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RESEARCH

Segregation, socioeconomics, and urban design produce spatial bias in community science biodiversity data: A case study in Saint Louis, Missouri, USA

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Abstract
Community science is a powerful tool to understand biodiversity and species richness globally and in urban settings. Community science initiatives deployed as smartphone apps such as iNaturalist are increasingly used by both members of the public and scientists. Previous research shows that socioeconomic factors affect biodiversity patterns and that people of varying ages, racial, and ethnic backgrounds use smartphone applications in different ways; combined, these patterns may produce systematic biases in community science databases. Recently, spatial biases in community science data have been linked to user identity, income, race, or 20th century housing segregation practices. Here we investigate social and environmental factors driving the spatial distribution of iNaturalist data across census tracts in Saint Louis, Missouri, USA. We gathered 11,066 iNaturalist observations and 18 potential predictor variables from 106 U.S. census tracts and built generalized linear models based on a priori hypotheses about the effects of predictor variables. We compared models using Akaike Information Criterion and determined that the best predictors of iNaturalist observations are socioeconomic status, racial and ethnic diversity, relative location to historically residentially segregated areas, and open accessible green space. Metrics that quantify local segregation and inequality are critical to describe the uneven distribution of iNaturalist observations within Saint Louis. Results have significant implications for how researchers incorporate community science data into biodiversity studies, how they interpret spatial trends of community science databases, and how they might strategize future campaigns to advocate for increasing involvement in community science social networks.

Keywords Community science · Citizen science · iNaturalist · Urban ecology · Socioeconomics

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Introduction

Community science has experienced a rapid rise in popularity since the early 2000s by both voluntary community scientists and researchers (Silvertown 2009). Before this rise in data availability, many biodiversity researchers and conservation managers have struggled to access broad ecological databases (Stephenson and Stengel 2020). Global community science data sources like iNaturalist (iNaturalist 2022a) offer publicly available data and enable larger, global data analysis (Farley et al. 2018). iNaturalist is a community science platform and self-described "social network" (iNaturalist 2022a) connecting biologists, ecologists, and amateur naturalists across the globe. Users take a photo on the app, and iNaturalist's artificial intelligence (AI) software identifies the species in the photo with high accuracy (Ceccaroni et al. 2019). Identifications are then verified by the iNaturalist community, and observations become "research grade" when the AI and two-thirds of community experts agree on the species (iNaturalist 2022a).

As of 2022, iNaturalist users have recorded 119 million observations globally (iNaturalist 2022b) and contributed research-grade observations to ecological databases such as the Global Biodiversity Information Facility (GBIF 2022) and numerous peer-reviewed publications. The app has even gained fame for "re-discovering" species once thought extinct (e.g., Wilson et al. 2019). Further, iNaturalist has been incorporated into science curricula in school districts throughout the United States (Echeverria et al. 2021; Niemiller et al. 2021; Unger et al. 2020). Researchers use iNaturalist's immense database of community-science observations for a variety of studies, and it is the preferred dataset for ecologists who want to incorporate community-science data into their research (Pimm et al. 2014).

iNaturalist user behaviors affect the type and location of their observations, which can create biased or uneven sampling (Aristeidou et al. 2021; Cecco et al. 2021; Lopez et al. 2019; Wittman et al. 2019). App usage tends to be greater in open green space, particularly recreation areas (Lopez et al. 2019). Users tend to focus on charismatic taxa or species (Cecco et al. 2021) and ignore smaller plants and animals or organisms that blend in with their environment (Wittman et al. 2019). During the COVID-19 pandemic, changes in observer daily routine and app use affected the quantity and quality of iNaturalist observations (Basile et al. 2021; Vardi et al. 2020). At the population level, Li et al. (2019) identified spatial gaps (e.g. Census Block groups) in an analysis of iNaturalist data in Los Angeles, and encouraged other researchers to further investigate underrepresented geographic areas in community science databases.

Beyond user behaviors, socioeconomic and historical forces can also shape community science datasets. Across the United States, evidence shows a mixed to high correlation between wealth and biodiversity, also known as the luxury effect (Hope et al. 2003; Leong et al. 2018; Magle et al. 2021; Schwarz et al. 2015). Recent Literature has expanded on the luxury effect to examine how structural inequalities affect patterns of biodiversity in cities. For example, Schell et al. 2020 reviews how racial composition and residential segregation patterns can be stronger predictors of species richness than neighborhood wealth. Similarly, tree canopy cover is correlated with Home Owners' Loan Corporation (HOLC) maps (Appel and Nickerson 2016), with modern-day areas that were zoned as "Grade A" (predominantly U.S.-born white populations) now having twice as much tree canopy cover as areas that were zoned as "Grade D" (predominantly racial and ethnic minorities) (Locke et al. 2021). Further, a meta-analysis revealed a significant race-based inequity in urban forest cover (Watkins and Gerrish 2017).

Understanding how racial and socioeconomic forces shape the distribution of community science data points is crucial for research that use these data (Chapman et al. 2024; Ellis-Soto et al. 2024). Recent studies show that contributors to other popular community science platforms and programs (e.g., eBird, Project FeederWatch, FreshWater Watch) tend to be of high income and white (Ellis-Soto et al. 2023; Grade et al. 2022; Lopez et al. 2019; Martin and Greig 2019; Pateman et al. 2021; Perkins 2020). The locations of eBird observations in multi-city studies are positively linked with income (Grade et al. 2022; Perkins 2020) and negatively with communities historically given "C" or "D" HOLC ratings (Ellis-Soto et al. 2023; Estien at al., 2024). However, in Buffalo, NY green space - and not socioeconomic factors - is the strongest predictor of the presence of eBird observations (Walker et al. 2017), suggesting that data disparity patterns may be city-specific. Further, while HOLC ratings may be useful for building a basic understanding of patterns of biodiversity observations across cities, these maps may obscure certain processes that create data deficits. For example, HOLC "D" rated areas also included industrial zones where people do not live or recreate, and therefore are unlikely to produce community science observations for different reasons than those typically being investigated. As outlined above, observation deficits in community science datasets may be driven by a suite of complex and interrelated factors including underlying biodiversity patterns, urban planning policy and design, structural inequities, and app user behavior. Therefore, understanding biases in community science datasets requires us to consider numerous potential drivers within the urban landscape.

Here we examine how social, historical, economic, and environmental variables that describe the natural and built landscapes explain the distribution of iNaturalist data within the City of Saint Louis, Missouri. Because of the deep history of structural racism in cities (Abel 2008; Heathcott and Murphy 2005; Lewis 2021; Nardone et al. 2016), especially in Saint Louis (Bumpers 2018; Gordon and Bruch 2019; Johnson 2016; Trivers and Rosenthal 2015), historical variables like redlining might influence the distribution of community science observations. But they only represent a static point in time in the complex histories of urban environments and may not factor in current disinvestment in communities (Ngom et al. 2016; Roberts-Gregory and Hawthorne 2016). A holistic understanding of the exact mechanisms driving the spatial distribution of community science data must also include modern socioeconomic, built, and natural variables. We expected that a combination of variables (see Table 1) explaining the physical environment and population demographics would be most influential in describing the distribution of iNaturalist observations across Saint Louis. Specifically, we predicted that the number of iNaturalist observations per census tract would be positively related to the amount of open accessible green space (Walker et al. 2017) and other metrics describing the presence of vegetation, but negatively related to impervious surface area and industrial zoning, which might both decrease habitat availability and accessibility to the public. We expected that while green space and accessibility might shape the potential areas where observations could occur, socioeconomic factors such as Tree Equity Score and the National Socioeconomic Status Index might also have a strong influence on the number of observations per census tract.

Methods

Study area

Saint Louis city has a population of 301,578, a median household income of $49,965, and a poverty rate of 20.4%. Its three most common racial or ethnic identities are: white (43.9%), Black or African American (43.0%), and Hispanic or Latino (5.1%) (U.S. Census 2010). Saint Louis has a long history of racial and economic segregation that can be attributed to its history of racist housing policy and development practices, as well as white flight (Bumpers 2018; Gordon and Bruch 2019; Johnson 2016; Trivers and Rosenthal 2015). The city's history of segregation has culminated into a modern-day spatial division known by local residents and recognized by scholars as "The Delmar Divide" (Fig. 1) (Gordon and Bruch 2019). Delmar Boulevard, a street that runs east to west across the city, exists as a symbolic and frequently discussed barrier between the northern and southern parts of the city. A demographic analysis of St. Louis using census data shows areas south versus north of Delmar Boulevard show significant differences in household income (40% higher), home values (70% higher), education levels (67% have a bachelors in the south while 5% in the north), and racial segregation (38% of the population is non-white in the south and 97% of the population is non-white in the north) (Tighe and Ganning 2015; Goodman and Gilbert 2013). Because most Saint Louis residents are familiar with the term "The Delmar Divide" and what it represents, it exists both as a clear, quantifiable racial and economic split and also as a culturally embedded local understanding of the region (Gordon and Bruch 2019; Strasser 2012; Trivers and Rosenthal 2015). While Saint Louis's demographics and history offer a unique case study into the effects of socioeconomic variables on community science data, it is part of a coalition of similar peer cities (Rise Community Development staff, personal communication, November 29, 2022) that are expected to show similar trends.

Data collection

We used the number of filtered, research-grade iNaturalist observations per census tract as our response variable. We downloaded research-grade observations of all taxa within St. Louis City created on or before December 3, 2020 (GBIF 2022; Accessed January 12, 2021). Because our analysis was at a fine resolution (census tracts), we filtered the set of iNaturalist observations to ensure the highest levels of locational accuracy (Table 1). We removed observations that had obscured geoprivacy, taxon geoprivacy, lacked coordinates, or had no status of positional accuracy. We also removed observations with a positional uncertainty measure greater than their distance to the nearest census tract border because in those cases, observations could not be reliably placed within a given census tract.

Spatial explanatory variables were chosen based on a priori hypotheses and previous studies describing factors driving patterns of urban biodiversity, and they were collected using ArcMap (v10.8.2; ESRI Core Team 2021) for each of the 106 census tracts in Saint Louis city. To organize and effectively analyze the large set of explanatory variables, they were grouped into three categories based on shared characteristics: natural, built, and social. Variables that represent accessibility to nature and greenery were grouped in the "natural" category. Variables that represent the built environment through artificial surfaces such as infrastructure, city layout, or impervious surface were grouped in the "built" category. Variables that represent socioeconomic forces such as standard of living, race, or historical housing policies were grouped in the "social" category. Built and natural variables were picked based on foundational understanding of the relationship between the urban ecological landscape and biodiversity patterns. "Natural" variables quantify aspects of the urban environment with plant

Table 1 Variable set with explanatory variables summarized by category. Predicted impact indicates expected effect on the number of iNaturalist observations per census tract. (+ indicates a prediction that variable will increase the number of observations, and - indicates a prediction that variable will decrease the number of observations.)

Study Variables				
Name	Description	Predicted Effect	Date Created	Source
Response Variable				
Filtered iNaturalist Observations	Number of filtered (see above) research-grade iNaturalist observations per census tract	N/A	Accessed January 12, 2021.	(GBIF 2022)
Natural Category				
Barren or Sparse	Proportion of barren area or sparse vegetation per census tract	+	2017	(East-West Gateway 2017)
Woody Vegetation	Proportion of each census tract that is woody vegetation	+	2017	(East-West Gateway 2017)
Herbaceous Vegetation	Proportion of each census tract that is herbaceous vegetation	+	2017	(East-West Gateway 2017)
Open Accessible Green Space	Proportion of census tract that is accessible open green space. It includes: public parks, playgrounds, cemeteries, community gardens, some university green space, and public school green space.	+	2017/2018	(Washington University Geospatial Resources 2014, 2017, 2018)
Tree Density	Number of trees per square kilometer in each census tract	+	2016	(Washington University in St. Louis Geospatial Data Library 2016)
Built Category				
Impervious Surface	Proportion of each census tract that is impervious surface	-	2017	(East-West Gateway 2017)
Light at Night	Mean radiance of pixels in each census tract	-	2020	(Elvidge et al. Earth Observation Group 2021)
National Walkability Index	Mean census block values of EPA Walkability Index in each census tract. The higher the Walkability Index score, the easier it is to move through neighborhoods by walking instead of using other forms of transportation	+	2019	(U.S. Environmental Protection Agency 2019)
Areas Zoned as J or K Industrial Zones	Proportion of each census tract that is defined as Zone J or Zone K	-	2013	(St. Louis MO GOV Land Use Data Sets 2020)
Social Category				
Tree Equity Score	Mean American Forests Tree Equity Score of census blocks within each census tract. The index combines tree density and socioeconomic variables. Higher scores indicate more tree equity.	+	2021	(American Forests 2021)
Proportion of Area North of Delmar Boulevard	Proportion of each census tract that is north of the Delmar Divide	-	2010	(U.S. Census Bureau 2010)
Delmar Boulevard	Categorical description of where a census tract lies in relation to Delmar Boulevard	-	2010	(U.S. Census Bureau 2010)
Historically Black Segregated Zones	Proportion of each tract that has been a historically Black segregated zone	-	2008	(Gordon 2008)
Historically White Segregated Zones	Proportion of each tract that has been a historically white segregated zone	+	2008	(Gordon 2008)
NSES Index	American Community Survey National Socioeconomic Status Index by census tract. Indexes are calculated from six common socioeconomic indicators and are normalized to 2015 levels in the United States. Higher index scores indicate more affluence, employment, and education.	+	2015	(American Community Survey 2015)
Diversity Index	Percent probability that any two people identify with a different race or ethnicity in each census tract	+	2010	(U.S. Census Bureau 2010)
Ice Index	Index of concentration of extremes. Provides a measure of segregation that produces a score of -1 (total segregation of the marginalized group) to 1 (total segregation of the privileged group).	+	2010	(U.S. Census Bureau 2010)
Population	Human population per census tract	+	2010	(U.S. Census Bureau 2010)

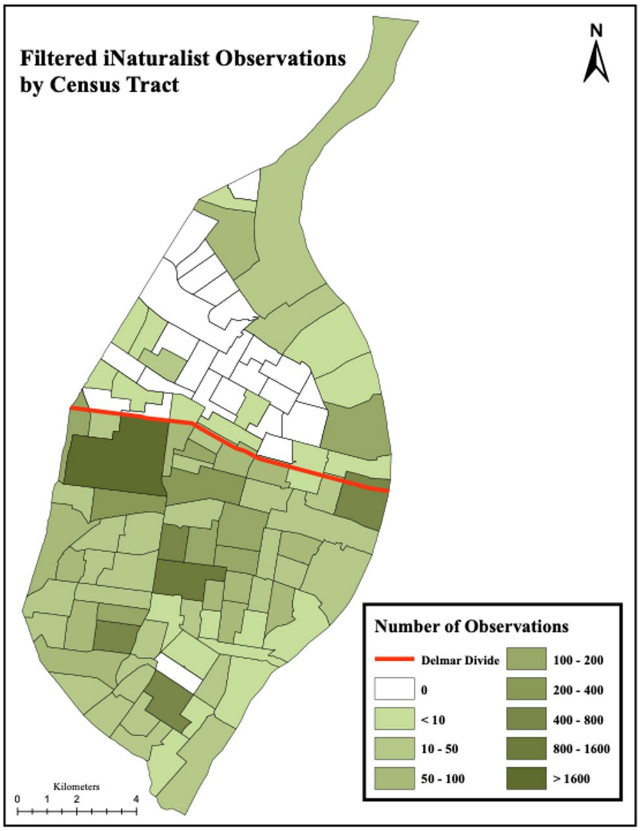

Fig. 1 Filtered iNaturalist Observations in the City of Saint Louis, Missouri, by census tract (GBIF 2022; Accessed January 12, 2021). The "Delmar Divide" refers to "bordering neighborhoods that have vastly different economic and racial make-ups, separated only by Delmar Boulevard" (Strasser 2012)

habitat, which in turn may create habitat for other taxa (e.g., green space, tree density, herbaceous land). "Built" variables include impervious surface, light at night, industrial zones, and elements of the urban environment where people may be living and moving around, creating the potential for more observations even without additional green space. Social variables were chosen based on predictions of the luxury effect (Burr et al. 2016; Hope et al. 2003; Leong et al. 2018; Magle et al. 2021; Perkins 2020; Schwarz et al. 2015) or the impact of segregation and discrimination (Ellis-Soto et al. 2023; Schell et al. 2020).

All variables were collected with the goal of creating a thorough explanation of the location of iNaturalist observations. Variables that capture the intricacies of the urban ecological landscape include both built and natural descriptors. For the group of socioeconomic explanatory variables, the goal was to include both present and past influences on the demographic landscape. Although variables like redlining are powerful, they only capture a static point in time that does not fully explain the demographic evolution of the area. As such, more recent socioeconomic descriptors also were included. After searching for indicators that could explain the response variable, 26 were selected. Based on redundancies, overlap, collinearities, and hypothesis refinement, some variables were eliminated, resulting in a final list of 18 explanatory variables (Table 1).

Statistical analyses

Prior to modeling, we used the DHARMa package (v4.2.2; Hartig 2022) in Program R (v4 2.2; R Core Team 2022) to determine the most appropriate error distribution for our response variable, the count of iNaturalist observations within census tracts. We compared residual deviance, residual diagnostics, and employed DHARMa's dispersion test on simple models specified with Poisson and negative binomial distributions. In our comparisons, we also considered an offset term due to our response variable's correlation with census tract area. Overdispersion was best accounted for using a negative binomial distribution with an offset term of the natural log of each census tract's area (Dispersion test: $p = 0.4$, compared to $p < 0.0001$ for Poisson model). To ensure comparable coefficient estimates, and to standardize effect sizes across variables of different units, all predictors were centered and scaled. To model the effects of predictor variables on the number of iNaturalist observations within census tracts, generalized linear models were constructed using the MASS package (v4.2.2; Venables and Ripley 2002) in R; all models specified a negative binomial distribution with the natural log of census tract area km^2 as the offset term. For each of the predefined variable categories (i.e., natural, built, and social), we developed a set of candidate models based on a priori hypotheses about what variables might be influential. As part of model development, we examined correlations among our sets of predictor variables, and avoided including in the same model any two predictors with a correlation coefficient greater than 0.6. The maximum number of iterations for each model was capped at 50. Because of large standard errors around coefficient estimates within some of the generated models, a few failed to converge and were subsequently removed from the model sets.

We compared models using Akaike Information Criterion corrected for small sample size (Anderson and Burnham 2002) through a two-step process with the R package AICcmodavg (v4.2.2; Mazerolle 2020). First, we compared models within each variable dimension (Table 1): natural (5 predictors, 13 models); built (4 predictors, 9 models); and social (9 predictors, 33 models), including null and global models specific to each dimension (Supplemental S). If no model within a particular model set performed better than the null, then those variables were excluded from the next set of models. Variables that were identified in top-performing models ($\Delta AICc \leq 2.0$) for their respective categories were used to develop a new set of models that combined variables from across the three categories (Table 3). This second model set was also developed based on a priori hypotheses and included null and global models. Models in the final set with **Δ**AICc ≤ 2.0 were identified as top performers overall.

Results

After filtering research grade observations for locational accuracy, there were 11,066 iNaturalist observations across the 106 census tracts in Saint Louis. The number of observations per tract ranged from zero to 4,805 and the median number of observations per tract was 16. Saint Louis demonstrates an unequal distribution of iNaturalist observations across the city (Fig. 1); observations were largely clustered south of the Delmar Divide, and all but one of the tracts with zero observations was north of Delmar Boulevard (Fig. 1).

We retained 17 variables after the first round of model comparisons across all three variable categories (built, natural, and social; [see Table S in the supplementary information (SI)]). In the built category, the global and null models had comparable AICc scores (ΔAICc < 2); nonetheless, we retained 4 predictors for the final model set in case they might influence our response variable differently alongside natural or social variables. We retained 4 predictors from the built category, 5 predictors from the natural category set, and 8 predictors from the social category. The second round of model comparison included 21 models with predictors from all three dimensions. Our top-ranked model included four predictors: the NSES Index, the Diversity Index, the proportion of area north of the Delmar Divide, and the proportion of open accessible green space (Table 3). The number of iNaturalist observations within census tracts were positively associated with the NSES Index, the Diversity Index, and the proportion of accessible green space, and negatively associated with census tracts primarily north the Delmar Divide (Table 2; Fig. 3). Overall, models with social variables outperformed models with variables from the natural or built categories, but models with social variables and open accessible green space better explain the distribution iNaturalist observations than models with social or natural variables alone.

The NSES Index (Fig. 2a) appeared in top models in all the model sets (Table S in [SI]). The Diversity Index

Table 2 Parameter estimates of the overall model of best fit

Coefficient	Estimate	Standard Error	95% CI	z	*P*
Intercept	2.706	0.123	2.48, 2.95	21.94	< 0.0001
NSES Index	0.950	0.16	0.63, 1.26	5.89	< 0.0001
Diversity Index	0.459	0.186	0.10, 0.81	2.46	0.014
Proportion Area North of Delmar Boulevard	-0.623	0.226	-1.01, -0.24	-2.76	0.006
Open Accessible Green Space	0.308	0.121	0.10, 0.56	2.55	0.011

Model statistics: AICc = 867.60; Θ = 0.710; Θ Standard Error = 0.108

Table 3 AICc table of combined model set that includes variables from built, natural, and social dimensions. All models were additive

Variables	k	Δ AICc	AICc Weight
NSES Index, Diversity Index, Proportion of Area North of Delmar Boulevard, Open Accessible Green Space	6	0.00	0.56
NSES Index, Proportion of Area North of Delmar Boulevard, Open Accessible Green Space, Population	6	3.09	0.12
NSES Index, Diversity Index, Delmar Boulevard, Open Accessible Green Space, Herbaceous Vegetation, Population	9	3.33	0.11
NSES Index, Diversity Index, Delmar Boulevard, Open Accessible Green Space	7	3.67	0.09
NSES Index, Diversity Index, Population, Open Accessible Green Space	6	8.57	0.01
NSES Index, Delmar Boulevard, Open Accessible Green Space	6	10.03	0.00
NSES Index, Diversity Index, Population, Open Accessible Green Space, Herbaceous Vegetation, Barren or Sparse, Tree Density	9	10.37	0.00
Tree Equity Score, Historically White Segregated Zones, NSES Index, Diversity Index, Population, Delmar Boulevard	9	10.49	0.00
NSES Index, Diversity Index, Population	5	11.46	0.00
NSES Index, Diversity Index, Population, Historically Black Segregated Zones, Open Accessible Green Space, Herbaceous Vegetation	8	11.97	0.00
NSES Index, Diversity Index, Population, Herbaceous Vegetation	6	12.20	0.00
NSES Index, Historically White Segregated Zones, Population	5	19.46	0.00
NSES Index, Population	4	23.74	0.00
NSES Index, Population, Open Accessible Green Space	5	25.20	0.00
NSES Index, Open Accessible Green Space	4	28.84	0.00
NSES Index, Historically Black Segregated Zones, Open Accessible Green Space	5	31.05	0.00
Proportion of Area North of Delmar Boulevard, Historically Black Segregated Zones, Population	5	33.30	0.00
Barren or Sparse, Herbaceous Vegetation, Open Accessible Green Space, Tree Density	6	70.66	0.00
Barren or Sparse, Woody Vegetation, Herbaceous Vegetation, Open Accessible Green Space	6	73.52	0.00
Impervious Surface, Light at Night, National Walkability Index, Area Zoned as J or K Industrial Zones	6	90.47	0.00
Null	2	92.37	0.00

(Fig. 2b) also appeared frequently in models with the best AIC scores. Both the categorical variable, Delmar Boulevard, and the proportion of area north of Delmar Boulevard also appeared in multiple top models. But the categorical variable's coefficient estimates (Delmar Boulevard) were difficult to interpret as many of the tracts with an inordinate amount of iNaturalist observations (such as Forest Park and the Arch Grounds) have northern borders that intersect the boulevard, resulting in them receiving a value of "cross" instead of "south." As such, the continuous variable that measures the proportion of the tract that lies north of the divide provided a better, and more interpretable fit. The proportion of area that is accessible open green space (Fig. 2c) was not a particularly strong predictor across all model sets but its inclusion improved model rank when combined with the top social variables. Notably, census tracts north of the Delmar Divide have a comparable average proportion of green space per tract (10.70%) to tracts south of the boulevard (11.93%).

Discussion

iNaturalist is an exceptional research tool but is inherently dependent on people and social systems. Our results show that variables describing race, socioeconomic status, and open green space are strong predictors of where iNaturalist observations occur within Saint Louis. We expected that a combination of natural and social variables would prove influential, and overall socioeconomic variables appeared more influential than variables related to the type and nature of urban green spaces. Systemic forces of structural inequality affect both the ecology/evolution of organisms (e.g., Schell et al. 2020) and exclusion of organismal observations from iNaturalist and other community science databases (Ellis-Soto et al. 2023; Perkins 2020), potentially confounding biodiversity studies in urban ecosystems.

Our best fit model included four variables: the National Socioeconomic Status (NSES) Index, the Diversity Index, the proportion of census tract area north of Delmar Boulevard, and open accessible green space (Tables 1 and 2; Fig. 3). Neighborhoods with higher NSES scores tend to have higher incomes, higher employment rates, more education, and more iNaturalist observations, as has been found with other community science platforms (Bateman et al. 2021; Ellis-Soto et al. 2023; Grade et al. 2022; Lopez et al. 2019; Martin and Greig 2019; Perkins 2020). Predictive plots generated of these four variables clearly highlight that the NSES Index is the strongest predictor of the data (Fig. 3). The Diversity Index is a calculation of the probability that any two people identify with a different race or ethnicity in a given neighborhood, and it was positively related to the number of iNaturalist observations. The proportion of area north of Delmar Boulevard is the fraction of each census tract that lies north of the Delmar Divide, a delineation of wealth and race distributions in Saint Louis where residents north of Delmar Boulevard tend to be African American and/or lower income (Gordon and Bruch 2019; Trivers and Rosenthal 2015). Tracts north of the divide tend to have fewer iNaturalist observations. Finally, the proportion of each tract that contains open accessible green space was positively related to numbers of iNaturalist observations.

We consider three potential mechanisms by which socioeconomic variables in Saint Louis impact the uneven distribution of iNaturalist observations. First, users of community science platforms tend to be of higher income and white (Ellis-Soto et al. 2023; Lopez et al. 2019; Perkins 2020) and thus make observations in green spaces south of the Delmar Divide. Though census tracts north and south of the Delmar Divide have a comparable average proportion of green space per tract (Fig. 2c), the area north of Delmar Boulevard has only 8.16 iNaturalist observations per tract on average while the area south has 169.3 observations on average. Green space north of Delmar Boulevard may be seen as less desirable for outdoor leisure activities by majority white, economically advantaged iNaturalist users (Ngom et al. 2016; Roberts-Gregory and-Hawthorne 2016). Reasons for this contrast are complex, but race and racial stereotypes undoubtedly play a significant role. The area north of Delmar Boulevard might be termed a "Black ecology"—environmental and economic networks in under-resourced, overcrowded, and pathologized Black communities in urban areas (Hare 1970). In the white imagination, Black people are geographically relegated to "unnatural spaces" (Finney 2014) and consequently the green spaces north of the Delmar Divide would be perceived differently by white iNaturalist users. Though this attitude is unjust, there is some grounding in material realities of segregated urban space. So, greater numbers of observations appear in popular green spaces in the southern, majority white, economically advantaged part of the city (Fig. 3) instead of in all green spaces.

Second, racial and socioeconomic indicators also highlight disparities in proximity/physical access to existing green space. Although the relative amount of accessible green space north and south of the Delmar Divide is comparable (Fig. 3), it is possible that lack of investment in public transportation, walkways, and other accessibility measures could explain why iNaturalist users venture to green space south of Delmar Boulevard but not north. The topic of improved public green space north of Delmar Boulevard arises frequently in plans for funding public and private development; these opportunities have been largely missed due to community grant mismanagement and the

a)
NSES Index Score
by Census Tract
N
Index Score (0 - 100)
Delmar Divide
> 65
60 - 65
55 - 60
50 - 55
45 - 50
40 - 45
35 - 40
30 - 35
< 30
Kilometers
0 1 2 4
b)
Diversity Index Score
by Census Tract
N
Index Score (0 - 100)
Delmar Divide
< 10
10 - 15
15 - 20
20 - 25
25 - 30
30 - 40
40 - 50
50 - 60
> 60
Kilometers
0 1 2 4
c)
Proportion of Area
That is Open Accessible
Green Space by Census Tract
N
Proportion (0 - 1)
Delmar Divide
0
< 0.01
0.01 - 0.02
0.02 - 0.04
0.04 - 0.08
0.08 - 0.12
0.12 - 0.2
0.2 - 0.4
> 0.4
Kilometers
0 1 2 4

Fig. 2 (**a**) - National Socioeconomic Status (NSES) Index by census tract (U.S. Census Bureau 2010). Indexes are calculated from six common socioeconomic indicators and are normalized to 2015 levels in the United States. The Median is 50. Higher index scores indicate more affluence, employment, and education. (**b**)- Diversity Index (DI) by census tract (U.S. Census Bureau 2010). The DI is the percent probability that any two people identify with a different race or ethnicity in a neighborhood. (**c**) - Open Accessible Green Space (Washington University Geospatial Resources, 2014, 2017, 2018). Proportion of census tract that is accessible open green space. It includes: public parks, playgrounds, cemeteries, community gardens, some university green space, and public school green space

abandonment of private funding of large scale "revitalization" projects (Petrin 2018).

Third, the unequal distribution of iNaturalist data may be explained by Saint Louis residents' more general lack of exposure to information about the importance of more racially and socioeconomically diverse public participation in environmental science on the local level. As such, iNaturalist has the potential to serve as a powerful tool for more inclusive education in the life sciences. In particular, primary and secondary school curricula provide an excellent opportunity to increase knowledge about and participation in iNaturalist. Incorporating community science into the classroom brings many benefits, such as awareness of the biodiversity crisis, engagement in their local community, and a better understanding of the scientific process to teachers, students, and researchers (Echeverria et al. 2021; Niemiller et al. 2021; Unger et al. 2020). Primary and secondary school educators might consider using iNaturalist as a teaching tool in classrooms. Further, The City of Saint Louis could incorporate iNaturalist into future public school curricula and provide increased support to existing non-profit organizations and public libraries working directly with teachers and students to develop Saint Louis-based life science curricula (Seed St. Louis 2017).

These factors also speak to larger concerns of environmental justice and environmental racism in the Saint Louis area and beyond (Bullard 1990). A deep history of environmental racism in Saint Louis results in conditions that present significant barriers to community science engagement in the primarily African American communities north of Delmar Boulevard. Existing and future green spaces in these areas are at increased risk of soil, air, and water contamination and municipal neglect. Decades of intentionally sited pollutants, municipal neglect of residential and recreational areas result in negative, racialized attitudes toward access to and interactions with nature and/or green space. (Hurley 1997; Martino-Taylor 2018; Randall and Germain 2017; Sierra Club 2014, 2022). Black communities have been deprived of opportunities for safe, recreational engagement with the natural environment close to home, especially as applies to both historic housing segregation and the policing of activities such as hiking, birdwatching, or picnicking in green spaces located near majority white areas (Levin 2018; Finney 2014; Johnson 2020; Nir 2020; Rogers 2011).

Further research is needed to discover more about the mechanisms by which racial and socioeconomic variables impact the spatial distribution of community science data points. Probing the three potential mechanisms proposed above is an obvious next step. Separating iNaturalist observations by those observed in public green space (parks, universities, government grounds, community gardens) versus private space (backyards or subdivisions) or surveying users could provide clarity on how far community scientists are traveling to make their observations. iNaturalist collects relatively little information about its users compared to other community science apps (Kelling et al. 2019), so surveying user information could be beneficial. We also suggest future research on whether socioeconomic variables affect the type of observations (i.e. which taxa) made in the app or just the location. Finally, this research should be replicated in other cities to better understand the relationship between socioeconomics, community science data, and urban ecology.

As described in Schell et al. (2020), biodiversity type and habitats can change based on systemic forces of structural inequality. Therefore, the spatial gaps in iNaturalist observations could mean that databases systematically lack observations of specific, distinct types of urban habitats and species assemblages. The results of this research emphasize that ecologists need to acknowledge and consider the mechanism by which systemic socioeconomic forces might skew the spatial distribution of iNaturalist observations used in their studies.

Conclusions

iNaturalist is an exceptional research tool but is inherently dependent on people and social systems. Research that uses iNaturalist data can be improved through the integration of social variables into their understanding of iNaturalist observation locations. Results from our investigation into iNaturalist observations across Saint Louis, Missouri demonstrate that community science data are much more abundant in urban census tracts with whiter and more socioeconomically advantaged populations with greater extents of open green spaces. Nearly all of the census tracts with zero iNaturalist observations were situated north of "The Delmar Divide," a well-known racial and economic divider in Saint Louis, creating a gap in biodiversity data in many neighborhoods that may have distinct ecological

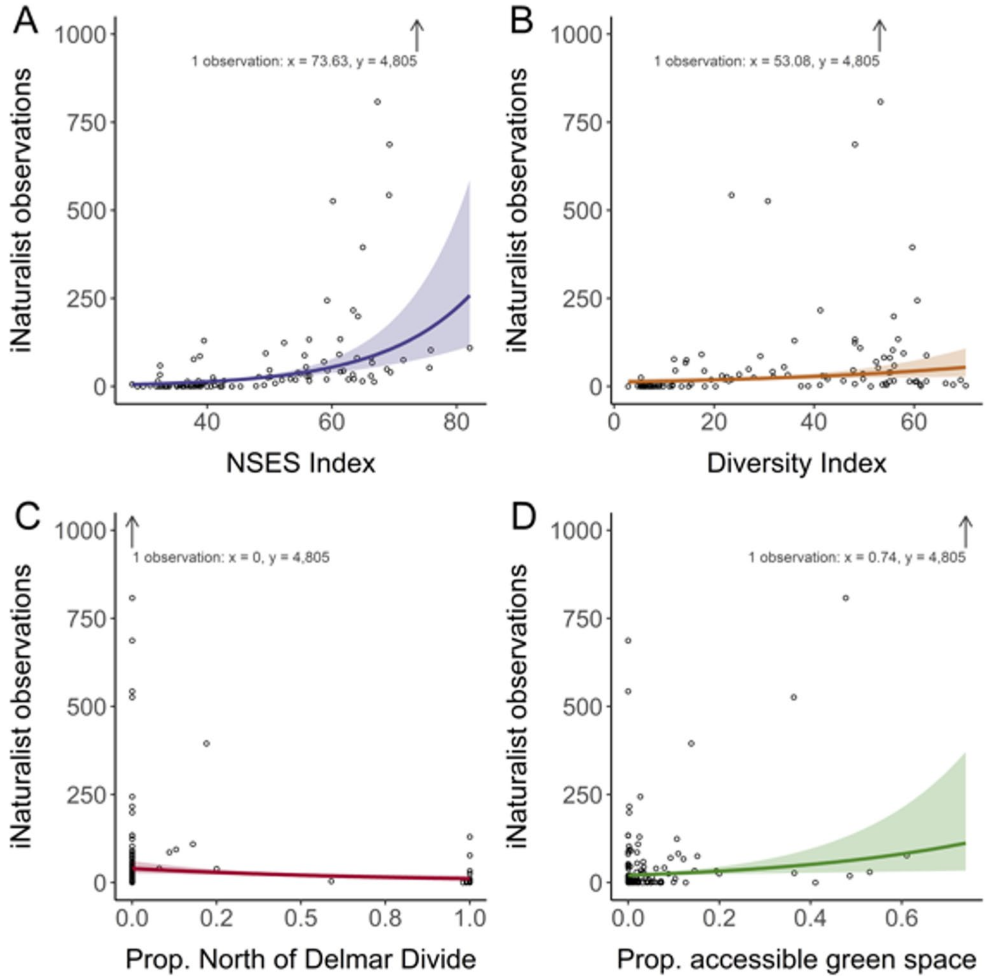

Fig. 3 Predictive plots of the four variables included in the model of best fit. Shaded areas correspond to 95% confidence intervals

communities but remain undersampled. Failure to acknowledge these gaps when using iNaturalist data may increase the possibility that results are confounded by historic and modern-day socioeconomic forces.

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Author contributions EGB and SAA conceived and designed the scope of the project. EKR and AG gathered and manipulated data for analysis. EKR initially described the data pattern and gathered references and resources for manuscript. SKH and WAS performed analysis. WAS wrote the main manuscript text, gathered covariate data and prepared all figures and tables with mentorship by SAA, EGB and SKH. RBM added historical and social context for the manuscript discussion. All authors reviewed the manuscript and edited the paper. All authors approve the submitted version.

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Declarations

Competing interests The authors declare no competing interests.

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