Persistent Social Vulnerability in Washington D.C. Communities and Green Infrastructure Clustering

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Abstract: Cities worldwide are presently contending with the intricate task of formulating urban infrastructure that seamlessly blends sustainability and resilience to effectively tackle urgent challenges. An increasingly prominent strategy gaining swift traction is the deployment of green infrastructure (GI), heralding a multitude of advantages for the urban milieu. As a growing body of research highlights the emergence of a new equity issue in our infrastructures from the perspective of environmental justice, it becomes evident that there is a significant gap in comprehensive studies investigating the combined temporal and spatial evolution of green infrastructure (GI) distribution. This research aims to address this gap by adopting a novel approach that explicitly considers the temporal dimension of GI distribution. Unlike previous studies that often rely on cross-sectional snapshots, this study employs a panel data analysis, which allows for a comprehensive examination of how GI distribution evolves over time. The primary research question addressed in this study is whether GI distribution in Washington D.C. exhibits a propensity to concentrate within certain communities. This inquiry delves into the pressing concern of the potential exacerbation of existing disparities through GI implementation. The study’s findings may drive evidence-based policy recommendations that foster equitable distribution strategies, guaranteeing that socially vulnerable communities reap the rewards of GI’s positive impacts.

Keywords: green infrastructure; social vulnerability; environmental justice

1. Introduction

In the ever-expanding urban landscapes across the globe, the imperative to design urban infrastructure that not only addresses pressing issues but also stands the test of sustainability and resilience has taken center stage [1]. As urbanization continues to escalate, one approach that is rapidly gaining momentum is the implementation of green infrastructure (GI), which offers a myriad of benefits for urban environments. Among the numerous advantages of GI, one notable feature is its remarkable ability to enhance water quality by effectively filtering pollutants and contaminants from stormwater runoff. Serving as a cost-effective alternative to conventional stormwater infrastructure like pipes and ponds [2], GI serves to curtail stormwater runoff and prevent flooding, enhance air quality, support biodiversity through habitat creation, and increasingly addresses urban heat island effects in the context of escalating global temperatures [3,4].

Despite the numerous benefits that GI offers for urban environments, its implementation has not been equitable across communities. Ironically, the communities that should stand to benefit the most from GI are often the least likely to have access to it [5]. Extensive research has shed light on the correlation between socioeconomic factors and the availability of GI or GI in different communities [6]. Several studies have demonstrated that access to, or the density of, GI may vary significantly based on factors such as racial minority status, income levels, or educational attainment of the communities [6–11]. The findings of these studies are particularly concerning as they highlight the emergence of a new equity issue in our infrastructures from the perspective of environmental justice. The implementation
of GIs, a promising new type of urban infrastructure, might unintentionally exacerbate existing disparities in society, given that infrastructure serves as a mechanism that causes unequal effects on communities both in their daily services and in mitigating the adverse outcomes of environmental extremes [12].

Several studies provide insight into the mechanisms through which certain socioeconomic factors drive the disproportionate distribution of green infrastructures (GIs). Mandarano and Meenar [10] and Dunn [13] discuss the most common approaches to public investment, regulation, and incentives for property owners’ voluntary implementation, each presenting its own set of challenges. These studies emphasize that all three approaches hold the potential to yield uneven benefits, with a particular impact on lower-income residents and underserved neighborhoods. The reason for this lies in the limited capacity of such communities to effectively implement and maintain GIs. It is worth noting that the role of community capacity is pivotal in determining the success of public investment and regulatory mandates [10,13]. On a different note, Lim [9] introduced the concept of information diffusion and applied it to the voluntary participation of property owners in the implementation of GIs. This concept effectively illustrates the tendency of GIs to cluster in more affluent communities. This phenomenon arises from the finding that wealthier communities often possess more abundant resources and extensive networks, facilitating their superior access to and dissemination of information about GI programs [9]. Consequently, these communities tend to be more actively engaged in GI initiatives. In essence, Lim’s [9] findings suggest that the unequal distribution of GIs remains an ongoing challenge.

However, previous studies that employed regression analysis with cross-sectional data [6–11] did not determine whether this unequal distribution is persisting and, consequently, if the disparity between communities has deepened. Because of their methodological limitations, they just provide snapshots of a specific moment, capturing relationships between variables within a fixed timeframe. While valuable insights can be gleaned from cross-sectional data, they fail to capture the intricate temporal trends and changes that may occur in GI distribution and its determinants.

GI programs are ongoing or being implemented as an equitable way to improve stormwater management and reduce the impacts of global warming in many places, and it indicates that the distribution of GI may continuously change. Neglecting GI development in socially vulnerable areas can lead to higher long-term costs for both communities and governments. Without proper GI development, these areas may face increased healthcare costs, property damage, and infrastructure repair expenses due to inadequate protection from environmental hazards. It is necessary to observe the temporal trends of GI distribution, considering that it can help (1) identify areas where additional investments in GI may be required to achieve more equitable distribution, (2) provide insights into the factors affecting the distribution, and (3) evaluate the effectiveness of policies and programs aimed at promoting the adoption of GI. To be specific, understanding the factors driving the adoption and the distribution of GI can help not only inform the development of more effective policies and programs for GI but also expect future distribution.

Despite the critical importance of understanding how green infrastructure (GI) distribution evolves over time, only a few studies captured the temporal trends or changes in GI distribution. Pallathadka et al. [14] investigate the historical GI data and show changes in GI distribution. However, their analysis to test the correlations between sociodemographic factors and GI density is based on cross-sectional data, which means they did not reveal the temporal driving factors of the GI distribution. Although Lim [9] employed the shuffle test method in his research and revealed that the previous GI location had an impact on the placement of new GI adoption in Washington D.C., his findings on the factors driving the GI distribution are based on a cross-sectional analysis using Geographically Weighted Regression, with a sample limited to voluntary participation in GIs, accounting for only about 12% of the total GIs as of 2020. Thus, spatial panel data analysis is necessary to identify the temporal trend of the whole GIs in Washington D.C. and find the factors that
continuously affect the distribution. It is an essential tool for examining the dynamic relationships between changing infrastructures and the driving factors.

This research fills the significant gap by adopting a novel approach that explicitly considers the temporal dimension of GI distribution. Unlike previous studies that often rely on cross-sectional snapshots, this study employs a balanced panel data analysis, which allows for a comprehensive examination of how GI distribution evolves over time. By utilizing panel data, I capture the dynamics and trends that cross-sectional analyses may overlook, thus providing a more accurate representation of the changing landscape of GI distribution. Moreover, this study introduces a crucial and previously unexplored dimension by integrating a social vulnerability index into the analysis. While previous research has highlighted the unequal distribution of GI, our study goes beyond this by assessing the relationship between socioeconomic characteristics and GI distribution over time, especially in the context of socially vulnerable communities. This innovative approach helps identify areas that are most in need of GI investment, ensuring that the benefits of GI are directed toward the communities facing the greatest challenges.

This research seeks to address the following research question: Has the distribution of GI in Washington D.C. shown a tendency to concentrate more in communities with higher racial majorities and greater wealth? It addresses a pressing concern regarding the potential exacerbation of existing disparities in GI. By investigating this question, this study has the potential to inform policymakers, urban planners, and community stakeholders about the fairness and inclusivity of GI implementation. The results could lead to evidence-based policy recommendations that promote more equitable distribution strategies, ensuring that disadvantaged communities benefit from the positive impacts of GI. This article is organized as follows. First, the next section focuses on presenting the methodology adopted and specifics about the data used. Next, I show the main results obtained in the spatial panel regression analysis and present a discussion based on the temporal correlations between GI and socially vulnerable status. Thereafter, limitations, future research directions, and main conclusions are discussed.

2. Data and Methods

2.1. Study Area—Washington D.C. and Green Infrastructure

Washington, D.C., like other global cities, stands at the forefront of its green infrastructure (GI) programs. Between 2010 and 2019, the annual increase in GIs was roughly 2000, resulting in a cumulative total of 22,756 GIs distributed across Washington D.C. by the end of 2019. Currently, approximately seven programs, such as D.C. Clean River projects and River Smart Homes, are actively being implemented by three D.C. agencies, including the Department of Energy and Environment (DOEE), the District Department of Transportation (DDOT), and the District of Columbia Water and Sewer Authority (D.C. Water). Although there is no singular comprehensive planning and implementation agency for GI programs, D.C. Water’s Long Term Control Plan (LTCP) strives to integrate diverse GI practices, thereby formalizing voluntary and community-based interventions [15]. The LTCP for combined sewer overflows identifies sewer sheds operating below capacity, specifying locations where GIs should be situated [16].

While DOEE, D.C. Water, and DDOT each administer distinct GI programs, they collectively adhere to a consistent definition and purpose of GI. This shared definition, as outlined in the Stormwater Management Guidebook and on the D.C. Water website [17–19], defines GI as a set of environmentally sustainable strategies implemented in urban areas to effectively manage stormwater quantity and quality, with the primary aim of reducing stress on sewer systems, mitigating aquatic resource pollution, and enhancing protection for urban water bodies. This shared interpretation underscores the focus of GI on stormwater management. Furthermore, the agencies recognize that GI extends its benefits beyond stormwater runoff, providing advantages across environmental, societal, and economic domains. Notable examples of GI practices in D.C. encompass rooftop collection systems, permeable pavements, and bioretention [17–19].
On the other hand, considering the array of options available in local strategies for implementing GI programs, including public investment, the inclusion of regulatory mandates within construction permits, and the offering of incentives to encourage voluntary involvement [13], Washington, D.C. employs all three of these approaches. However, given that the predominant drivers behind GI adoption in D.C. are redevelopment and new construction initiatives, coupled with voluntary engagement [15], and the local GI strategies may drive the unequal distribution of GIs in advantaged communities, GI programs over ten years may result in an unequal distribution of GIs across communities.

Washington, D.C., exhibits longstanding wealth disparities between White communities and communities of color [20]. Kijakazi et al. [20] reveal racial and ethnic differences in net worth and illustrate how discrimination and systemic racism have contributed to the current wealth gap in the nation’s capital. White households in D.C. possess a net worth 81 times greater than that of Black households, with White households having a net worth of USD 284,000 compared to Black households’ net worth of USD 3500 in 2013 and 2014. Additionally, the typical home value for Black households in D.C. is USD 250,000, approximately two-thirds of the value for White and Latino households [20]. The following maps depict the enduring socioeconomic disparities between Northwest D.C. (where White communities are predominant) and Southeast D.C. (where Black communities form the majority). While the population density maps may not intuitively illustrate this gap, the D.C. Policy Center [21] reports that in areas of Washington, D.C. where White residents remained, many local authorities employed zoning ordinances and other measures to maintain neighborhoods characterized by low-density, single-family homes. Simultaneously, they directed the development of apartment buildings toward low-income areas predominantly inhabited by Black communities. In light of these disparities, it becomes evident that Washington, D.C. has exhibited persistent social vulnerability from 2010 to 2019 (see Figure 1).

2.2. Data

The panel dataset used in this study was sourced from multiple data sources. The green infrastructure data was obtained from OpenData D.C., which includes information on the location, type, and size of green infrastructure projects. The data was regularly updated, and the latest version, which was released in May 2022 and includes a total of 22,756 GI projects, was used in the analysis. Using Geoprocessing in ArcMap, the annual increase in the number of green infrastructures was calculated based on this raw data. The National Land Cover Dataset provided information on imperviousness rates, which were used to calculate the average proportion of impervious surfaces in each census block group using the Zonal statistic tool. Socioeconomic indicators, including median income, median house value, median rent price, etc., were sourced from the American Community Survey (ACS).

The dataset for spatial panel regression comprises a 10-year observation of 450 census block groups in Washington D.C. The dataset includes the annual increase in green infrastructure, landscape and urbanization proxies, 10 socioeconomic indicators, and a social vulnerability index consisting of the indicators (see Table 1). The dependent variable is the annual increase in green infrastructure. The independent variable is the social vulnerability index, which measures the social and economic characteristics of the population living in each census block group, consisting of the 10 socioeconomic indicators of a census block group. These indicators include median income, median house value, median rent price, the educational attainment level representing the proportion of people without a high school degree, the proportion of households living below the poverty level, the proportion of renters, and the proportion of female-headed households. The analysis unit for this study is the census block group. Census block groups are often preferred over census tracts for analyzing community characteristics because they provide a finer level of geographic detail. According to the United States Census Bureau, a census block group is a “statistical subdivision of a county that is a combination of blocks, having a population of
“600 to 3000 people” [22]. The dataset is a perfectly balanced panel from 2010 to 2019 and observing 450 census block groups in D.C. Having a balanced panel dataset allows for the examination of changes that occur over time within each census block group. Some null values in the ACS data have been replaced with the median value.

Figure 1. Persistent socioeconomic disparities in Washington, D.C. The maps above illustrate that socioeconomic disparities in racial composition (a), income (b), population density (c), and community social vulnerability (d) have endured in the city from 2010 to 2019. Specifically, the gap between the communities of Northwest and Southeast is evident. Washington D.C. is organized into four administrative geographical quadrants (a).
Table 1. Variable list and the sources.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Description</th>
<th>Unit</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>Annual increase in GI</td>
<td>Annual increase in the number of GIs in a census block group</td>
<td></td>
<td>D.C. open data</td>
</tr>
<tr>
<td>Building area</td>
<td>Sum of building floor area in a census block group</td>
<td>square foot</td>
<td>D.C. open data</td>
</tr>
<tr>
<td>Building age</td>
<td>Average building age in a census block group</td>
<td>years</td>
<td>ACS 2010–2019 (5-year estimates)</td>
</tr>
<tr>
<td>Impervious rate</td>
<td>Proportion, sum of impervious surface area/area of census block group</td>
<td>%</td>
<td>The National Land Cover Dataset 2016</td>
</tr>
<tr>
<td>Average elevation</td>
<td>Average altitude above sea level of a census block group</td>
<td>foot</td>
<td>D.C. open data</td>
</tr>
<tr>
<td>Average slope</td>
<td>Average slope of a census block group</td>
<td>%</td>
<td>D.C. open data</td>
</tr>
<tr>
<td>MS4 system</td>
<td>Dummy variable (0: the census block does not include MS4 shed; 1: the whole area of a census block group has MS4 system)</td>
<td></td>
<td>D.C. open data</td>
</tr>
<tr>
<td>Population density</td>
<td>Population density people/square mile</td>
<td></td>
<td>D.C. open data</td>
</tr>
<tr>
<td>Social Vulnerability Index</td>
<td>Sum of standardized values of (1) median house value; (2) median rent price; (3) median income; (4) percent of rent households; (5) percent of female householders; (6) percent of children (under 5 years old); (7) percent of elderly people (more than 65 years old); (8) percent of people with less than high school graduation; (9) percent of families below poverty level; and (10) percent of African American population</td>
<td></td>
<td>ACS 2010–2019 (5-year estimates)</td>
</tr>
</tbody>
</table>

The control variables are the landscape and urbanization proxies, which include building age, imperviousness rate, average surface slope, and average elevation. These variables provide insights and details about the built environment. They represent factors that possess the potential to influence the placement of green infrastructure, particularly in light of its functions, such as mitigating pluvial flood risks and alleviating urban heat island effects. The selection of these variables aligns with the analysis models from the existing literature on green infrastructure [6–8,10,14], which has examined both the cooling effects and the distribution of green infrastructures within different communities. Additionally, guidance from a Maryland design manual has informed this selection [23].

2.3. Social Vulnerability Index

Although numerous vulnerability indicators appear in the literature on social vulnerability, there is no specific standard for which indicators are most significant for social vulnerability. Social vulnerability studies often use a diverse set of proxies for their indicators, with different studies using different proxies for the same indicators [24]. Based on these practices for determining SoVI and the available data provided by the ACS, I chose 4 social vulnerability indicators of personal wealth, gender, race, and age, and 10 common proxy variables representing the indicators from the disaster literature [25–30], as seen in Table 1.

The choice of these four social vulnerability indicators—personal wealth, gender, race, and age—alongside ten common proxy variables, stems from several key considerations. Firstly, an individual’s income and assets play a crucial role in enhancing their ability to
prepare for and recover from climate-related extremes or disasters, a point underscored by Cutter et al. [31]. Furthermore, Fothergill and Peek [28] highlight that poverty in the United States amplifies vulnerability to natural disasters due to factors like geographical location, housing conditions, construction quality, and social exclusion. The role of education is also significant in this context. Individuals with lower levels of education, as described by Morrow [32], frequently encounter practical and bureaucratic challenges when dealing with disaster preparedness and recovery processes, while people with higher educational backgrounds generally have better access to and make more effective use of information related to hazards. Meanwhile, children and the elderly emerge as particularly vulnerable groups during disasters due to their limited coping capabilities, as evidenced by Aldrich and Benson [27] and Peek and Stough [26]. Minority status compounds vulnerability, with racial and ethnic groups facing elevated risks due to social and economic marginalization, as well as real estate discrimination, as documented by Morrow [32], Cutter et al. [31], and Bullard [33]. Finally, Enarson [29] and Fothergill [30] shed light on how women in female-headed households often shoulder primary caregiving responsibilities, a circumstance that can curtail their involvement in income-generating activities and community-based disaster preparedness initiatives, ultimately making evacuation and seeking shelter during disasters more challenging for them.

I standardized the 10 variables using the mean and standard deviation for each variable. All standardized scores were then summed under the assumption that each proxy contributes equally to the overall vulnerability of the block group, similar to the approach taken in the study by Cutter et al. [31].

2.4. Spatial Clustering of GI

In order to assess the spatial clustering of green infrastructure in Washington D.C., I utilized the Local Moran’s I with queen contiguity-based spatial weight matrix and the hot spot analysis. The analysis was conducted using ArcMap 10.5 software. In addition to Moran’s I, I used an optimized hot spot analysis tool to further confirm the clustering of GI in Washington D.C. Hotspot analysis is a spatial mapping and analysis method that focuses on identifying clusters of spatial phenomena, which are typically represented as points on a map, and it was conducted using the Getis–Ord Gi* statistic [34]. The Getis–Ord Gi* statistic was developed by Getis and Ord [35] as an extension of the standard spatial autocorrelation statistic, Moran’s I. The Gi* statistic measures the degree of concentration of a variable within a defined neighborhood, taking into account both the intensity and spatial pattern of the variable.

In the hot spot analysis, I chose the “count-incidents-within_fishnet-polygons” option. It allows me to aggregate point data into a grid of equally sized rectangular cells called a fishnet. The tool then counts the number of point incidents that fall within each cell of the fishnet grid. I set the cell size of 500 feet by 500 feet. The chosen cell size of 500 feet by 500 feet results in an area of 250,000 square feet. The area of census block groups in D.C. varies from 335,347.62 to 122,896,846.26 square feet, making it evident that the analysis cell size is smaller than the census block group area. By setting a smaller analysis cell size, the potential averaging of data within each block group can be reduced, providing a more accurate representation of the specific location of GIs and enabling a more precise analysis of their clustering.

2.5. Spatial Panel Regression

Spatial panel regression is a statistical method used to analyze panel data where both spatial dependence and time dependence are present. It extends the standard panel regression by incorporating spatial autocorrelation and heterogeneity in the data. I used the “spgm” function from the “splm” package in R to estimate spatial panel data models using the generalized-moments (GM) estimator. The generalized-moments (GM) estimator has two advantages over the maximum-likelihood approach; the first advantage is that the GM estimator’s consistency is not affected by whether or not the errors follow a normal
distribution, and the second advantage is that the calculation of the is straightforward, even for extremely large samples [36,37]. Also, GM estimation is a flexible method that can be used to estimate a wide range of models, including those that suffer from endogeneity [38]. Considering these advantages and the fact that the panel dataset in this study is a balanced panel with 4500 observations and makes the spatial weight matrix consist of 450 census block groups, GM estimation would serve as a good alternative to the maximum-likelihood estimation method.

In the spatial panel dataset, except for the social vulnerability index, population density, and building age, most variables representing landscape factors and urbanization factors are time invariant. This indicates that the fixed-effect model cannot be estimated because there is no variation in the explanatory variables within each individual observation. In this case, the random-effects model is the only feasible option. The random-effects model assumes that the unobserved heterogeneity that affects the outcome variable is uncorrelated with the independent variables, including the time-invariant variables. This assumption allows the random-effects model to capture the unobserved heterogeneity among the individuals in the sample and estimate the average effects of the observed variables on the outcome variable. To statistically detect random effects empirically, I used Lagrange Multiplier tests using the “splm” package and its “bsktest” function. The tests are commonly used to detect random effects and correlation (serial or cross-sectional) in panel data models [38]. I estimated both the spatial lag and spatial error models within the framework of the random-effects model. I then compare the goodness-of-fit of these models using model selection criteria, including the Akaike Information Criterion (AIC), the Bayesian Information Criterion (BIC), and the assessment of statistical significance for spatial parameters.

3. Results

3.1. GI clustering

The interpretation of Univariate Local Moran’s I depends on the sign of the index and the significance level of the test. The statistic of the spatial autocorrelation suggests that the pattern of GIs at census block groups is clustered. The Moran’s Index is 0.371 with a z-score of 14.065, and the p-value is 0.001. Although it is difficult to say that there is a stronger clustering given that the value close to 1 indicates perfect clustering, the probability that the observed clustering pattern is due to random chance is less than 1 percent as the critical value is greater than 2.58.

Additionally, the below cluster map identifies areas where there is a significant spatial concentration of high or low values of a variable of interest, which can provide insight into the spatial patterns (see Figure 2). The presence of a high–high (HH) cluster on the LISA cluster map suggests that there is a spatial concentration of GIs in a specific area in D.C. Northeast and Northwest, where there are many GIs surrounded by neighboring areas with similarly high numbers of GIs. On the other hand, a low–low (LL) cluster in some communities in D.C. Southeast and around the National Mall indicates a spatial concentration of areas with fewer GIs, surrounded by neighboring areas with similarly low numbers of GIs. Overall, these patterns suggest that the concentration of GIs across D.C. varies across different spatial areas.

The optimized hot spot analysis also suggests that GIs in D.C. are clustering. If a z-score of Gi* statistic returned for each data cell of 500 feet by 500 feet is statistically significant and positive, it means that there is a strong clustering of high values, also known as a hot spot. In such cases, the larger the z-score, the stronger the clustering of high values. Conversely, if a z-score is statistically significant and negative, it means that there is a strong clustering of low values or a cold spot. In such cases, the smaller the z-score, the stronger the clustering of low values. Thus, the map output of the hot spot analysis illustrates that GIs are highly concentrated near the border of the Northeast and Northwest and in the Northeast. Although the concentration of GI is also observed in Southeast D.C., its size is much smaller than that of Northeast and Northwest D.C. The hot spot that exists around
the central part of D.C. is a different point compared to the above cluster map. This reflects that analyzing the spatial clustering using Moran’s I can distort information about the true location of GI clusters.

Figure 2. GI clustering in Washington D.C.
Both the Univariate Local Moran’s I and the optimized hot spot analysis indicate that the pattern of GIs in D.C. is clustered. Although the two tools output different results regarding Southeast D.C., the LISA cluster map identifies significant clusters in the Northeast and Northwest, and the optimized hot spot analysis also shows that the GIs are highly concentrated in the same area of D.C. These results suggest that the concentration of GIs across D.C. varies across different spatial areas.

3.2. Spatial Panel Regression Results

The Table 2 displays the Lagrange multiplier test results. The test includes SLM1, SLM2, and LM*-lambda conditional tests as proposed by Baltagi et al. [39], which investigate the panel data regression model with spatial error correlation by combining ideas from two previous research strands. The output shows the statistically significant LM1 test statistic. The SLM1 is for testing spatial autocorrelation in linear regression models with random effects [39], and thus the result indicates strong evidence against the null hypothesis of no spatial correlation in the model, in favor of the alternative hypothesis of random effects. Both SLM2 and the Conditional Lagrange Multiplier (LM*)-Lambda tests examine the presence of spatial autocorrelation in the specified regression model in which the dependent variable is cnt and the independent variables are sovi, popden, impvs, slope, and elev. Only with SLM2, researchers cannot exclude the possibility of incorrect inference when the “variance component” referring to the variability of the random effect is large [38]. To address this issue, Baltagi et al. [39] developed a conditional LM test that tests for the existence of spatial autocorrelation in the regression model while allowing for the possibility that the variance component may or may not be zero. Based on both test results, I can reject the null hypothesis of no spatial autocorrelation and conclude that there is evidence of spatial autocorrelation in the model.

**Table 2. Baltagi, Song, and Koh LM test for spatial panel.**

<table>
<thead>
<tr>
<th>Model</th>
<th>GIs’ Annual Increase ~ Sovi + Popden + Impvs + Slope + Elev</th>
<th>Test Statistic</th>
<th>Statistic</th>
</tr>
</thead>
<tbody>
<tr>
<td>SLM1</td>
<td>Alternative Hypothesis: Random Effects</td>
<td></td>
<td>48.853 *</td>
</tr>
<tr>
<td>SLM2</td>
<td>Alternative Hypothesis: Spatial Autocorrelation</td>
<td></td>
<td>23.753 *</td>
</tr>
<tr>
<td>LM*-lambda conditional</td>
<td>Alternative Hypothesis: Spatial Autocorrelation</td>
<td></td>
<td>11.556 *</td>
</tr>
</tbody>
</table>

*: p < 0.01.

The Table 3 show the coefficients and statistical significance of a spatial panel regression model estimated using three different methods: Pooled OLS, Panel Spatial Autoregressive (SAR), and Panel Spatial Error Model (SEM). The analysis is based on a dataset with 4500 observations over a panel length of 10 years and 450 census block groups. The dependent variable is the annual increase in GI, and the independent variables are the social vulnerability index, population density, the proportion of imperviousness surface, the average slope of the community, and the average altitude of the community.
Table 3. Spatial panel regression results.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Pooled OLS</th>
<th>Panel SAR</th>
<th>Panel SEM</th>
</tr>
</thead>
<tbody>
<tr>
<td>Annual increase in GI</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>SoVI</td>
<td>−0.011025 ***</td>
<td>−0.017741 ***</td>
<td>−0.020207 ***</td>
</tr>
<tr>
<td>Popden</td>
<td>−0.000029527 ***</td>
<td>−0.000011272 ***</td>
<td>−0.000016773 ***</td>
</tr>
<tr>
<td>Impervious</td>
<td>−0.96456 ***</td>
<td>−0.46629</td>
<td>−1.491 ***</td>
</tr>
<tr>
<td>Slope</td>
<td>−0.42821 ***</td>
<td>−0.15351 *</td>
<td>−0.32335 ***</td>
</tr>
<tr>
<td>Elevation</td>
<td>0.14735 ***</td>
<td>0.031555</td>
<td>0.12163 ***</td>
</tr>
<tr>
<td>Intercept</td>
<td>2.5074 ***</td>
<td>0.75368 **</td>
<td>2.4722 ***</td>
</tr>
<tr>
<td>ρ (Spatial)</td>
<td>0.8270 ***</td>
<td></td>
<td></td>
</tr>
<tr>
<td>λ (Error)</td>
<td>0.3456</td>
<td></td>
<td></td>
</tr>
<tr>
<td>R square</td>
<td>0.1557</td>
<td>0.1560</td>
<td>0.1425</td>
</tr>
<tr>
<td>Lag</td>
<td>611.23 ***</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Robust Lag</td>
<td>47.53 ***</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Error</td>
<td>564.21 ***</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Robust Error</td>
<td>0.51679</td>
<td></td>
<td></td>
</tr>
<tr>
<td>AIC</td>
<td>15,818.42</td>
<td>14,563.40</td>
<td>15,888.23</td>
</tr>
<tr>
<td>BIC</td>
<td>15,863.31</td>
<td>14,621.11</td>
<td>15,933.11</td>
</tr>
</tbody>
</table>

*: $p < 0.1$, **: $p < 0.05$, ***: $p < 0.01$.

The results of the “locally robust panel Lagrange multiplier test” for spatial dependence [38], which is based on the OLS estimation, show that there is strong evidence of spatial lag dependence, as the LM test statistic of 611.23 for spatial lag dependence has a very low $p$-value ($<2.2 \times 10^{-16}$). This suggests that the value of the dependent variable in each observation is spatially correlated with the value of the dependent variable in neighboring observations. Also, the locally robust LM test for spatial lag dependence supports this conclusion, with a statistic of a low $p$-value of $5.418 \times 10^{-12}$. On the other hand, the LM test for spatial error dependence also has a statistically significant value of 564.21, indicating that there is evidence of spatial error dependence in the data. This means that the errors in the regression model are not independent, but rather, are correlated with the errors in neighboring observations. However, the locally robust LM test for spatial error dependence, which accounts for spatial heterogeneity, does not support the presence of spatial error dependence, as the $p$-value is relatively high (0.4722). This may indicate that the spatial autocorrelation in the errors is not consistent across all observations, but rather varies locally.

Like these results, the coefficient of the spatial parameter $\rho$ (spatial) is positive and statistically significant at the 1% level, indicating the presence of spatial autocorrelation in the data. On the other hand, the coefficient of the spatial parameter $\lambda$ (error) is positive but not statistically significant, suggesting that the spatial errors are not systematically related to the independent variables. Additionally, the AIC and BIC values show that the Panel SAR model has the lowest information criteria, and the r-squared value of the SAR is slightly higher than the other two models. In sum, the results from the Lagrange multiplier test and the estimation of regression models indicate that the Panel SAR model is the best model among the three in terms of balancing goodness of fit and model complexity. The Panel SAR model accounts for the spatial autocorrelation between dependent variables by incorporating a spatial lag of the dependent variable in the regression equation, which would improve the accuracy of the parameter estimates, considering that the coefficient estimates for the annual Increase in GI in the Panel SAR model are smaller than the Pooled OLS and Panel SEM models.
The results show that the variables representing social vulnerability and population density are negatively associated with the annual increase in GI, and the coefficients are statistically significant at the 1% level in all three models. This analysis is a kind of panel regression, which reveals that a statistically significant negative coefficient means that as the independent variable increases within each individual entity over time, the dependent variable tends to decrease. Thus, the relationship implies that communities with much socially vulnerable or higher population density had experienced lower increases of GI annually, from 2010 to 2009. Also, considering that the SAR model is the best, the significant spatial parameter $\rho$ means that the annual increase in GI in one census block group is positively correlated with the annual increase in GI in neighboring census block groups. In other words, the results suggest that neighboring communities’ increases in GI are affected by the annual increase in GI within their neighboring communities. Also, consider that the coefficient estimates for the annual increase in GI in the Panel SAR model are smaller than the Pooled OLS and Panel SEM models.

On the other hand, while the coefficients of the proportion of imperviousness surface, the average slope of the community, and the average altitude of the community are significant in the pooled OLS and the panel SEM, their influence on GI is not directly observable in the panel SAR model. The estimated effects of these independent variables may be overestimated or biased due to unobserved spatial factors in the pooled OLS and the panel SEM.

4. Discussion

4.1. Social Vulnerability and Green Infrastructure Growth

The analysis results indicate that communities with higher social vulnerability have experienced relatively fewer advancements or developments in terms of GI compared to other communities. This could imply that disparities in GI investment or development have persisted or even worsened for socially vulnerable communities during the 2010s. In other words, the communities that are more socially vulnerable have not seen as much progress in terms of increasing their GI compared to communities that are less vulnerable. This link between social vulnerability and GI growth has led to an uneven clustering of GIs across communities in Washington D.C., which carries significant implications for vulnerable groups during extreme weather conditions. The lack of sufficient GI in socially vulnerable communities can hinder their ability to adapt to changing climatic conditions and cope with the adverse effects of extreme weather events. In scenarios involving pluvial flooding or excessive heat, these deepening unequal distributions of GIs can result in varying levels of protection for different communities. Consequently, the exacerbation of disparities in GI development could lead to increased health disparities, reduced quality of life, and heightened social and economic vulnerabilities for these communities.

This disparity in protection can further exacerbate existing inequities during environmental extremes, as observed in previous disaster cases. Bolin and Kurtz [25], Bullard [33], and Fothergill and Peek [28] demonstrate that individuals from groups already vulnerable before disaster experience relatively greater property damage and disproportionate support from societies during such events. This phenomenon intensifies the pre-existing socioeconomic disparities among communities.

Examining the aftermath of Hurricane Katrina in New Orleans allows us to dissect the specific mechanisms through which unequal infrastructure protection can heighten vulnerabilities and perpetuate long-standing patterns of marginalization. This focused approach facilitates drawing vital parallels between the New Orleans case and our current study area, shedding light on broader implications for urban planning and equity. Bullard [33] delves into how factors such as race, socioeconomic status, and place intersected with environmental concerns during and after the disaster. Before Hurricane Katrina struck, African Americans in New Orleans settled in areas that were relatively more vulnerable to flooding within a discriminatory context, ultimately resulting in greater flood damage for them. However, Bullard [33] argues that institutionalized racism played a role in the
post-disaster processes of cleaning up, sheltering, providing housing, and levee protection. He asserts that they experienced discrimination during these processes. Specifically, this case illustrates how already vulnerable groups, once again, faced discrimination in protective measures of infrastructure after the disaster, ultimately placing them at greater risk once more. Bullard [33] posits that the unequal protection from infrastructure in New Orleans can be traced back to historical, social, and political structures and institutions that have systematically maintained unequal access to resources and opportunities for disadvantaged populations. Socially vulnerable groups could be excluded or unrecognized in decision-making processes related to protective infrastructure or mitigation measures, which can lead to increased vulnerability to disasters and climate change. This suggests that socially vulnerable people may experience the perpetuation of historical patterns of marginalization through disaster events and inequitable infrastructure settings.

It is important to note that measures aimed at mitigating or adapting to climate change can, ironically, result in unintended consequences that exacerbate vulnerability. While these ‘good’ measures are often conceived with the intention of alleviating risk and vulnerability [40], their practical impact may fall short of this goal if their distribution lacks equity, given that vulnerability is a relative concept [31]. Reckien et al. [41] assert that adaptation and mitigation policies may disproportionately affect vulnerable populations when not adequately designed. Thus, the introduction and implementation of mitigation or adaptation measures should not solely center on enhancing overall social vulnerability reduction and resilience at a citywide scale. Instead, they must also encompass considerations of potential discrimination against vulnerable groups or the exacerbation of their vulnerabilities. In other words, infrastructure development addressing climate change and disaster challenges necessitates more than just technical solutions. It involves decision-making processes, policies, and social contexts that influence the implementation and distribution of these measures. The presence of infrastructural disparities in certain neighborhoods is not due to a single event, act of discrimination, or capital improvement project [42]. Rather, these disparities result from a series of entrenched obstacles woven into planning practices, policies, and implementation frameworks [42]. I defer the investigation of this potential to be explored in future studies.

4.2. Higher Density and Green Infrastructure

The findings derived from the analysis unveil a significant and noteworthy negative correlation between population density and the annual growth of green infrastructure (GI) in the context of Washington D.C. This association underscores the potential challenges that arise when attempting to introduce and expand GI initiatives within densely populated urban environments. The observed negative relationship suggests that higher population densities within the city are intertwined with constraints on the adoption and integration of green infrastructure, primarily due to limitations in available land and restricted space for implementation. These limitations can impede the effective implementation of GI programs, resulting in an intricate interplay between the pressing need for urban sustainability and the inherent constraints posed by dense urbanization. Exploring innovative strategies for integrating green infrastructure within densely populated areas becomes paramount. Designing adaptable and space-efficient GI solutions that can thrive within the constraints of limited urban space holds promise for mitigating the challenges imposed by high population densities. Such strategies could encompass vertical greenery, rooftop gardens, pocket parks, and other creative approaches that optimize available space while enhancing urban livability and resilience.

Ferguson et al. [43], Wolch et al. [11], and McConnachie and Shacketon [44] suggest that when investigating the reasons behind unequal green space access for certain racial groups, researchers are increasingly acknowledging that it is not just about any one factor in isolation. Rather, they are exploring how multiple elements converge to shape these disparities. Further investigation could delve into the potential ripple effects of the observed negative correlation. For instance, understanding how this relationship inter-
acts with other socioeconomic factors, such as ethnicity and deprivation, could provide a deeper understanding of the complex dynamics underlying unequal green space access. This expanded analysis might shed light on whether certain demographic groups face compounded challenges due to the overlapping effects of multiple factors.

4.3. GI Clustering Mechanism and Policy Implications

The spatial autoregressive panel model accounts for spatial dependence in this panel dataset by introducing a spatial lag variable that reflects the average value of the dependent variable in neighboring units. That is, the results show that GI’s annual increase in a community is influenced not only by its own characteristics (here, social vulnerability and other independent variables) but also by neighboring communities’ GI increase. This spatial dependence between communities in GIs in part corresponds to Lim’s finding [9] that the property owners’ voluntary participation in GI implementation is influenced by the locations of previous installations. However, his research was limited to voluntary GI implementation by property owners, which accounts for only 5012 of the total 33,813 GIs in D.C. as of 2022. Focusing solely on voluntary participation by property owners may not provide a complete picture of GI implementation patterns. A more comprehensive understanding of GI clustering is necessary to effectively address issues related to GIs and environmental justice. As Mandarano and Meenar [10] noted, current GI programs in the United States, regardless of whether they are direct public investment, regulatory mandates, and incentives for voluntary implementation, require collaboration and engagement with communities and stakeholders and the capacity of communities, in terms of economic and political aspects, for effective implementation. Poor or racial minority communities often lack the capacity to get information about the incentives for GI, install GI on their properties, or engage in local decision-making processes, which indicates that GIs would cluster in wealthier and politically powerful communities as seen in the above results.

Promoting a more equitable distribution of GI has the potential to improve both capacity to weather extremes and social equity outcomes [45]. For more equitable distribution of GIs in D.C., planners and engineers in the D.C. government need to become conscious of the current distribution of GIs and analyze the potentials of the distribution in reducing stormwater runoff or urban heat island effect, prioritizing equitable distribution of GIs across communities. To be specific, given that the current GI implementation inevitably leans on market forces [6,10], planners and engineers should also recognize that socially vulnerable people who lack social and economic resources can be excluded from the GI programs whether they are implemented by public or private and promote community engagement and participation in the decision-making process surrounding GI programs.

The concurrent efforts of several government agencies, including the District Department of Energy and Environment, D.C. Water, and the District Department of Transportation, to implement GI programs in Washington, D.C. is commendable. Their GI programs are designed to achieve a broad spectrum of program goals and offer numerous benefits, including increased sustainability and resilience. However, despite these efforts, it is unlikely that the current implementation of GI programs will properly achieve any one of those goals with regard to environmental justice due to the uneven distribution of GIs across communities. A more comprehensive approach is needed that integrates GI programs with other environmental justice initiatives, such as affordable housing and public transportation, to address the underlying social and economic inequalities that perpetuate environmental injustices [11]. As suggested by Wolch et al. [11], such an approach would be necessary to ensure that the benefits of GI are distributed equitably across communities, especially those that have been historically underserved. Therefore, a more holistic and integrated approach is needed to achieve true environmental justice and ensure that all communities in Washington, D.C. can reap the benefits of GI.
4.4. Limitations

There are several limitations in this study. In order to investigate the association between GI and independent variables, I utilized the count of GI units in each census block group as a proxy for the multifaceted capacity of GI. This approach was necessary due to the absence of variables in the raw GI data that could effectively represent its diverse functions. While the raw data did contain a value indicating retention or storage volume associated with stormwater processing, this value solely represented the capacity linked to stormwater management by the GI. Additionally, a significant portion (approximately 9%) of the retention volume data had null values, rendering it unsuitable for use. However, relying solely on the count of GI facilities within a given census block group as a stand-in for the true capacity of GI to manage stormwater or mitigate the heat island effect in that area might not accurately capture the complete extent of GI’s capabilities. GI is a heterogeneous form of infrastructure encompassing various types (such as bioswales, rain gardens, green roofs, and trees), which can be constructed in different sizes and locations within a given area. The effectiveness of GI in managing stormwater runoff or mitigating extreme heat can vary based on these factors. Consequently, additional interdisciplinary research is imperative to determine whether the distribution of GI considered in this study can genuinely represent the ability of communities’ green infrastructure to effectively address diverse weather extremes at the infrastructure level.

Furthermore, it should be noted that this study’s exclusive focus on Washington D.C. could be considered a limitation. While Washington D.C. serves as a suitable case study for exploring the connection between social vulnerability and GI distribution, its findings may not be directly transferable to other cities or regions due to the diverse programs being implemented for various purposes across different urban areas. The correlation between social vulnerability and GI distribution may exhibit variations in other urban locales, influenced by the distinct socioeconomic, environmental, and political factors that characterize each city. Similarly, the environmental and political considerations impacting GI distribution might diverge among urban regions, contingent upon localized policies, regulations, and stakeholder engagement. As a result, the applicability of this study’s findings beyond Washington D.C. could be constrained. Researchers who seek to investigate the relationship between social vulnerability and GI distribution in alternative cities or regions must consider these variations and contextual factors during their study’s design and analysis.

5. Conclusions

In conclusion, this study rigorously examined the relationship between social vulnerability and the annual increase in GI in Washington D.C. Through the application of a spatial panel dataset and advanced regression models, Pooled OLS, Panel Spatial Autoregressive (SAR), and Panel Spatial Error Model (SEM) were tested. Among the models, the Panel SAR approach proved most effective in explaining the observed dynamics and it was established that socially vulnerable communities and areas with higher population density experienced comparatively lower annual increases in GI. The presence of spatial parameters further emphasized that the annual increase in GI in one census block group positively influenced the increase in neighboring block groups.

These findings underscore an enduring nexus between social vulnerability and the disproportionate growth of GI, leading to varying levels of vulnerability during extreme weather events. This uneven distribution perpetuates disparities, wherein communities endowed with greater social and economic capital experience augmented protection, while their more vulnerable counterparts confront heightened susceptibility. These results may illuminate the pivotal roles played by the planning mechanism, particularly its reliance on infrastructure privatization, and the subsequent implementation mechanism. The unequal provision of infrastructure protection can be traced back to entrenched inequalities in access to resources and opportunities for marginalized populations [33]. Additionally, a nega-
tive association between population density and the annual increase in GI highlights the challenges posed by limited space and competition for land use in densely populated areas.

Collectively, these findings underscore an urgent imperative to confront social vulnerability and champion an equitable distribution of GI. They accentuate the integral role of comprehensive urban planning and engineering practices in the effective implementation of GI programs. It is essential for planners and engineers to recognize the potential absence of incentives and engagement opportunities for socially vulnerable communities. Advocating for an equitable distribution of GI presents a pathway to fortify sustainability and advance social equity [46]. To achieve this, planners should assess GI distribution through a lens of social vulnerability, thereby prioritizing communities in need. Moreover, the integration of GI with other environmental justice initiatives, encompassing affordable housing and public transportation, becomes imperative to ensure the even-handed dispersion of benefits [11]. This study reaffirms the inescapable necessity for a comprehensive and integrated approach to secure equitable GI benefits across all communities in Washington, D.C.

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References

3. Balany, F.; Ng, A.W.; Muttil, N.; Muthukumaran, S.; Wong, M.S. Green Infrastructure as an Urban Heat Island Mitigation Strategy—A Review. Water 2020, 12, 3577. [CrossRef]
42. Hendricks, M.D. The Infrastructures of Equity and Environmental Justice. Ph.D. Dissertation, Texas A&M University, College Station, TX, USA, 2017.
44. McConachie, M.M.; Shackleton, C.M. Public Green Space Inequality in Small Towns in South Africa. Habitat Int. 2010, 34, 244–248. [CrossRef]


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