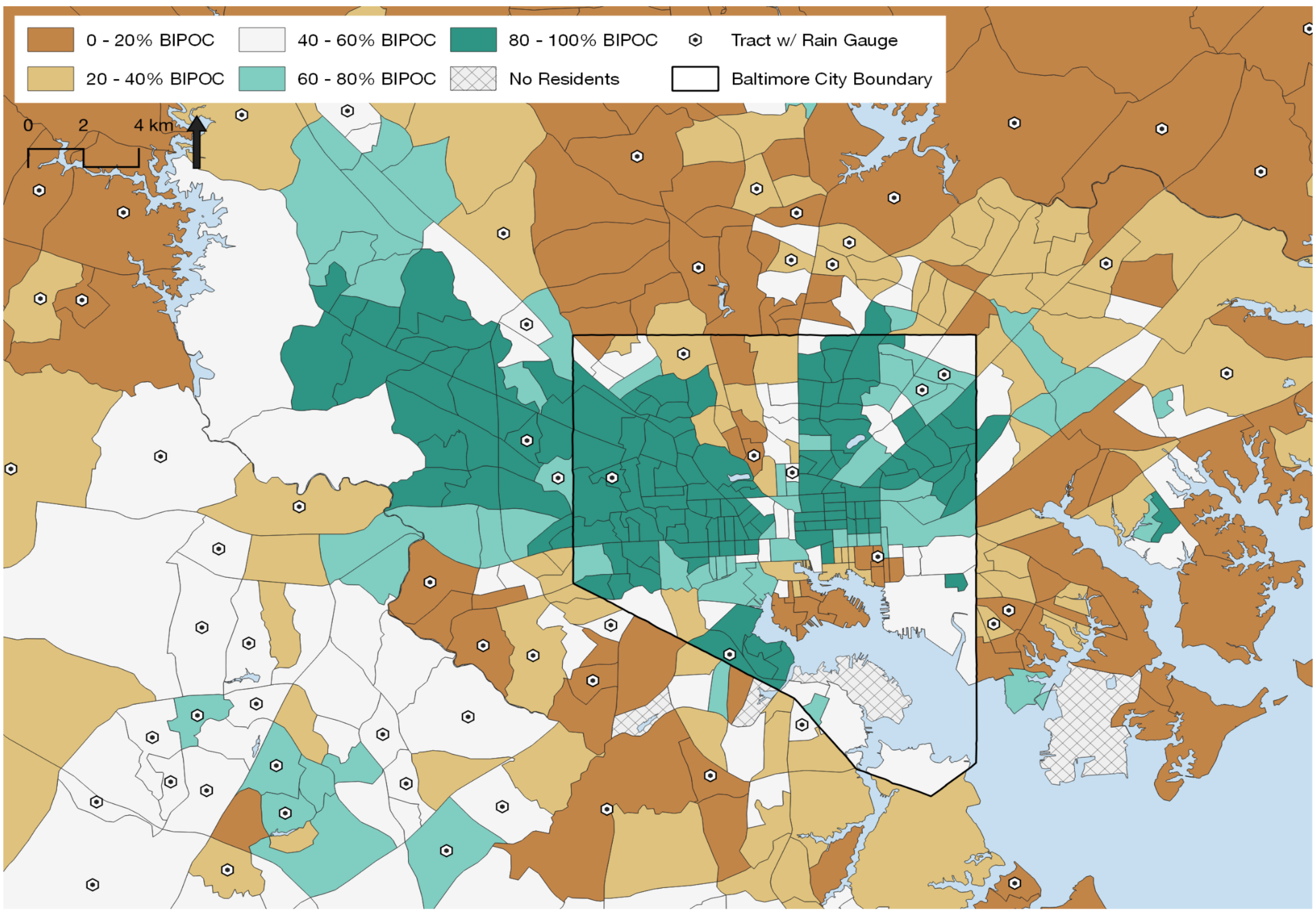

Figure 1. Baltimore city and surrounding area showing the geography of race/ethnicity and the locations of tracts that contain at least one rain gauge. Large portions of Baltimore that are majority BIPOC have little or no nearby rain gauge.

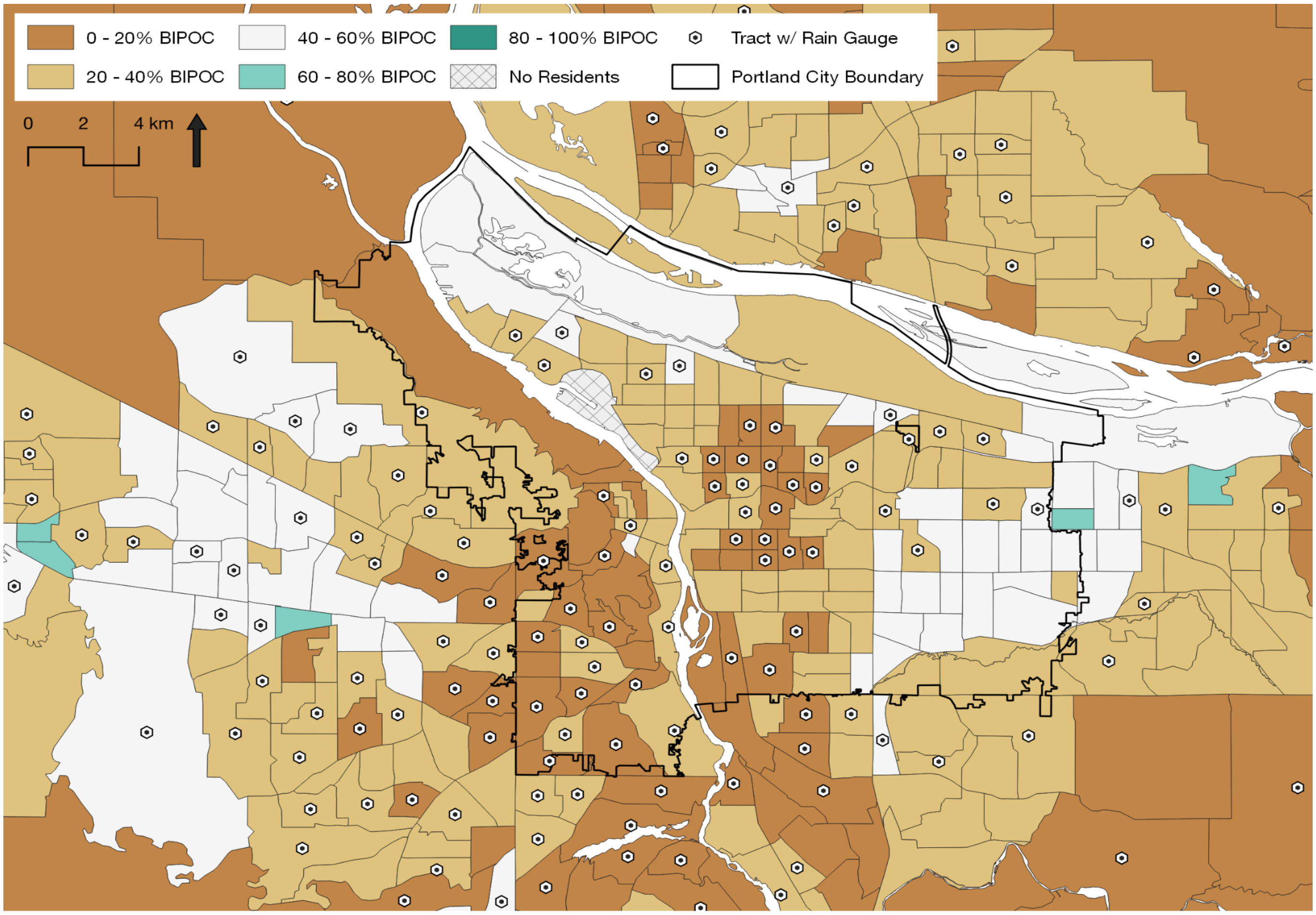

Figure 2. Portland city and surrounding areas. There are only 5 tracts in this view that are over 60% BIPOC, none of which have a rain gauge. Rain gauges are primarily located in areas that are over 80% white, except for the affluent Western suburbs near a large Intel engineering office and fabrication plant.

Finally, results from our hurdle regression model confirm the significant statistical relationship in the patterns we described above. The probability that a Census Tract has at least one rain gauge increases as both the percentage of white residents and the median household income increases for Sub/Urban and Rural tracts (zero hurdle model coefficients in Table 2). In tracts with gauges, percent white and income have different impacts on the number of rain gauges in Sub/Urban tracts than they do in Rural tracts. In Sub/Urban tracts with rain gauges, the percentage of white residents is a significant predictor of rain gauge count, but income is not. In Rural tracts with rain gauges, income and percent white are significant predictors of rain gauge count. The effect size for percent white is negligible and is inversely related, unlike the Sub/Urban model indicated a complex relationship (count model coefficients in Table 2).

Hurdle Model Results

	Dependent variable: Count of Rain Gauges in a Census Tract	
	(1)	(2)
	Sub/Urban Tracts	Rural Tracts
	Count model coefficients (truncated negative binomial with log link)	
Tract Percent White (non-Hispanic)	1.621***(0.070)	-0.227* (0.130)
Tract Median Household Income (Scaled)	0.083 (0.051)	2.072*** (0.205)
Constant	-12.219 (17.012)	-10.249 (23.962)
Log(theta)	-11.899	-11.097
	Zero hurdle model coefficients (binomial with logit link)	
Tract Percent White (non-Hispanic)	2.587*** (0.037)	0.478*** (0.090)
Tract Median Household Income (Scaled)	0.063** (0.027)	2.257*** (0.150)
Constant	-2.353*** (0.029)	-1.047*** (0.083)
Observations	60,173	11,859
Log Likelihood	-61,702	-20,993
Note:		*p<0.1; **p<0.05; ***p<0.01

Table 2. Results from our tract-level hurdle model that tests the relationship between the count of rain gauges and the independent continuous predictors of percent non-Hispanic white and the scaled Median Household Income. Census data is from the ACS 2019 5-year data (U.S. Census Bureau 2020) which aligns with the 2017 CoCoRaHS dataset (CoCoRaHS 2017). The bottom part of the model treats the data as zeros and non-zeros and uses a binomial model to model the probability of a non-zero value–or the probability of a rain gauge given the predictors. The top part of the model uses a truncated negative binomial model to model the non-zero observations—the strength of the relationship in predicting the count of rain gauges in tracts with rain gauges.

Conclusion: Bringing It Back to Critical GIS

This paper connects to an emergent theme in Critical GIS of mapping absences, presences, and relationships (Mahmoudi and Shelton *this issue*). We deployed Critical GIS methods to explore the deep social and ecological connections between rain gauges and knowledge production. Through our Census

Tract-level hurdle model (Table 2), we demonstrate that the presence of a rain gauge is significantly higher in tracts that are whiter and more affluent. For tracts with rain gauges, higher shares of white residents significantly predict larger numbers of rain gauges in Sub/Urban tracts and higher median income predicts larger numbers of rain gauges in Rural tracts. The uneven distribution of volunteer generated CoCoRaHS data demonstrates a larger problem for citizen science projects: large-scale citizen science data used to develop environmental models will not serve all places because data, and participation, is more frequently absent in tracts with higher shares of BIPOC residents. Understanding the geography of missing data, in this case intimately tied to race and class, is important in citizen science projects like CoCoRaHS because of the highly localized nature of precipitation and racial inequities connected to storm-water infrastructure. This data is vital for researchers, city planners, policy makers, and other stakeholders that need fine detail data to forecast threats or identify and address long-standing issues. Missing rain gauge data occur often in poorer, non-white places in concert with historical and on-going racism and segregation. The uneven geography of rain gauges and their intertwined social and ecological relationships could yield an uneven knowledge that further exacerbate the negative consequences of climate change for communities of color and low-income communities that are already at higher risk of climate disaster. We hope that this provides a blueprint for other interrogations of the geography data.

Earlier, we noted from the literature that the uneven geography produced through racial capitalism is not exclusive to social outcomes—that these outcomes are connected to, and sometimes drive, functionally different socio-ecological terrains. Citizen science, as a term, encompasses a wide variety of projects whose purpose is to produce new scientific knowledge both for scientists and for the general public (Cooper et al. 2021). Our results show how ecologically-oriented geographic citizen science projects might be subject to bias by producing knowledge about, or for, white affluent places—to the detriment of communities of color and low-income communities that may be most susceptible to climate change and micro-climate events.

These findings compel a more purposeful engagement with people of color, communities of color, and low-income communities. There are clear barriers that may prevent or reduce involvement from such participants and places. For CoCoRaHS, there is a financial hurdle to purchase the rain gauges. Most importantly, the project design does not intentionally include underrepresented groups, and is instead geared toward participants that are already interested in weather monitoring rather than people most at risk from flooding and/or climate change. The knowledge generated from citizen science projects is used to make regulatory decisions, create climate change plans, and make biodiversity assessments. By not engaging diverse participants, low-income communities, and communities of color in large-scale monitoring efforts, citizen science projects run the risk of perpetuating social and environmental inequality through racialized and class-based knowledge creation.

Coinciding with other citizen science-focused scholarship that highlight the importance of project design and communities of color (Callaghan et al. 2019; Blake, Rhanor, and Pajic 2020), we demonstrated how citizen science projects may produce a spatial data gap that is a racial data gap. We caution against attempting to simply increase citizen-as-a-sensor types of token participation that passively produce VGI. We highlight an emergent paradox in which decreasing the racial data gap might in fact continue to unfairly burden participants and communities of color due to the time and participation costs related to the volunteering nature of projects. To address these issues, we point to passive projects that incorporate equity in all stages of design and to the lessons learned from co-created projects. For example, the work of Montanari et al (2021) may offer a path forward, as geography is integral to project design. While often locally focused, we also see potential for active engagement projects that are co-created and for their capacity to find new and creative ways to scale up, perhaps creating coalitions of co-created projects. Ultimately, citizen science projects must improve their spatial coverage to produce more just ecological knowledge.

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