Applied Geography 158 (2023) 103030

Contents lists available at ScienceDirect

Applied Geography

journal homepage: www.elsevier.com/locate/apgeog

A Planner's quest for identifying spatial (in)justice in local communities: A case study of urban census tracts in North Carolina, USA

Russell M. Smith [a,b,*], Debzani Deb [c,d], Zach Blizard [d], Rachel Midgett [d]

[a] Department of History, Politics and Social Justice, Winston-Salem State University, Winston-Salem, NC 27110, USA
[b] Spatial Justice Studio, Center for Design Innovation, Winston-Salem State University, Winston-Salem, NC 27110, USA
[c] Department of Computer Science, Winston-Salem State University, Winston-Salem, NC 27110, USA
[d] Center for Applied Data Science, Winston-Salem State University, Winston-Salem, NC 27110, USA

ARTICLE INFO

Handling Editor: Dr. Y.D. Wei

ABSTRACT

For the past several decades, spatial justice has been presented as a conceptual framework to understand and address geographic inequalities. To date, most work associated with spatial justice has been qualitative and case study based. This paper seeks to explore the issue of spatial justice through the development of a Spatial Justice Index (SJI). The SJI quantitatively explores geographic based variables of urban census tracts in North Carolina to apply the underlying concepts of spatial justice in the real world. Using a principal components analysis approach, the SJI incorporates variables related to the following categories that comprise the concept of spatial justice: Public Goods, Basic Services, Cultural Goods, Economic Opportunities and Healthy Environments and are explored across the following spatial measures: spatial density, spatial proximity, spatial diversity, and spatial connectivity. The results highlight the benefits of dense, mixed use development patterns, that are well connected in achieving higher levels of spatial justice. The development of a Spatial Justice Index can be applied by urban planners and government officials across the entire Country to help communities comprehend, accept, and combat spatially injustices.

1. Introduction

Communities and neighborhoods across the United States are calling for assistance in developing more equitable, sustainable and just spaces and places for residents. Growing levels of income inequality, environmental injustice, residential segregation, and discrepancies in the provision of public infrastructure are but a few problems facing communities across the country that result in a divided citizenry (Chetty, Hendren, Kline, Saez, & Turner, 2014; Corak, 2013; Fainstein, 2010; Bullard, 1990). These societal ills can be partial attributed to political and socio-economic organization of space, which privies private property, profit, and the individual (Harvey, 1973; Levebre 1968). The byproduct of these systems has been the creation of grave spatial inequalities across regional and urban landscapes (Jankauskaitė-Jurevičienė, 2022; Pirie, 1983; Soja, 2010; Wei, 2015). Soja (2010) stated that "location in space will always have attached to it some degree of relative advantage or disadvantage" (73). However, efforts can be made to recognize and ameliorate these advantages and disadvantages to create a more just and equitable future for all.

Spatial justice is a concept that seeks to begin this process of understanding the root causes of spatial inequalities and begin rectifying them in order to create a more just world for all. Originally, coined by Edward Soja (2010), spatial justice has become a concept closely associated with efforts to make geographies more equitable and sustainable. Rocco de Campos Pereira (2014) stated that "Spatial Justice refers to general access to public goods, basic services, cultural goods, economic opportunity and healthy environments" (14). Achieving spatial justice would be a means by which to address the inequitable distribution of public and private goods, services and resources in communities around the world. But how can we measure spatial (in)justice)? Progress? Success?

To date, spatial justice research has tended to focus on the use of case studies and examples to highlight specific types of spatial injustices and further develop the theory of spatial justice. For example, Soja (2010) highlights the *Bus Riders Union Case* as an example of a transportation spatial injustice that was perpetrated against parties in Los Angeles that needed and wanted equitable access to the public transportation system and were originally overlooked in favor of more suburban and well to do

* Corresponding author. Department of History, Politics and Social Justice, Winston-Salem State University, Winston-Salem, NC 27110, USA .
E-mail address: smithrm@wssu.edu (R.M. Smith).

https://doi.org/10.1016/j.apgeog.2023.103030
Received 20 January 2023; Received in revised form 6 April 2023; Accepted 1 July 2023

public transit riders. Soja (2010) stated, the case "was also a stirring expression of the environmental justice movement, combatting racial injustice and discrimination based on place of residence" (vii). Fainstein (2010) used the backdrop of a select few world cities (i.e., New York, London, and Amsterdam) to explore the idea of a "just city", which Soja believed was on a parallel discourse with spatial justice. Through examples of planning and development projects within in each of the cities Fainstein seeks to determine "how just" each city has become.

Left under-explored by these case studies and examples is empirically based, quantitatively analyzed examinations into what makes a geography spatially just/unjust. How do you measure spatial (in)justice? Numerous studies have explored individual components of unjust geographies including school performance issues, gentrification, food insecurity, and public transit (Chang, Chen, Li, & Li, 2019; Garcia, Garcia-Sierra, & Domene, 2020; Jones, Mamudu, & Squires, 2020; Liu & Duan, 2020; Rodríguez-Pose & Storper, 2020; Wei, Xiao, Simon, Liu, & Ni, 2018). However, little scholarship has been focused on exploring how these manifestations of spatial inequality are connected to broader instances of spatial injustice.

Environmental justice, which is a form of spatial justice, has been rigorously explored by quantitative researchers and offers some potential guidance for the development of a Spatial Justice Index (Mohai, Pellow, & Roberts, 2009; Schlosberg, 2007, 2012). Beginning with Bullard's examination into the citing of waste dumps in Houston, TX (1983), to more recent studies of water quality issues in Flint, MI (Kruger, Cupal, et al., 2017a; Kruger, Kodjebacheva, & Cupal, 2017b), environmental justice research has utilized empirically based, quantitative research methodologies to define, explore and offer solutions to environmental injustices in a wide variety of geographies. Environmental justice research can motivate the analysis of other urban issues with a critical lens.

The goal of this study is to begin the development of a Spatial Justice Index through which multiple spatial inequalities can be combined into one measure by which geographies can be compared, explored, and evaluated. This will help to turn theory into practice. This paper utilized a quantitative analysis to begin the development of a Spatial Justice Index (SJI) (see Fig. 1), which will be used to identify, benchmark and help rectify spatial injustices experience by urban census tracts in North Carolina (N·C.). This methodology builds on the more critical use of positivist research methods, which seek to use rationale, empirically based, quantitative methodologies to explore difficult urban questions (Sheppard, 2001, 2014; Wyly, 2009, 2014). To accomplish this, a wide variety of geographic attributes were collected by census tract and examined through a Principal Component Analysis (PCA) to create a measure of spatial injustice through an statistical analysis of differing types of spatial injustices, which are consistently linked to spatial inequality. Specifically, variables related to the following categories that comprise the concept of spatial justice: Public Goods, Basic Services, Cultural Goods, Economic Opportunities and Healthy Environments and are explored across the following spatial measures: spatial density, spatial proximity, spatial diversity, and spatial connectivity.

The remainder of this paper is organized as follows. Section 2 discusses related literature, then Section 3 elaborates the detailed methodology utilized in this study. Section 4 discusses the results and explores two census tracts (SJI value high and SJI value low) in an effort to understand the specific factors that influence spatial justice within each geography. Section 5 concludes the paper and offers a discussion of next steps.

2. Literature review/background

The theoretical underpinnings of what Soja (2010) called spatial justice has its origins in the works of Lefebvre (1968), Harvey (1973) and Pirie (1983). Lefebvre (1968) broke from the neo-liberal agenda that was beginning to consume cities by espousing a concept he called the 'right to the city'. This novel approach to urban space was built upon the notion of reclaiming the city for 'all' in the face of increasing levels of commercialization, privatization, and public-private partnerships. Harvey (1973) built upon Lefebvre's 'right to the city' and he called on geographers to bring together spatial and social analysis to improve

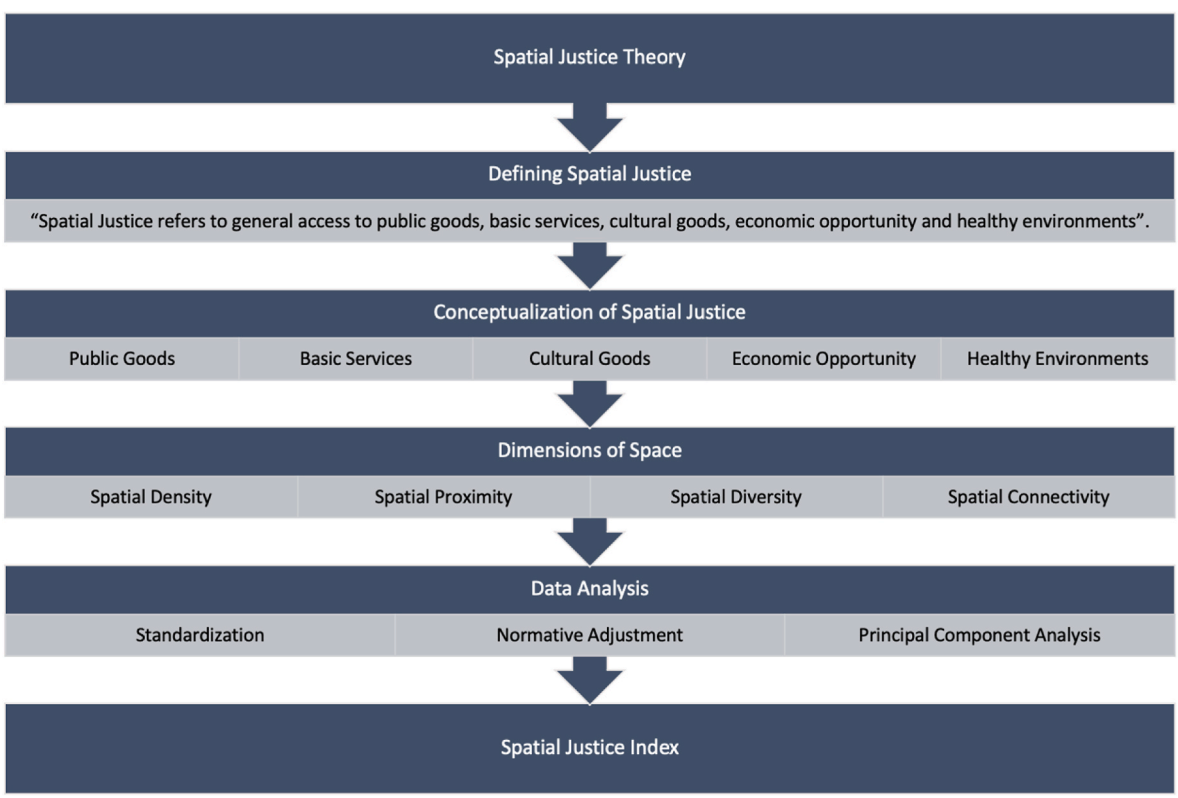

Fig. 1. Conceptualization of research methodology.

urban spaces. Harvey believed that you couldn't divorce the spatial and social aspects of development in urban locations. Pirie (1983) discusses the idea of 'territorial social justice' and states that, "Surely it would be another string in their bow if geographers could answer questions such as these: is a person's living at place x just? Is the spatial distribution of grocery stores just? Is the siting of some new airport just? Is the re-siting of the hospital just? Is the removal and rehousing of squatters just? These questions range over the justness of absolute and relative location as well as over the justness of processes of siting and relocation" (470). Left unanswered by these early efforts at creating more just geographies is the lack of a concrete definition from which to advance the study of spatial (in)justice (Weck, Madanipour, & Schmitt, 2022; Philippopoulos-Mihalopoulos, 2019).

Soja (2010) discusses the importance of spatial justice as a concept, applications of spatial justice, and the need for urban planners to engage in proactive spatial justice efforts, but his pivotal work leaves much to be desired as it relates to providing a concrete definition of spatial justice. Rocco provides one of the only succinct definitions of spatial justice, which includes access to a minimum level of economic opportunity, clean environment and basic public infrastructure and services (2014).

Absent a fully formed and agreed upon definition, most scholars have opted to provide the characteristics that would help make a place more spatially just. These characteristics tend to focus on three fundamental components of a just geography: access, equity and opportunity. Soja was interested in how differing geographies have access, opportunities and equity as it relates to resources and services. Rocco goes a step further and adds public goods, basic services, cultural goods, economic opportunity and healthy environments to the list of features that the population should have equal access to, opportunities for and equitable distribution of. Fainstein offers her own opinion on how planners can contribute to what she calls 'The Just City" by focusing on three factors: democracy, diversity and equity (2010). In the end, the concept of spatial justice and related ideas provides a needed lens for exploring issues of geographic inequality, but how to measure spatial justice and define the term is difficult.

While the concept of spatial justice continues to evolve over the years, numerous studies have attempted to quantify the impacts of spatial injustices across a wide variety of geographies and topics. While many of these studies do not use the term spatial (in)justice explicitly, the focus of their analysis is clearly centered in the study of geographic inequality. These studies exploring spatial inequalities across geographies focus on environmental injustices, education, healthcare, transportation, and parks to name a few (Bullard, 1990; Chang et al., 2019; Garcia et al., 2020; Jones et al., 2020; Liu & Duan, 2020; Wei et al., 2018). Alrobaee (2021) provides an interesting examination of spatial justice across several different measures including spatial diversity, spatial connectivity, spatial resilience, spatial security, and spatial empowerment across several traditional Islamic cities in Iraq. This work provides some of the inspiration for the development of an index by which spatial justice can explored more fully.

Recently, scholars have used the lens of spatial justice to explore specific topics of spatial injustice in research endeavors from across the globe. This work has included exploring urban gardening as a mechanism for improving spatial justice in Rome, Italy (Certomà & Martellozzo, 2019); spatial injustice in school access in Jakarta (Muhaimin, Gamal, Setianto, & Larasati, 2022); public transport in Greece (Tzanni, Nikolaou, Giannakopoulou, Arvanitis, & Basbas, 2022); and urban services in Iran (Hajat, Tasouj, & Shoeibi, 2022). However, these 'one-off' explorations of spatial injustice do not provide the necessary depth of analysis to understand the complexity of unjust geographies. Simply stated, the presence of one spatial injustice often means the presence of additional spatial injustices (Deb & Smith, 2020, 2021). For example, a community that suffers from poor educational opportunities for its youth often also has limited employment opportunities for residents as well.

As a result, this paper seeks to develop a Spatial Justice Index to unite multiple spatial (in)justice attributes under one measure for potential use in the identification, exploration, and remediation of spatial injustice in communities. The SJI will be created using data-science and machine learning based approaches to empirically evaluate the impact of a set of spatial attributes on these various indices. This process will yield a set of geographic attributes that are significant across the indices, and which will be subsequently included in the Spatial Justice Index.

3. Materials and methods

3.1. Study area –

N.C. is located along the eastern seaboard of the United States (see Fig. 2) and is home to more than 10 million residents according to the U.S. Census (2020 U.S. Census). Comprised of mountain, piedmont and coastal zones, N·C.'s economy was originally agrarian in nature, which supported a large rural population. Beginning in the 1900's N.C. transitioned to a manufacturing economy and then to a service/technology-based economy with a predominately urban population (Powell and Mazzocchi 2006). The State of N.C. is divided into 100 counties and more than 500 municipalities that range in size from a few dozen to more than 800,000 residents, like in the city Charlotte.

N.C. was selected as the study area for several reasons. First, the authors have a familiarity with the State, their university is in the State. Additionally, previous research related to the development of the SJI has been conducted in N.C. and the research presented in this paper builds upon this foundation (Deb & Smith, 2020, 2021). Next, most of the data needed to complete this study was readily available from an online governmental source, "NC OneMap is a strategic resource providing a collection of authoritative data and web services" focused on N.C. and combining local, state, federal, private sector, and academic data sources (NC OneMAP, 2022). Finally, N.C. ranks in the top half of all U.S. states for income inequality (Ratio of top 1% income to bottom 99% income). This level of inequity highlights the spatial injustice experienced by N.C. residents. As Sommeilleer and Price state, "In North Carolina, the top 1 percent captured all the income growth from 2009 to 2015 (while income declined for the bottom 99 percent)" (2018).

3.2. Unit of measurement: census tract

The unit of measurement for our analysis is the census tract. The U.S. Census Bureau uses census tracts to establish relatively stable geographic entities to calculate statistics. Tracts range in population from 1,200 to 8,000 people and the geographic size of census tracts can vary widely depending on the density of people in the area. N.C. has 2,672 census tracts as of the 2020 Census. Census tracts are regularly used in empirical research to approximate neighborhoods and are a common geographic unit for analysis (Duncan, Kawachi, White, & Williams, 2013; Jones & Pebley, 2014; Wang & Immergluck, 2018).

3.3. Urban census tracts

For our study, we specifically examine census tracts that are urban, as opposed to rural. This decision was largely based upon the differing characteristics of the built environment between the urban and rural areas. Rural census tracts tend to be large and do not incorporate the density of geographic attributes explored in this study, tend to be more homogenous in land uses and population, have limited connectivity, and are further away from public goods compared with urban tracts (Cromartie & Bucholtz, 2008, pp. 28–35). All census tracts that were included in an Urbanized Area, based upon the US Census, were included in the final dataset. In sum, N.C. had 1,386 urban census tracts based upon this definition in 2020. This definition is widely used throughout the relevant empirical literature (Berke et al., 2010; Sharkey, 2014; Wight et al., 2006).

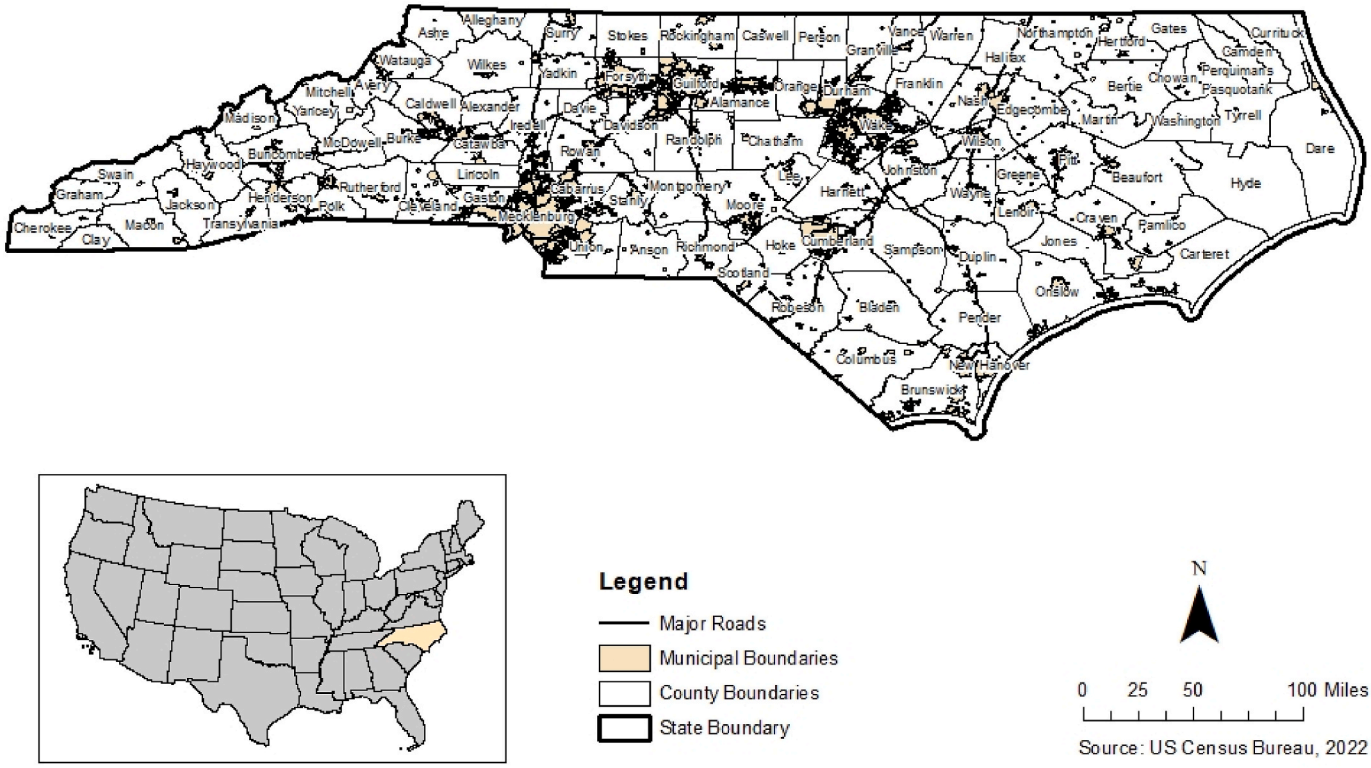

Fig. 2. State of North Carolina.

3.4. Concepts and variables

Four spatial measures of justice within census tracts were utilized in the development of the Spatial Justice Index (SJI) including spatial density, spatial proximity, spatial diversity, and spatial connectivity. Spatial density refers to how many of a particular thing are in a specified area. In the context of our study, these will consist of things relevant to spatial justice, such as public goods, basic services, cultural goods, economic opportunities, and healthy environmental entities (Rocco de Campos Pereira, 2014). The concept of spatial proximity describes how close things tend to be to people living in a specified area. Like the set of density variables, the set of things we consider for spatial proximity are variables like public goods, basic services, cultural goods, economic opportunities, and healthy environments. Proximity will be measured as the distance from the closest thing (example, hospital) to the centroid of a census tract. Spatial diversity describes the homogeneity of a specified area in terms of features and was utilized by Alrobaee (2021) in a previous study. We consider features related to the environment, people, and housing stock. Spatial connectivity explores how connected a specified area is across several factors (Alrobaee, 2021). For our study, we consider a census tract's digital connectivity, transportation connectivity, built environment connectivity, and social connectivity. See APPENDIX for more information on the variables and their sources (Table A1 - A4 in APPENDIX) along with their descriptive statistics before standardization (Table A.1.1 – A.4.1 in APPENDIX).

While additional spatial measures exist (e.g. spatial resiliency, spatial empowerment, spatial security, etc.), our four measures were included in this exploratory analysis for several reasons. First, the components of the spatial measures of justice are readily available across the United States, making the future application of the SJI methodology to other states possible. Second, previous research into Spatial Justice utilized several of these measures, which were found to be important for achieving spatial justice (Alrobaee, 2021). Finally, these four measures and concepts (density, proximity, diversity, and connectivity) are straightforward and provide useful context for the initial exploration of the geographic attributes included in our study.

3.5. Analytical method and approach

Prior to running a principal component analysis (PCA), we generated the correlation matrices (Table A5- A8 in APPENDIX) and took several steps to standardize the input data and make normative adjustments. We describe these steps in the following sections.

3.5.1. Standardization and normative adjustments

For each variable in our dataset, we standardize them to have means of 0 and standard deviations of 1. This ensures that variables of different scales can be compared and that no variables with large scales drive the results of the PCA. Once the variables are standardized, we adjust the direction of their standardized distributions depending on whether high or low values are indicative of spatial justice or injustice. High values of some variables are more indicative of high justice levels, while high values of other variables are more indicative of high injustice levels. To ensure high values are only associated with high spatial justice levels, we invert the distributions for several of the variables, following a similar approach as Malega and Stallings (2016). These are summarized in Table A9 in the APPENDIX.

3.5.2. Principal components analysis (PCA)

With the standardized and normatively adjusted values, we test for the appropriateness of using PCA to create our index. To do this, we use two standard tests. The first is the Kaiser–Meyer–Olkin (KMO) test, which is a measure of sampling adequacy. The KMO test is used to gauge how suitable our datasets are for factor analysis. The KMO measure ranges from 0 to 1, with values closer to 1 indicating that the data is more suitable for factor analysis. Various thresholds have been proposed to determine whether data is suitable or not. Kaiser and Rice (1974) propose a cutoff of 0.6, while Dziuban and Shirkey (1974) propose 0.5. Both cutoffs have been widely used in the literature (Abdul Rahman, Bani Issa, and Naing, 2021; Figueiredo & Franco, 2018; Ferguson,

2001). For our data, all four datasets have KMO measures above 0.5, suggesting they are suitable for factor analysis. For the density variables, the KMO measure was 0.804. For the proximity variables, the KMO measure was 0.784. For the diversity variables, the KMO measure was 0.616. For the connectivity variables, the KMO was 0.510.

The second test we use is Bartlett's test of sphericity to measure whether the variables are correlated and if they can be adequately summarized with a smaller set of factors. Based on the Bartlett test results for our four datasets, there is significant correlation between the variables, further suggesting that our data is suitable for factor analysis (the Bartlett test results are in Table A10 of APPENDIX).

With our data being determined suitable for factor analysis, we then use PCA as our factor analysis method of choice. PCA, which is a method of dimensionality reduction, is widely used for creating indices, ranging from water quality to urban sprawl (Tripathi & Singal, 2019; Ewing & Hamidi, 2014). PCA extracts several components from a dataset based on the shared variance among the dataset's variables. The components are estimated to be orthogonal to one another and are linear combinations of the input variables. Each variable within a component has a weight, indicating the strength of the variable in terms of the shared variance and explanatory importance it has relative to the other variables.

We deploy PCA to collect the number of components necessary to explain at least 50% of the total variance, which is a threshold that has been used before (Ewing & Hamidi, 2014; Primpas, Tsirtsis, Karydis, & Kokkoris, 2010). Ideally, we would need only one component, which would then represent the dimension of spatial justice (example, a component representing spatial density). This is a similar approach to the one used by Ewing, Pendall, and Chen (2002) and Ewing and Hamidi (2014). In instances where more than 1 component is necessary to explain at least 50%, we simply standardize the component values and then calculate the average.[1] Once completed, we have component scores for our four categories (density, proximity, diversity, and connectivity). We run separate PCA for the four categories for several key reasons. First, spatial justice is a complex concept, with its underlying theoretical elements being quite distinct. Running PCA for the distinct elements would allow for the analysis of these individual "pieces" of spatial justice. Second, many studies have carried out a similar approach when creating quantitative indices for complex concepts, especially when the underlying categories are theoretically distinctive (Ewing & Hamidi, 2014; Gwartney, Block, & Lawson, 1996; Gwartney & Lawson, 2003; Van Beuningen & Schmeets, 2013).

The components are standardized to have means of 100 and standard deviations of 25, following Ewing and Hamidi (2014). Like Ewing and Hamidi (2014), we sum the four standardized component scores and regress the sum of the scores on the natural log of census tracts' population, since more heavily populated urban census tracts in NC may appear more spatially just simply because they contain more people. The residual of the regression, which is no longer correlated with population, is further standardized to have a mean of 100 and a standard deviation of 25. This final value represents our spatial justice index.

3.5.3. *Validating the index*

To validate the index, we use several approaches, which have been used in previous studies. First, following the literature, we use a method known as item analysis to ensure that the underlying variables that went into the index are still correlated with the final index value (Demers, Weiss-Lambrou, & Ska, 2000; Hartman & Hylton, 2000; Rey, Jougla, Fouillet, & Hémon, 2009). We estimate correlation coefficients for the index with each of the underlying variables to evaluate whether they remain significantly correlated and have the expected sign. Second, we evaluate how accurately the spatial justice index predicts other indicators that the relevant literature suggests should be negatively or positively correlated with it. Based on the literature (Guzman, Oviedo, Arellana, & Cantillo-García, 2021; Jian, Chan, Xu, & Owusu, 2021; Jian, Luo, & Chan, 2020), the Spatial Justice Index should be significantly correlated with other key socioeconomic and economic indicators. For example, a measure of spatial justice should be positively correlated with variables like median household income, median home value, and homeownership rates. Moreover, based on the literature, the index should be negatively and significantly related to variables like poverty rates, vacancy rates, percentage of the population that is non-white, and the unemployment rates. We will estimate the Pearson coefficient estimates for the correlation between the spatial justice index and these variables and evaluate the sign and significance. This strategy has been similarly used in other studies to evaluate an index (Bjørnskov, 2006). Table 1 summarizes the variables we test against the index along with the expected sign and significance. Third, we test the sensitivity of the index to our use of a 50% variance-explained threshold when collecting the number of components from each PCA by re-estimating an index that instead uses a 75% threshold. If the original index is robust, then the two indices should be highly positively correlated with one another (Malik, Lo, & Wu, 2018).

Table 1
Final index value.

N	Mean	Std Dev	Minimum	Maximum
1,343	100	25	6.82	226.51

4. Results

The results of our method are summarized in Table 1.[2] As was established in the calculation process, the mean of the SJI is 100 and has a standard deviation of 25. The minimum value, once the index is calculated for all of NC's urban census tracts, is 6.8 and the maximum value is 226.5. The distribution of the index is presented in Fig. 3. It follows closely to a normal distribution, as expected, though it is slightly positively skewed. Tables containing the eigenvalues, eigenvectors, and descriptive statistics associated with the PCA results are in the APPENDIX (Tables A11-A22). The complete list of all SJI values for all NC urban census tracts are available in the Spatial Justice Index Data Repository (Spatial Justice Index Data Repository, 2023), https://github.com/CADS-WSSU/CADS-Research-Projects/tree/main/Spatial%20Justice2023).

Table 2 presents the 10 census tracts with the highest SJI value. Census tract 103 in Mecklenburg County has the highest SJI value at around 226, which is being driven by its large density score. This census tract's SJI value is around 50 points higher than the next highest census tract, which is census tract 52601 in Wake County. Five of the top 10 census tracts are in Wake County (which has the largest population of any County in N·C.) and 2 of the top 10 are in Durham County (which is west of Wake County).

Table 3 presents the 10 census tracts with the lowest SJI value. Census tract 1501 in Wake County has the lowest SJI value at around 6.8, which is being driven by its low connectivity score at just under 50. Two of the bottom 10 census tracts are in Durham County, N·C., 2 of the top 10 are in Guilford County, and 2 of the top 10 are in Onslow County. The census tracts with the lowest SJI values are more evenly dispersed compared to the top 10 tracts previously discussed.

Fig. 4 highlights the SJI value by urban census tract across the State of N.C. and within select urban geographies including the Triangle, the Triad, the Charlotte-Mecklenburg Region, and Cumberland County (City

[1] Averaging the component values has been used in a variety studies (see Adams-Kane, Jia, & Lim, 2012; Chan et al., 2015; Ganusova, Vo, Abraham, O'Neal Yoder, Hettich & Alexandre, 2021; Prisciandaro & Roberts, 2005; Yoder, Hettich, and Alexandre, 2021).

[2] See APPENDIX for more information on the results for the intervening steps.

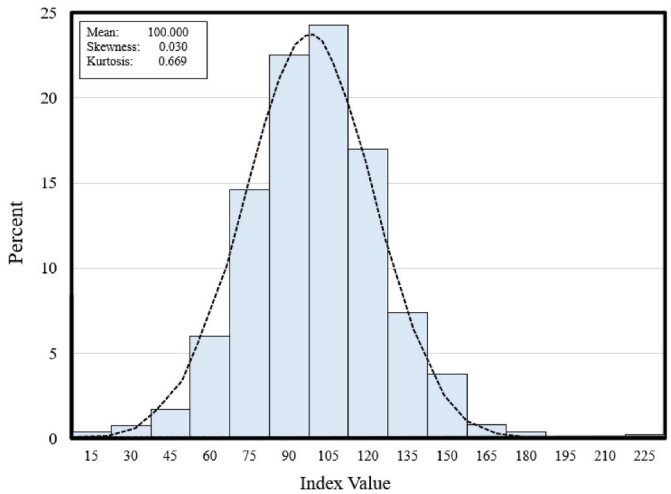

Fig. 3. Distribution of the Spatial Justice Index.

of Fayetteville). In general, census tracts that are closer to the traditional core of an urban area tended to score higher on the SJI compared with census tracts in more outlying locations. This result may be influenced by several factors that directly impacted the measures of spatial density, spatial proximity, spatial diversity, and spatial connectivity. These include suburban patterns of development which separated land uses (diversity), limited street connectivity through the proliferation of cul-de-sacs (connectivity), encouragement of larger lot development patterns through minimum lot sizes (proximity), and lowered the population per acre of land through exclusionary zoning (density) (Ewing & Hamidi, 2015; Jackson, 1987). These factors all influenced the built environment and have ramifications on spatial (in)justice and the equitable distribution of public goods, basic services, cultural goods, economic opportunity, and healthy environments for residents. The following section will explore two census tracts (one that received a high SJI value and one that scored low on the SJI) to examine the specifics of each geography to better understand the local dynamics of the built environment that contributed to its SJI value.

4.1. *Case studies – Tract 103: Mecklenburg County*

Census Tract 103 in Mecklenburg County, North Carolina has the highest Spatial Justice Index score due to its high density of and proximity to many desirable spatial attributes (see Figs. 5–8). The density of this tract is largely due to the abundance of basic services, public goods such as a park, recreation center, public library, grocery store, and pharmacy, as well as a diverse range of jobs within the area. Additionally, a significant percentage of residents have a commute of less than 15 minutes, contributing to the high proximity score. The tract's proximity is also influenced by its closeness to the interstate and the availability of basic goods and services. While connectivity may not be a strong point for this tract, it has a high level of digital and social capital, as indicated by the high percentage of residents (58%) with access to fiber-optic internet and the high self-response rate (61%) for the 2020 Census.

Mecklenburg County is home to over one million residents. Census data from 2020 shows that the county is diverse and relatively young with a median age of 35 years (U.S. Census Bureau, 2020a). The racial composition of the county is 46% non-Hispanic white, 31% Black or African American, 14% Hispanic, 6% Asian, and 2% two or more races. The median income was $69,240. Approximately 15% of the population are foreign-born and over one-third are naturalized U.S. citizens (U.S. Census Bureau, 2020d).

Data on Census Tract 103 of Mecklenburg County shows an estimated population of 2,137 with a median age of 29 years for (U.S. Census Bureau, 2020a). The median income for the tract was $121,590 in 2020, well above the median income of the county for the same time. The racial composition of the population is majority non-Hispanic white

Table 2
Top 10 census tracts with the highest Spatial Justice Index.

Rank	Census Tract FIPS Code	County FIPS Code	County Name	Largest City in County	Spatial Justice Index	Density Score	Proximity Score	Diversity Score	Connectivity Score
1	103	119	Mecklenburg County	Charlotte	226.51	236.30	122.19	90.22	89.86
2	52601	183	Wake County	Raleigh	177.03	101.37	102.47	135.08	146.51
3	54011	183	Wake County	Raleigh	175.90	99.14	102.42	138.74	143.33
4	1100	21	Buncombe County	Asheville	168.66	112.83	110.47	118.17	136.10
5	51700	183	Wake County	Raleigh	167.62	93.65	101.83	137.07	142.45
6	1713	63	Durham County	Durham	159.83	104.41	96.92	131.11	133.75
7	51501	183	Wake County	Raleigh	159.69	92.90	98.21	131.76	143.74
8	53721	183	Wake County	Raleigh	159.59	92.01	78.33	151.91	143.95
9	11606	129	New Hanover County	Wilmington	159.24	100.91	116.91	114.16	134.64
10	2008	63	Durham County	Durham	159.19	97.62	96.84	150.51	120.85

Table 3
Bottom 10 census tracts with the lowest Spatial Justice Index.

Rank	Census Tract FIPS Code	County FIPS Code	County Name	Largest City in County	Spatial Justice Index	Density Score	Proximity Score	Diversity Score	Connectivity Score
1	1501	63	Durham County	Durham	6.82	76.21	107.03	63.64	49.40
2	10702	81	Guilford County	Greensboro	7.86	27.26	117.90	61.34	93.19
3	970903	31	Carteret County	Morehead	12.81	95.98	31.34	121.82	49.55
4	11201	81	Guilford County	Greensboro	19.30	53.49	116.73	44.56	94.90
5	1303	63	Durham County	Durham	19.71	62.58	111.38	71.95	65.59
6	501	119	Mecklenburg County	Charlotte	22.02	30.18	115.49	64.74	100.97
7	404	133	Onslow County	Jacksonville	23.03	89.85	8.02	140.05	71.46
8	600	133	Onslow County	Jacksonville	26.52	90.30	34.77	134.55	62.68
9	11002	107	Lenoir County	Kinston	26.58	90.44	26.74	124.96	76.55
10	20504	19	Brunswick County	Leland	29.21	90.32	42.12	108.06	78.83

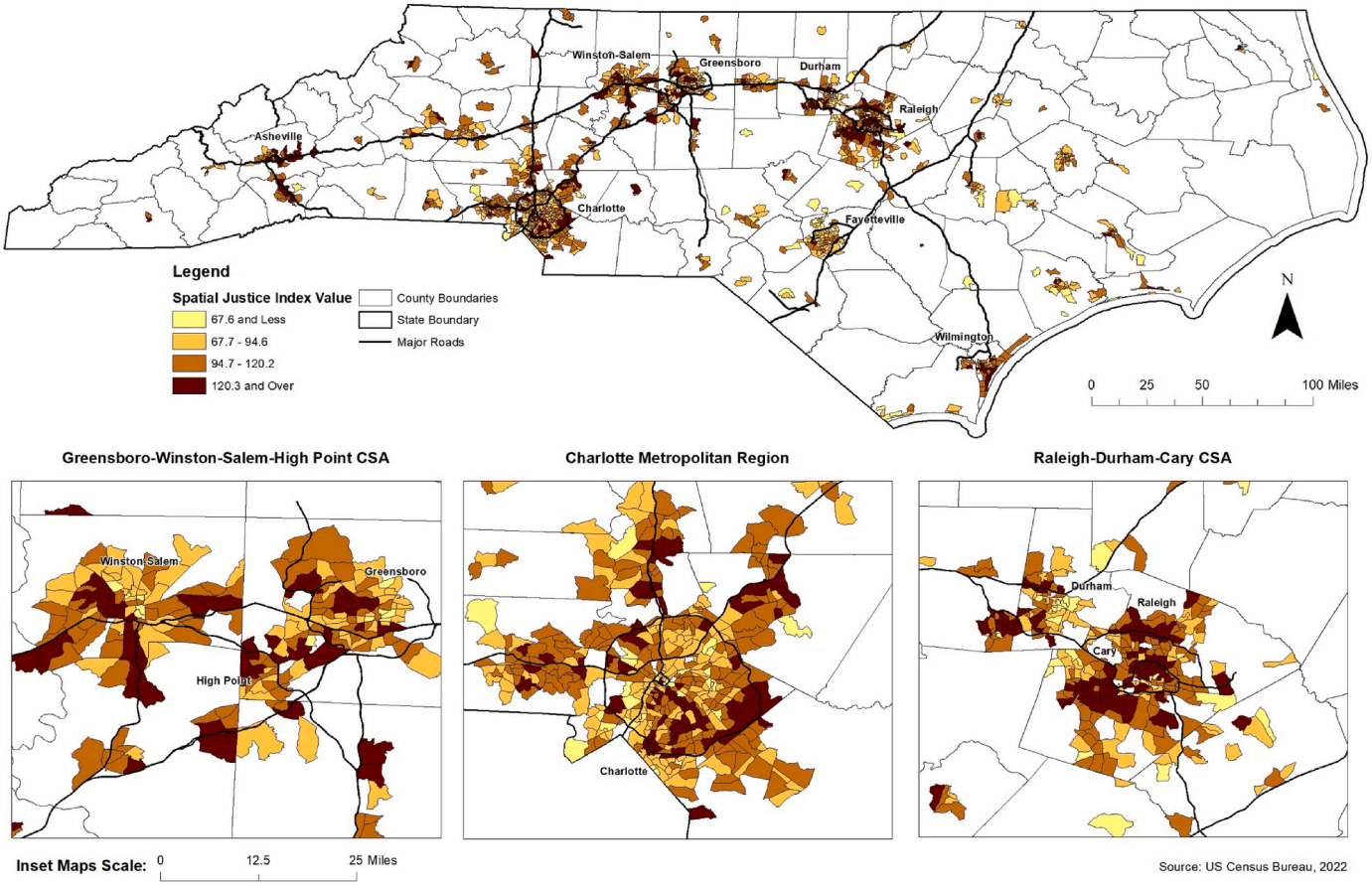

Fig. 4. Spatial Justice Index for NC urban census tracts, including select urban geographies.

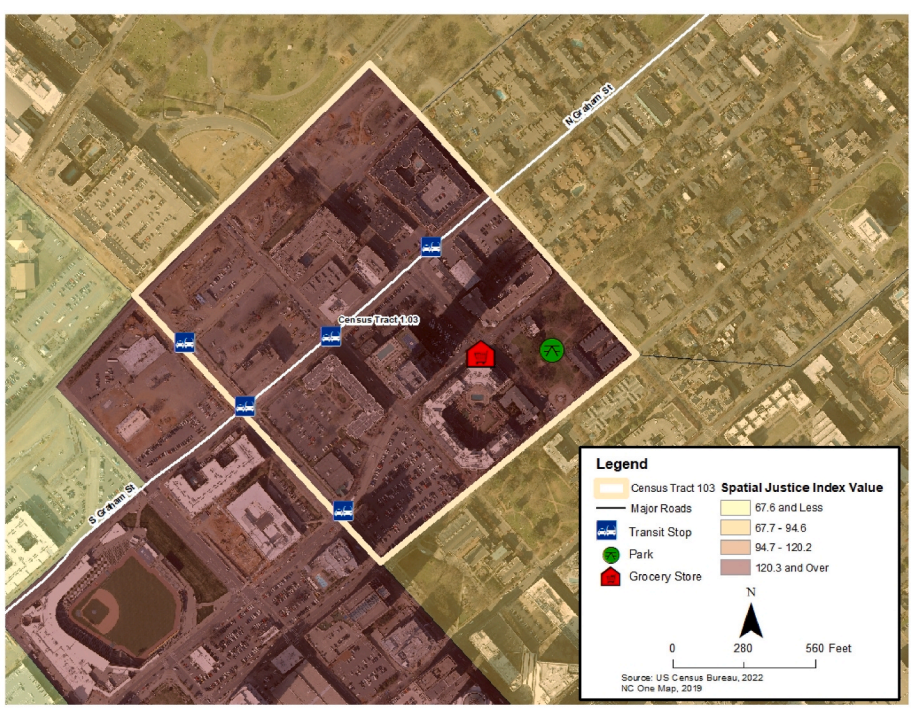

Fig. 5. Area map census tract 103, Mecklenburg County.

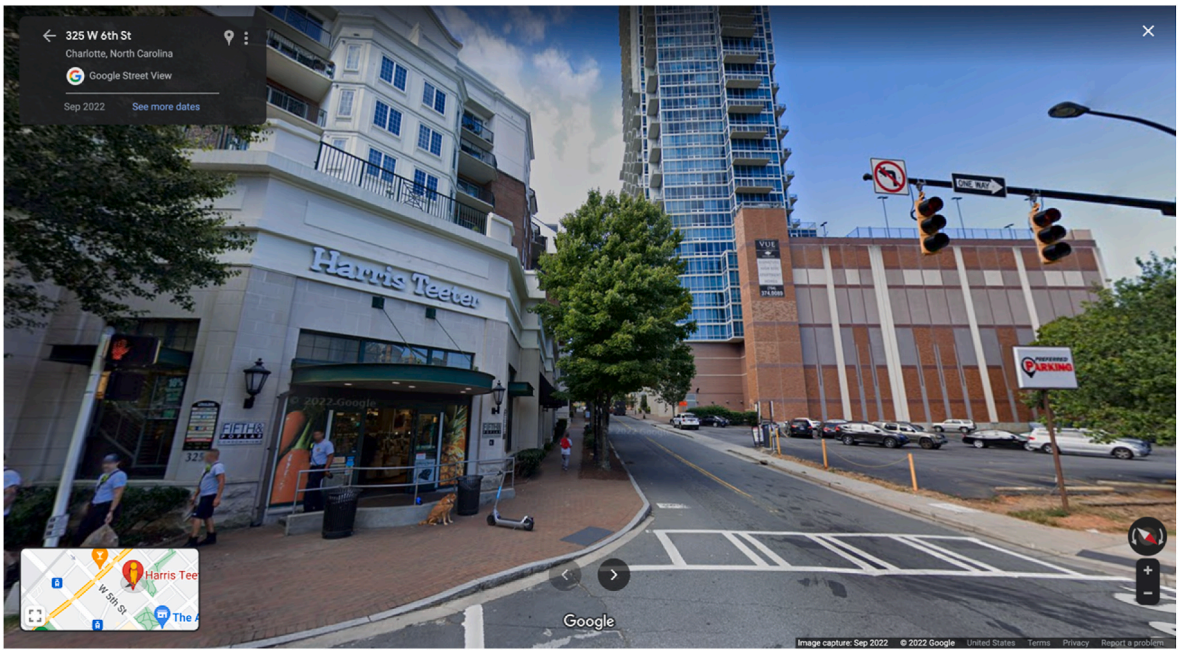

Fig. 6. Grocery Store in The Fourth Ward (Google Maps, 2022a, 2022b).

Fig. 7. Intersection of 6th and Graham (Google Maps, 2021a, 2021b).

(51%), 17% Black or African American, and 17% Asian; 8% are ethnically Hispanic, 4% are two or more races, and the remaining 2% identify as some other race. The sex ratio is approximately even (52% male) and over half of the total population who responded to the 2020 census have never married (57%). The foreign-born population is 20% and over half are naturalized U.S. citizens (U.S. Census Bureau, 2020d).

Census Tract 103 of Mecklenburg County is in the Fourth Ward neighborhood of historic downtown Charlotte, North Carolina. This census tract is directly adjacent to Charlotte's financial district which is known as the largest banking sector in the Southern United States and the second largest in the nation (Industry Insights: Financial Services in the Charlotte Region, 2021). The high-rises from Charlotte's Center City border the southern horizon of the Fourth Ward.

This census tract is urban, comprising approximately nine blocks. The predominant structures are mid-rise mixed-use buildings. Office space, residential apartments and condominiums with retail store fronts, parking garages and lots define the use of this area. The commercial entities range from investment services and design firms, to lawyers, realtors, and a general contractor. There are many dining and retail businesses in the area as well as a chain grocery store. The architecture of the area is a mixture of newer development and structures dating back to the late 19th century (Local History | Charlotte-Mecklenburg Historic Landmarks Commission, n.d.). The streets comprise a grid system which feature sidewalks and designated crosswalks with pedestrian crossing lights. Much of the sidewalk area is dotted with road verge in the form of healthy trees, soil, and plants. Over two acres of the Fourth Ward

Fig. 8. Downtown Condominium (Google Maps, 2022a, 2022b).

Neighborhood Park is within the tract. The park contains walking paths, a fountain, playground facilities, and greenspace with mature trees. There are multiple modes of public transportation accessible within Census Tract 103. A section of the CityLYNX Gold Line Streetcar, 10-mile-long streetcar system, lies on a border street of this tract (Transportation, n.d.). There are also multiple bus stops throughout the area.

Data from Esri shows a total of 86 businesses and 546 employees (Data Axle, 2022). Two-thirds of people employed in the area are either in professional, scientific and tech service, or working in retail trade and real estate entities. The remaining jobs are in health care, entertainment, accommodation and food, finance, administration, and information. Nearly 50% of the industry within this tract are services, 18% are finance, insurance, and real estate, and 8% retail and trade. The remaining businesses are government and unclassified establishments.

4.2. Tract 13.03: Durham County

The results of the index measurement for Census Tract 13.03, located in Durham County, North Carolina, showed a significant deficiency in the diversity variables (see Figs. 9–12). This is primarily due to the lack of essential amenities such as grocery stores, pharmacies, and fire

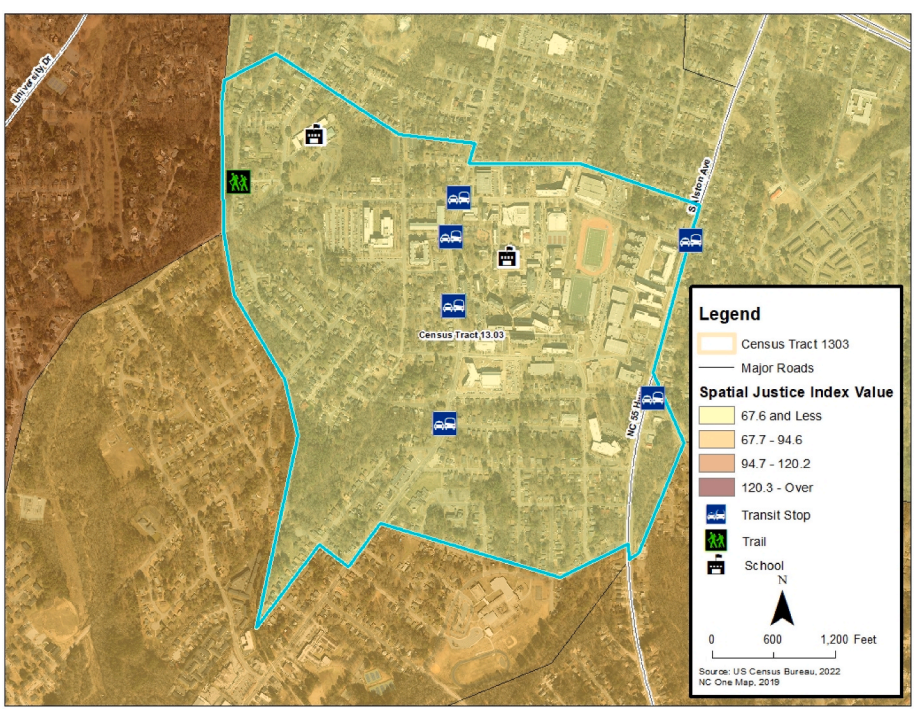

Fig. 9. Area map census tract 13.03, Durham County.

Fig. 10. American Tobacco Trail (Google Maps, 2015).

stations in the area. While proximity is a strong feature for this tract, closeness to medical facilities, parks, and grocery stores are limited. The diversity score is negatively impacted by high levels of racial segregation. Lastly, low levels of digital and social capital, as defined by Table 3, hinder the tract's connectivity score. For example, only 10% of the population in this tract has access to fiber-optic internet and a low census response rate.

In 2020, Durham County, North Carolina had a total population of approximately 317,000 residents with a median age of 35 (U.S. Census Bureau, 2020c). The racial composition of the county are as follows: 43% non-Hispanic white, 35% African American, 13% Hispanic, 5% Asian, and 5% two or more races. The median income was $62,812. Approximately 14% of the population are foreign-born and over one-third are naturalized U.S. citizens.

U.S. Census Bureau (2020c) data on tract 13.03 of Durham County shows an estimated population of 4,483 with a median age of 21 years. The racial composition of the population is majority Black or African American (72%), 17% non-Hispanic white, 7% Hispanic, 2% Asian and 3% two or more races. The sex ratio is majority female (57%) and over three-quarters of the total population have never married (78%). The foreign-born population is 6% and over half are naturalized U.S. citizens. The median income for the tract was $48,053 in 2020, over a quarter below the median income of the county for the same time.

Census Tract 13.03 of Durham County is within the City of Durham, North Carolina. The tract is located a little more than one mile south of the city center, on the opposite side of Highway 147; it is three miles east of Duke University and is approximately 7 miles west of the state capital, the city Raleigh. It is directly south of the historic African American neighborhood known as the Hayti District (*Hayti | Open Durham*, n.d.). Most notable within this census tract is North Carolina Central University, a historically Black university founded in 1910 (National Religious Training School and Chatauqua/North Carolina Central University | Open Durham, 2011). The campus accounts for 0.2 sq miles of land within the 0.6-mile tract. Most of the campus was built in the early twentieth century and the Georgian style architecture featured on campus dates to the 1930's and 40's. The campus has begun expanding into the surrounding neighborhood and the new modern structures juxtapose with the dated housing stock. Much of the housing was built between 1940 and 1960 and are single family homes (U.S. Census Bureau, 2020b). As the campus expands, newer housing stock is slowly appearing. While much of the older housing is well-maintained there are multiple abandoned properties. Historical street views captured from Google Maps shows the areas that are currently under construction were previously housing in various conditions. Through this visual data a theme of displacement emerges. To the northwest of the tract is a public elementary school which has ties to African American history in the area. Much of the older housing on the street across from the elementary school has been recently replaced with larger more modern housing.

This census tract exhibits suburban sprawl, and as such, the land use surrounding the campus are predominantly residential with little commercial use. There is a mid-sized retirement home, multiple churches, and a small public high school. Other uses include daycare centers, fast food, a convenience store, a tobacco shop, a barbershop, and residential service businesses such as shoe repair and custom clothing. The streets are winding and while most have sidewalks on at least one side of the road, some streets are without. The area is heavily car dependent and there are many bus stops throughout the tract. There is one small residential park with shade trees and picnic tables. Mature trees and kudzu thickets contribute to the green space. The eastern border is a four-lane road that serves as a main city corridor, North Carolina Central University's campus is directly adjacent. The opposite border to the west is a section of the 22 mile long American Tobacco Trail, a nature trail used for recreation. Towards the south of this trail, it connects to the Rocky Creek Trail and deviates east, forming the southern border of the tract.

Data from Esri shows a total of 100 businesses and 1,963 employees (Data Axle, 2022). 71% of the people employed in the area are in academic institutions and libraries, 15% work in retail, and the remaining jobs are in other services or government. Nearly 50% of industry within the tract are listed as other services (33%) or as unclassified establishments (15%). The remaining businesses are academic institutions and libraries (13%), amusements (7%), health services (4%), retail (21%), transportation and manufacturing (4%), and finance and real estate (3%).

Fig. 11. Single Family Homes on Utah Ave (Google Maps, 2019).

Fig. 12. Local Businesses and Fast-Food Chain (Google Maps, 2021a, 2021b).

4.3. Validation of spatial justice index

4.3.1. Correlations

For all the tested correlations, the SJI values are significantly correlated with the tested covariates and have the expected sign. NC's urban tracts with higher spatial justice tend to have higher median household incomes, home values, homeownership rates, and percentages of their population that are white. These tracts also have lower poverty rates, housing vacancy rates, unemployment rates, and percentages of their population that are non-white (see Table A23 in the APPENDIX).

4.3.2. Item analysis

The results of the item analysis can be found in the APPENDIX (in Tables A24-A27). Thirty of the 37 input variables are statistically significantly correlated with the final index. Of the 37 input variables, 31 have the expected correlation sign with the final spatial justice index value (around 84% of the variables). For the 6 variables that have an unexpected correlation to the index, four are statistically significant. Overall, the final index remains highly correlated with the underlying input variables.

4.3.3. Sensitivity

We test the sensitivity of our results, which use a 50% threshold determining the number of components we collect from each PCA. To do this, we re-create the index using a 75% threshold and compare the results to the original index values. Our primary interest is to examine whether there still exists a strong correlation between each index. The results of this test can be found in the APPENDIX in Table A28. According to the results, the original and modified indices are highly and significantly correlated with one another. The Pearson correlation coefficient is 0.63 and is significant at the 0.01 level. Moreover, regressing the modified index on the original index shows that the estimated equation explains nearly 40% of the variation in the modified index (see Figure A1 in the APPENDIX).

5. Conclusion

Developing a quantitative index for exploring issues of spatial (in) justice is difficult since spatial injustices can come in many different forms ranging from economic to environmental to educational. With that said, this paper provides a critical first step in the process of identifying which spatial variables are the most important factors for exploring spatial justice in urban communities. Through the efforts outlined in the development of the SJI it is possible to identify which spatial factors are critical in understanding the creation and continuation of spatial injustices in communities across the nation and provide planners with a new tool for developing more sustainable communities (Fainstein, 2010; Agyeman, 2005; Soja, 2010).

At the most basic level, the SJI developed in this paper provides a new tool and a first step in empirically analyzing spatial justice in geographic spaces. While, focused on US Census Tracts, the SJI has the potential to be applied in geographies outside the United States. Through the collection of relevant and local data, neighborhoods from Kolkata to Cairo could utilize the methodology outlined in this paper to identify and correct spatial injustices in their communities.

As applied to urban census tracts within N·C., the SJI highlights the large range of values that a tract might receive (226.51 vs. 6.82), thus underscoring the huge discrepancy in spatial justice that exist within one state. In general, the SJI value tended to be higher in more centrally located urban census tracts in N.C. While more outlying and suburban tracts tended to have lower SJI values. This demonstrates the influence that the built environment can have on spatial justice.

Though we focus specifically on urban census tracts in this exploratory analysis, a similarly motivated index could be developed for rural tracts. Rural tracts, as opposed to urban tracts, may face a different set of challenges regarding spatial justice/injustice, which could require different theoretical approaches and statistical methodologies. Urban tracts are compact, geographically smaller, and often oriented around a city. This is often not the case, however, for rural tracts. Future studies that incorporate rural tracts in with urban tracts, or specifically analyze rural tracts, to develop a different spatial justice index may need to consider other quantitative techniques. Considering the wide variation between urban and rural tracts, even in a single state like N·C., PCA may not be appropriate for developing a spatial justice index. Future research may consider techniques like Geographically Weighted PCA, which could better control for the spatial and geographic variations between urban and rural tracts, especially if other diverse states in the U.S. are included, as opposed to just a single state.

For urban planners and governmental parties, the SJI can be used to assess spatial justice conditions across geographies and help prioritize place-based interventions. Urban planners can identify spatially unjust spaces within their community. The SJI can also be utilized to quantitatively confirm the existence of spatial injustices within a jurisdiction and not just rely upon community perception. The SJI may also be implemented in communities to evaluate interventions into spatial injustices over time by monitoring the SJI. Finally, the SJI can be used to prioritize which neighborhoods should have their spatial injustices combated first by utilizing the SJI value generated for each census tract.

This study is not without its limitations. First, the choice of a census tract as the geographic unit by which to explore spatial (in)justice has its limitations and might not always be the best proxy for a neighborhood in which people live, work and play. With that said, the census tract does provide a standardized unit from which analysis can be compared across the U.S. and for which data is readily available. A second limitation of the chosen geographic container is the lack of universality of use outside the U.S. The census tract does not transcend the border of the U.S., thus limiting its use in future studies which seek to explore urban areas in other locations. Finally, conceptualization of spatial justice using Rocco's definition and the four spatial measures might not be the best fit for all geographies, but the methodology presented in this paper provides a template and starting point for additional quantitative explorations into measuring spatial (in)justice.

The results presented in this paper highlight the creation of a Spatial Justice Index by which multiple geographies can be compared and spatially injustices can be identified, explored, and rectified to create neighborhoods that are more just, equitable and sustainable across the U.S. Future research will begin the process of exploring these issues across the globe in the hope of developing a universal measure of spatial (in)justice to tackle the numerous challenges facing urban communities. In the end, a quantitatively robust index that can explore multiple spatial injustices would be a welcome addition to any planner's toolkit.

Authors statement

Russell Smith: Conceptualization, Methodology, Investigation, Writing – Original Draft, Writing – Review & Editing, Visualization, Supervision, Project Administration; Zach Blizard: Methodology, Validation, Formal Analysis, Investigation, Data Curation, Writing – Original Draft, Writing – Review & Editing, Visualization; Debzani Deb: Methodology, Validation, Formal Analysis, Investigation, Supervision; Rachel Midgett: Investigation, Writing – Original Draft.

Acknowledgements

This research is supported by UNC Research Opportunities Initiative (ROI) award "Winston-Salem State University Center for Applied Data Science". (FY2020-2023). This research is supported by the Spatial Justice Studio @ CDI.

APPENDIX

Concepts and Variables

Table A1
Density Variables and their Sources

Variable	Definition	Type	Data Source
Density of Grocery Stores	Count of the number of grocery stores per sq mi	Basic Services	USDA SNAP Retailer Database
Density of Pharmacies	Count of the number of pharmacies per sq mi	Basic Services	NC OneMap Database
Density of Gas Stations	Count of the number of gas stations per sq mi	Basic services	NC OneMap Database
Density of Nursing Homes	Count of the number of nursing homes per sq mi	Basic Services	NC OneMap Database
Density of Parks/Rec Facilities	Count of the number of parks or recreation facilities per sq mi	Public Goods	ESRI Business Analyst Database
Density of Transit Stops	Count of the number of transit stops per sq mi	Public Goods	Bureau of Transportation Statistics Database
Density of Redlined Areas	Count of the number of redlined areas per sq mi	Historical	Mapping Inequality Database
Density of Fire Stations	Count of the number of fire stations per sq mi	Public Goods	NC OneMap Database
Density of Hospitals	Count of the number of hospitals per sq mi	Public Goods	NC OneMap Database
Density of Public Schools	Count of the number of public schools per sq mi	Public Goods	NC OneMap Database
Density of Medical Facilities	Count of the number of medical facilities per sq mi	Public Goods	NC OneMap Database
Density of Brownfields	Count of the number of brownfields per sq mi	Healthy Environments	NC OneMap Database
Density of Hazardous Waste Sites	Count of the number of hazardous waste sites per sq mi	Healthy Environments	NC OneMap Database
Density of NPDES	Count of the number of NPDESs per sq mi	Healthy Environments	NC OneMap Database
Density of Regional Underground Storage (RUS)	Count of the number of RUS sites per sq mi	Healthy Environments	NC OneMap Database
Density of Public Libraries	Count of the number of public libraries per sq mi	Cultural Goods	NC OneMap Database
Density of Colleges	Count of the number of colleges per sq mi	Cultural Goods	NC OneMap Database
Density of Jobs	Count of the number of Jobs per sq mi	Economic Opportunities	ESRI Business Analyst Database

Note: The variables will all be divided by the total square miles of the census tract, to convert them to densities.

Table A2
Proximity Variables

Variable	Definition	Type	Data Source
Proximity to Nearest Grocery Store	Distance from a census tracts centroid to the closest grocery store	Basic Services	USDA SNAP Retailer Database
Proximity to Nearest Park/Rec Facility	Distance from a census tracts centroid to the closest park/rec facility	Public Goods	ESRI Business Analyst Database
Proximity to Nearest Hospital	Distance from a census tracts centroid to the closest hospital	Public Good	NC OneMap Database
Proximity to Nearest Medical Facility	Distance from a census tracts centroid to the closest medical facility	Public Good	NC OneMap Database
Proximity to Nearest Public Library	Distance from a census tracts centroid to the closest library	Public Good	NC OneMap Database
Proximity to Nearest Interstate	Distance from a census tracts centroid to the closest interstate	Public Good	NC OneMap Database
Proximity to Nearest Brownfield	Distance from a census tracts centroid to the closest brownfield	Healthy Environments	NC OneMap Database
Proximity to Nearest Hazardous Waste Site	Distance from a census tracts centroid to the closest hazardous waste site	Healthy Environments	NC OneMap Database
Proximity to Nearest Redlined Area	Distance from a census tracts centroid to the closest redlined area	Historical	Mapping Inequality Database
Proximity to Work	Percent of workers with commutes less than 15 min	Economic Opportunities	American Community Survey 5-Year Estimate Database

Table A3
Diversity Variables[3 4]

Variable	Definition	Type	Data Source
Percent Impervious Surface	Percent of land that is covered by impervious surfaces	Environmental	Multi-Resolution Land Characteristics (MTLC) Consortium Database
Racial Segregation	Measured as the Isolation Index between black and white residents	People	Decennial Census Database
Housing Stock Diversity	Measured as a Simpson's Index of diversity across the Census defined housing structure types	Housing	American Community Survey 5-Year Estimate Database

Table A4
Connectivity Variables[5 6 7]

Variable	Definition	Type	Data Source
Street Connectivity	Gamma index measuring street connections	Built Environment	U.S. Census
Internet Fiber	Percent of households with access to fiber	Digital	NC OneMap Database
Social Capital	Social capital, proxied with census return rates.	Social	Census Planning Database
Internet Providers	Percent of households without access to an internet provider	Digital	NC OneMap Database
Transit Route	Indicator for whether a tract contains a public transit route	Built Environment	Bureau of Transportation Statistics Database
Interstate	Indicator for whether a tract contains an interstate access point	Built Environment	NC OneMap Database

Descriptive Statistics for Original Variables (Before Standardization)

Table A.1.1
Descriptive Statistics for the Unstandardized Density Variables

Variable	Mean	STD	Min	Max
Density of Grocery Stores	2.1968	2.6203	0.0000	28.9855
Density of Pharmacies	0.7794	1.2977	0.0000	14.4928
Density of Gas Stations	1.0884	1.2610	0.0000	14.7059
Density of Nursing Homes	0.2058	0.4858	0.0000	5.2083
Density of Parks/Rec Facilities	0.9144	1.9752	0.0000	28.9855
Density of Transit Stops	2.6623	8.9295	0.0000	109.6257
Density of Redlined Areas	0.5186	2.3856	0.0000	39.4737
Density of Fire Stations	0.1751	0.3599	0.0000	5.4348
Density of Hospitals	0.0462	0.2636	0.0000	4.5147
Density of Public Schools	0.4867	0.8206	0.0000	7.5188
Density of Medical Facilities	1.8411	2.6401	0.0000	21.7786
Density of Brownfields	0.1666	1.0084	0.0000	16.7364
Density of Hazardous Waste Sites	0.7296	1.2835	0.0000	14.4928
Density of NPDES	0.0878	0.3454	0.0000	5.7405
Density of Regional Underground Storage (RUS)	8.3341	14.8600	0.0000	188.4058
Density of Public Libraries	0.0936	0.5024	0.0000	14.4928
Density of Colleges	0.0433	0.2455	0.0000	3.3784
Density of Jobs	1,545.3800	4,116.8900	0.0000	84,984.2900
N = 1,343				

Correlations

[3] The isolation index is defined as $Iso = \sum\left(\frac{n_{i,b}}{N_b}\right)\left(\frac{n_{i,w}}{n_i}\right)$, where $n_{i,b}$ is the number of black residents in the ith block, and $n_{i,w}$ is the number of white residents in the ith block. N_b is the total number of black residents in the census tract. n_i is the total population in the ith block. Iso is the probability of isolation between the average black resident from the average white resident in a census tract. A value of 0.15, for example, suggests that the probability that the average black resident interacts with the average white person is 0.15. Block-level census data was downloaded from IPUMS NHGIS website.

[4] The Simpson's Index is defined as $SI = \sum_{i=1}^{T} p_i^2$, where p_i is the proportion of all the housing types (T) that are of the ith kind. For our study, we follow a similar approach as Chakraborty and McMillan (2022) in defining housing types by their Census designations. Hence, there are 6 types of housing kinds, which are single-family detached, single-family attached, small multi-family, medium multi-family, large multi-family, and other. Once we calculate SI, we subtract it from 1 so that higher values of the final index represent more diversity.

[5] We follow Molaei, Tang, and Hardie (2021) is measuring street connectivity with the Gamma Index. $GI_i = \frac{STREETS_i}{3\times(INTERSECTIONS_i - 2)}$, where $STREETS_i$ denotes the number of streets in the ith census tract and $INTERSECTIONS_i$ is the number of intersections in the ith census tract. GI_i is the ratio of streets to the maximum possible number of streets between intersections in the ith census tract (Molaei et al., 2021). For streets and intersections, we consider only Department of Transportation (DOT) roads.

[6] For the fiber and internet provider variables, they are made available at the census tract level but with the 2010 census tract boundaries. To convert them to 2020 boundaries, we use ariel interpolation.

[7] Census return rates have been used in numerous studies as a proxy for social capital (Martin & Newman, 2015; Smith & Blizard, 2021).

Table A.2.1
Descriptive Statistics for the Unstandardized Proximity Variables

Variable	Mean	STD	Min	Max
Proximity to Nearest Grocery Store	0.0107	0.0072	0.0002	0.0635
Proximity to Nearest Park/Rec Facility	0.0227	0.0271	0.0003	0.3374
Proximity to Nearest Hospital	0.0544	0.0399	0.0003	0.3040
Proximity to Nearest Medical Facility	0.0123	0.0126	0.0003	0.1415
Proximity to Nearest Public Library	0.0357	0.0237	0.0012	0.1781
Proximity to Nearest Interstate	0.2826	0.4310	0.0002	2.6630
Proximity to Nearest Brownfield	0.0762	0.1091	0.0004	0.9329
Proximity to Nearest Hazardous Waste Site	0.0161	0.0140	0.0002	0.1466
Proximity to Nearest Redlined Area	0.4743	0.6226	0.0000	3.2105
Proximity to Work	29.7246	14.8297	0.3272	92.3763

Table A.3.1
Descriptive Statistics for the Unstandardized Diversity Variables

Variable	Mean	STD	Min	Max
Percent Impervious Surface	45.3095	21.7245	3.1433	100.0000
Racial Segregation	0.4570	0.2234	0.0136	0.9439
Housing Stock Diversity	0.4718	0.2033	0.0000	0.8025

Table A.4.1
Descriptive Statistics for the Unstandardized Connectivity Variables

Variable	Mean	STD	Min	Max
Street Connectivity	0.0821	0.1537	0.0000	1.0000
Internet Fiber	52.6060	34.1806	0.0000	100.0000
Social Capital	66.0927	12.2355	1.9000	92.5000
Internet Providers	0.0043	0.0430	0.0000	0.8880
Transit Route	0.3075	0.4616	0.0000	1.0000
Interstate	0.2584	0.4379	0.0000	1.0000

Table A5
Correlations Between the Density Variables

	Grocery Stores	Pharmacies	Gas Stations	Nursing Homes	Parks/Rec Facilities	Transit Stops	Redlined Areas	Fire Stations	Hospitals	Public Schools	Medical Facilities	Brownfields	Hazardous Waste Sites	NPDES	RUS	Public Libraries	Colleges	Jobs
Grocery Stores	1.000	0.482***	0.569***	0.098***	0.351***	0.141***	0.370***	0.147***	0.043	0.227***	0.358***	0.252***	0.468***	0.041	0.463***	0.319***	0.031	0.314***
Pharmacies	0.482***	1.000	0.290***	0.222***	0.312***	0.210***	0.306***	0.083***	0.394***	0.226***	0.372***	0.146***	0.477***	0.001	0.353***	0.328***	0.084***	0.425***
Gas Stations	0.569***	0.290***	1.000	0.138***	0.101***	0.125***	0.101***	0.096***	0.085***	0.206***	0.315***	0.086***	0.217***	−0.070***	0.260***	0.065**	0.021	0.121***
Nursing Homes	0.098***	0.222***	0.138***	1.000	0.008	0.036	−0.010	0.016	0.185***	0.000	0.356***	0.000	0.030	−0.030	0.042	0.000	0.004	0.066**
Parks/Rec Facilities	0.351***	0.312***	0.101***	0.008	1.000	0.333***	0.528***	0.194***	0.028	0.141***	0.160***	0.281***	0.400***	0.132***	0.521***	0.462***	0.147***	0.395***
Transit Stops	0.141***	0.210***	0.125***	0.036	0.333***	1.000	0.000	0.173***	0.117***	0.153***	0.118***	0.072***	0.247***	−0.020	0.187***	0.076***	0.085***	0.273***
Redlined Areas	0.370***	0.306***	0.101***	−0.010	0.528***	0.000	1.000	0.121***	0.100***	0.223***	0.248***	0.519***	0.357***	0.106***	0.546***	0.337***	0.184***	0.380***
Fire Stations	0.147***	0.083***	0.096***	0.016	0.194***	0.173***	0.121***	1.000	−0.010	0.092***	0.055**	0.127***	0.141***	0.013	0.127***	0.083***	0.018	0.105***
Hospitals	0.043	0.394***	0.085***	0.185***	0.028	0.117***	0.100***	−0.010	1.000	0.054**	0.300***	0.028	0.157***	−0.030	0.102***	−0.020	0.111***	0.284***
Public Schools	0.227***	0.226***	0.206***	0.000	0.141***	0.153***	0.223***	0.092***	0.054**	1.000	0.225***	0.197***	0.206***	−0.050**	0.232***	0.085***	0.257***	0.136***
Medical Facilities	0.358***	0.372***	0.315***	0.356***	0.160***	0.118***	0.248***	0.055**	0.300***	0.225***	1.000	0.170***	0.230***	−0.040	0.304***	0.119***	0.047*	0.250***
Brownfields	0.252***	0.146***	0.086***	0.000	0.281***	0.072***	0.519***	0.127***	0.028	0.197***	0.170***	1.000	0.318***	0.046*	0.372***	0.030	0.155***	0.239***
Hazardous Waste Sites	0.468***	0.477***	0.217***	0.030	0.400***	0.247***	0.357***	0.141***	0.157***	0.206***	0.230***	0.318***	1.000	0.114***	0.472***	0.355***	0.211***	0.417***
NPDES	0.041	0.001	−0.070***	−0.030	0.132***	−0.020	0.106***	0.013	−0.030	−0.055**	−0.040	0.046*	0.114***	1.000	0.090***	0.104***	0.084***	0.223***
RUS	0.463***	0.353***	0.260***	0.042	0.521***	0.187***	0.546***	0.127***	0.102***	0.232***	0.304***	0.372***	0.472***	0.090***	1.000	0.424***	0.166***	0.533***
Public Libraries	0.319***	0.328***	0.065**	0.000	0.462***	0.076***	0.337***	0.083***	−0.020	0.085***	0.119***	0.030	0.355***	0.104***	0.424***	1.000	0.039	0.210***
Colleges	0.031	0.084***	0.021	0.004	0.147***	0.085***	0.184***	0.018	0.111***	0.257***	0.047*	0.155***	0.211***	0.084***	0.166***	0.039	1.000	0.108***
Jobs	0.314***	0.425***	0.121***	0.066**	0.395***	0.273***	0.380***	0.105***	0.284***	0.136***	0.250***	0.239***	0.417***	0.223***	0.533***	0.210***	0.108***	1.000

Note: Cells contain the Pearson correlation coefficient estimate. ***$p < 0.01$, ** $0.01 \leq p < 0.05$, *$p \leq 0.05$.

Table A6
Correlations Between the Proximity Variables

	Proximity to Nearest Grocery Store	Proximity to Nearest Park/Rec Facility	Proximity to Nearest Hospital	Proximity to Nearest Medical Facility	Proximity to Nearest Public Library	Proximity to Nearest Interstate	Proximity to Nearest Brownfield	Proximity to Nearest Hazardous Waste Site	Proximity to Nearest Redlined Area	Proximity to Work
Proximity to Nearest Grocery Store	1.000	0.242***	0.306***	0.464***	0.470***	0.065**	0.221***	0.546***	0.063**	−0.240***
Proximity to Nearest Park/Rec Facility	0.242***	1.000	0.226***	0.246***	0.246***	0.190***	0.180***	0.303***	0.234***	0.026
Proximity to Nearest Hospital	0.306***	0.226***	1.000	0.407***	0.338***	0.155***	0.319***	0.391***	0.176***	−0.280***
Proximity to Nearest Medical Facility	0.464***	0.246***	0.407***	1.000	0.507***	0.178***	0.267***	0.510***	0.153***	−0.160***
Proximity to Nearest Public Library	0.470***	0.246***	0.338***	0.507***	1.000	0.097***	0.299***	0.487***	0.113***	−0.250***
Proximity to Nearest Interstate	0.065**	0.190***	0.155***	0.178***	0.097***	1.000	0.555***	0.218***	0.895***	0.298***
Proximity to Nearest Brownfield	0.221***	0.180***	0.319***	0.267***	0.299***	0.555***	1.000	0.346***	0.556***	0.085***
Proximity to Nearest Hazardous Waste Site	0.546***	0.303***	0.391***	0.510***	0.487***	0.218***	0.346***	1.000	0.232***	−0.220***
Proximity to Nearest Redlined Area	0.063**	0.234***	0.176***	0.153***	0.113***	0.895***	0.556***	0.232***	1.000	0.327***
Proximity to Work	−0.240***	0.026	−0.280***	−0.165***	−0.250***	0.298***	0.085***	−0.220***	0.327***	1.000

Note: Cells contain the Pearson correlation coefficient estimate. ***$p < 0.01$, ** $0.01 \leq p < 0.05$, *$p \leq 0.05$.

Table A7
Correlations Between the Diversity Variables

	Percent Impervious Surface	Racial Segregation	Housing Stock Diversity
Percent Impervious Surface	1.000	−0.392***	0.332***
Racial Segregation	−0.392***	1.000	−0.248***
Housing Stock Diversity	0.332***	−0.248***	1.000

Note: Cells contain the Pearson correlation coefficient estimate. ***$p < 0.01$, ** $0.01 \leq p < 0.05$, *$p \leq 0.05$.

Table A8
Correlations Between the Connectivity Variables

	Street Connectivity	Internet Fiber	Social Capital	Internet Providers	Transit Route	Interstate
Street Connectivity	1	0.048*	−0.011	0.031	0.108***	0.853***
Internet Fiber	0.048*	1	0.284***	0.004	0.125***	0.045*
Social Capital	−0.011	0.284***	1	0.002	0.024	−0.024
Internet Providers	0.031	0.004	0.002	1	0.026	0.035
Transit Route	0.108***	0.125***	0.024	0.026	1	0.115***
Interstate	0.853***	0.045*	−0.024	0.035	0.115***	1

Note: Cells contain the Pearson correlation coefficient estimate. ***$p < 0.01$, ** $0.01 \leq p < 0.05$, *$p \leq 0.05$.

Normative Adjustments

Table A9
Explaining the Normative Adjustments

Variable	Measure	Normative Explanation	Adjustment
Density of Parks/Rec Facilities	Spatial Density	Higher density of parks/rec centers suggests ***greater*** spatial justice	None
Density of Transit Stops Facilities	Spatial Density	Higher density of transit stops suggests ***greater*** spatial justice	None
Density of Redlined Areas	Spatial Density	Higher density of redlined areas suggests ***lower*** spatial justice	Invert Distribution
Density of Brownfields	Spatial Density	Higher density of brownfields suggests ***lower*** spatial justice	Invert Distribution
Density of Colleges	Spatial Density	Higher density of colleges suggests ***higher*** spatial justice	None
Density of Medical Facilities	Spatial Density	Higher density of medical facilities suggests ***higher*** spatial justice	None
Density of Grocery Stores	Spatial Density	Higher density of grocery stores suggests ***greater*** spatial justice	None
Density of Gast Stations	Spatial Density	Higher density of grocery stores suggests ***greater*** spatial justice	None
Density of Hazardous Waste Sites	Spatial Density	Higher density of hazardous waste sites suggests ***lower*** spatial justice	Invert Distribution
Density of Hospitals	Spatial Density	Higher density of hospitals suggests ***higher*** spatial justice	None
Density of NPDES	Spatial Density	Higher density of NPDES suggests ***lower*** spatial justice	Invert Distribution
Density of Fire Stations	Spatial Density	Higher density of fire stations suggests ***greater*** spatial justice	None
Density of Pharmacies	Spatial Density	Higher density of pharmacies suggests ***greater*** spatial justice	None

(*continued on next page*)

Table A9 (*continued*)

Variable	Measure	Normative Explanation	Adjustment
Density of Nursing Homes	Spatial Density	Higher density of nursing homes suggests ***greater*** spatial justice	None
Density of Public Libraries	Spatial Density	Higher density of public libraries suggests ***greater*** spatial justice	None
Density of Public Schools	Spatial Density	Higher density of public schools suggests ***greater*** spatial justice	None
Density of RUS Sites	Spatial Density	Higher density of RUS sites suggests ***lower*** spatial justice	Invert Distribution
Density of Jobs	Spatial Density	Higher density of jobs suggests ***greater*** spatial justice	None
Proximity to Work	Spatial Proximity	Higher percentages of workers with commutes less than 15 min suggest ***higher*** spatial justice	None
Proximity to Nearest Park/Rec Facility	Spatial Proximity	Higher distances to nearest rec facility/park suggest ***lower*** spatial justice	Invert Distribution
Proximity to Nearest Brownfield Site	Spatial Proximity	Higher distances to nearest brownfield suggest ***greater*** spatial justice	None
Proximity to Nearest Hazardous Waste Site	Spatial Proximity	Higher distances to nearest hazardous waste site suggest ***greater*** spatial justice	None
Proximity to Nearest Grocery Store	Spatial Proximity	Higher distances to nearest grocery store suggest ***lower*** spatial justice	Invert Distribution
Proximity to Nearest Redlined Area	Spatial Proximity	Higher distances to nearest redlined area suggest ***greater*** spatial justice	None
Proximity to Nearest Medical Facility	Spatial Proximity	Higher distances to nearest medical facility suggest ***lower*** spatial justice	Invert Distribution
Proximity to Nearest Hospital	Spatial Proximity	Higher distances to nearest hospital suggest ***lower*** spatial justice	Invert Distribution
Proximity to Nearest Public School	Spatial Proximity	Higher distances to nearest public school suggest ***lower*** spatial justice	Invert Distribution
Proximity to Nearest Interstate	Spatial Proximity	Higher distances to nearest interstate suggest ***lower*** spatial justice	Invert Distribution
Percent Impervious Surface	Spatial Diversity	Higher percentage of land covered by impervious surface suggests ***lower*** spatial justice	Invert Distribution
Racial Segregation	Spatial Diversity	Higher values of the Isolation Index suggest ***greater*** spatial justice.	None
Housing Stock Diversity	Spatial Diversity	Higher housing stock diversity suggests ***greater*** spatial justice	None
Internet Fiber	Spatial Connectivity	Higher percentages of the population with access to fiber suggests ***greater*** spatial justice	None
Internet Providers	Spatial Connectivity	Higher percentages of the population without an internet provider ***lower*** spatial justice	Invert Distribution
Interstate	Spatial Connectivity	The presence of interstate access suggests ***greater*** spatial justice	None
Transit Route	Spatial Connectivity	The presence of a transit route suggests ***greater*** spatial justice	None
Social Capital	Spatial Connectivity	Higher levels of social capital suggest ***greater*** spatial justice	None
Street Connectivity	Spatial Connectivity	Higher levels of street connectivity suggest ***greater*** spatial justice	None

PCA Test Results

Table A10
Bartlett Test Results for the Four Datasets

Sets of Variables	Chi-Square	df	*p*-value
Density	6,714.8865	153	<0.001
Proximity	5,551.5574	45	<0.001
Diversity	405.5410	3	<0.001
Connectivity	1,900.4572	15	<0.001

Table A11
Eigenvalues for the PCA of Density-Related Variables

Components	Eigenvalue	Difference	Proportion	Cumulative
1	4.75541	3.00837	0.264	0.264
2	1.74704	0.45848	0.097	0.361
3	1.28855	0.04147	0.072	0.433
4	1.24709	0.08526	0.069	0.502
5	1.16182	0.16304	0.065	0.567
6	0.99878	0.05316	0.056	0.622
7	0.94562	0.05394	0.053	0.675
8	0.89169	0.09469	0.050	0.724
9	0.79700	0.08189	0.044	0.769
10	0.71511	0.07879	0.040	0.808
11	0.63632	0.07831	0.035	0.844
12	0.55801	0.03298	0.031	0.875
13	0.52503	0.09061	0.029	0.904
14	0.43442	0.04976	0.024	0.928

(*continued on next page*)

Table A11 (*continued*)

Components	Eigenvalue	Difference	Proportion	Cumulative
15	0.38467	0.07474	0.021	0.949
16	0.30993	0.00310	0.017	0.967
17	0.30683	0.01014	0.017	0.984
18	0.29669		0.017	1.000

Table A12
Eigenvectors for the PCA of the Density-Related Variables

Variable	PC1	PC2	PC3	PC4
Density of Grocery Stores	0.3183	0.1265	0.3840	0.1240
Density of Pharmacies	0.3080	0.2571	−0.1238	0.1479
Density of Gas Stations	0.1924	0.3339	0.4611	0.0015
Density of Nursing Homes	0.0745	0.4301	−0.1533	0.0866
Density of Parks/Rec Facilities	0.3068	−0.2746	−0.0234	0.1543
Density of Transit Stops	0.1586	0.0468	−0.1095	0.0481
Density of Redlined Areas	−0.3075	0.2511	0.0024	0.1562
Density of Fire Stations	0.1104	−0.0704	0.1826	−0.0013
Density of Hospitals	0.1286	0.3606	−0.5112	−0.0623
Density of Public Schools	0.1768	0.0628	0.1611	−0.4943
Density of Medical Facilities	0.2311	0.3939	−0.0201	−0.0614
Density of Brownfields	−0.2190	0.1956	−0.0496	0.4079
Density of Hazardous Waste Sites	−0.3222	0.0608	0.0341	−0.0390
Density of NPDES	−0.0601	0.2608	0.2996	−0.1973
Density of Regional Underground Storage (RUS)	−0.3514	0.1456	−0.0322	−0.0278
Density of Public Libraries	0.2301	−0.2067	0.0822	0.4029
Density of Colleges	0.1157	−0.1031	−0.2363	−0.5197
Density of Jobs	0.2980	−0.0456	−0.3325	0.1128

Table A13
Descriptive Statistics for the Standardized. Density-Related Components

Variable	Mean	Standard Deviation	Minimum	Maximum
Standardized PC1	100	25	78.76	428.47
Standardized PC2	100	25	−127.17	284.80
Standardized PC3	100	25	−135.69	221.75
Standardized PC4	100	25	−188.48	459.11
N = 1,343				

Table A14
Eigenvalues for the PCA of Proximity-Related Variables

Component	Eigenvalue	Difference	Proportion	Cumulative
1	3.53582	1.32803	0.35360	0.35360
2	2.20779	1.31608	0.22080	0.57440
3	0.89171	0.11728	0.08920	0.66350
4	0.77443	0.17574	0.07740	0.74100
5	0.59869	0.04506	0.05990	0.80080
6	0.55363	0.05188	0.05540	0.85620
7	0.50175	0.07458	0.05020	0.90640
8	0.42717	0.01906	0.04270	0.94910
9	0.40811	0.30721	0.04080	0.98990
10	0.10090		0.01010	1.00000

Table A15
Eigenvectors for the PCA of the Proximity-Related Variables

Variable	PC1	PC2
Proximity to Nearest Grocery Store	0.3332	0.2673
Proximity to Nearest Park/Rec Facility	0.2517	−0.0138
Proximity to Nearest Hospital	0.3208	0.1525
Proximity to Nearest Medical Facility	0.3679	0.1900
Proximity to Nearest Public Library	0.3521	0.2355
Proximity to Nearest Interstate	0.2947	−0.4974
Proximity to Nearest Brownfield	−0.3497	0.2577
Proximity to Nearest Hazardous Waste Site	−0.3992	−0.1662
Proximity to Nearest Redlined Area	−0.2997	0.5024
Proximity to Work	0.0716	0.4688

Table A16
Descriptive Statistics for the Standardized. Proximity-Related Components

Variable	Mean	Standard Deviation	Minimum	Maximum
Standardized PC1	100	25	−61.86	136.70
Standardized PC2	100	25	14.77	239.90

Table A17
Eigenvalues for the PCA of Diversity-Related Variables

Component	Eigenvalue	Difference	Proportion	Cumulative
1	1.65194	0.89407	0.55060	0.55060
2	0.75787	0.16768	0.25260	0.80330
3	0.59019		0.19670	1.00000

Table A18
Eigenvectors for the PCA of the Diversity-Related Variables

Variable	PC1
Percent Impervious Surface	0.6187
Racial Segregation	0.5756
Housing Stock Diversity	−0.5346

Table A19
Descriptive Statistics for the Standardized. Diversity-Related Components

Variable	Mean	Standard Deviation	Minimum	Maximum
Standardized PC1	100	25	39.59	161.90

Table A20
Eigenvalues for the PCA of Connectivity-Related Variables

Component	Eigenvalue	Difference	Proportion	Cumulative
1	1.89276	0.58311	0.31550	0.31550
2	1.30964	0.30757	0.21830	0.53370
3	1.00208	0.05042	0.16700	0.70070
4	0.95165	0.25460	0.15860	0.85940
5	0.69705	0.55023	0.11620	0.97550
6	0.14682		0.02450	1.00000

Table A21
Eigenvectors for the PCA of Connectivity-Related Variables

Variable	PC1	PC2
Street Connectivity	0.6892	−0.0884
Internet Fiber	0.1017	0.6880
Social Capital	0.0107	0.6633
Internet Providers	−0.0564	−0.0141
Transit Route	0.1884	0.2634
Interstate	0.6898	−0.0966

Table A22
Descriptive Statistics for the Standardized. Connectivity-Related Components

Variable	Mean	Standard Deviation	Minimum	Maximum
Standardized PC1	100	25	79.84	198.31
Standardized PC2	100	25	11.73	162.63

Validation and Robustness Output

Correlations

Table A23
Correlations with the Spatial Justice Index

Variables	Pearson Coefficients	*p*	Expected Sign?
Median Household Income ($)	0.31005	<0.001	Yes
Median Home Value ($)	0.25012	<0.001	Yes
Household Poverty Rate (%)	−0.31742	<0.001	Yes
Homeownership Rate (%)	0.34849	<0.001	Yes
Housing Vacancy Rate (%)	−0.26307	<0.001	Yes
Percent of the Population that is White	0.40404	<0.001	Yes
Percent of the Population that is Non-White	−0.40404	<0.001	Yes
Unemployment Rate (%)	−0.24949	<0.001	Yes

Item Analysis

Density-Related

Table A24
Item Analysis for the Density-Related Variables and the SJ Index

Standardized Variables	Pearson Coefficient	*p*	Expected Sign?
Density of Grocery Stores	0.0575	0.035	Yes
Density of Pharmacies	0.1585	<0.001	Yes
Density of Gas Stations	0.1002	<0.001	Yes
Density of Nursing Homes	0.0777	0.004	Yes
Density of Parks/Rec Facilities	0.0823	0.003	Yes
Density of Transit Stops	0.0792	0.004	Yes
Density of Redlined Areas	−0.0370	0.176	Yes
Density of Fire Stations	0.0578	0.034	Yes
Density of Hospitals	0.0253	0.354	Yes
Density of Public Schools	−0.1042	<0.001	No
Density of Medical Facilities	0.0366	0.180	Yes
Density of Brownfields	−0.1262	<0.001	Yes
Density of Hazardous Waste Sites	0.0124	0.649	No
Density of NPDES	−0.0754	0.006	Yes
Density of Regional Underground Storage (RUS)	0.0835	0.002	No
Density of Public Libraries	0.1237	<0.001	Yes
Density of Colleges	−0.2728	<0.001	No
Density of Jobs	0.0330	0.227	Yes

Proximity-Related

Table A25
Item Analysis for the Proximity-Related Variables and the SJ Index

Variable	Pearson Coefficient	*p*	Expected Sign?
Proximity to Nearest Grocery Store	0.128	<0.001	Yes
Proximity to Nearest Park/Rec Facility	0.189	<0.001	Yes
Proximity to Nearest Hospital	0.238	<0.001	Yes
Proximity to Nearest Medical Facility	0.232	<0.001	Yes
Proximity to Nearest Public Library	0.195	<0.001	Yes
Proximity to Nearest Interstate	0.122	<0.001	Yes
Proximity to Nearest Brownfield	−0.123	<0.001	Yes
Proximity to Nearest Hazardous Waste Site	−0.198	<0.001	Yes
Proximity to Nearest Redlined Area	−0.139	<0.001	Yes
Proximity to Work	−0.012	0.656	No

Diversity-Related.

Table A26
Item Analysis for the Diversity-Related Variables and the SJ Index

Variables	Pearson Coefficient	*p*	Expected Sign?
Percent Impervious Surface	−0.12504	<0.001	Yes
Racial Segregation	0.42496	<0.001	Yes
Housing Stock Diversity	−0.32432	<0.001	No

Connectivity-Related

Table A27
Item Analysis for the Connectivity-Related Variables and the SJ Index

Variable	Pearson Coefficient	*p*	Expected Sign?
Street Connectivity	0.28907	<0.001	Yes
Internet Fiber	0.38127	<0.001	Yes
Social Capital	0.49878	<0.001	Yes
Internet Providers	−0.02541	0.352	Yes
Transit Route	0.17966	<0.001	Yes
Interstate	0.26362	<0.001	Yes

Sensitivity

Table A28
Correlation Between Original and Modified Indices

Pearson Correlation Coefficient	*p*
0.630	<0.001

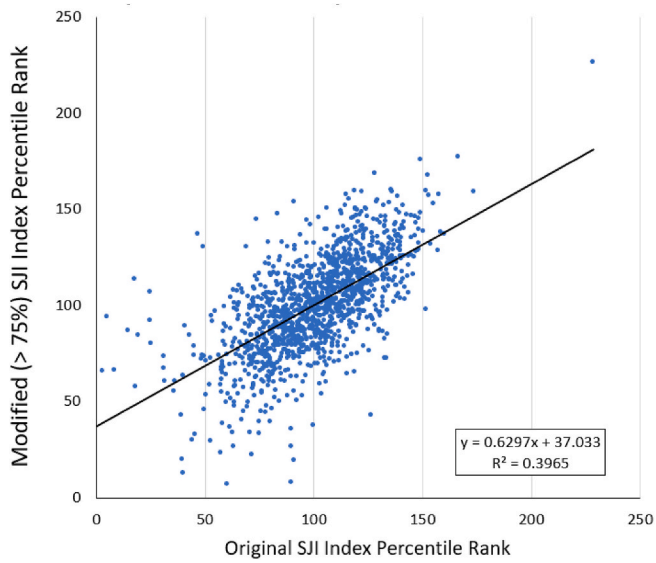

Fig. A1. Plot of the Original and Modified Indices

References

Abdul Rahman, H., Bani Issa, W., & Naing, L. (2021). Psychometric properties of brief-COPE inventory among nurses. *BMC Nursing, 20*, 73. https://doi.org/10.1186/s12912-021-00592-5

Adams-Kane, J., Jia, Y., & Lim, J. J. (2012). *Channels of transmission of the 2007/09 global crisis to International Bank Lending in developing countries*. World Bank Policy Research Working Paper, (6011).

Agyeman, J. (2005). *Sustainable communities and the challenge of environmental justice*. New York, NY: New York University Press.

Alrobaee, T. R. (2021). Measuring spatial justice indices in the traditional islamic cities by using gis, an-najaf holy city, Iraq A case study. *Journal of Geoinformatics & Environmental Research, 2*(1), 1–13.

Axle, D. (2022). Business summary: Esri total residential population forecasts for 2022. In *Esri business analyst*.

Berke, E. M., Tanski, S. E., Demidenko, E., Alford-Teaster, J., Shi, X., & Sargent, J. D. (2010). Alcohol retail density and demographic predictors of health disparities: A geographic analysis. *American Journal of Public Health, 100*(10), 1967–1971.

Bjørnskov, C. (2006). The multiple facets of social capital. *European Journal of Political Economy, 22*(1), 22–40.

Bullard, R. (1983). Solid waste sites and the black Houston community. *Sociological Inquiry, 53*(2-3), 273–288.

Bullard, R. (1990). *Dumping in dixie*. Boulder, CO: Westview.

Certomà, C., & Martellozzo, F. (2019). Cultivating urban justice? A spatial exploration of urban gardening crossing spatial and environmental injustice conditions. *Applied Geography, 106*, 60–70.

Chakraborty, A., & McMillan, A. (2022). Is housing diversity good for community stability? Evidence from the housing crisis. *Journal of Planning Education and Research, 42*(2), 150–161.

Chang, Z., Chen, J., Li, W., & Li, X. (2019). Public transportation and the spatial inequality of urban park accessibility: New evidence from Hong Kong. *Transportation Research Part D: Transport and Environment, 76*, 111–122.

Chan, E., Serrano, J., Chen, L., Stieb, D. M., Jerrett, M., & Osornio-Vargas, A. (2015). Development of a Canadian socioeconomic status index for the study of health outcomes related to environmental pollution. *BMC Public Health, 15*(1), 1–8.

Chetty, R., Hendren, N., Kline, P., Saez, E., & Turner, N. (2014). Is the United States still a land of opportunity? Recent trends in intergenerational mobility. *The American Economic Review, 104*(5), 141–147.

Corak, M. (2013). Income inequality, equality of opportunity, and intergenerational mobility. *The Journal of Economic Perspectives, 27*(3), 79–102.

Cromartie, J., & Bucholtz, S. (2008). *Defining the" rural" in rural America*. No. 1490-2016-127511.

Deb, D., & Smith, R. M. (2020). Use of machine learning in exploring spatial. In *Justices. In2020 19th IEEE international Conference on machine Learning and applications (ICMLA)* (pp. 1211–1217). IEEE.

Deb, D., & Smith, R. M. (2021). Application of random forest and SHAP tree explainer in exploring spatial (in) justice to aid urban planning. *ISPRS International Journal of Geo-Information, 10*(9), 629.

Demers, L., Weiss-Lambrou, R., & Ska, B. (2000). Item analysis of the Quebec user evaluation of satisfaction with assistive technology (QUEST). *Assistive Technology, 12*(2), 96–105.

Duncan, D. T., Kawachi, I., White, K., & Williams, D. R. (2013). The geography of recreational open space: Influence of neighborhood racial composition and neighborhood poverty. *Journal of Urban Health, 90*(4), 618–631.

Dziuban, C. D., & Shirkey, E. C. (1974). When is a correlation matrix appropriate for factor analysis? Some decision rules. *Psychological Bulletin, 81*(6), 358–361. https://doi.org/10.1037/h0036316

Ewing, R., & Hamidi, S. (2014). *Measuring urban sprawl and validating sprawl measures*. Retrieved from https://gis.cancer.gov/tools/urban-sprawl/sprawl-report-short.pdf.

Ewing, R., & Hamidi, S. (2015). Compactness versus sprawl: A review of recent evidence from the United States. *Journal of Planning Literature, 30*(4), 413–432.

Ewing, R., Pendall, R., & Chen, D. (2002). *Measuring sprawl and its impact*. Retrieved from https://community-wealth.org/sites/clone.community-wealth.org/files/downloads/report-ewing-et-al14.PDF.

Fainstein, S. (2010). *The just city*. Nueva York: Cornell University Press-Cornell Paperbacks.

Ferguson, E. (2001). Personality and coping traits: A joint factor analysis. *British Journal of Health Psychology, 6*(4), 311–325.

Figueiredo, V., & Franco, M. (2018). Wine cooperatives as a form of social entrepreneurship: Empirical evidence about their impact on society. *Land Use Policy, 79*, 812–821.

Ganusova, E. E., Vo, L. T., Abraham, P. E., O'Neal Yoder, L., Hettich, R. L., & Alexandre, G. (2021). The Azospirillum brasilense core chemotaxis proteins CheA1 and CheA4 link chemotaxis signaling with nitrogen metabolism. *mSystems, 6*(1), Article e01354, 20.

Garcia, X., Garcia-Sierra, M., & Domene, E. (2020). Spatial inequality and its relationship with local food environments: The case of Barcelona. *Applied Geography, 115*, Article 102140.

Google Maps. (2015). *American tobacco trail [image capture]*. Retrieved December 2022 https://goo.gl/maps/14psheMA2vmsgzHU6.

Google Maps. (2019). *Single family Homes on Utah Ave [image capture]*. Retrieved December 2022 https://goo.gl/maps/ujQ4MHKxVds6pfKa7.

Google Maps. (2021a). *Intersection of 6th and Graham [image capture]*. Retrieved December 2022 https://goo.gl/maps/GPpv5kfmAgGneN458.

Google Maps. (2021b). *Local Businesses and fast-food chain [image capture]*. Retrieved December 2022 https://goo.gl/maps/TPcYtVNsxctmUpR7A.

Google Maps. (2022a). *Grocery Store in the Fourth ward [image capture]*. Retrieved December 2022, from https://goo.gl/maps/ArR6qaamq5UQ7QAv6.

Google Maps. (2022b). *Downtown condominium [image capture]*. Retrieved December 2022 https://goo.gl/maps/ggaHtkM6hWBsVwYe7.

Guzman, L. A., Oviedo, D., Arellana, J., & Cantillo-García, V. (2021). Buying a car and the street: Transport justice and urban space distribution. *Transportation Research Part D: Transport and Environment, 95*, Article 102860.

Gwartney, J., Block, W., & Lawson, R. (1996). *Economic freedom of the world: 1975–1995*. Vancouver: Fraser Institute.

Gwartney, J., & Lawson, R. (2003). The concept and measurement of economic freedom. *European Journal of Political Economy, 19*(3), 405–430. https://doi.org/10.1016/S0176-2680(03)00007-7

Hajat, M. G., Tasouj, M. A., & Shoeibi, M. (2022). Spatial distribution of urban services from the spatial justice perspective: Case study of tehran. *Economy of Regions, 18*(3).

Hartman, S. E., & Hylton, J. (2000). Factor-analytic item analysis of the hemispheric mode indicator. *Personality and Individual Differences, 29*(2), 283–299.

Harvey, D. (1973). *Social justice and the city (revised edition)*. Athens, GA: University of.

Hayti | Open Durham. (n.d.). https://www.opendurham.org/category/neighborhood/hayti.
Industry Insights: Financial services in the Charlotte region. (2021, February 25). https://charlotteregion.com/blog/2021/02/25/research-data/industry-insights-financial-services-in-the-charlotte-region/.
Jackson, K. T. (1987). *Crabgrass frontier: The suburbanization of the United States*. Oxford University Press.
Jankauskaitė-Jurevičienė, L. (2022). Assumptions of the concept of spatial justice in the theory and practice of urban planning processes. *Architecture and urban planning, 18*(1), 111–119.
Jian, I. Y., Chan, E. H., Xu, Y., & Owusu, E. K. (2021). Inclusive public open space for all: Spatial justice with health considerations. *Habitat International, 118*, Article 102457.
Jian, I. Y., Luo, J., & Chan, E. H. (2020). Spatial justice in public open space planning: Accessibility and inclusivity. *Habitat International, 97*, Article 102122.
Jones, A., Mamudu, H. M., & Squires, G. D. (2020). Mortgage possessions, spatial inequality, and obesity in large US metropolitan areas. *Public Health, 181*, 86–93.
Jones, M., & Pebley, A. R. (2014). Redefining neighborhoods using common destinations: Social characteristics of activity spaces and home census tracts compared. *Demography, 51*(3), 727–752.
Kaiser, H. F., & Rice, J. (1974). Little jiffy, mark iv. *Educational and Psychological Measurement, 34*, 111–117. https://doi.org/10.1177/001316447403400115
Kruger, D. J., Cupal, S., Franzen, S. P., Kodjebacheva, G., Bailey, E. S., Key, K. D., et al. (2017a). Toxic trauma: Household water quality experiences predict posttraumatic stress disorder symptoms during the Flint, Michigan, water crisis. *Journal of Community Psychology, 45*(7), 957–962.
Kruger, D. J., Kodjebacheva, G. D., & Cupal, S. (2017b). Poor tap water quality experiences and poor sleep quality during the Flint, Michigan Municipal Water Crisis. *Sleep health, 3*(4), 241–243.
Lefebvre, H. (1968). *Le droit à la ville* (Vol. 3). Paris: Anthropos.
Liu, C., & Duan, D. (2020). Spatial inequality of bus transit dependence on urban streets and its relationships with socioeconomic intensities: A tale of two megacities in China. *Journal of Transport Geography, 86*, Article 102768.
Local History | Charlotte-mecklenburg historic Landmarks commission. (n.d.). http://landmarkscommission.org/local-history/.
Malega, R., & Stallings, R. Y. (2016). Regional differences in affluent black and affluent white residential outcomes. *Geographical Review, 106*(1), 72–91.
Malik, J., Lo, Y. L., & Wu, H. T. (2018). Sleep-wake classification via quantifying heart rate variability by convolutional neural network. *Physiological Measurement, 39*(8), Article 085004.
Martin, D. C., & Newman, B. J. (2015). Measuring aggregate social capital using census response rates. *American Politics Research, 43*(4), 625–642.
Mohai, P., Pellow, D., & Roberts, J. T. (2009). Environmental justice. *Annual Review of Environment and Resources, 34*, 405–430.
Molaei, P., Tang, L., & Hardie, M. (2021). Measuring walkability with street connectivity and physical activity: A case study in Iran. *World, 2*(1), 49–61.
Muhaimin, A. A., Gamal, A., Setianto, M. A., & Larasati, W. L. (2022). The spatial justice of school distribution in Jakarta. *Heliyon*, Article e11369.
National Religious Training School and Chatauqua. (2011). *North Carolina central university | open Durham*. Open Durham https://www.opendurham.org/buildings/national-religious-training-school-and-chatauqua-north-carolina-central-university.
NC OneMAP. (2022). *North Carolina department of information technology, government data analytics center, center for geographic information and analysis*. Available at www.nconemap.gov.
Philippopoulos-Mihalopoulos, A. (2019). The inconclusive spatial justice. In *Spatial justice in the city* (pp. 156–163). Routledge.
Pirie, G. H. (1983). On spatial justice. *Environment and Planning A, 15*(4), 465–473.
Powell, W. S., & Mazzocchi, J. (Eds.). (2006). *Encyclopedia of North Carolina*. University of North Carolina Press.
Primpas, I., Tsirtsis, G., Karydis, M., & Kokkoris, G. D. (2010). Principal component analysis: Development of a multivariate index for assessing eutrophication according to the European water framework directive. *Ecological Indicators, 10*(2), 178–183.
Prisciandaro, J. J., & Roberts, J. E. (2005). A taxometric investigation of unipolar depression in the national comorbidity survey. *Journal of Abnormal Psychology, 114*(4), 718.
Rey, G., Jougla, E., Fouillet, A., & Hémon, D. (2009). Ecological association between a deprivation index and mortality in France over the period 1997–2001: Variations with spatial scale, degree of urbanicity, age, gender and cause of death. *BMC Public Health, 9*(1), 1–12.
Rocco de Campos Pereira, R. C. (2014). Why discuss Spatial Justice in urbanism studies. *Atlantis, 24*(4).
Rodríguez-Pose, A., & Storper, M. (2020). Housing, urban growth and inequalities: The limits to deregulation and upzoning in reducing economic and spatial inequality. *Urban Studies, 57*(2), 223–248.
Schlosberg, D. (2007). *Defining environmental justice: Theories, movements, and nature*. Oxford: OUP.
Schlosberg, D. (2012). Climate justice and capabilities: A framework for adaptation policy. *Ethics and International Affairs, 26*(4), 445–461.
Sharkey, P. (2014). Spatial segmentation and the black middle class. *American Journal of Sociology, 119*(4), 903–954.
Sheppard, E. (2001). Quantitative geography: Representations, practices, and possibilities. *Environment and Planning D: Society and Space, 19*(5), 535–554.
Sheppard, E. (2014). We have never been positivist. *Urban Geography, 35*(5), 636–644.
Smith, R. M., & Blizard, Z. D. (2021). A census tract level analysis of urban sprawl's effects on economic mobility in the United States. *Cities, 115*, Article 103232.
Soja, E. W. (2010). *Seeking spatial justice* (Vol. 16). U of Minnesota Press.
Transportation. (n.d.). City of Charlotte government. https://charlottenc.gov/transportation/Pages/default.aspx.
Spatial Justice Index Data Repository. (2023). https://github.com/CADS-WSSU/CADS-Research-Projects/tree/main/Spatial%20Justice.
Tripathi, M., & Singal, S. K. (2019). Use of principal component analysis for parameter selection for development of a novel water quality index: A case study of river ganga India. *Ecological Indicators, 96*, 430–436.
Tzanni, O., Nikolaou, P., Giannakopoulou, S., Arvanitis, A., & Basbas, S. (2022). Social dimensions of spatial justice in the use of the public transport system in thessaloniki, Greece. *Land, 11*(11), 2032.
U.S. Census. (2020). *Census tract reference map*. Retrieved from https://www.census.gov/geographies/reference-maps/2020/geo/2020pl-maps/2020-census-tract.html.
U.S. Census Bureau. (2020a). Demographic and housing estimates. In *2016-2020 American Community Survey 5-Year Estimates (Table: DP05)*. https://data.census.gov/table?q=demographic&g=1400000US37119000103&tid=ACSDP5Y2020.DP05.
U.S. Census Bureau. (2020b). Physical housing characteristics for occupied housing units. In *2016-2020 American Community Survey 5-Year Estimates (Table: S2504)*. https://data.census.gov/table?q=housing&g=1400000US37063001303&tid=ACSST5Y2020.S2504.
U.S. Census Bureau. (2020c). Selected characteristics of the native and foreign-born populations. In *2016-2020 American community survey 5-year estimates (Tables: S0501, S0601)*. https://data.census.gov/table?q=demographic+foreign&g=0500000US37063&tid=ACSST5Y2020.S0501.
U.S. Census Bureau. (2020d). Selected social characteristics in the United States. In *2016-2020 American Community Survey 5-Year Estimates (Table: DP02)*. https://data.census.gov/table?q=demographics+foreign+born&g=0500000US37119&tid=ACSDP5Y2020.DP02.
Van Beuningen, J., & Schmeets, H. (2013). Developing a social capital index for The Netherlands. *Social Indicators Research, 113*, 859–886.
Wang, K., & Immergluck, D. (2018). The geography of vacant housing and neighborhood health disparities after the US foreclosure crisis. *Cityscape, 20*(2), 145–170.
Weck, S., Madanipour, A., & Schmitt, P. (2022). Place-based development and spatial justice. *European Planning Studies, 30*(5), 791–806.
Wei, Y. D. (2015). Spatiality of regional inequality. *Applied Geography, 61*, 1–10.
Wei, Y. D., Xiao, W., Simon, C. A., Liu, B., & Ni, Y. (2018). Neighborhood, race and educational inequality. *Cities, 73*, 1–13.
Wight, R. G., Aneshensel, C. S., Miller-Martinez, D., Botticello, A. L., Cummings, J. R., Karlamangla, A. S., et al. (2006). Urban neighborhood context, educational attainment, and cognitive function among older adults. *American journal of epidemiology, 163*(12), 1071–1078.
Wyly, E. (2009). Strategic positivism. *The Professional Geographer, 61*(3), 310–322.
Wyly, E. (2014). The new quantitative revolution. *Dialogues in Human Geography, 4*(1), 26–38.