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Original article

Unveiling environmental justice in two US cities through greenspace accessibility and visible greenness exposure

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ABSTRACT

Uneven access to greenspaces or visible greenness is an environmental justice (EJ) issue. In this paper, we use a social equity lens to develop geospatial models that measure convenient walking access to urban greenspaces such as parks and street-level green exposure en route to greenspaces. We utilized earth science, geospatial, and demographic datasets to develop two models—Greenspace Accessibility and Visible Greenness Exposure—and applied them in Camden and Jersey City, USA, two communities experiencing environmental injustices. Modeling results show that greenspace accessibility is a concern in both cities, with Jersey City experiencing more prominent disparities. We observed significant positive relationships in Camden between greenspace accessibility and two EJ variables: Black segregation and Hispanic segregation. Most streets in both cities have poor greenness exposure, although Jersey City faces higher inequality compared to Camden. We also observed significant negative relationships in Jersey City between street-level greenness exposure and low-income populations. We conclude the paper by explaining the implications of our findings for greenspace planning and policymaking.

1. Introduction

Environmental justice (EJ) seeks to ensure no group bears disproportionate environmental consequences from industrial, governmental, or commercial activities, and involves people in decisions affecting their environment and health so that they can influence regulatory choices with a focus on community concerns (Mohai et al., 2009; Meenar et al., 2018). This study looks into how greenspaces and visible greenness exposure are distributed in two cities in New Jersey, USA. We define greenspaces as publicly accessible parks and visible greenness exposure as green features such as trees, shrubs, planters, and flower beds visible on city streets. Greenspaces and visible green play a pivotal role in advancing health equity among communities (Twohig-Bennett & Jones, 2018). Beyond serving as recreational spaces, they form integral parts of a thriving community, fostering both physical and mental well-being, and promoting social equity, environmental sustainability, and quality of life for residents (Gianfredi et al., 2021; Tirri et al., 2023; Meenar et al., 2019). Although parks and other green recreational spaces are considered critical for active living in all communities, not all people have equitable access to these spaces (Nesbitt et al., 2019; Locke et al., 2021). Uneven accessibility of greenspaces or visible greenness exposure is an EJ and spatial equity issue because greenspaces or green features are not always equitably distributed in communities enduring environmental injustices. With roots in top-down urban planning and development, racial inequality and white supremacy are just two causes of inequitable access to greenspaces (Anguelovski et al., 2022). For instance, a California-based study suggests the inadequate distribution of recreational spaces among low-income households, low fiscal capacity, minority populations, and multifamily housing, increases health risks among those populations (Dahmann et al., 2010). According to the 2023 ParkScore Index created by the Trust for Public Land (TPL), minority neighborhoods in the USA typically have 43 percent less access to park space, while residents in low-income neighborhoods have 42 percent less access compared to those in high-income neighborhoods

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(TPL, n.d.). On the contrary, several studies also have found that there is little or no difference in minority access to greenspaces (Cutts et al., 2009; Zhou & Kim, 2013).

Greenspace location or proximity is one of the most dominant factors in examining greenspace accessibility and equity. Studies have considered 5-minute, 10-minute, or 15-minute walking access to nearby greenspaces as convenient accessibility measures. However, the nationwide movement "The 10-Minute Walk Campaign" in the USA, created and led by the Trust for Public Land in collaboration with the National Recreation and Park Association and the Urban Land Institute, aims to ensure that everyone has safe access to a quality park or greenspace within 10 minutes of their home by the year 2050 (Lau, 2020). The 10-minute walk metric—approximately 0.8 km or 0.5 miles for an able-bodied person—represents the typical distance people are willing to walk to reach a destination and has been used in greenspace accessibility studies (Hughey et al., 2021; Macfarlane et al., 2021). In addition to debates over easy walking distance, most studies inconsistently use greenspace locations as points (centroids) or polygons (greenspace boundaries) when calculating the distance to or from neighboring residential areas. Many studies, however, did not consider important factors, including the walkability index surrounding greenspaces, actual entrance points, and the quality of greenspaces. It is, therefore, important to measure equitable access to urban greenspaces by examining significant understudied factors like location, size, entrance, and quality, and comparing greenspace accessibility with EJ variables.

While greenspaces play a role as hubs for congregating, street-level greenery provides a dimension of flexibility as green corridors. Streets can become easily accessible greenspaces outside of the designated greenspace (park) context, improving the overall living conditions of a neighborhood (Zhou & Kim, 2013; Labib et al., 2021). Street-level greenery, such as lush foliage and tree-lined sidewalks, offers a myriad of benefits: it provides a soothing view and a calming environment that can reduce mental stress, fatigue, and aggression (Kaplan, 1995; Zhou & Kim, 2013); reduces harmful exposure to air, noise, and heat pollution (Gunawardena et al., 2017; Wang et al., 2021a); contributes to lower childhood asthma rates and the quality of life of older individuals (Zhou & Kim, 2013); increases sleep, physical activity, and social interactions (Wang et al., 2021b).

Measuring green exposure at eye level on streets is a relatively recent approach compared to previous top-down methods, such as the bird's-eye-view perspective using the Normalized Difference Vegetation Index (NDVI) (Labib et al., 2020; Larkin & Hystad, 2019). Several studies have shown that greenery measurements from top-view images (e.g. aerial photographs and satellite imagery) often differ from the amount and type of greenery identified by people capturing greenery images at eye level, including shrubs that are growing underneath tree canopies (Ye et al., 2019; Larkin & Hystad, 2019). One standard method to measure eye-level visible greenness is to use a diverse dataset (e.g., street view images, digital elevation model) to capture and measure greenness using various indexes (Aikoh et al., 2023; Labib et al., 2021; Biljecki & Ito, 2021; Wang et al., 2022). Examples include the Green View Index (GVI) (Aikoh et al., 2023), Viewshed Greenness Visibility Index (VGVI) (Labib et al., 2021), and the Street View Index (Biljecki & Ito, 2021). Generally, GVI and Street View Index use image data such as Google Street View images to model eye-level visible greenness; however, they are often restricted due to a lack of access to quality image data (Larkin & Hystad, 2019; Sánchez & Labib, 2024). Compared to GVI and other image-based methods, the VGVI model can apply geo-computation approaches to estimate eye-level greenness visibility at a large scale by utilizing viewshed modeling approaches leveraging high-resolution LiDAR and earth observation data on the presence of plants (Labib et al., 2021; Yan et al., 2023).

Greenspace inequalities are generally measured by greenspace access across cities and neighborhoods (Boone et al., 2009; Jennings et al., 2017), and by examining the racial and ethnic composition of greenspace access to investigate EJ (Rigolon et al., 2018). Zhou and Kim (2013), for example, used GIS and remote sensing in six Illinois cities to assess park accessibility and quantify tree canopy, and found less tree canopy in racial/ethnic minority neighborhoods, with little difference in greenspace accessibility. Similarly, Nesbitt et al. (2019) evaluated park accessibility and vegetation coverage in 10 US cities, while Locke et al. (2021) explored housing segregation and tree canopy coverage in 37 US cities, but neither study directly compares visibility and accessibility to assess the spatial inequality of these metrics.

Previously used metrics included the presence vs. absence of a greenspace or recreation facility near homes, the density of facilities, total greenspace acreage within a given radius of homes, or percentages of tree canopy coverage. Studies have yet to concurrently assess both greenspace access and greenness exposure within the same communities enduring environmental injustices. Recognizing the comparable significance of street-level visible green exposure during transit to parks and access to parks, our study addresses both aspects in these communities. Thus, this study aims to apply a social equity lens in developing geospatial models to assess convenient walking access to urban greenspaces and street-level visible greenness exposure en route to greenspaces. We focus on the City of Camden and Jersey City in New Jersey, USA, and address the following two research questions.

1) Is limited or lack of convenient walking access to high-quality greenspaces related to vulnerable population groups in communities enduring environmental injustices?
2) Is limited or lack of visible greenness exposure on streets related to vulnerable population groups in communities enduring environmental injustices?

This study holds significant implications for planning green streetscapes and ensuring equitable access to greenspaces in cities. Highlighting spatial inequities and their correlation with vulnerable population groups provides valuable insights and policy recommendations to mitigate any disparities and promote fairer access to greenspaces in similar cities.

2. Context and Methodology

2.1. Study Areas

Camden and Jersey City, located in the state of New Jersey, are highly suitable for this project. With the passing of its Environmental Justice Law in 2020, New Jersey became the first state in the nation to subject all permits for new facilities to increased scrutiny through EJ analyses and to issue mandatory denials if those analyses discover disproportionate effects for overburdened communities (NJDEP, 2022b). The legislation culminates New Jersey's commitment to correcting the historical injustices its most vulnerable residents have experienced because of the state's legacy of siting heavily polluting industries in overburdened communities and therefore limiting those residents' chances of economic and health-related success.

Both Camden and Jersey City are illustrative examples of the historical injustices New Jersey now seeks to remediate, for both cities rapidly developed during the late 19th and early 20th centuries as either transportation or manufacturing hubs for their neighboring metropolitan areas of Philadelphia and New York City, respectively. In the mid-to late-20th century, major industries began to relocate or cease operations completely, and residents began to move into the surrounding suburbs, leaving behind a wide array of environmental hazards and building stock that quickly fell into dereliction (Gillette, Jr, 2006; Jacobs, 2000). In recent years, however, political forces in both cities have made significant investments in parks and open spaces. Not only have the cities published plans regarding these areas, but they have also developed new greenspaces or revitalized existing ones. Table 1 illustrates demographic and greenspace-related information for both cities based on 2022 data.

Table 1
Demographic and greenspace-related information for Camden and Jersey City, 2022.

Variables	Camden	Jersey City
Total population	70,996	286,670
% White	15.7	32.1
% Black	42.9	22.5
% Hispanic	52.8	27.5
% Older adults (65 years and above)	10.6	11.4
% Young population (10–17 years old)	29.1	20.8
% Low-income population*	33.6 %	16.1 %
Number of parks**	43	77
Total park area (in acres)	560.5	1312.9
Per capita parkland acres	0.008	0.004
% of city land area for parks and recreation***	8 %	12 %
Number of Census block groups	60	195

*Low-income population refers to households that are at or below twice the U.S. Census poverty threshold, according to NJDEP.
**Includes all the public and private parks that are accessible to the public.
***The national median of % of city land area for parks and recreation is 15 %.

2.2. Data

We collected Earth observation, and other geospatial and socio-demographic data from a variety of local, state, national, and international sources. LiDAR point cloud data was downloaded from USGS 3DEP LiDAR explorer, which was originally collected through the Delaware Valley 2015 LiDAR project and New Jersey Post Sandy LiDAR project 2014. LiDAR data is used to create a detailed digital elevation model (DEM) and digital surface model (DSM) to generate viewshed. Global vegetation height products were collected from EcoVision Lab (Lang et al., 2022) to generate a green versus non-green raster for VGVI model. ORNL landscape gridded nighttime population data at 90 m resolution was collected from Oak Ridge National Laboratory (ORNL, n.d.) to estimate demand and supply for each greenspace in the study area. Block group demographic and income data, including total population, race, and age, were collected from the U.S. Census ACS five-year estimate in 2021. Additional geospatial data, including city boundaries and greenspace boundaries, were collected from the New Jersey Geographic Information Network (NJGIN, n.d.) and the Jersey City Open Data (JCOD, n.d.). Street network graph data was collected from the Openstreet Network data set, which is used for analyzing walk time between population grids to park entrances. The EPA National Walkability Index was collected from the smart location data portal (EPA, 2021) to adjust the accessibility score. Park public rating data was collected from Google Maps, which is used as a quality indicator for weighing the supply of quality greenspaces. The research team also mapped park entrance locations and edited newly developed parks through field surveys and the visual interpretation of fine-resolution Google Map images.

We used Black and Hispanic population concentrations as racial segregation variables. Many studies utilize the Index of Concentration at the Extremes (ICE), developed by Massey (2001), to determine racial segregation at the community level because ICE has an advantage over other indicators, such as the percentage of minority populations (Krieger et al., 2016 and Sonderlund et al., 2022). ICE measures the extent of residents' concentration in the extreme of distribution. In this study, we calculated ICE using demographic and race/ethnicity data at the block group level. The following formula (Eq. 1) was used to calculate Black segregation:

$$ICE_i = \frac{A_i - P_i}{T_i} \tag{1}$$

Where A_i represents the number of non-Hispanic white populations, P_i is the number of non-Hispanic Black populations, and T_i is the total population at block group i. Similarly, to calculate Hispanic segregation above, P_i is the number of Hispanic populations. The value of ICE ranges from −1 to +1 where −1 indicates a concentration of deprived condition (fully Black or Hispanic concentration) and +1 indicates a concentration of a privileged population (fully white).

2.3. Methodology

2.3.1. Assessing greenspace accessibility

The Greenspace Accessibility model was developed to assess the accessibility of greenspace incorporating multiple input parameters: grid-level population data, greenspace size, greenspace quality, greenspace entrance points, street network, walkability scores, and city boundaries. Newly constructed or renovated greenspaces were added to the greenspace boundary data through editing, using information from community partners involved in the project and validated by both high-resolution Google Earth images and field surveys. Greenspace entrance data was generated through a combination of field surveys (windshield surveys, walking surveys) and visual interpretations of Google Earth images. Greenspace quality was assessed by deriving Google Map public ratings for each greenspace. The EPA National Walkability Index ranges from 1 to 20, where 1–5.75 scores indicate least walkable and 15.26–20 indicates most walkable (Chapman et al., 2021). In our modeling, we converted the block group walkability index at the 90-meter population grid cell level to match our walk accessibility modeling aerial unit using the "nearest neighbor" technique. The raw walk accessibility scores were then standardized to a range of 0–1 using maximum-minimum standardization.

A Modified Enhanced Two-step Floating Catchment Area (ME2SFCA) approach calculated the greenspace accessibility score at the grid level. The first step was to compute the supply-demand ratio of greenspaces by using Eq. 2. The supply was defined as the area of a greenspace multiplied by the rating (quality) of that greenspace.

$$R_j = \frac{A_j \times Q_j}{\sum_{k \in \{d_{kj} \le d_0\}} G(d_{kj}, d_0) P_k} \tag{2}$$

Where, R_j is the supply-demand ratio of greenspace j; A_j is the area of greenspace j; Q_j is the greenspace rating; $G(d_{kj}, d_0)$ is the distance decay function; and P_k is the number of populations at grid cell k. The distance decay function is defined by the following Gaussian distribution function (Eq. 3):

$$G(d_{kj}, d_0) = \begin{cases} \dfrac{e^{-\frac{1}{2}\times\left(\frac{d_{kj}}{d_0}\right)^2} - e^{-\frac{1}{2}}}{1-e^{-\frac{1}{2}}}, & d_{kj} \le d_0 \\ 0, \quad d_{kj} > d_0 \end{cases} \tag{3}$$

In the second step, the greenspace accessibility score was calculated at each population grid cell by combining the supply-demand ratio of all greenspaces accessible from the grid cell. The accessibility scores were then multiplied by the walkability index (WI) at the grid level where AS_k is the greenspace accessibility score at grid cell k (Eq. 4):

$$AS_i = WI\sum\nolimits_{k\in\{d_{kj}\le d_0\}} G(d_{kj}, d_0)R_j \tag{4}$$

Next, grid-level greenspace accessibility scores were aggregated at the census block group level by taking the median of all grids within a block group. Raw continuous scores were converted to three greenspace accessibility categories: low, moderate, and high. Thresholds for categories were calculated using the following hypothetical scenario. We considered a hypothetical greenspace (Greenspace j) in a city with 1000 residents. Grid cell A (near Greenspace j) has 1 person at a distance of one meter to Greenspace j, while grid cell B (at the periphery) has 999 people at a distance of 803 m (at the periphery of ½ mile catchment) to greenspace j. Considering the World Health Organization (WHO) recommended minimum of 9 m^2 of greenspace per capita (Russo & Cirella, 2018), greenspace j's area should be at least 9000 m^2 to serve 1000 people. Further, we assumed two ideal scenarios: the hypothetical greenspace had the highest quality (1.0), and the neighborhood had the highest walkability index (1.0). Using Eq. 2-4, the accessibility score for grid cell B is 5.9 with low accessibility, and if it is halfway (¼ mile), the score is 9.0, indicating the cut-off for moderate accessibility.

2.3.2. *Assessing Visible Greenness Exposure*

Visible Greenness Exposure (VGE) was assessed in our model using the Viewshed Greenness Visibility Index (VGVI) by aggregating eye-level greenness along the street network at a defined distance interval (e.g., 5 m) (Labib et al., 2021). The VGVI index used two primary datasets: LiDAR point clouds and vegetation coverage data (indicating the presence or absence of vegetation). From the LiDAR point clouds, a digital elevation model (DEM) and a digital surface model (DSM) were derived at a spatial resolution of 0.5 m. The vegetation coverage data was created from a vegetation height dataset, indicating the continuous value of vegetation height. We used the height information in each pixel to determine if a pixel represents vegetation or not. This approach created a data layer with binary values where 0 indicated no vegetation and 1 indicated the presence of vegetation.

As outlined in Labib et al. (2021), VGVI is defined as the ratio of the green viewshed to the total viewshed for an observer standing at any given location in a city. For this study, VGVI scores at observer locations at the 5-meter interval were calculated by a distance-weighted viewshed algorithm. The modeling process executed multiple line-of-sight (LOS) in all directions from an observer (360 degrees) with a distance decay weighted algorithm because the visual prominence of a green object in space reduces with increasing distance from the observer. The maximum distance was set to 300 m with the assumption that visible green beyond this distance threshold had no impact on the observer's eyes. The

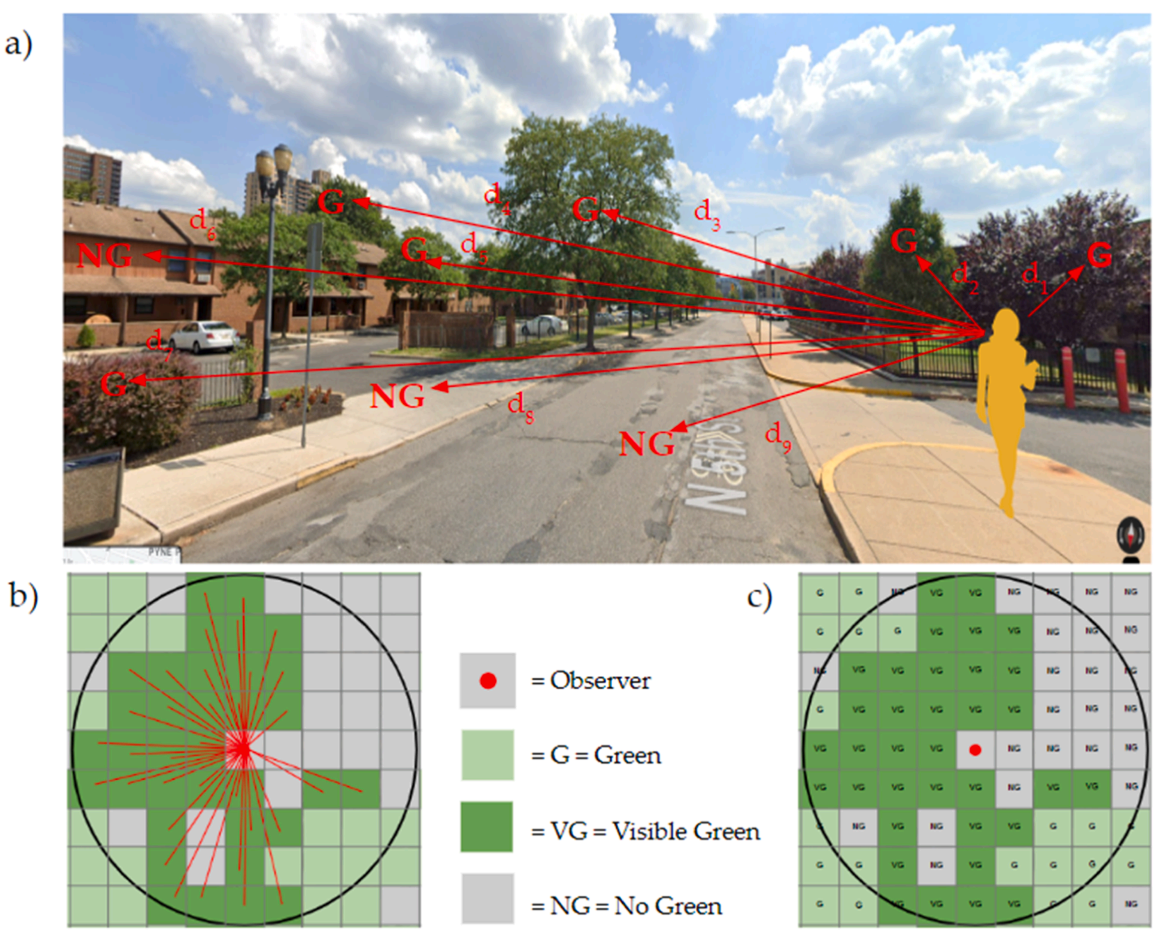

Fig. 1. A conceptual diagram of the Viewshed Greenness Visibility Index (VGVI). The street scene was captured from Google Street View. Adapted from Labib et al. (2021).

observer's height was set to 1.7 m, an average human height in North America. In this modeling process, all visible pixels were first selected from an observer location using DEM and DSM through the LOS algorithm. Then, these visible pixels were flagged as visible green and no green using a binary green layer. A value of 1.0 was assigned to visible green pixels and a value of 0.0 was assigned to no visible green pixels (See Fig. 1 for a conceptual diagram).

Each visible pixel was weighted using the following exponential distance decay function (Eq. 5)

$$w_{ij} = \frac{1}{1 + b(d_{ij})^m} \tag{5}$$

where w_{ij} is the weight of the distance decay function for the distance d_{ij}; b is the coefficient; and m is the power. For this study, m=1 and b=3 were used for Eq. 5 to fit the curve. The visible green and non-visible green scores were then calculated using a weighted sum of all pixels in the viewshed.

This model utilized the GreenExp R package (Koster & Labib, 2023) to calculate VGVI at an observer's location using Eq. 6:

$$\mathrm{VGVI}_j = \frac{\sum_{i=1}^{n} G_i \times w_{ij}}{\left(\sum_{i=1}^{n} G_i \times w_{ij}\right) + \left(\sum_{i=1}^{n} V_i \times w_{ij}\right)} \tag{6}$$

where VGVI_j denotes the VGVI at observer location j; G_i and V_i are visible green and visible no green pixels respectively; and W_{ij} is the weight between the observer and the object.

Since we aimed to measure VGVI along streets, observer locations were deliberately chosen on streets to achieve city-wide mapping. To facilitate comparisons between the two study areas and among block groups, VGVI values were subsequently normalized by street length, leading to the representation of VGE per meter of streets at the block group level.

2.4. *Measuring Equity in Greenspace Accessibility and Visible Greenness Exposure using EJ Variables*

To examine the relationships between environmental justice-seeking communities and results from Greenspace Accessibility and Visible Greenness Exposure models, we assessed five population variables: Black segregation, Hispanic segregation, low-income, young (age 10–17), and older adults (age 65 and above). The descriptive statistics of EJ variables are shown in Table 2. These variables were selected based on localized contextualization of scholarly literature on EJ (NJDEP, 2022b; Meenar et al., 2022). The relationships were then tested using a four-step method. The following description pertains to the Visible Greenspace Access model results, while the analysis for the VGE model followed the same methodology.

First, greenspace inequalities were measured at the grid level and block group level for Camden and Jersey City using the spatial Gini coefficient. Unlike the traditional Gini coefficient that measures locationally invariant inequality, the spatial Gini measures inequality by addressing spatial autocorrelations jointly with overall inequality (Sheriff & Maguire, 2020). The inequality Python package was utilized to compute the spatial Gini coefficient. Second, the Ordinary Least Squares Regression (OLS) was used to identify the relationships between greenspace accessibility with the five EJ variables mentioned above. The spatial autocorrelation was measured using Moran's I on the OLS regression residuals to ensure that the variables were random since spatially significant clustering of high and low residuals indicated misspecifications. Third, if there were spatial clusters, spatial lag regression was performed to determine the relationship between greenspace accessibility and explanatory variables. Finally, Geographically Weighted Regression was performed to determine the local relationship between greenspace exposure metrics and EJ variables.

3. Results

The results section comprises four subsections to present the spatial distribution of outcomes as well as the equity justifications of outcomes from two models. Subsections 3.1 and 3.2 illustrate the spatial distribution of greenspace accessibility scores and the relationship between the aggregated greenspace accessibility score and EJ variables at the block group level, respectively, for two study areas. The spatial distribution of visible greenness exposure scores and EJ variables is found in subsections 3.3 and 3.4, respectively, for both Camden and Jersey City.

3.1. *Greenspace accessibility in Camden and Jersey City*

Based on the Greenspace Accessibility model results, Figs. 2a and 2b illustrate the spatial distribution of greenspace accessibility in Camden: residential block groups in the northern and some eastern parts of the city had high or moderate walk accessibility to greenspaces. Central, western, and southern parts of the city had low accessibility. As seen in Figs. 2c and 2d, only a few residential block groups in Jersey City had high or moderate accessibility.

3.2. *Equity in greenspace accessibility in Camden and Jersey City*

The spatial Gini coefficient for greenspace accessibility at both grid and block group levels in Camden were 0.702 and 0.546 respectively (p-value 0.01). For Jersey City, the values were 0.918 and 0.917 respectively (p-value 0.01). Upon analyzing the results, we observed substantial disparities in greenspace accessibility within both cities. Particularly noteworthy is the significant unequal distribution of greenspaces in Jersey City, in contrast to the moderate inequalities observed in Camden.

To explore the relations between accessibility and sociodemographic variables, we performed spatial lag regression models since it is not appropriate to use OLS regression because Moran-I indicates a clustered pattern of variables. As shown in Table 3, a statistically significant ($p < 0.05$) positive relationship existed in Camden between greenspace accessibility and Black segregation, as well as greenspace accessibility and Hispanic segregation. The positive correlation coefficient indicates high greenspace accessibility associated with a positive value of ICE (privileged population), which means that white-dominated areas (privileged population) have high greenspace accessibility scores. One unit increase in the greenspace accessibility score is associated with about 15 times increase in Black segregation and about

Table 2
Descriptive statistics of EJ variables used in this study.

Variables	Camden (n=57)				Jersey City (n=193)			
	Minimum	Maximum	Mean	Standard Deviation	Minimum	Maximum	Mean	Standard Deviation
% Low-income population	0.00	94.18	61.43	19.32	0.73	100	32.3	19.85
Black segregation	−0.87	0.069	−0.36	0.26	−0.94	0.65	0.02	0.35
Hispanic segregation	−0.97	0.24	−0.43	0.27	−0.78	0.62	−0.04	0.27
% Older adult	0.00	48.80	11.73	8.97	0.00	100	12.32	12.06
% Young population	0.00	32.59	13.42	8.09	0.00	38.38	7.16	6.50

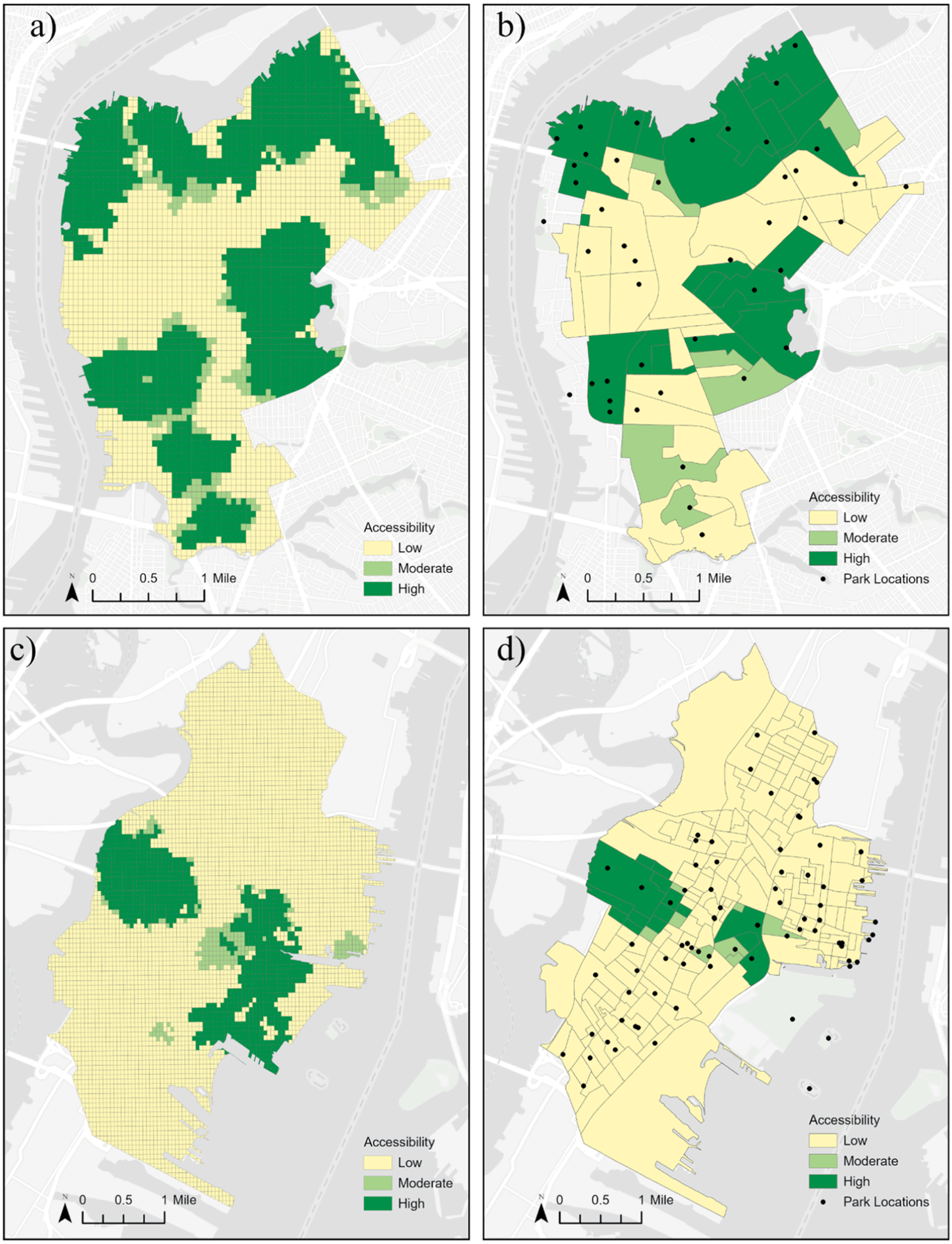

Fig. 2. Greenspace accessibility in Camden and Jersey City. a) Grid level accessibility in Camden, b) block group level accessibility in Camden, c) Grid level accessibility in Jersey City, d) block group level accessibility in Jersey City.

18 times increase in Hispanic segregation. We also observed statistically insignificant inverse relationships between greenspace accessibility and low-income populations, older adults, and young populations. For Jersey City, the spatial lag model indicated no significant relationship between greenspace accessibility and EJ variables.

Fig. 3 illustrates the results of Geographically Weighted Regression (GWR) in Camden and Jersey City, depicting the local variation of relationships between greenspace accessibility and socio-demographic variables among census block groups. In Camden, the variable representing the low-income population exhibited a strong positive correlation with greenspace accessibility in the northern and central parts of the city, but a strong negative correlation in the southern part. The percentage of older adult populations showed a negative correlation throughout the city. For the young population, the correlation exhibits a positive relation mostly in the eastern part of the city and a negative relation western part of the city. Finally, variables representing Black and Hispanic segregation showed a positive correlation, with the correlation being stronger in the northern and eastern parts of the city for

Table 3
Summary of spatial lag regression for greenspace accessibility in Camden and Jersey City.

	Camden				Jersey City			
Variables	Coefficient	Standard Error	Z-Statistics	p-value	Coefficient	Standard Error	Z-Statistics	p-value
Constant	21.59	5.30	4.07	0.000*	36.40	17.16	2.1	0.033*
Low-income	−0.04	0.06	−0.72	0.474	−0.37	0.44	−0.83	0.405
African American Segregation	15.02	5.86	2.56	0.010*	−31.67	25.49	−1.24	0.214
Hispanic Segregation	17.94	5.75	3.11	0.002*	−0.22	35.02	−0.01	0.995
Older Adult	−0.06	0.14	−0.41	0.681	−1.12	1.27	−0.87	0.380
Young Population	−0.12	0.13	−0.95	0.340	−0.36	0.63	−0.57	0.564
Weight Walk Accessibility	0.69	0.09	7.09	0.000*	0.06	0.11	0.46	0.641

* An asterisk next to a number indicates a statistically significant p-value ($p < 0.05$).

Black and Hispanic segregated block groups, respectively. In Jersey City, the variable representing the low-income population exhibited a negative correlation with greenspace accessibility throughout the city, strongest in the southern part. For the young and older adult populations, a similar pattern emerged, with a strong negative correlation in the northern and northeastern parts of Jersey City. The variables representing Black and Hispanic segregation showed negative correlations throughout Jersey City, respectively, with the southern part displaying a strong correlation for Black segregation and the northern part for Hispanic segregation.

3.3. Visible greenness exposure in Camden and Jersey City

Fig. 4 illustrates the VGVI and VGE scores in Camden and Jersey City, and Fig. 5 displays examples of streets with high and low VGVI scores in Camden using 3D GIS and street views. At the city level, the varying shades of green in the left map from each row signify different levels of VGVI, with dark green representing a high exposure score (1.0) and light green representing a low exposure score (0.0). The middle and right maps in each row illustrate the VGVI and VGE scores along streets and at block group levels, respectively. As observed, certain block groups in North, East, and South Camden exhibit high VGE, characterized by low-density residential areas and proximity to large greenspaces. Conversely, downtown and industrial zones, primarily located in the eastern part of Camden, indicate low VGE. In Jersey City, block groups around the periphery of the city with large greenspaces, except for the downtown area, show high VGE.

3.4. Equity in visible greenness exposure in Camden and Jersey City

The spatial Gini coefficient for street-level VGE in Camden and Jersey City block groups was 0.203 and 0.409, respectively (p-value 0.01). The results indicate a high inequality in the distribution of VGE in Jersey City and a moderate to low unequal distribution of VGE among block groups in Camden. Next, spatial lag regression models were performed because Moran-I showed a clustered pattern of variables (see Table 4). In Jersey City, a statistically significant ($p < 0.05$) negative relationship existed between street-level VGE scores and low-income populations, while a significant positive relationship ($p < 0.05$) existed between VGE and young populations. No variables in Camden showed any statistically significant relationship with VGE, either positive or negative.

Fig. 6 depicts local variations in regression coefficients at the block group level for Camden and Jersey City. The coefficients show a weak relationship between VGE and EJ variables in both areas. In Camden's southern region, there is a notable positive correlation for the percentage of low-income, Black segregation, and Hispanic segregation, while the percentages of older adults and young population exhibit negative correlations in the south and southwest. In Jersey City, there is a negative coefficient for the percentage of low-income population citywide, indicating an inverse relationship with VGE. Black segregation has a negative coefficient, while Hispanic segregation shows a positive coefficient across the entire city, suggesting lower VGE in Hispanic-dominated neighborhoods and higher VGE in Black-dominated ones. The correlation coefficient for low-income is lowest in central Jersey City, while half of the southern part exhibits the lowest coefficient for Hispanic segregation. Black segregation shows the highest coefficient in the southeastern parts and the lowest in the northwestern parts of Jersey City. The percentage of the young population has a strong correlation with the VGE of block groups in the central business district of Jersey City.

4. Discussion

This study adopts a social equity framework along with geospatial methods to assess pedestrian accessibility to urban greenspaces, particularly parks, and exposure to eye-level visible greenness along greenspace access routes. By integrating geospatial and demographic datasets, we established two distinct models—Greenspace Accessibility and Visible Greenness Exposure—and applied them in Camden and Jersey City, two cities enduring environmental injustices.

Findings from the Greenspace Accessibility model highlight concerns about equitable access to greenspace in both cities. Notably, Jersey City exhibits more pronounced disparities in greenspace accessibility and visibility, emphasizing the need for targeted interventions to address these imbalances. In Camden, accessibility varies across different areas, with significant relationships observed between greenspace accessibility and EJ variables, such as Black segregation and Hispanic segregation. Importantly, the study brings to light the nuanced nature of greenspace equity within environmental justice-seeking communities, highlighting that the relationships between greenspace accessibility and EJ variables manifest differently in various parts of the city.

The existing body of literature on greenspace accessibility and EJ presents a complex and sometimes contradictory landscape. Several studies, including those by Rowangould et al. (2016) and Dahmann et al. (2010), have consistently reported disparities in access to greenspace among minority and low-income populations. These disparities often highlight challenges faced by these communities in terms of proximity to and availability of greenspaces. In contrast, other studies, such as those by Cutts et al. (2009) and Zhou & Kim (2013), suggest more equitable access to greenspaces.

Our study emphasizes the need to move beyond a singular focus on access to greenspace. Instead, we underscore the importance of considering additional factors such as greenspace size, quality, safety, entrance points, and maintenance. These factors are crucial determinants of the overall usability and enjoyment of greenspaces. Importantly, many lower-income and ethnic or racial minority groups may face challenges in accessing greenspaces that not only exist in close proximity but also meet the standards of size, quality, safety, and maintenance (Abercrombie et al., 2008; Rigolon et al., 2018).

The findings from our study reveal nuances in the relationship between equitable access to greenspace and EJ variables in Jersey City and Camden. Despite Jersey City having overall more equitable access to greenspace compared to Camden, the association with EJ variables was not significant. This suggests that while there may be disparities in

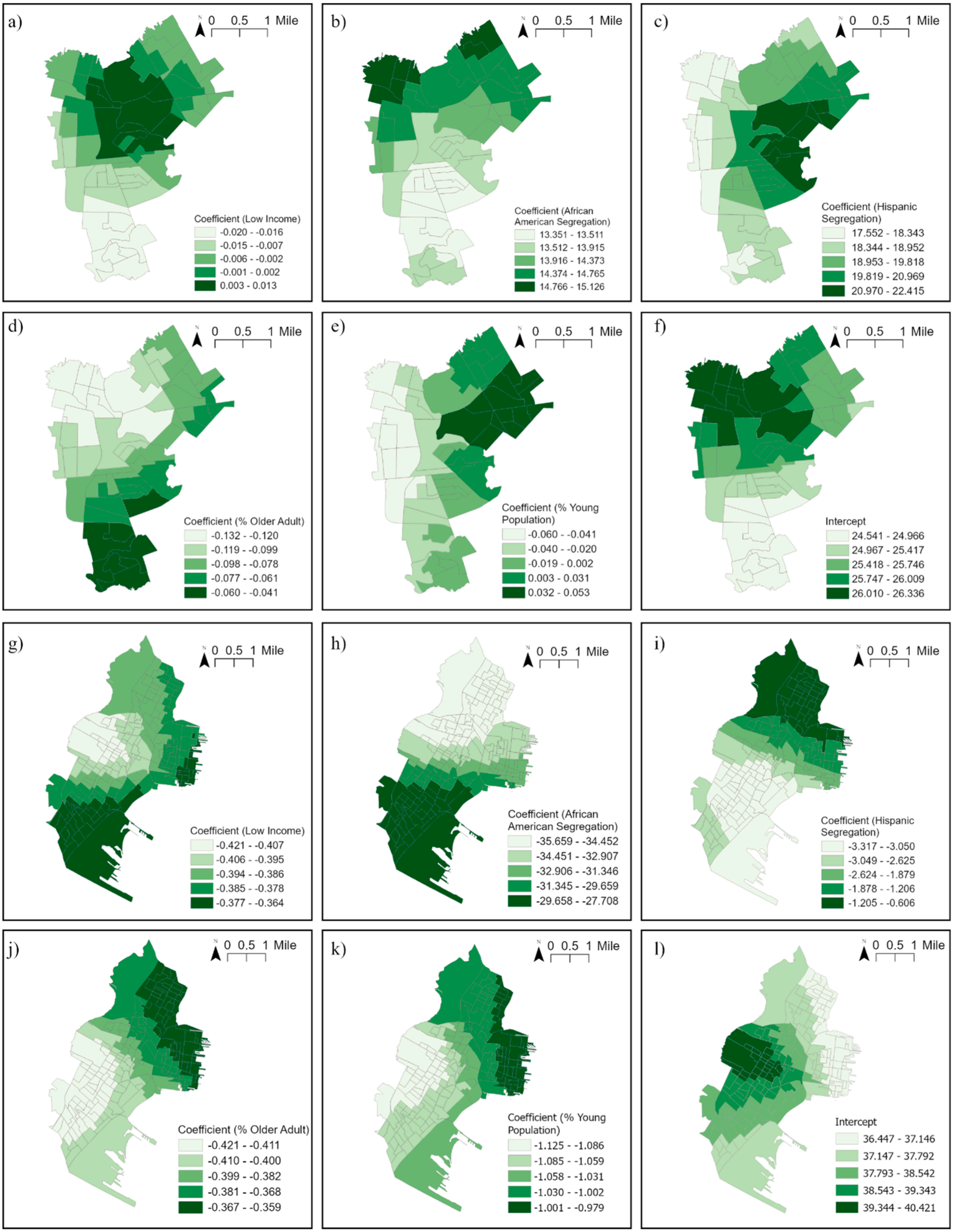

Fig. 3. Geographically weighted regression of greenspace accessibility in Camden (a-f) and Jersey City (g-l).

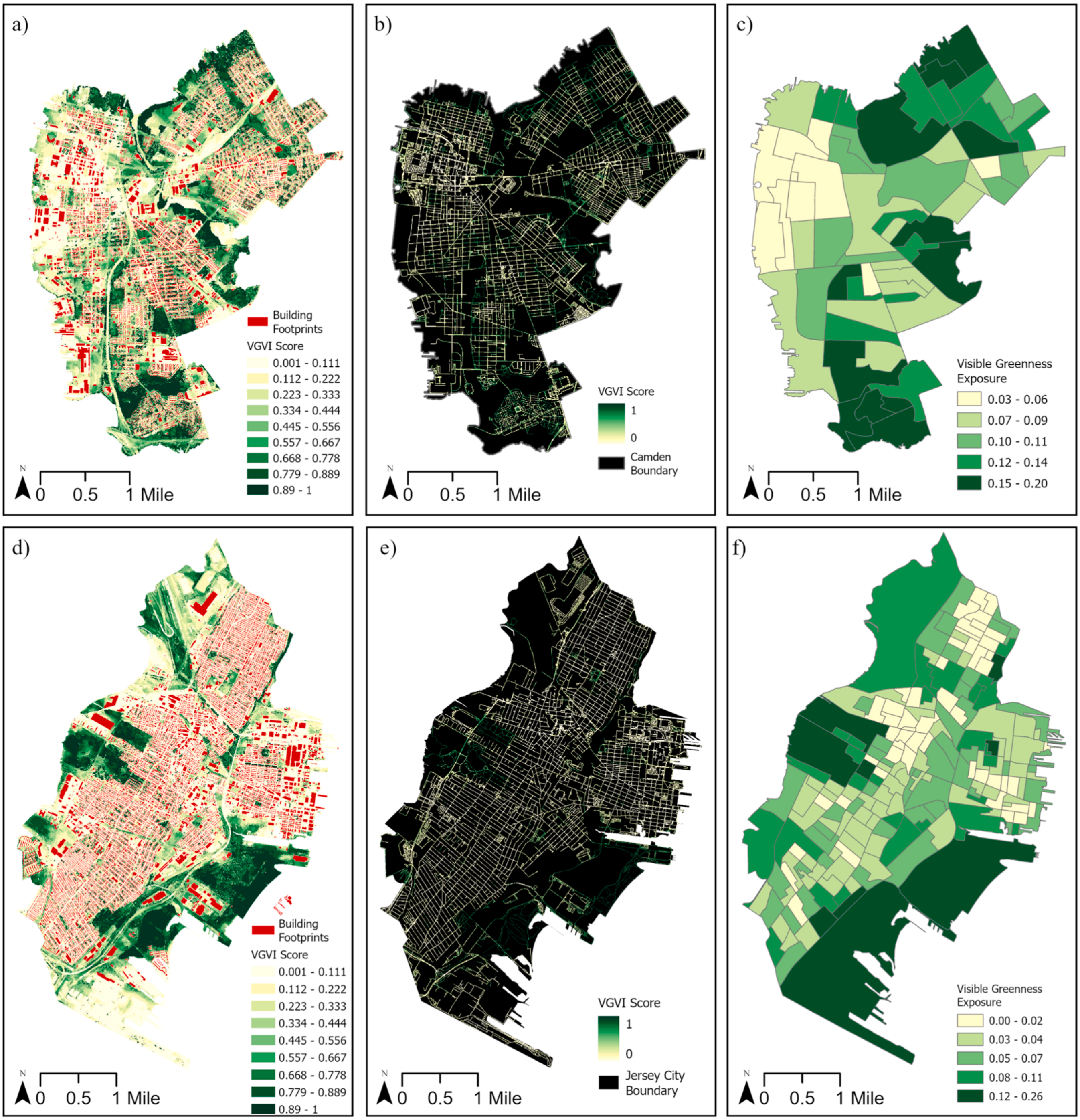

Fig. 4. a) Camden Viewshed Greenness Visibility Index (VGVI), b) VGVI along streets in Camden, c) Visible Greenness Exposure (VGE) at block level in Camden; d) Jersey City Viewshed Greenness Visibility Index (VGVI), e) VGVI along streets in Jersey City, f) Visible Greenness Exposure (VGE) at block level in Jersey.

greenspace accessibility within Jersey City, these disparities may not align closely with traditional EJ factors. Conversely, in Camden, where the overall equitable access to greenspace access is lower, Black and Hispanic populations in segregated areas face challenges in greenspace accessibility. These findings underscore the importance of conducting nuanced analyses that go beyond broad measures of greenspace accessibility. Moreover, the challenge of achieving equitable greenspace accessibility was not consistent across different communities enduring environmental injustices, nor did it affect all vulnerable population groups uniformly.

The disparities in greenspace accessibility observed between Camden and Jersey City prompt further inquiry into potential factors contributing to these differences. Despite Jersey City's abundance of greenspaces and a higher greenspace area per capita, our study reveals significant disparities. Several factors may be contributing to this scenario, such as the presence of large greenspaces like Liberty State Park, which may not adequately serve overburdened neighborhoods. Additionally, issues related to greenspace quality and community engagement may play a role. Even if there are greenspaces available, their condition and how well they meet the needs of the local population are critical factors in determining equitable accessibility.

The findings from the Visible Greenness Exposure model highlight the discrepancy between city-level greenness exposure and street-level visible greenness exposure in Camden and Jersey City. While many

Fig. 5. Examples of streets with high to low VGVI scores in Camden using 3D GIS (represented by darker to lighter green color respectively) and street views.

Table 4
Summary of spatial lag regression for visible green exposure for Camden and Jersey City.

	Camden				Jersey City			
Variable	Coefficient	Standard Error	z-Statistic	p-value	Coefficient	Standard Error	z-Statistic	p-value
Constant	0.049	0.025	1.984	0.047*	0.019	0.007	2.744	0.006*
Low-income %	−0.000	0.000	−0.749	0.454	- 0.000	0.000	−2.152	0.033*
Black Segregation	−0.001	0.023	−0.024	0.981	−0.004	0.009	−0.440	0.660
Hispanic Segregation	−0.012	0.023	−0.524	0.600	0.013	0.012	1.113	0.266
Older Adult %	0.000	0.001	0.159	0.874	0.001	0.000	1.181	0.238
Young population %	−0.000	0.001	−0.041	0.967	0.000	0.000	2.028	0.043*
Weight Visible Green Exposure (VGE)	0.597	0.122	4.881	0.000*	0.587	0.077	7.587	0.000*

* An asterisk next to a number indicates a statistically significant p-value ($p < 0.05$).

areas within these cities exhibit moderate to high levels of greenness exposure when viewed from a broader perspective, street-level analysis reveals poor greenness exposure along most streets, including those connecting residential neighborhoods to nearby greenspaces. This disparity underscores the importance of considering not only overall accessible greenspace within urban areas but also visible greenness exposure at the street level, particularly in relation to pedestrian access to greenspaces. A specific example highlighted in this study is Phoenix Park in Camden, situated amid active and abandoned industrial facilities. Residents from nearby neighborhoods must traverse streets characterized by poor VGE to access the greenspace. This scenario highlights how unappealing walking paths can discourage individuals accustomed to walking to greenspaces, exacerbating issues of equitable access and enjoyment of greenspaces within urban environments. Additionally, our findings indicate that the relationship between greenness exposure and EJ variables is complex. Areas characterized by high concentrations of poverty in Jersey City experience inadequate greenness exposure on the streets, while areas with a younger population display more favorable levels of greenness exposure.

While the measurement of eye-level visible greenness on streets is gaining traction in research studies (Labib et al., 2021; Larkin & Hystad, 2019; Aikoh et al., 2023; Ye et al., 2019; Larkin & Hystad, 2019), the explicit investigation of its relationship with EJ variables remains relatively limited in the literature (Zhou & Kim, 2013). Our study addresses this gap by highlighting how disparities in street-level visible greenness exposure intersect with socioeconomic factors, such as poverty and age demographics, within urban contexts. This contribution sheds significant light on the nuanced connections between visible greenness on streets and social equity, particularly in underserved communities like Camden and Jersey City. Our findings emphasize the potential of initiatives aimed at improving street-level visible greenness, such as tree planting initiatives and green stormwater projects, to enhance pedestrian experiences and promote equitable access to greenspaces.

Tree planting initiatives and green stormwater projects not only enhance the aesthetic appeal of urban streets but also offer tangible and wide-ranging benefits for urban environments (Nguyen et al., 2021). They can contribute to improving air quality, reducing urban heat island effects, and mitigating stormwater runoff (Xiao et al., 2018). Beyond

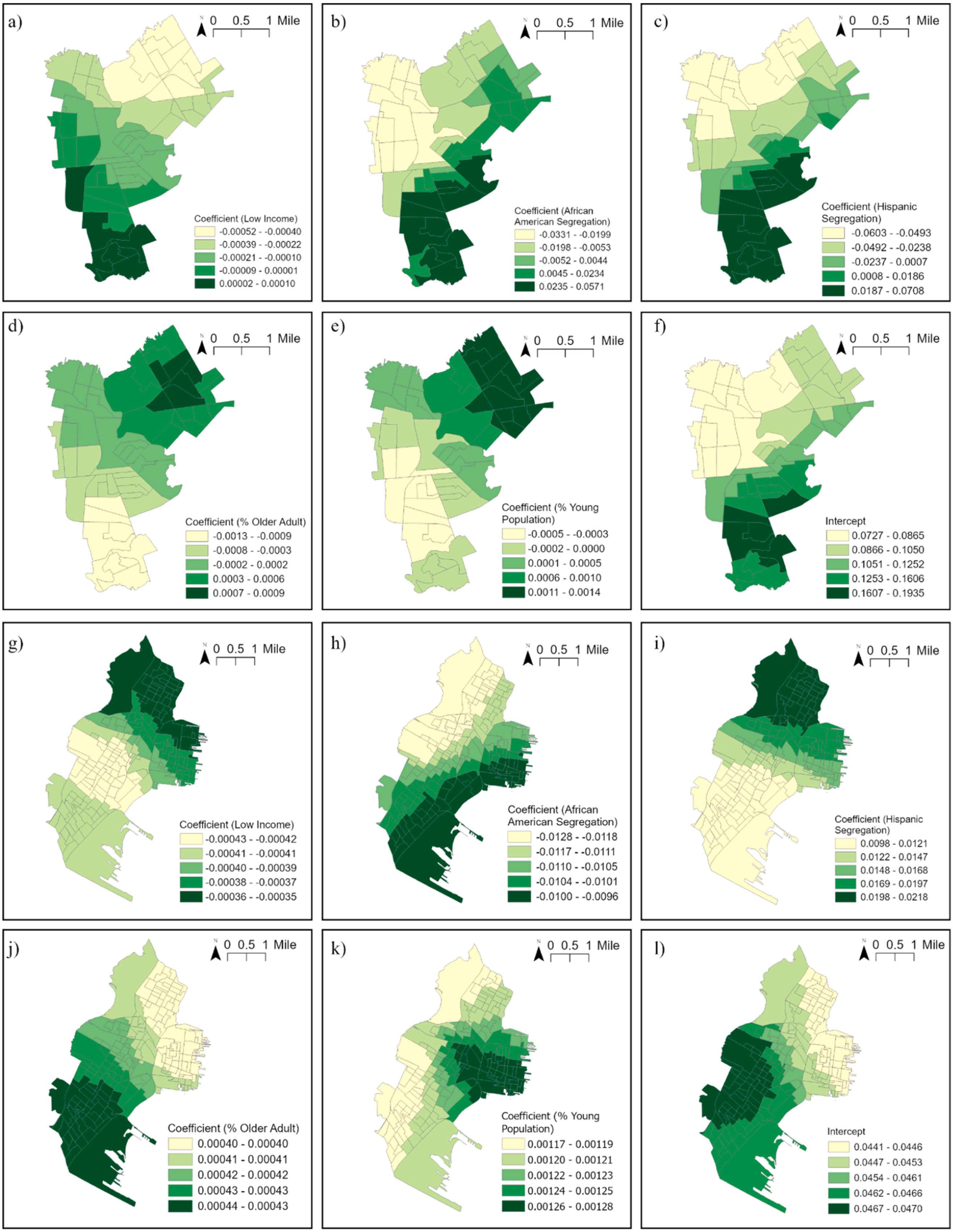

Fig. 6. Coefficient of variables from Geographically Weighted Regression between visible green exposure and EJ variables for Camden (a-f) and Jersey City (g-l).

their environmental advantages, these initiatives have the potential to create more walkable and enjoyable environments. This, in turn, encourages residents to engage with greenspaces more actively. However, it is essential to recognize the disparities in street-level visible greenness exposure highlighted in our study. Despite the potential benefits of tree planting and green stormwater projects, there is a risk that these advantages may not be equally distributed, exacerbating existing environmental justice issues. Therefore, efforts to implement such initiatives should prioritize equitable distribution and accessibility to ensure that all residents can reap the rewards of a greener and healthier urban environment.

5. Conclusion

Our research presents a novel contribution to urban planning and EJ literature by introducing a coupled analysis of equitable greenspace accessibility and street-level visible greenness exposure. This unique approach has not been explored previously. By integrating these two critical dimensions, we provide a comprehensive understanding of the complexities surrounding access to and enjoyment of urban greenspaces. This study is one of the first to systematically examine greenspace accessibility and visible greenness exposure along roads, often overlooked in prior research efforts.

The novelty of our work is further extended to the development of a Greenspace Accessibility model that incorporates factors such as greenspace quality rating, entrance points, and walkability index. The refined model enhances the accuracy of our analyses and facilitates a more nuanced examination of greenspace accessibility within medium-sized urban environments. By incorporating these additional variables, our study moves beyond traditional metrics of greenspace accessibility such as measuring greenspace area within a given distance (Nesbitt et al., 2019). The result is a more holistic assessment of equitable access to greenspace in our study area. Moreover, our investigation into the relationship between street-level visible greenness exposure using the VGVI metric and EJ variables fills a critical gap in the literature, providing valuable insights into the intersectionality of socioeconomic factors and urban green infrastructure that have implications for equitable urban development and community well-being.

The findings from our study hold critical implications for the strategic development of greenspaces and the formulation of policies in Camden and Jersey City and align with recent initiatives aimed at enhancing urban greenspaces in both cities. Camden Mayor Moran's ambitious goal of providing safe and high-quality outdoor spaces within a 10-minute walk of every Camden resident by 2050 resonates strongly with the insights derived from our study, which highlights that successful greenspace planning extends beyond factors such as the number and locations of greenspaces. Instead, it insists on the necessity of taking multiple factors like greenspace entrance points, greenspace quality, and walkability indices, all of which play a pivotal role in ensuring equitable access to greenspaces. These considerations are vital for realizing a more accessible and inclusive urban greenspace network in Camden.

A crucial strategy for greenspace improvement projects is close integration with street and sidewalk improvement initiatives. An integrated approach only enhances safety and increases street-level greenness exposure. By incorporating street greenness concerns into the greenspace planning process, policymakers can address the needs of vulnerable populations, including, older adults, young people, and the urban poor, who rely on walking or public transportation to access greenspaces.

By identifying areas where specific population groups may require better access to quality greenspaces or streets with enhanced greenness, policymakers can guide future capital investment and improvement to ensure equitable and sustainable urban development. This approach aligns with Jersey City Mayor Fulop's vision for 2022 as "the year of open space: in Jersey City and contributes to the broader goal of creating cities that are equitable for all residents.

While our study provides valuable insights into the intersection of greenspace accessibility, visible greenness exposure, and EJ variables within two minority-majority communities, it is important to acknowledge several limitations inherent in our study design and methodology. First, our focus on only two environmental justice-seeking communities may limit the generalizability of our findings to broader urban contexts with more diverse population distributions. Additionally, the use of Google quality ratings for greenspace quality assessment may introduce biases, as these ratings tend to be skewed toward negative responses. Future studies could improve upon this limitation by employing comprehensive greenspace quality scores derived from objective assessments of greenspace conditions.

Furthermore, the VGVI Index utilized in our study may not fully capture all aspects of greenness exposure, particularly greenery obscured by structures. Future studies could explore alternative methodologies to address this limitation, such as incorporating visible green elements tall enough to be seen behind structures. Also, in this study we only extracted VGVI values on the street, ignoring the visibility of greenery beyond the streetscape. This may have resulted in an incomplete representation of greenness visibility.

Moving forward, there is a need for continued refinement and improvement of accessibility and greenness visibility exposure models. Factors such as greenspace quality and the inclusion of previously unexplored aspects of visible greenness must be considered to better inform urban planning and policymaking efforts aimed at promoting equitable access to greenspaces. By understanding the specific challenges faced by diverse demographic groups and communities, urban planners and policymakers can develop more effective strategies to address EJ concerns.

CRediT authorship contribution statement

Md Shahinoor Rahman: Writing – review & editing, Writing – original draft, Visualization, Software, Methodology, Formal analysis, Data curation, Conceptualization. **Mahbubur Meenar:** Writing – review & editing, Writing – original draft, Visualization, Supervision, Resources, Project administration, Methodology, Funding acquisition, Data curation, Conceptualization. **SM Labib:** Writing – original draft, Methodology, Formal analysis. **Ted Howell:** Writing – review & editing, Writing – original draft, Resources. **Deepti Adlakha:** Writing – review & editing, Writing – original draft, Resources. **Ben Woodward:** Writing – original draft, Visualization, Data curation.

Declaration of Competing Interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Mahbubur Meenar reports financial support was provided by the National Aeronautics and Space Administration (NASA). If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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