Landscape and Urban Planning 223 (2022) 104417

Contents lists available at ScienceDirect

Landscape and Urban Planning

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

Research Paper

Urban flood risk and green infrastructure: Who is exposed to risk and who benefits from investment? A case study of three U.S. Cities

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HIGHLIGHTS

- We developed a framework for relating pluvial flood risk and GI prevalence.
- We related pluvial flood risk and GI prevalence to sociodemographic characteristics.
- GI prevalence inconsistently overlapped with pluvial flood risk.
- Non-white and low-income populations were found to be at a disadvantage.
- Phoenix and Portland demonstrated transition to equitable flood risk management.

ARTICLE INFO

Keywords:
Pluvial flood risk
Green infrastructure
Environmental justice
Equity
Urban planning

ABSTRACT

Pluvial flooding is a serious hazard in inland U.S. cities. City managers and communities are increasingly interested in reducing their pluvial flood risk through the development of green infrastructure (GI) features. This research explores the relationship between pluvial flood exposure and GI placement in three inland cities–Atlanta, Phoenix, and Portland–and analyzes the variation of sociodemographic variables in census block groups (CBG) located in pluvial flood zones. Using the Arc-Malstrøm method, we estimated areas of pluvial flooding in the CBGs of our selected cities by relating pluvial flood area to the density of GI in CBGs and assigning CBGs one of four classifications: i) managed (large flood area, abundant GI), ii) prepared (small flood area, abundant GI), iii) vulnerable (large flood area, scarce GI), and iv) least concern (small flood area, scarce GI). Then, using the historical GI data, we examined the proportionality of GI investment over time to pluvial flood area. We found relationships between GI density, flood area, ethnic and racial minority populations, age, educational attainment, and median household incomes that indicated inequalities and potential discrimination in flood risk management, but also some evidence of equitable and appropriate management given differences in flood risk, especially in Phoenix and Portland. In Atlanta, newer GI installation prioritized white and wealthy neighborhoods where relatively higher flood risk exists (less equitable). Our classification framework may assist city flood risk managers to distribute GI more equitably according to equitability and need.

1. Introduction

In the United States, the extent of urban areas relative to total land area is estimated to increase from 3.1% in 2000 to 8.1% in 2050, an increase in area of 392,400 km^2, which is larger than the state of Montana (Nowak & Walton, 2005). Over the 20th century, the most noticeable sign of urbanization is land transformation to impervious surfaces (Greiner, Shtob, & Besek, 2020). Impervious surfaces convert the majority of incident precipitation to runoff. Common impervious surfaces include, but are not limited to, rooftops, walkways, patios, driveways, parking lots, storage areas, and concrete or asphalt (Scalenghe & Marsan, 2009; Strohbach et al., 2019). Between 2012 and 2017, impervious surface areas increased on average by 326,000 ha/year (Nowak & Greenfield, 2020) and will continue to increase unless development practices are reformed.

Many studies have explored the adverse roles impervious surfaces play in the hydrological cycle (Walsh et al., 2005; Vamvakeridou-lyroudia et al., 2020; La Rosa & Pappalardo, 2020). The rise of

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https://doi.org/10.1016/j.landurbplan.2022.104417
Received 14 July 2021; Received in revised form 21 March 2022; Accepted 22 March 2022
Available online 1 April 2022

impervious areas in cities has increased the frequency of flood occurrence, primarily by replacing land-cover types that would convert a greater proportion of precipitation to infiltration (Cutter, Emrich, Gall, & Reeves, 2018). Major rain events occurring in regions with large impervious areas are the primary source of urban flooding, causing enormous losses of property and life (Cutter et al., 2018). This type of flooding, known as pluvial flooding, occurs because rates of precipitation exceed the capacity of natural and engineered drainage systems to store rainwater or convey it safely away from buildings and people (Rosenzweig et al., 2018). The coupling of intensifying storm events driven by climate change and increasing areas of impervious surfaces is exacerbating urban pluvial floods (Trenberth, 2011; Dong, Esmalian, Farahmand, & Mostafavi, 2020).

The rapid growth of urban areas (Grimm et al., 2008) often coincides with increasing social and economic inequality. Decades of research have shown that communities of color suffer disproportionate damages from various forms of natural disasters, such as hurricanes, tropical storms, and tornadoes (Fothergill & Peek, 2004; Peacock & Girard, 1997; Peacock, Dash, & Zhang, 2006), as well as flooding (Zahran, Brody, Peacock, Vedlitz, & Grover, 2008). Most studies have focused on the vulnerability of racial and economic minorities to fluvial floods, leaving out the pluvial flood association. For example, research shows that aside from multidimensional poverty (Bahls, 2011; KewalRamani, Gilbertson, & Ann Fox, 2007), minority racial and ethnic groups are more likely than their white peers to be negatively impacted by fluvial flooding (Knighton, Hondula, Sharkus, Guzman, & Elliott, 2021; Messager, Ettinger, Murphy-Williams, & Levin, 2021). Similar inequitable patterns exist for disaster mitigation (Eisenman, Cordasco, Asch, Golden, & Glik, 2007; Hartman & Squires, 2013) and the deployment of green infrastructure (GI; Dai, 2011; Heynen, Perkins, & Roy, 2006; Nesbitt, Meitner, Girling, Sheppard, & Lu, 2019).

With increasing interest in the causes and impacts of pluvial flooding, and given the disproportionate impact and exposure of racial and ethnic minorities to other forms of flooding, we identify a need to explore the possibility of differential exposure of racial and ethnic minorities to pluvial flooding. Though many cities have deployed GI with the primary intent of managing water quality rather than quantity (Rosenzweig et al., 2018), models have shown that GI can be effective at reducing the risk of pluvial flooding (Pappalardo, La Rosa, Campisano, & La Greca, 2017; Maragno et al., 2018). Researchers have specifically recommended the usage of GI to reduce pluvial flood risk (Lawson et al., 2014). Yet deployment of, and access to, GI in cities can be inequitable, leaving racial and ethnic minority and economically disadvantaged populations with relatively fewer nearby GI elements, but also more reliant on GI for ecosystem services, than their majority and economically advantaged counterparts (De Sousa Silva, Viegas, Panagopoulos, & Bell, 2018; Lin, Meyers, & Barnett, 2015).

Thus, in this study, we explore how urban green infrastructure (GI) is distributed in Atlanta (GA), Phoenix (AZ), and Portland (OR) at the census block group (CBG) scale (U.S. Census Bureau, 2011), in order to highlight potential opportunities for urban planners to increase environmental equity in the siting of GI, as it relates to pluvial flood risk. Although the appropriate definition of GI depends on the context in which the term is used (Sussams, Sheate, & Eales, 2015), for the purposes of this study, we define GI as the following: GI is an interconnected network of green space that conserves natural ecosystem values and functions and provides associated benefits to human populations (Benedict & McMahon, 2002).

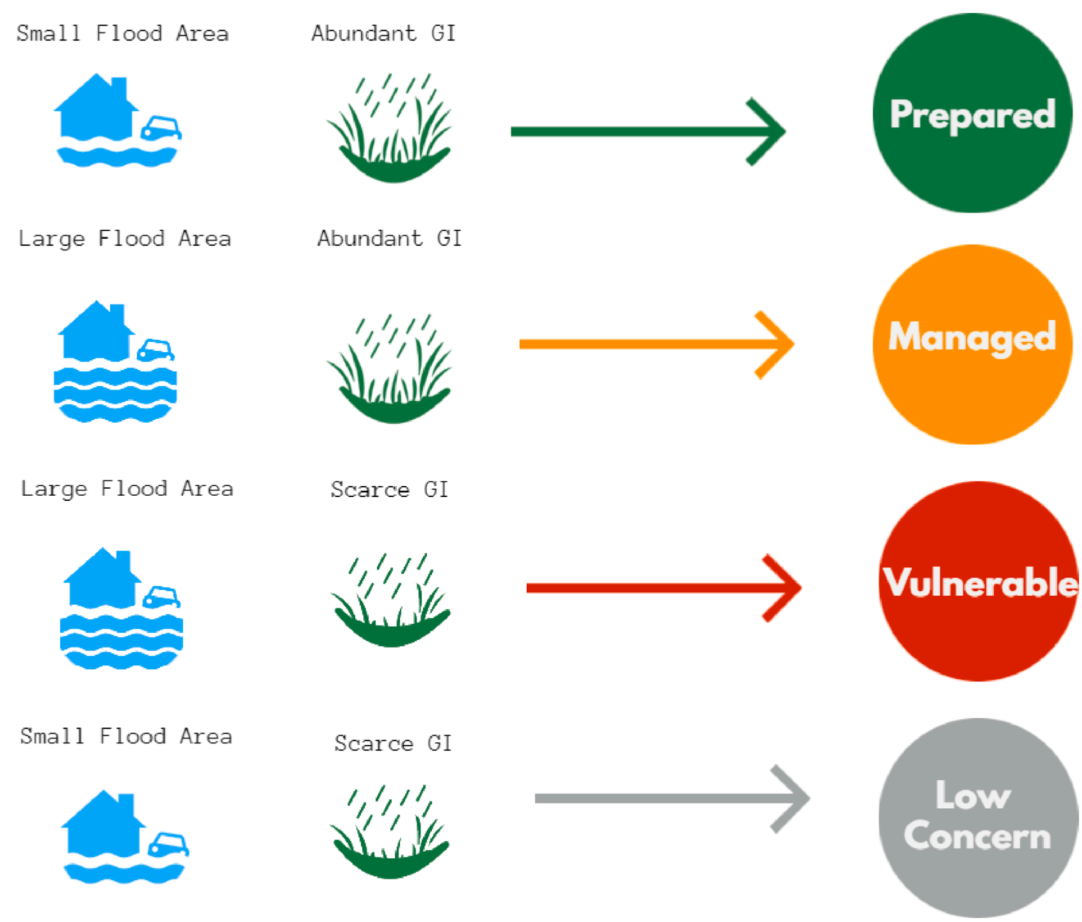

Fig. 1. A conceptual framework for understanding the distribution and implications of urban pluvial flood risk and green infrastructure (GI) in urban communities. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

While racial inequality has been well studied, there is a notable lack of literature exploring the relationships between the distribution of pluvial flood zones, GI that can manage stormwater, racial and ethnic minorities, and economically marginalized populations. Existing stormwater and GI manuals specifically address GI implementation efforts in Atlanta (Chattahoochee Riverkeeper, 2019), Phoenix (AECOM, 2020), and Portland (City of Portland, 2019; City of Portland, 2020). These manuals reveal the priorities of city governments in implementing GI with stakeholder participation for equitable access. This study may then be viewed as a supplement to such efforts in our cities, but may provide a basis on which cities without such manuals might begin to address environmental equity as it pertains to flooding.

Equitable distribution refers to a form of distribution that is neither excessive nor insufficient, but is based upon justice and fairness (Hayward, 2007). Our conceptual framework (Fig. 1) describes the distribution of pluvial flood risk and GI, and we argue that this distribution has implications for sociodemographic variables discussed in this paper. This analysis can help us better understand flood-related risks and implement GI in a more equitable manner to ensure environmental justice for all residents. Therefore, in this study, we relate patterns of GI distribution to pluvial flood risk. With the help of a GIS-based spatial analysis, we answer the following research questions:

Q1: How are GI, racial groups, and economically disadvantaged groups distributed with respect to areas at risk of pluvial flooding?

Q2: What are the sociodemographic characteristics of CBGs that are prepared, managed, vulnerable, or of low concern to pluvial flooding?

Q3: Is GI distribution becoming more or less concentrated in CBGs of racial and ethnic minorities and among economically disadvantaged groups?

2. Study area

The study area consists of three inland US cities—Atlanta, Phoenix, and Portland—that are prone to pluvial flooding. These cities are diverse in terms of physical and social characteristics (Table 1 and Fig. 2), providing scope for comparative analysis. All cities in this study are growing in population (U.S. Census Bureau, 2020) and have long histories of pluvial flooding, with major pluvial flooding events occurring in the past 15 years (Chang, Yu, et al., 2021b; Ferguson & Ashley, 2017; Yang, Smith, & Niyogi, 2019). Future climate models show precipitation increases for most parts of the United States, and, particularly in the Northeast, Southeast, and Northwest, the number of extreme rainfall events expected to occur in a given year is expected to increase (Hayhoe et al., 2018). These changes in annual precipitation and in the number of extreme precipitation events are expected to increase even further in response to the expansion of urban areas (Georgescu, Broadbent, Wang, Krayenhoff, & Moustaoui, 2021; Hayhoe et al., 2018).

Additionally, our study cities are notable for featuring detectable inequalities in assessing green space among various socioeconomic and racial/ethnic groups. In Phoenix, AZ, tree canopy cover in neighborhoods is negatively correlated with the proportion of the neighborhood population that is low-income Hispanic (Jenerette, Harlan, Stefanov, & Martin, 2011; Nelson, Grubesic, Miller, & Chamberlain, 2021); and in Atlanta, GA, tree canopy is negatively correlated with poverty and renter-occupied housing (Koo, Boyd, Botchwey, & Guhathakurta, 2019). In Portland, impoverished and non-white populations have greater exposure to extreme heat and less access to refuge to escape from it (Voelkel, Hellman, Sakuma, & Shandas, 2018).

Furthermore, we selected our study cities because racial diversity varies among the three cities. While Atlanta has the highest proportion of Black people (54.3%), Phoenix has the highest proportion of Hispanic people (43.9%). Portland is majority white (70.3%), but the Asian population (7.8%) is proportionately highest among the three cities. Additionally, we have previous research experience examining flood risk and sociodemographic characteristics in these cities (Chang, Pallathadka, et al., 2021a). Beyond research experience, we also have a body of lived experience in them to draw on, which is critical for identifying potential errors in flood risk, land cover, and sociodemographic analyses.

3. Data and methods

3.1. Background on the Arc-Malstrøm method

To estimate areas where pluvial flooding is likely to occur during intense precipitation events, we employed the Arc-Malstrøm method developed by Balstrom and Crawford (2018). This method uses high-resolution digital elevation models (DEMs), typically generated through LiDAR methods, to create a one-dimensional model of sinks in the landscape, hereafter referred to as blue-spots, as well as the hydrological pathways between blue-spots. This method also calculates the areas and potential storage volumes of blue-spots before they are considered filled. Once a blue-spot fills to its capacity, any excess water flows through the identified hydrological pathways to the next blue-spot, and upon filling this blue-spot flows through its respective hydrological pathway, and so on until the parcel of water reaches either a blue-spot that does not fill to capacity or until the hydrological pathway meets the DEM boundary.

The Arc-Malstrøm method assumes that the rainfall rate exceeds rates of infiltration and evapotranspiration in the landscape, and also the rate at which any drainage infrastructure can effectively remove water from the surface. As such, the Arc-Maelstrøm method is most accurate when modeling pluvial flooding that occurs as a result of very intense (e.g., of 100-year return period or more) storms, such as monsoons and cloudburst events. Arc-Malstrøm produces more accurate estimates of pluvial flooding in areas where there is very low infiltration, such as

Table 1
Key social and physical characteristics of the three study cities.

Characteristic	Study city: *Atlanta*	*Phoenix**	*Portland*
Climate (Mean annual precipitation, annual temperature range)	1263 mm 11.7–22.2 °C	211 mm 17.2–30.6 °C	915 mm 7.8–17.2 °C
Impervious Surface Areas % (2016)	40%	52%	56%
Population (2018)	470,684	1,575,554	665,667
Population Density (2018)	1328/km^2	1240/km^2	1773/km^2
Average Annual Population Growth Rate (2020)	1.67%	1.54%	0.59%
Demography (2018)	White: 35% Black: 54.3% Hispanic: 4.6% Asian: 3.8% Native American: 1.0%	White: 41.5% Black: 6.7% Hispanic: 43.9% Asian: 3.4% Native American: 2.0%	White: 70.3% Black: 5.6% Hispanic: 9.9% Asian: 7.8% Native American: 1.3%

*Phoenix boundary slightly readjusted to fit the study area based on DEM coverage area.

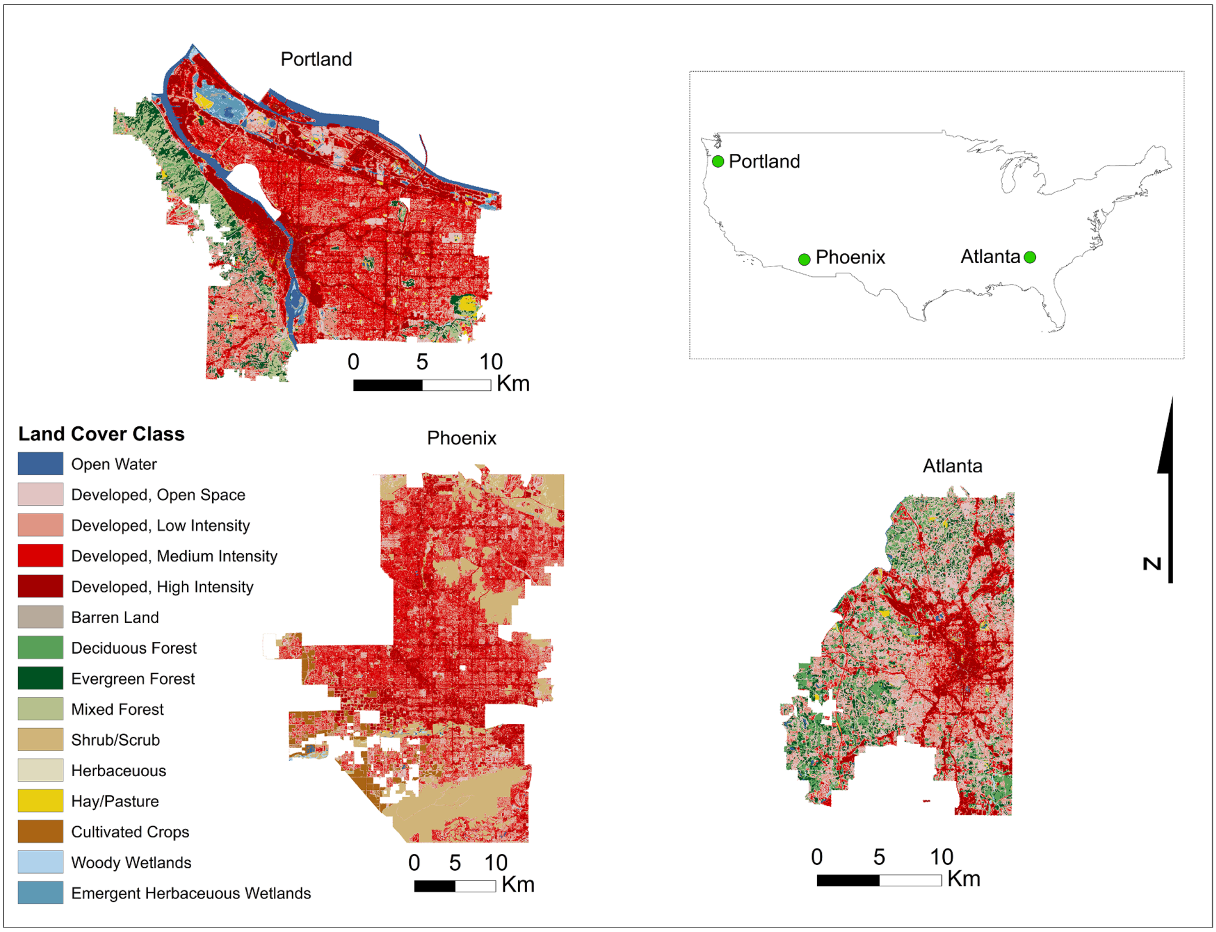

Fig. 2. Study areas classification based on land-cover characteristics of National Land Cover Database (NLCD) 2016 (Dewitz, 2019).

urban areas with extensive impervious surfaces, and less accurate estimates in areas with natural land-cover types or engineered land covers that promote infiltration.

The original Arc-Malstrøm model was designed for use in Python 2.7 (Python Software Foundation, 2021) environments and has not been maintained to function on more recent Python releases. In order to run the model on more recent Python architecture, we used the Septima fork (Septima.dk & Balstrom, 2020) of the original Arc-Malstrøm repository (Septima.dk & Balstrom, 2016), which as of June 2020 ran on Python 3.6.

3.2. Required inputs for Arc-Malstrøm

To simulate a high-intensity precipitation event, that would likely generate substantial damages in our study cities, and that would overwhelm infiltration and drainage systems in each of our cities, we used precipitation amounts representative of 100-year return-period storms with 24-hour durations, that were representative of storms of such return periods and durations in each of our cities. For Atlanta and Phoenix, we used the National Oceanic and Atmospheric Administration's (NOAA) rainfall atlas, Atlas 14 (NOAA, 2020), to determine representative precipitation amounts for a 24-hour storm event. Atlas 14 does not contain rainfall estimates for the Pacific Northwest region of the US, so for Portland, we calculated rainfall intensity (in/hr) for a 100-year storm event via the following equation provided in Portland's Sewer Design Manual (2019):

Table 2
Input data for Arc-Malstrøm model for our study cities of Phoenix, AZ; Atlanta, GA, and Portland, OR.

Arc-Malstrøm input data	Study city: *Atlanta, GA*	*Phoenix, AZ*	*Portland, OR*
Precipitation data (Publication year)	NOAA Atlas 14 (2018)	NOAA Atlas 14 (2018)	IDF curve from City of Portland Sewer Design Manual (2019)
Digital elevation model resolution (Publication year)	1.83 m (2016)	0.914 m (2014)	0.5 m (2014)

$$y = 0.0255 ln(x) + 0.0805 \quad (1)$$

In this equation, y is the rainfall intensity (in/hr) and × is the return period of interest. We solved for intensity after using 100 years for ×, and multiplied the resulting value by 24 to account for a 24-hour day, and converted this value to centimeters for use in the Arc-Malstrøm model. The precipitation values for 100-year return period, 24-hour duration storm events for Atlanta, Phoenix, and Portland that we used in the Arc-Malstrøm method were 8.7 cm, 19.1 cm, and 12.1 cm, respectively. For input DEMs to the Arc-Malstrøm model, we used the most recent, highest resolution topographic datasets available for each of our cities (Table 2). The Arc-Malstrøm model produces more accurate estimates of blue-spot dimensions with higher resolution DEM inputs.

3.3. Arc-Malstrøm model setup and post-processing

We input into the Arc-Malstrøm code each city's respective precipitation values and DEMs, and limited the model's outputs to blue-spots whose depths would be greater than 5 cm. This depth accounts for the margins of error in the vertical resolution of the DEM data, and also selects blue-spots whose depths would be impactful on pedestrians, cyclists, and potentially even damage buildings that are level with the surrounding area. After running the model, we then removed all blue-spots with areas $<12\ m^2$, the area of a typical U.S. parking space. This threshold area of blue-spots was selected so that our identified areas of flooding would likely impair a primary mode of transportation, automobiles, in addition to being a nuisance for pedestrians and cyclists. This threshold area of blue-spots is also greater than the resolution of any of our input DEMs, making these blue-spots identifiable by any of our models.

3.4. Green infrastructure data background and selection

Local city governments produce and administer all GI datasets utilized in this study (Table 3). We investigated whether the GI systems were publicly funded before adding them to the analysis. For the scope of this analysis, we consider the entire network of green spaces (e.g., street planters, rain gardens, bioswales) as a single system rather than isolating specific types within it because the GI definition is fluid, and practical applications of specific types vary from city to city. Hence, viewing GI as a single system allows us to conduct a thorough analysis of the public GI network and relate it to flood risk and other sociodemographic variables. The private dataset is not readily available and, to be clear, is beyond the scope of our study, as our efforts are focused on better informing the public implementation of GI. We also did not include soft surfaces such as parks or street trees as part of storm GI. Thus, we acknowledge that our GI datasets may underreport the true number of GIs placed on landscape, potentially underestimating the true benefits of GI in mitigating pluvial flood risk.

3.5. Calculating green infrastructure density and pluvial flood risk, and determining census block group "preparedness" for pluvial flooding

To calculate GI density at the CBG scale, we divided the number of GI features that intersect a CBG by the area of the CBG. We used this method of calculating GI density over other potential methods, such as dividing GI area by CBG area, because GI in our analysis was represented by points rather than polygons.

To characterize the blue-spot coverage for a CBG, which is a measure of the CBG's pluvial flood risk, we calculated the percentage of the CBG's area that intersected with blue-spot areas defined in section 3.1.2. We then normalized our calculated GI density and blue-spot coverage values between their minimum and maximum values for each study city (Equation (2)):

$$\widehat{x}_{i,j} = \frac{x_{i,j} - x_{mini,j}}{x_{maxi,j} - x_{mini,j}} \tag{2}$$

Table 3
Type of GI included in this study.

City	Type of GI included	Source
Atlanta	Rain Gardens, Rainwater Harvesting, French Drains, Vegetated Filter Strips, Dry Wells, Bioswales	*City of Atlanta*
Phoenix	Bioswales, Retention Basins, Rain Gardens	*City of Phoenix*
Portland	Street Planters, Rain Gardens, Bioswales	*City of Portland*

i is the variable being analyzed, in this case either GI density or blue-spot coverage$j$ is the city in which the analysis is being done: Phoenix, AZ; Atlanta, GA; or Portland, OR.$\hat{x}_{i,j}$ is the normalized value of variable i for a given CBG in city j.$x_{i,\,j}$ is the value of variable i for a given CBG in city j. $x_{min\ i,\ j}$ is the minimum value of variable i for all CBGs in city j.$x_{max\ i,\ j}$ is the maximum value of variable i for all CBGs in city j.

Toward creating our preparedness categories, we first ranked the CBGs of each city according to their normalized values of GI density and blue-spot coverage. We assigned the top 25% of CBGs in terms of GI density a preparedness category of 1, indicating that they were considered to be prepared for pluvial flooding relative to other CBGs in their city. We assigned the top 25% of CBGs in terms of blue-spot coverage a preparedness category of 2, indicating that they were considered to be vulnerable to pluvial flooding relative to other CBGs in their city. We assigned the CBGs that were ineligible for preparedness categories 1 and 2 instead a category of 3, indicating that their pluvial flood risk was managed relative to other CBGs in their city. We assigned the remaining CBGs preparedness categories of 0, indicating that they were considered to be of lower concern for pluvial flooding relative to other CBGs in their city (Chang, Yu, et al., 2021b). We named these four unique preparedness categories *Prepared*, *Vulnerable*, *Managed*, and *Low concern* according to their assigned preparedness categories (Table 4). These categories are relative to each other and should not be interpreted in absolute terms, although the selection of the top 25% through a quartile classification has precedence (Chang, Pallathadka, et al., 2021a; Pallathadka, Chang, & Ajibade, 2021). For example, Chang, Pallathadka, et al. (2021a) classified flood vulnerability areas into four quartiles and derived the high flood vulnerability areas from the top 25% quartile. This study modifies that approach to create four unique categories. Given the uncertain nature of future flood risk, other cut-off points such as the top 5 or 10%, for example, could leave out some important areas that need to improve their preparation, thus the current selection of 25% would ensure reasonable coverage of important areas that need to be prepared for future extreme events.

3.6. Sociodemographic data

We used 5-year estimates of sociodemographic variables from the year 2018, produced by the U.S. Census Bureau as part of the American Community Survey (ACS). We selected the CBG as the unit of analysis because it was the finest geographic resolution for which the desired demographic sample data were available. The selected variables shown in Table 4 have been established in prior research to be key markers of vulnerability to pluvial flooding (Chang, Pallathadka, et al., 2021a; Fahy, Brenneman, Chang, & Shandas, 2019). Our spatial analysis focused on racial groups and median household income, but the spatial regression analysis included all of the variables in Table 5. Additional figures for the remaining variables are included in the supplementary materials.

3.7. Hotspot spatial analysis

We used the Getis-Ord Gi* method of hotspot analysis to identify tendencies for positive spatial clustering of demographic characteristics

Table 4
Preparedness categories for census block groups (CBGs) and their relation to GI density and blue-spot coverage. CBGs were only ranked against other CBGs within their same city.

	Ranking	
Preparedness category	*GI density*	*Blue-spot coverage*
Prepared	Top 25%	Bottom 75%
Vulnerable	Bottom 75%	Top 25%
Managed	Top 25%	Top 25%
Low concern	Bottom 75%	Bottom 75%

Table 5
American Community Survey (2018) variables (5-year estimates) used for sociodemographic analysis and hypothesized relationship with pluvial flood risks.

American Community Survey variable name	Hypothesized relationship	References
% White Population	–	Cutter, Boruff, & Shirley, 2003; Chakraborty et al., 2014
% Black Population	+	Cutter et al., 2003; Chakraborty et al., 2014; Pallathadka et al., 2021
% Hispanic Population	+	Cutter et al., 2003; Chakraborty et al., 2014; Pallathadka et al., 2021
% Asian Population	+	Cutter et al., 2003; Chakraborty et al., 2014; Pallathadka et al., 2021
% Native Population	+	Rufat, Tate, Burton, & Maroof, 2015; Pallathadka et al., 2021
Median household income	–	Rufat et al., 2015; Chang, Pallathadka, et al., 2021
Population with Bachelor's degree	–	Pallathadka et al., 2021
Population aged 65 and above	+	Borden, Schmidtlein, Emrich, Piegorsch, and Cutter, 2007; Foster, Leichenko, Nguyen, Blake, Kunreuther, Madajewicz, and Ravenborg, 2019; Chang, Pallathadka, et al., 2021

in cities, and to distinguish between CBGs of high and low spatial associations (Getis & Ord, 1992; Ord & Getis, 1995). The hotspot method used the fixed distance band conceptualization and the Euclidean distance method (Danielsson, 1980; Stopka, Krawczyk, Gradziel, & Geraghty, 2014). We used the Getis-Ord Gi* method of hotspot analysis to simplify the distribution of racial population groups into two broad categories: percent white and percent non-white. We then extracted all the hotspots for the white population and non-white population groups using ArcMap 10.8.1 (ESRI, 2019). Additionally, household income data were simplified with two broad categories: high-income clusters and low-income clusters. The threshold distances for the Getis-Ord Gi* hotspot analysis for Atlanta, Phoenix, and Portland were 2300 m, 2500 m, and 2800 m, respectively. These threshold distances represent approximate neighborhood boundary distances in the respective cities.

3.8. *Examining the relationship between preparedness index and sociodemographic data*

We first used chi-squared tests of independence to examine potential relationships between our sociodemographic data and our preparedness indices. Additionally, we overlaid our preparedness indices with our hotspot layers and calculated the percent overlap of the CBGs in each. Finally, given the presence of spatial autocorrelation in our data (Moran, 1950), we used spatial error regression analysis to identify how sociodemographic and GI data further explain the spatial variation of pluvial flood risk at the CBG scale. Spatial regression analysis was conducted in GeoDa version 1.20 (Anselin, Syabri, & Kho, 2006).

3.9. *Temporal analysis of GI distribution*

We explored temporal variations in GI distribution for the study cities using publicly available data and installation year information. For Phoenix and Portland, the GI temporal analysis was done using data from the year 2010 to 2020, while for Atlanta, it was done using data from the year 2015 to 2019, given that GI implementation in Atlanta is relatively new. The old GI count was subtracted from the new GI count to compute the difference between GI numbers. The difference was then divided by the original values and multiplied by 100 to obtain the percentage change. The result was aggregated into four classes — *no change, low-increase, medium-increase, and high-increase* — using a quantile

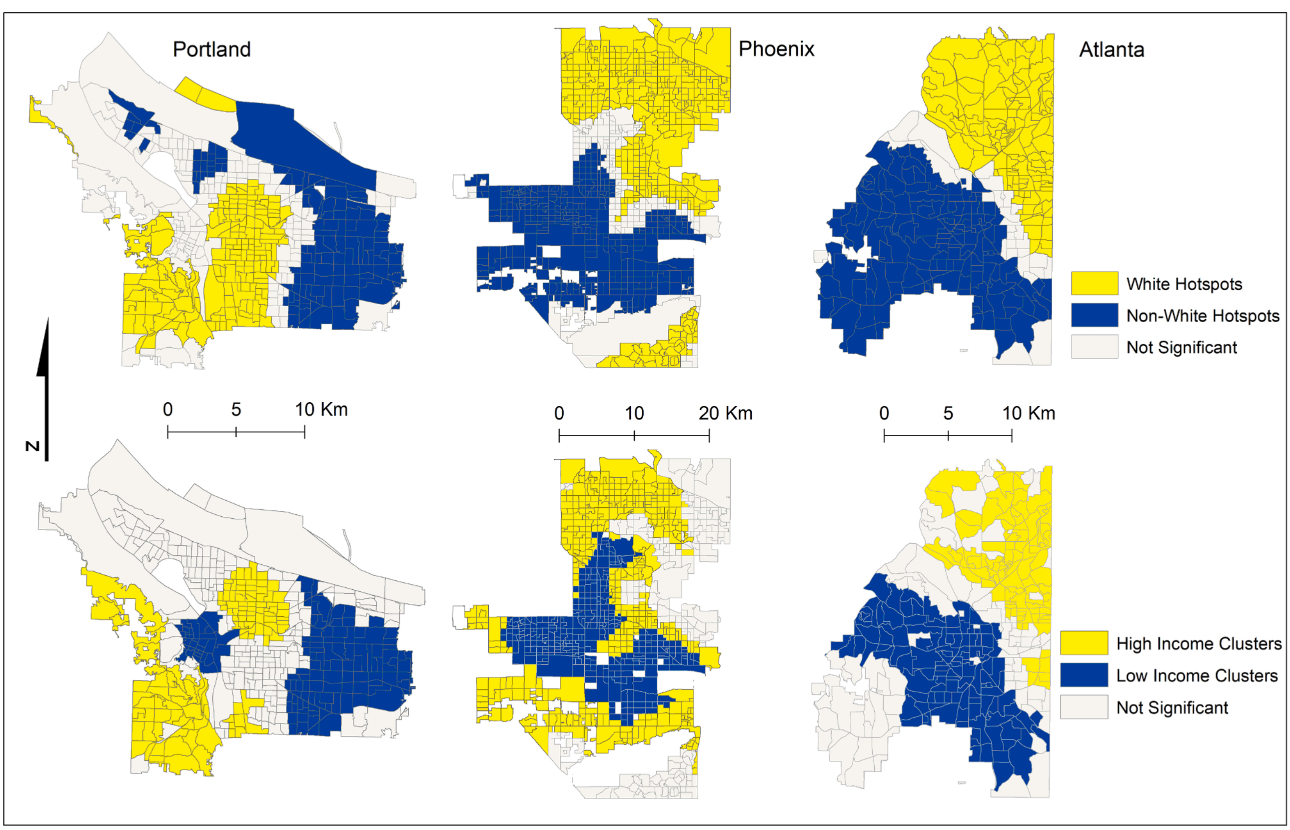

Fig. 3. Hotspot-based classification of white and non-white population groups, and median household income in Atlanta, GA; Phoenix, AZ; and Portland, OR. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

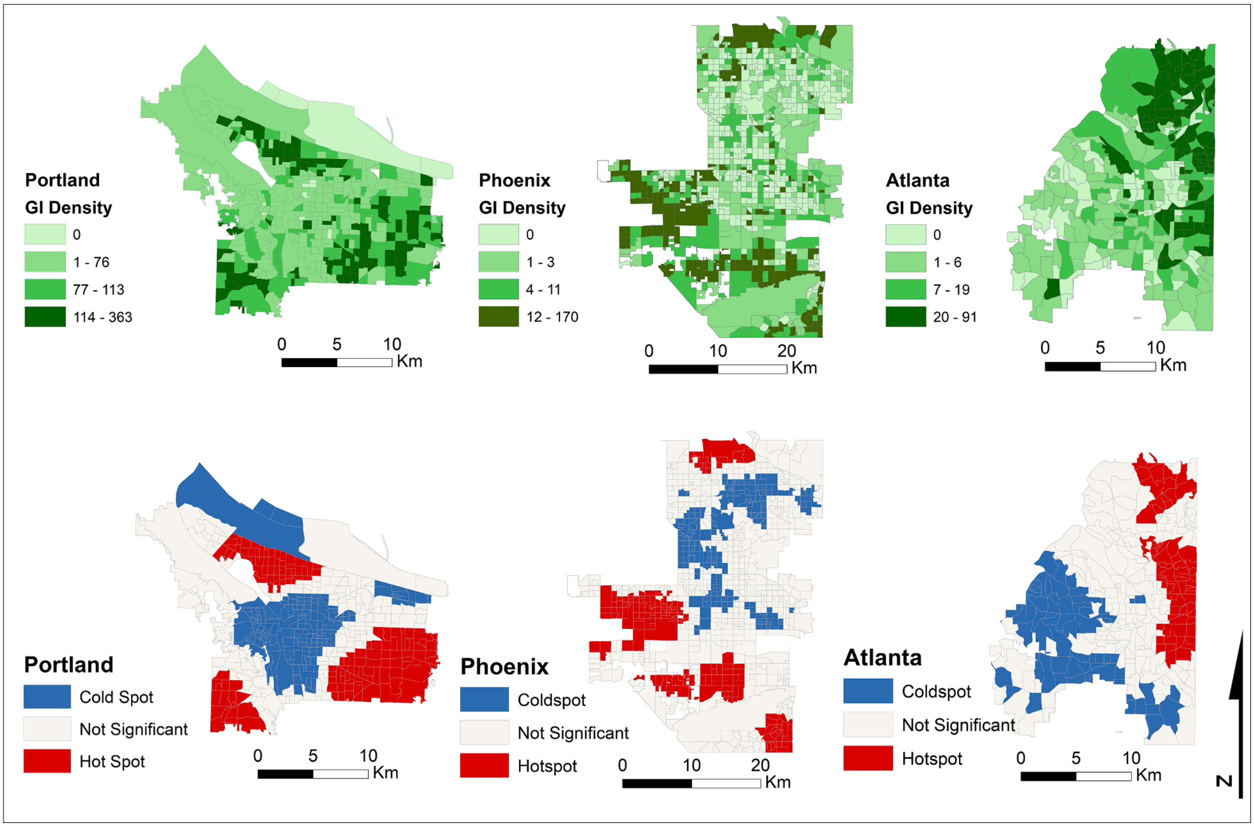

Fig. 4. Distribution of GI density in Atlanta, GA; Phoenix, AZ; and Portland, OR (top); and hotspot analysis results of GI density (bottom). GI Density is the number of GI elements in a CBG per square kilometer of the CBG. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

classification method.

4. Results

4.1. Hotspot analysis of racial groups and median household income

In all three of our study cities, our hotspot spatial analysis revealed significant clustering of white and non-white racial groups (Fig. 3). In Atlanta, GA, and Portland, OR, these groups were agglomerated into two areas of the city; in Phoenix, AZ, they were agglomerated into three areas (Fig. 3). In Atlanta, Phoenix, and Portland, the overlap between household income hotspots, indicating high median household income, and white population hotspots, were 100%, 97%, and 89%, respectively.

4.2. Spatial analysis of sociodemographic groups and their relations to green infrastructure density and blue-spot coverage

In Atlanta, relatively high-GI-density areas are located in the north, northeast, and east areas of the city while low-GI-density areas are found in the northwest, west, south, southwest, and southeastern areas of the city (Fig. 4). The high-GI-density areas generally coincide with the hotspots of white populations while the low-GI-density areas were found in the hotspots of non-white populations (Fig. 3). No GI hotspots overlapped with non-white population hotspots. Similar to low-density GI areas, high blue-spot areas are found in the city's northwest, central, and east areas (Fig. 4). Overlap between blue-spot hotspots and white population hotspots was 41% and for non-white population hotspots was 25%. Relatively low-blue-spot coverage is primarily in the south, southwest, and southeast areas of the city (Fig. 5).

In Phoenix, high-GI-density areas are located in west, south-central, and northern areas of the city and relatively low-GI-density in central and east-central areas of the city (Fig. 4). We found that 24% of GI hotspots overlapped with white population hotspots, while 76% overlapped with non-white population hotspots. (Fig. 3). We estimated relatively high blue-spot coverage in southwest, west, north, and central areas of the city (Fig. 4). The southwestern and central areas of Phoenix are relatively flat compared to the northern and southern areas of the city; they also contain the city's main river, the Salt River. These areas are also characterized as hotspots for Phoenix's non-white population (Fig. 3). There was a 76% overlap between blue-spot hotspots and non-white population hotspots. We found the northern and southern areas of Phoenix to have areas of relatively lower estimated blue-spot coverage compared to its southwestern and central areas (Fig. 5). The former areas contain hotspots of white populations while the latter areas contain hotspots of non-white populations (Fig. 3). Only 18% of blue-spot hotspots overlapped with white population hotspots.

In Portland, relatively high GI-density areas are located in the southwest, southeast, and north-central areas of the city, while low GI-density areas are found in the north, northwest, and central areas (Fig. 4). We found that 75% of GI density hotspots overlapped with non-white population hotspots. Across the whole city, 14% of GI density hotspots overlapped with white population hotspots. We estimated relatively high blue-spot coverage in the southeast and northeast corners of the city, with scattered coverage in the east-central areas (Fig. 5).

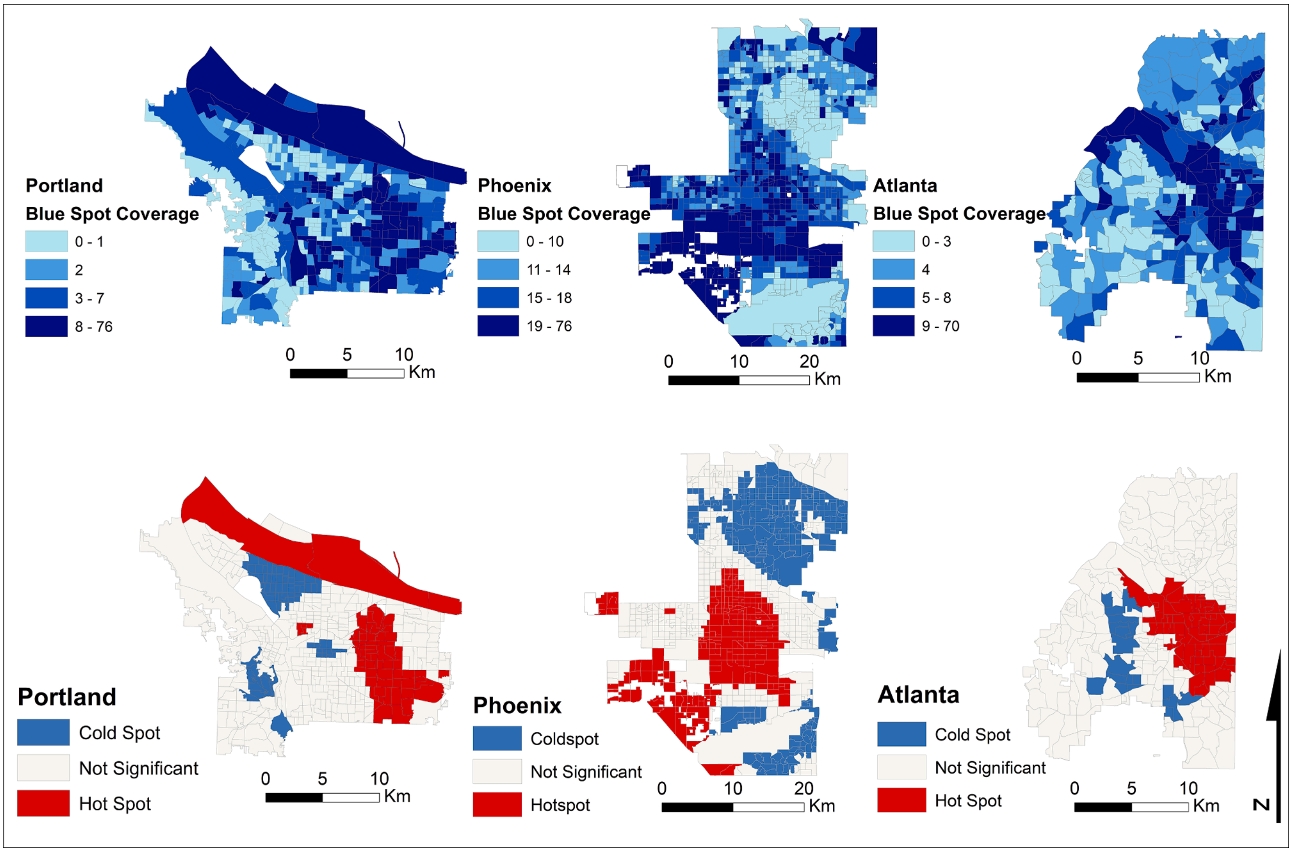

Fig. 5. Distribution of blue-spot coverage in Atlanta, GA; Phoenix, AZ; and Portland, OR (top) and hotspot analysis results of blue-spot coverage (bottom). Blue-spot coverage is the percentage of CBG area that is covered in blue-spots. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Table 6
Results of ordinary least squares (OLS) and spatial error model (SER) for explaining spatial variation of pluvial flood hazard potential. N = number of census block groups included in analysis. AIC = Akaike information criterion. ** indicates $p < 0.01$; * indicates $p < 0.05$.

	Atlanta (N = 302)		*Phoenix* (N = 944)		*Portland* (N = 449)	
Variables	Coefficient OLS	SER	Coefficient OLS	SER	Coefficient OLS	SER
% Black Population			0.156**			
% Hispanic Population			0.073**			
% Asian Population					0.201**	0.171**
% Native Population			0.150**		0.295*	0.324*
GI Density			0.035*	0.014**	−0.034**	−0.021**
Median Household Income						
% Population Aged 65 and Above	−0.112*		−0.093**	0.024**		
% Population with Bachelor’s Degree			0.061**		−0.144**	−0.126**
Spatial lag coefficient		0.563**		0.624**		0.449**
AIC	2076.4	2031.71	6297.14	6082.7	3289.32	3246.61
R^2	0.065	0.246	0.146	0.371	0.132	0.240

These areas of Portland are generally flat and low-lying and contain the majority of the city’s non-white populations (Fig. 3). City-wide, 81% of all blue-spot hotspots overlapped with non-white population hotspots. Relatively low blue-spot coverage is primarily in the northwest and southwest areas of Portland. These areas of Portland contain some neighborhoods distinguished for their hilly terrain. Northwest Portland is also the location of Forest Park, one of the largest urban parks in the United States.

4.3. Spatial regression analysis

As shown in Table 6, the spatial regression analysis demonstrated that the spatial error model performed better than ordinary least squares regression for all three models, with higher R^2 value and lower Akaike Information Criterion (AIC). In Atlanta, there are no statistically significant variables except the spatial autoregressive coefficient (0.563) using the spatial error model to explain the pluvial flood risk. In Phoenix, GI density (0.014) and population aged 65 and above (0.024) are positively associated with pluvial flood risk. In Portland, % Native population (0.324) and % Asian population (0.171) are positively

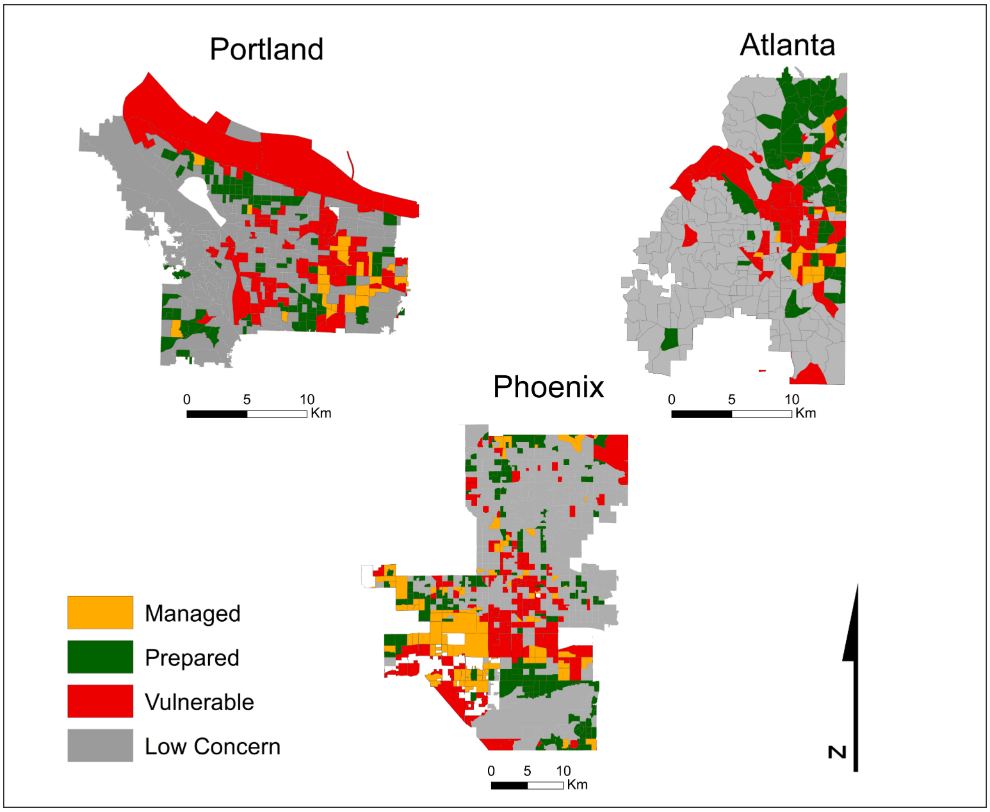

Fig. 6. Quartile-based classification of census block groups corresponding to their combined blue-spot coverages and GI density rank. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Table 7
Overlap between sociodemographic hotspots and preparedness categories in our study cities. ** indicates $p < 0.01$.

Atlanta	*Managed*	*Vulnerable*	*Prepared*	*Low concern*
White population	5.79%**	21.5%**	40.5%**	32.2%**
Non-white population	2.07%**	11.0%**	5.52%**	81.4%**
High income	6.52%**	18.5%**	41.3%**	33.7%**
Low-income	2.52%**	16.8%**	5.04%**	75.6%**
Phoenix	*Managed*	*Vulnerable*	*Prepared*	*Low concern*
White population	2.86%**	9.05%**	16.0%**	72.1%**
Non-white population	18.7%**	21.9%**	19.2%**	40.2%**
High income	2.89%**	7.51%**	19.7%**	69.9%**
Low-income	11.5%**	22.7%**	14.3%**	51.6%**
Portland	*Managed*	*Vulnerable*	*Prepared*	*Low concern*
White population	1.18%**	18.8%**	11.2%**	68.8%**
Non-white population	15.6%**	27.0%**	27.9%**	29.5%**
High income	1.75%**	15.8%**	21.9%**	60.5%**
Low-income	14.7%**	30.9%**	15.4%**	39.0%**

associated, while % population with Bachelor's degree (−0.126) and GI density (−0.021) are negatively associated with pluvial flood risk. Racial variables are statistically significant in the OLS model in Phoenix, but they are no longer significant when spatial autocorrelation is taken into account. Relatively, Phoenix has the highest spatial lag coefficient (0.624), while Portland has the lowest spatial lag coefficient (0.449).

4.4. Preparedness index

In Atlanta, there is a total of 302 CBGs, of which 20.2% (61) were *Prepared*, 20.2% (61) were *Vulnerable*, 4.97% (15) were *Managed*, and 54.6% (165) were of *Low concern* (Fig. 6). White population hotspots were more often categorized to be categorized as *Managed*, *Vulnerable*, or *Prepared* than were non-white population hotspots, while non-white population hotspots were more often categorized as *Low concern* (χ^2 (3, N = 266) = 71.6, $p < 0.01$; Table 7). Similarly, high-income hotspots were more often categorized as *Managed*, *Vulnerable*, or *Prepared* than were low-income hotspots, while low-income hotspots were more often classified as *Low concern* (χ^2 (3, N = 266) = 50.7, $p < 0.01$; Table 7).

In Phoenix, there is a total of 944 CBGs (readjusted), of which 15.8% (149) were *Prepared*, 15.8% (149) were *Vulnerable*, 9.32% (88) were *Managed*, and 59.1% (558) were of *Low concern* (Fig. 6). White population hotspots were more often classified as *Low concern* than were non-white population hotspots, while non-white hotspots were more likely to be categorized as *Prepared*, *Vulnerable*, or *Managed* than were white population hotspots (χ^2 (3, N = 763) = 102, $p < 0.01$; Table 7). High-income hotspots were more likely to be categorized as *Prepared* or *Low concern* than were low-income hotspots, while low-income hotspots were more often to be categorized as *Vulnerable* or *Managed* (χ^2 (3, N = 763) = 33.3, $p < 0.01$; Table 7).

In Portland, there is a total of 449 CBGs, of which we calculated 19.8% (89) to be *Prepared*, 19.8% (89) to be *Vulnerable*, 5.35% (24) to be *Managed*, and 55.0% (247) to be of *Low concern* (Fig. 6). White population hotspots more often were categorized as *Low concern* than were non-white population hotspots, while non-white hotspots were more often classified as *Prepared*, *Vulnerable*, or *Managed* (χ^2 (3, N = 292) = 54.5, $p < 0.01$; Table 7). High-income hotspots were more often categorized as *Prepared* or *Low concern* than were low-income hotspots, while low-income hotspots were more often to be categorized as *Managed* or *Vulnerable* (χ^2 (3, N = 292) = 25.0, $p < 0.01$, Table 7).

4.5. Temporal analysis on number of GI elements in cities over time

GI has increased between 2010 and 2020 in Phoenix and Portland,

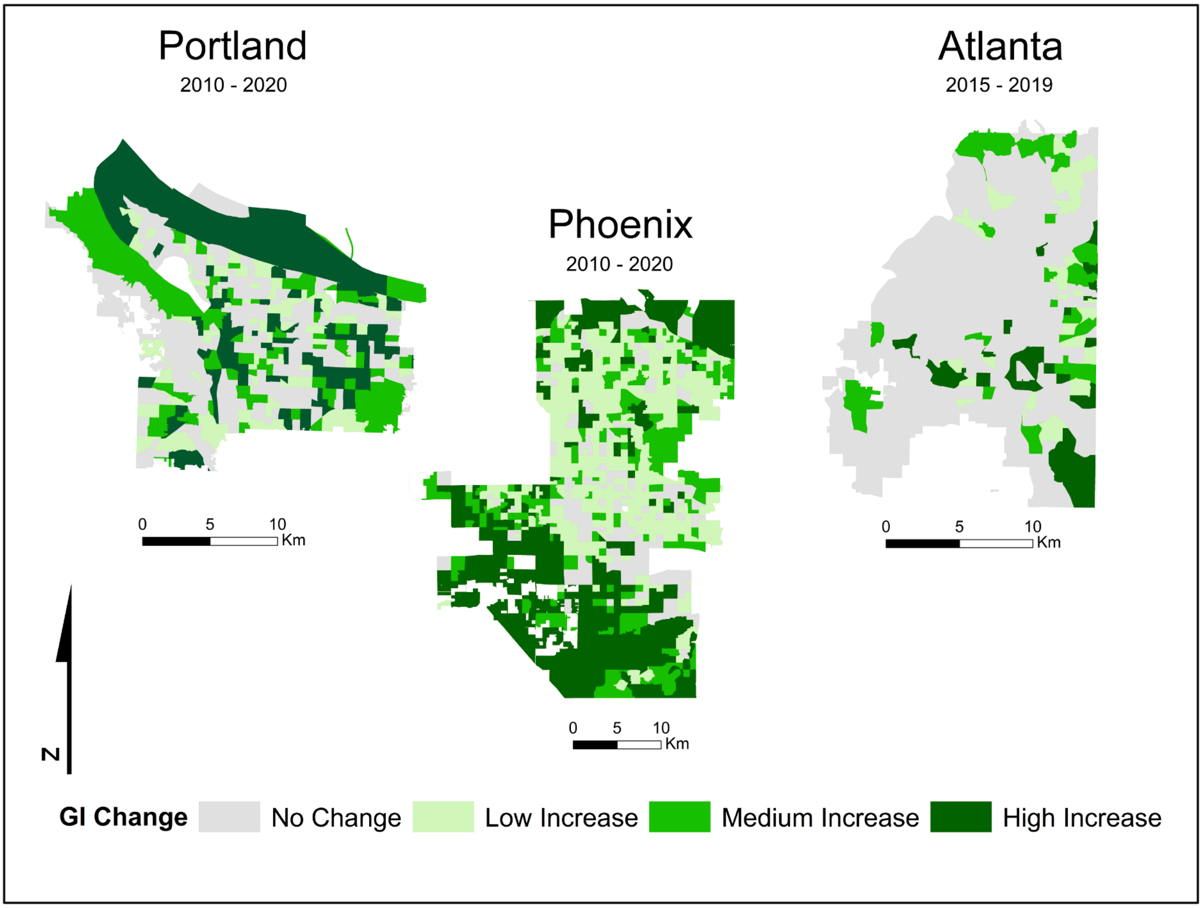

Fig. 7. Change in green infrastructure distribution in Portland (2010–2020), Phoenix (2010–2020) and Atlanta (2015–2019). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

and 2015 and 2019 in Atlanta (Fig. 7). In Atlanta, high GI-increase areas are primarily in the downtown and southern sections, while medium GI-increase areas are in the northern sections of the city. The remaining sections have seen little change. Newer GI developments in Phoenix can be found in the south, west, and north sections, and they are generally expanding in both low-risk and high-risk communities. Similarly, in Portland, newer GI developments have been observed in low- and high-risk communities. Portland's high GI-increase areas are in the north, southeast, and towards the center in downtown.

5. Discussion

5.1. Spatial analysis of disparity in pluvial flood risk

Urban planning in the US has at many times in history been a tool wielded by whites and the wealthy for discrimination against ethnic minority and relatively impoverished groups (Babcock & Bosselman, 1973; Dettling et al., 2017; Hagman, 1971). Although urban-planning ethics have been substantially re-evaluated over time (Barrett, Horne, & Fien, 2016), the repercussions of past discriminatory planning remain visible, and discriminatory planning still propagates in the modern era in intentional and unintentional ways (Koo et al., 2019; Nelson et al., 2021; Voelkel et al., 2018). Our results variably reinforce and challenge the argument that urban resources are unequally shared, by relating the spatial distribution of population clusters and associated GI deployment with respect to the risk of pluvial flooding.

Summarily, in our study cities, some of the relationships between GI density, blue-spot coverage, white and ethnic and racial minority populations, and median household incomes indicated inequalities and the potential for discriminatory flood-risk management measures. For Phoenix and Portland, low-income and non-white populations were more likely to be exposed to pluvial flooding than were high-income and white populations. Our results are then similar to findings of disproportionate exposure of non-white populations to environmental hazards such as fluvial flooding (Maldonado, Collins, Grineski, & Chakraborty, 2016 Messager et al., 2021) and pluvial flooding (Baker, Brenneman, Chang, McPhillips, & Matsler, 2019; Chan & Hopkins, 2017). However, non-white populations in Phoenix and Portland were more likely to live among greater amounts of GI, perhaps indicating that efforts to manage flood risk were directed appropriately toward communities more at risk. We note that our temporal analysis showed newer GI installed in areas with high non-white populations and blue-spot coverage. We recommend that studies examining disparities in GI deployment also examine the proportionality of deployment to natural hazard risk.

In Atlanta, many of these relationships are reversed, where white populations tended to be more exposed to pluvial flooding and to have greater GI density, indicating that there may be active efforts to manage flood risk in these communities. We also found that GI increased over time in areas with predominantly white populations. However, we found no significant overlap between GI change and blue-spot coverage. Given the relatively greater blue-spot coverage in white and high-income communities, flood risk could be driving some of the GI investment in Atlanta, although the disparity in terms of equitable distribution of GI is still notable. It may be then that GI investment in Atlanta follows wealth and the white population, in addition to flood risk. Previous scholarship found that another form of GI, tree canopy, is negatively correlated with poverty and renter-occupied housing in Atlanta (Koo et al., 2019). It may be then that socioeconomic forces rather than need are driving GI investment in the city.

5.2. Sociodemographic variables, GI, and pluvial flood risk

The spatial error regression analysis did not produce significant spatial relationships between sociodemographic variables and flooding in Atlanta; however, in Phoenix, a positive association of GI and flooding may indicate efforts toward GI deployment to address pluvial flood risk. Also in Phoenix, the elderly population appears to be at greater relative risk of pluvial flooding, substantiating previous research finding that the elderly population is more vulnerable to natural disasters (Bell, Abir, Choi, Cooke, & Iwashyna, 2018). For Portland, non-white communities, mainly Asians and Native Americans, are at substantial risk of pluvial flooding. It has been well documented that these racial groups are disproportionately exposed to flood hazards (Chakraborty, Collins, Montgomery, & Grineski, 2014; Collins, Grineski, & Chakraborty, 2018), and the hotspots of pluvial flood risk coincide with Asian immigrant communities in Portland. The population with college degrees, on the other hand, is less at risk of pluvial flooding, suggesting that educational attainment may contribute to increased flood-risk awareness in Portland (Fahy et al., 2019). Education is well-established as a critical determinant of flood risk perception (Lechowska, 2018; Zabini, Grasso, Crisci, & Gozzini, 2021), thus it may be that our results are evidence of people acting on their flood risk perceptions. The negative relation between GI density and blue-spot coverage in Portland, however, highlights a gap in pluvial flood-risk management efforts.

5.3. Implications for spatial planning

Worldwide, investment in GI has increased substantially in the last decade (McPhillips & Matsler, 2018). This increase indicates a willingness to pursue multifunctional, nature-based solutions in urban settings (Hobbie & Grimm, 2020), and perhaps even demonstrates a more specific recognition of the efficacy of GI toward significantly reducing pluvial flooding (Benedict & McMahon, 2002). Based on the results of our study, we advise stakeholders to review their priorities in how GI is distributed and align future GI investment with exposure, racial equity, and economic vulnerability. Our results emphasize that existing methods for the distribution of GI to address pluvial flooding may be incongruent with cities' stated goals of addressing environmental equity. Cities must work together with stakeholders to implement local, community-level solutions for GI deployment based on a shared framework (Jerome, 2017).

Atlanta, Phoenix, and Portland's stormwater manuals reveal that these cities strive to ensure equitable resource allocation. Our conceptual framework outlines a straightforward approach to analyzing the spatial distribution of pluvial flood risk and GI, as well as evaluating how well these equity goals are being met. Patterns of classification such as *Vulnerable*, *Managed*, *Prepared*, and *Low concern* would better inform stakeholders about how to deploy GI to address pluvial flood risk. Such an approach would be useful for informing stakeholders and coming to decisions on GI deployment (Jerome, 2017).

5.4. Temporal analysis of GI deployment and histories of green gentrification

While GI investment is increasing in all three study cities, temporal analysis of GI change indicated inconsistent matching of pluvial flood risk with GI investment. In Atlanta, we found increases in GI investment in areas with less pluvial flood risk and greater white populations, indicating that sociodemographic factors may be the main driver of GI investment. In Phoenix, in contrast, we found increases in GI investment in areas of higher pluvial flood risk with greater non-white populations. Nonetheless, even though non-white populations in Phoenix tended to have lower median household incomes, GI investment was still more common in areas with higher median household incomes. It may be that GI investment in Phoenix is biased toward wealthier non-whites, but we leave an exploration of this possibility to future research. As a notable precedent for this sort of exploration, Koo et al. (2019) found that economic condition was an important interacting factor with racial and ethnic category in the analysis of environmental equity of tree canopy distribution in Atlanta.

If cities intend to match GI investment with flood risk and forms of equity, they should be mindful of the pathways through which they will accomplish such a task, lest they risk propagating or deepening historical inequities via green gentrification (Gould & Lewis, 2016), a phenomenon referring to how the development of green spaces can lead to the displacement of socially and economically vulnerable populations by attracting residents from more advantaged socioeconomic groups (Hackworth, 2002; Brueckner & Rosenthal, 2009, Dooling, 2009). Certain forms and configurations of GI might promote green gentrification (Rigolon & Németh, 2020), and researchers have recommended pairing GI investment initiatives with policy controls on housing and jobs in order to mitigate green gentrification or direct the value that GI investment adds to neighborhoods to its residents (Wolch, Byrne, & Newell, 2014). Indeed, all three of our study cities have histories of gentrification, green or otherwise, that warrant judicious GI investment plans (Immergluck, 2009; City of Portland, 2013a, City of Portland, 2013b; Immergluck & Balan, 2018; McPhillips & Matsler, 2018; NCRC, 2019; Richardson et al., 2020).

6. Limitations

Differences in topography, climatic conditions, data availability, and documentation present challenges to comparative analysis between cities. We used the Arc-Malstrøm method to estimate locations of pluvial flood zones, and we acknowledge that this method has significant limitations. For example, it does not account for routing through subterranean drainage infrastructure, nor does it involve on-the-ground verification of water networks. Further, the method is limited by the availability of high-resolution and recent DEMs in our cities, some of which lagged behind our sociodemographic data by four years. Nonetheless, based on our discussion with modeling experts and city practitioners, the general utility of the Arc-Malstrøm method to indicate potential areas of flooding during extreme precipitation events is not disputed.

We used ACS data for identifying hotspots of white and non-white population groups, which have their own limitations. We are aware of some criticism of ACS data for the margin of error, which is typically reported for census statistics at a 90 percent confidence level; however, some scholars argue for a more desirable confidence level of 95 or 99 percent (Spielman, Folch, & Nagle, 2014). Based on a review of several publications by local and state governments, we are confident that our use of ACS data is representative of the actual distribution of population based on race.

6.1. Future research

Decades of systemic racism have led to unequal distribution of risk among various sociodemographic groups, and in recent decades the deployment of GI has in some cases been inequitable, leading to a continuation of inequity of investment in the safety and quality of life of citizens based on sociodemographic characteristics (Dai, 2011; Fothergill & Peek, 2004; Immergluck & Balan, 2018; Zahran, Brody, Peacock, Vedlitz, & Grover, 2008; Chapple & Thomas, 2020). Spatial analysis can reveal unequal and disproportionate investment in GI in cities, but knowledge of the cultural geography and political ecology of the cities is needed to provide historical context to findings and to assess how future GI investment may help redress historical and modern environmental injustices. Promoting environmental equity through correction of urban planning, government regulations, and deconstruction of residential segregation is essential. Future research should also engage with lessons from green gentrification literature, by evaluating the forms, locations, and intensity of GI investment that can lead to gentrification, as well as by exploring various policy tools that can be used to control or redirect added value from GI investment to local residents.

7. Conclusions

Systemic racism and racial disparities in society contribute to the configuration and management of urban spaces. In this study, we analyzed disparities of pluvial flood exposure and GI investment in different sociodemographic groups. Although our analysis revealed inequalities and potential discrimination in GI investment, we also found evidence of equitable and appropriate management, given differences in flood risk among groups, especially in Phoenix and Portland. We delineated urban pluvial flood zones and compared them with GI density and change over time at the scale of the CBG. We classified CBGs as *Vulnerable*, *Managed*, *Prepared*, and *Low concern* to describe the relationship between a CBG's flood risk and the amount of GI available to manage flood risk. In Phoenix and Portland, we found that non-white and low-income populations were more often classified as *Vulnerable* or *Managed* than were white and high-income populations, whereas white and high-income populations were more often classified as *Prepared* or *Low concern*. In Atlanta, non-white and low-income populations were more likely to live in *Low concern* area than were white and high-income populations, but white and high-income populations were more likely to live in *Prepared* and *Managed* areas.

Our analysis also revealed inconsistent evidence that GI investment in Atlanta and Phoenix was a response to pluvial flooding, as there were also strong correlations between GI investment and certain sociodemographic variables. Finally, we conclude that risks of green gentrification must be addressed in flood-mitigation planning.

CRediT authorship contribution statement

Arun Pallathadka: Conceptualization, Formal analysis, Investigation, Methodology, Software, Visualization, Writing – original draft, Writing – review & editing. **Jason Sauer:** Conceptualization, Formal analysis, Investigation, Methodology, Software, Visualization, Writing – original draft, Writing – review & editing. **Heejun Chang:** Conceptualization, Project administration, Supervision, Writing – review & editing. **Nancy B. Grimm:** Conceptualization, Project administration, Supervision, Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

This research was supported by the Urban Resilience to Extremes Sustainability Research Network, the SETS Convergence project, and the CAP LTER under the National Science Foundation grants SES-1444755, 1934933, and 1832016, respectively. The research was also supported by the resources of Water as an Integrated System and Environment (WISE) Lab at Portland State University and the Grimm Laboratory at Arizona State University. We also thank the two anonymous reviewers for their careful reading of our work and their many insightful comments and suggestions that has resulted in an improved manuscript.

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