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Spatial analysis of landscape and sociodemographic factors associated with green stormwater infrastructure distribution in Baltimore, Maryland and Portland, Oregon

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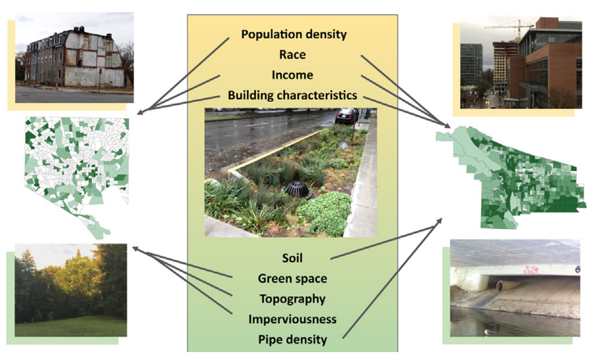
HIGHLIGHTS

- GSI facilities are spatially clustered in Portland but not in Baltimore.
- GSI density was analyzed at census block group and census track scale.
- In Baltimore, scale of analysis altered significance of explanatory variables.
- In Portland, pipe density and median income explain GSI density at both scales.
- Environmental justice is a critical consideration of GSI implementation.

GRAPHICAL ABSTRACT



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ABSTRACT

This study explores the spatial distribution of green stormwater infrastructure (GSI) relative to sociodemographic and landscape characteristics in Portland, OR, and Baltimore, MD, USA at census block group (CBG) and census tract scales. GSI density is clustered in Portland, while it is randomly distributed over space in Baltimore. Variables that exhibit relationships with GSI density are varied over space, as well as between cities. In Baltimore, GSI density is significantly associated with presence of green space (+), impervious surface coverage (+), and population density (−) at the CBG scale; though these relationships vary over space. At the census tract scale in Baltimore, a different combination of indicators explains GSI density, including elevation (+), population characteristics, and building characteristics. Spatial regression analysis in Portland indicates that GSI density at the CBG scale is associated with residents identifying as White (−) and well-draining hydrologic soil groups A and B (−). At both census tract and CBG scales, GSI density is associated with median income (−) and sewer pipe density (−). Hierarchical modelling of GSI density presents significant spatial dependence as well as group dependence implicit to Portland at the census tract scale. Significant results of this model retain income and sewer pipe density as explanatory variables, while introducing the relationship between GSI density and impervious surface coverage. Overall, this research offers decision-relevant information for urban resilience in multiple environments and could serve as a reminder for cities to consider who is inherently exposed to GSI benefits.

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1. Introduction

More than two-thirds of the world's population is expected to live in cities by 2050 (United Nations, 2014). This ongoing trend toward urbanization drives complex changes within hydrologic systems. The uncertainties of climate change are expected to further exacerbate water resource issues, affecting urban resilience (Rosenzweig et al., 2018). In the Pacific Northwest, for example, temperatures are expected to rise as much as 3 °C by 2099 (Rana et al., 2017), while shifting atmospheric rivers will result in more intense precipitation events (Dannenberg and Wise, 2017; Loikith et al., 2017); these changes will influence the infrastructure needs in cities, potentially endangering urban residents where infrastructures cannot mitigate these changes (Meerow, 2017).

Increasing urbanization often results in specific hydrologic changes, including flooding, higher peak flow, more combined sewer overflows (CSOs), and higher pollutant transport (Connop et al., 2016; Pennino et al., 2016; US EPA, 2017; Golden and Hoghooghi, 2018). As impervious surfaces decrease infiltration capacity of watersheds, hydrologic flow is generally shifted to a complex series of pipes (often referred to as 'grey' infrastructure) as well as engineered and natural stream networks (Kaushal and Belt, 2012; Pennino et al., 2016). These traditional designs of stormwater management, while intended to control stormwater runoff, often produce localized and large-scale unintended consequences, including altered hydrograph characteristics, increased pollutant concentrations, altered river channel morphology, and shifting of native ecologic assemblages (Walsh et al., 2005).

Green stormwater infrastructure (GSI) provides an alternative or complement to traditional grey infrastructure by incorporating ecological or 'green' elements (e.g., trees, grasses, soils) to manage stormwater. GSI can mediate many of the negative effects of urbanization in cities and enhance ecosystem services (Pappalardo et al., 2017; Prudencio and Null, 2018) while potentially compensating for or negating unintended consequences of grey infrastructure approaches. These benefits, along with the cost-effectiveness of implementation (American Rivers et al., 2012; Keeley et al., 2013), have made GSI an increasingly common design element in urban planning initiatives (Schueler and Claytor, 2009; US EPA, 2012; Baltimore Department of Planning, Office of Sustainability, 2015; City of Portland, 2016; Mei et al., 2018). The decision whether to include GSI facilities is complex, and it is assumed that most cities incorporating GSI will have a wide range of designs distributed over space, reflecting socioeconomic acceptance, technological feasibility, and governance context.

Important regulatory drivers of GSI implementation in urban settings in the United States are based on the multiple hydrologic benefits of GSI facilities, such as improved water quality, runoff regulation, flood management, and city drought preparation (City of Portland, 2007, 2016; Pennino et al., 2016; Chan and Hopkins, 2017; Massoudieh et al., 2017; Schubert et al., 2017; Tao et al., 2017; US EPA, 2017; Zhang and Chui, 2019). However, it is not well understood how different planning approaches and regulatory concerns manifest in certain spatial patterns on the ground, which can include counterintuitive clustering of GSI facilities. At the federal level, the Clean Water Act (CWA) drives a majority of GSI implementation through regulating and permitting the pollution discharge from CSOs and municipal separate storm sewer systems (MS4). These regulations are primarily addressed through publicly-built and maintained facilities, which increasingly includes GSI (Heck, 2018; McPhillips and Matsler, 2018; US EPA, 2017). At the state and local level, stormwater management guidelines influence what is built on private and corporate property. For example, in Maryland, Environmental Site Design (ESD), which includes most GSI facility types, is required by the state's Stormwater Design Manual (Maryland Department of the Environment, 2007) to be implemented for most new and re-development sites. This policy increases the number of GSI facilities that are designed and managed by private entities, as well as influencing where facilities are built. Lastly, community groups have pushed forward GSI implementation by influencing local governance context. In Pittsburgh, local community advocacy groups protested the creation of a CSO plan that included only grey infrastructure solutions and asked local engineers to incorporate GSI solutions because of the additional perceived benefits GSI facilities can provide to struggling communities (Finewood, 2016). All of this means that many facilities are built opportunistically when construction opportunities, regulatory mandates, and political will line up, rather than systematically where plans or residents indicate they are most needed. Therefore, it is important to examine the spatial trends of GSI on-the-ground rather than relying solely on plan review to see where clusters manifest and where they don't.

Additionally, it is crucial to examine on-the-ground spatial patterns of GSI to begin to better understand environmental justice concerns. There is concern about who is receiving benefits from GSI, and whether they are being equitably distributed over space. The environmental justice literature has exposed national and international trends in distributional equity surrounding environmental benefits and burdens (Cutter, 1995). For example, the concentration of environmental burdens, like air and water polluting industries and institutions, is higher in low-income communities and communities of color throughout the United States (e.g., Evans and Kantrowitz, 2002; Bullard, 2008). Conversely, environmental benefits like access to parks and green spaces are often concentrated in majority White and affluent neighborhoods (Heynen et al., 2006; Davis et al., 2012; Wolch et al., 2014; Schwarz et al., 2015, Frey, 2017; Ferguson et al., 2018; Grove et al., 2018; Table 1). Green space may appear evenly distributed across a city, but the quality, diversity, and size of these green spaces can differ dramatically between different neighborhoods (Wendel et al., 2011). Historic legacies of racist social and financial programs and policies through time also have a profound influence on distributional equity of environmental burdens and benefits in US cities (Grove et al., 2018). Indeed, urban greening strategies have been primarily focused on biophysical functions (Liu et al., 2017) and managerial aspects (Rutt and Gulsrud, 2016) and have not been socially inclusive in many cities (Haase et al., 2018; Rigolon and Németh, 2018).

There is a small but growing body of literature focusing on equity of engineered GSI and the increasing influence of green infrastructure discourse on environmental planning efforts (Heckert and Rosan, 2016; Bissonnette et al., 2018). In Portland, Oregon, GSI may be providing increased benefits to citizens of lower socioeconomic status and a higher percentage of people of color (Chan and Hopkins, 2017). However, several studies indicate issues with inequitable distribution of GSI. This is the case in Philadelphia, Pennsylvania, where it appears to be driven by market forces (i.e. mandated implementation) of GSI with new development (Mandarano and Meenar, 2017). GSI placement was generally constrained by biophysical and urban form characteristics in Melbourne, Australia (Kuller et al., 2018), indicating prioritization of hydrologic and/or ecological function over sociodemographic factors. Additionally, hedonic pricing analysis indicated that aboveground stormwater control measures may decrease prices of adjacent homes in Baltimore County, Maryland (Irwin et al., 2017) and Portland, Oregon (Netusil et al., 2014). Several planning approaches have been proposed for future GSI implementation, which integrates streams of data on urban form and socioeconomic status to aid in equitable and hydrologically effective implementation of GSI (Garcia-Cuerva et al., 2018; Porse, 2018). While all of these approaches have pros and cons, each highlights the fact that intentional inclusion and consideration of residents' voices in planning actions are required of GSI if equitable outcomes are to be obtained (Wendel et al., 2011; Goodling and Herrington, 2015; Mandarano and Meenar, 2017; Bendor et al., 2018; Bissonnette et al., 2018; Grove et al., 2018; Finewood et al., 2019).

This study seeks to build upon this previous work by introducing several novel elements to an analysis of landscape and sociodemographic variables influencing spatial clustering of GSI. First, the research examines GSI within two different U.S. cities, whereas other past studies typically examine only one city or watershed. Second,

Table 1
Review of selected relevant studies on spatial relationships between green space or green stormwater infrastructure and landscape or sociodemographic explanatory variables. Positive or negative relationships are denoted by (+) or (−) respectively.

Author	Year	Study area	Spatial unit	Green infrastructure (GI) examined	Relationships between GI & explanatory variables
Wendel et al.	2011	Tampa, USA	City region (Tampa, East Tampa)	Public and private green space, Natural water features, Green stormwater infrastructure	While access to GI did not vary substantially, the type, quality, and size of GI varied spatially and suggested inequity issues
Davis et al.	2012	Chicago, USA	Census tract	Open space, lake, trees	Low-to mid-income Hispanic residents (−)
Kabisch & Haase	2014	Berlin, Germany	Sub-district, block, site	Green space	There was inequity in GI access by immigrant status and age; access to and use of GI were different at an individual area, highlighting scaling issues
Lin et al.	2015	Sydney, Australia	Mesh Blocks	Public and private green space	Dwelling density (−), suburbs of higher socio-economic status (+)
Chan & Hopkins	2017	Portland, USA	Census block group	Green stormwater infrastructure	Income (−); age (−); minority (+); education/Bachelor's (−)
Mandarano & Meenar	2017	Philadelphia, USA	Census tract	Green stormwater infrastructure	Minority (−); Hispanic (−); single parent (−); income inequality (+); vacant land (+) (note: this is for all GSI; they also broke down by private regulatory/voluntary + public)
Arshad & Routray	2018	Pakistan	Housing scheme	Public green space	Housing density (−), population density (−)
Porse	2018	LA, USA	Census tract	Density of storm sewer, channel infrastructure.	Land cost (−), average runoff coefficient (+), number of buildings (+), impervious areas (+), population density (+), percent rental house (−), percent multi-family household (−)
Ferguson et al.	2018	Bradford, UK	Lower Layer Super Output Area	Street tree density (STD), public green space (PGS)	STD vs. Asian/Asian British residents (+), STD vs. lower socioeconomic status (+), PGS vs. income (+), PGS vs. White households (+), STD vs. Population density (+), PGS vs. population density (−)

this research also utilizes multiple statistical models to explore the relationship between GSI density distribution and multiple landscape and sociodemographic variables, which may be more robust than the previous work in this area (Chan and Hopkins, 2017). Additionally, we investigate how significant variables might vary across scales and examine cross-scale interactions. Past work focusing on the distribution of green space or GSI has typically occurred at a single scale (often census block group (CBG) or tract; Table 1). Our approach provides a consistent method for identifying patterns in the spatial distribution of GSI, regardless of environmental differences observed across study areas. In this way, we can begin to examine how past planning and implementation strategies have manifested in certain distributions of GSI, which has important implications for the delivery of benefits. We seek to address the following specific questions:

(1) Is there a distinct spatial pattern of GSI in Baltimore, MD and Portland, OR?
(2) Which landscape and sociodemographic variables explain the spatial distribution of GSI in both cities? Do the significant explanatory variables differ at different scales?
(3) How do landscape and sociodemographic factors interact across scales to explain the spatial distribution of GSI density?

2. Study area

The two US cities selected for this study - Baltimore and Portland - have many similar characteristics, particularly in the landscape realm, along with important infrastructural and sociodemographic differences (see Fig. 1 and Table 2). Both cities have a similar total population. However, Baltimore, the older city, has a higher population density than Portland. In recent years Portland has experienced significant population growth, in contrast to Baltimore, which has experienced population loss since the late 1950s. Portland is the more affluent city, with a median income nearly 32% higher than the median income of Baltimore. Racial demographics differ between the two cities with Portland being predominantly White (~80%) while the opposite is true for Baltimore where approximately 68% of the population is African American. The cities have many landscape similarities, with variable topography draining to a major river or harbor, and around 1000 mm of rainfall annually. Regarding storm sewer infrastructure, Portland has a partially combined sewer system, while Baltimore's sanitary sewers are separated from their storm sewers. While both cities have variable topography and similar rainfall, the two cities experience very different climates controlling the temporality and intensity of precipitation across the city's surface. Additionally, Baltimore's soils are mostly clay while Portland's soils include clay, silt, silt/loam and gravel, which affects the infiltration rate of flow. Due to these notable differences, the two cities also present unique variation in the main drivers behind their utilization of GSI. In Baltimore, state-level stormwater management regulations along with a desire to improve water quality in the Chesapeake Bay have motivated much of the GSI installation, while Portland has been steadily installing GSI since the 1990s primarily to reduce combined sewer overflow (CSO) events (McPhillips and Matsler, 2018). Additionally, both cities' institutional capacities and political motivations related to sustainability differ (Fink, 2018), which may influence the deployment of GSI across their respective cities.

3. Data and methods

3.1. Data

We obtained GSI data from local municipal stormwater managers, which we assumed to be the most recent and complete datasets suitable for this analysis. Other sociodemographic and land cover data were obtained from US government databases. We kept the data sources as consistent as possible across cities, when feasible. The exceptions to this were sewershed data, which was unobtainable for Baltimore, and hydrologic soil group data for Portland, which required interpolation. Within these data, we derived 16 variables for further analysis (Table 3), with regards to their suitability as indicators for the locations of GSI facilities.

3.1.1. Landscape and sociodemographic data subgroup

We grouped explanatory variables as possessing either predominantly landscape or sociodemographic characteristics. Although this distinction is arbitrary, it serves as a tool for interpreting and contextualizing results. For this study, variables derived from either naturally occurring or modified topography and land cover were grouped as landscape. Variables collected with the intention of identifying population characteristics were sociodemographic.

3.1.2. GSI in Baltimore and Portland

For this cross-city comparison, we processed the data for consistency across study areas. To accomplish this, all above ground GSI facility

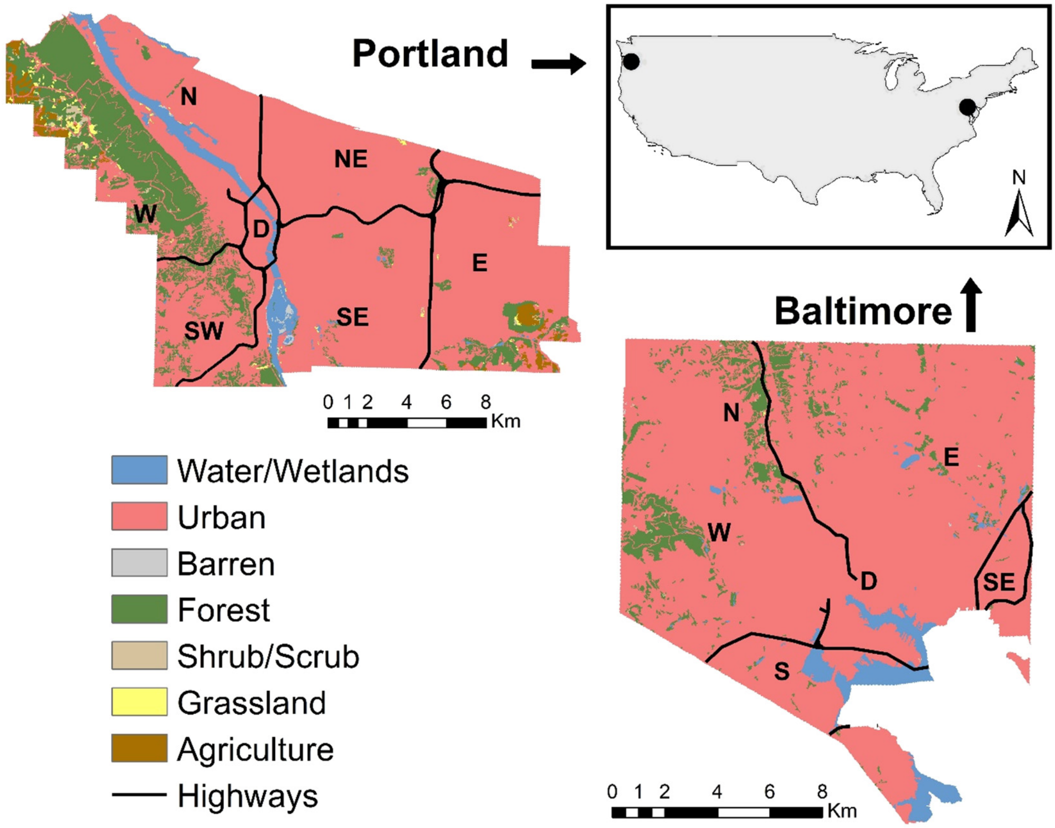

Fig. 1. Study areas containing representative NLCD 2011 (Homer et al., 2015) simplified classification.

types (Table 4) were combined and summarized within their corresponding CBG and tract to facilitate comparison of census sociodemographic data. Attention was paid to the public visibility of different GSI and facilities were categorized as either 'above ground' or 'below ground'. We separated these different types of GSI because GSI facilities that contain vegetation at street level provide a very different range of ecosystem services than buried facilities that mimic ecological processes with 'grey' infrastructure materials (McPhillips and Matsler, 2018). Although many cities consider both above and below ground facilities to be a part of their GSI portfolio, underground facilities, such as sedimentation manholes, dry wells, and underground filters were excluded as GSI facilities in this dataset, and the focus was placed on visible, above ground facilities such as bioswales, green roofs, and detention ponds.

The density of GSI facilities within each CBG and census tract served as the dependent variables for all spatial analyses. This approach accounted both for differences within the nomenclature used regarding different above ground GSI designs within each city, and also accounted for variability in CBG size. This approach of grouping and summarizing GSI facilities was considered appropriate as it may be assumed that all GSI designs will provide a variety of water-related ecosystem services to the surrounding area (e.g., Meerow and Newell, 2017). Additionally, separating GSI by facility type would have yielded too few GSI per block group for adequate statistical analysis in many cases. Given that Portland's GSI data are more extensive and include years of installation, we further analyze GSI density using a multilevel spatial model (see Section 3.2.2).

Two approaches were used to prepare the dependent variables, necessitated by data distribution. In Baltimore, a substantial 508 out of 650 CBGs did not contain any GSI facilities. Thus, we converted GSI density to binary form (i.e. GSI present or not) to address the concern of skewed data resulting from many zero values. The dependent variable for Portland was not converted to binary form, as only 18 CBGs did not contain GSI. As such, both cities may not be directly compared, but the relative association of GSI to landscape and sociodemographic variables in each city can be gleaned from regression analysis.

Table 2
Climate, landscape and sociodemographic characteristics of study cities. Data sources: mean annual rainfall from National Centers for Environmental Information, 2018a, 2018b; US Census Bureau, 2018.

	Baltimore	Portland
Mean annual rainfall (mm)	1063	915
Köppen climate classification	Cfa	Csb
Mean elevation (m)	60	95
Standard deviation of elevation (m)	42	76
Mean slope (degrees)	5	8
Standard deviation of slope (degrees)	6	9
Population (July 2017)	611,648	647,805
Area (km^2)	210	346
Population density (person per km^2)	2918	1875
Population change (%, 2010–2017)	−1.5	11.0
Median income (2016 USD)	44,262	58,423

3.2. Methods

3.2.1. Geographic Information Science (GIS) and mapping

After normalizing all independent and dependent variables to the CBG and census tract scale in both Baltimore and Portland, the variables were analyzed with GSI density as the dependent variable using exploratory regression in ArcMap 10.5. The CBG scale is the highest resolution at which socioeconomic data exists in Baltimore and Portland and thus defined our default lower-level spatial resolution. Data summarized to the census tract level represented the higher-level units. The exploratory regression tool produced potential combinations of variables while taking into account variable significance, multicollinearity, spatial autocorrelation, R^2, and Akaike information criterion (AIC). For both

Table 3
Sources of data utilized in analysis.
*NLCD Land cover 2011 (Homer et al., 2015), NLCD Impervious surface (Xian et al., 2011).

Data	Derived variables	Source
Landscape variables		
Digital elevation model (m)	x̄ Elevation[a] (m)	MD iMap Maryland.gov; Portland Metro Regional land information system (RLIS)
	σ Elevation (m)	
	x̄ Slope (degrees)	
	σ Slope (degrees)	
Impervious surface coverage	% Impervious[a]	City of Portland Bureau of Environmental Services; National Land Cover Database (NLCD) 2011 Percent Developed Imperviousness
Land use/cover	% Green space[a]	NLCD 2011 Land Cover classes 21, 41, 42, 43
	% A/B soil[a]	USDA National Resources Conservation Service (NRCS) soil survey 2017
Sewer system	Combined sewer (CS) pipe density[a] (m/km^2)	City of Portland Bureau of Environmental Services
	Total pipe density[a] (m/km^2)	
Building characteristics	x̄ Building age[a] (years)	Baltimore County tax assessor; Portland Metro Regional land information system (RLIS)
	x̄ Taxlot value[a] ($)	
	x̄ Building area (ft^2)	
Sociodemographic variables		
Census data	% Monolingual English[a]	US Census American Community Survey 2011–2015
	% Higher education	
	Median income[a] ($)	
	Population density[a] (person/km^2)	
	% White[a]	
	% Poverty[a]	

[a] Present in final model(s).

Baltimore and Portland, this tool was used at both CBG and census tract scales independently. Additionally, we mapped Univariate Local Moran's I of GSI density within each study area at the CBG scale using GeoDa (Anselin et al., 2006). These maps help to visualize high and low-density clusters of the dependent variable across space. We also mapped the spatial distribution of significant explanatory variables as well as residual maps using a quintile classification.

3.2.2. Multiple regression models

Variables showing potential for significant spatial relationships were retained and included in four separate types of models using GeoDa (Anselin et al., 2006) and GWR4 (Nakaya et al., 2016) software. These included ordinary least squares, spatial lag, spatial error, and geographically weighted logistic regression (GWLR) models. Ordinary least squares, spatial lag, and spatial error models are global models with one coefficient value for each explanatory variable. GWLR models are local models designed to account for the potential spatial nonstationarity detected between the dependent and independent variables for each CBG or tract. Additionally, the GWLR was necessary in accounting for the high number of census blocks within Baltimore that did not contain any GSI. Best-fit models for the multiple regression analysis within each city, performed independently at each scale, were determined based on a number of standard model diagnostics. The value of significant coefficients (at the 5% significance level) for each explanatory variable in the local models was mapped to show a spatially varying relationship between dependent and independent variables.

To account for the nested structure of CBGs within census tracts, in addition to regional influence on GSI distribution, a Hierarchical Spatial Autoregressive Model, or HSAR (Dong et al., 2016), was used in Portland. This model provides values that indicate spatial autocorrelation at both the higher and lower levels, as well as direct and indirect influences of all independent variables weighted for both scales. Succinctly, this model was used to determine group dependence within the data. To explore higher-level group controls upon CBGs, the HSAR model was implemented with all landscape variables remaining at a CBG level, and all sociodemographic variables represented at the census tract level. Topographic data such as elevation and slope typically vary over a small geographical area, providing the possibility that this variation could be masked at a larger area. While there is inherent uncertainty using census or American Community Survey (ACS) data, other work has shown that the coefficient of variation of ACS estimates is greater at smaller scales (i.e., CBGs); typically a census tract will have a smaller margin of error than a CBG (Folch et al., 2016).

Table 4
GSI facility types included in analysis.

Baltimore	Portland
Green roofs	Green roofs (4in)
Dry detention pond	Dry detention pond
Wet retention pond	Wet retention pond
Infiltration facility	Infiltration facility
Porous pavement	Porous pavement
Filter (bio/sand)	Filters (leaf/sand)
Swale	Swales & vegetative strips
Rainwater harvest	

4. Results

4.1. Spatial patterns of GSI

Moran's I cluster analysis ($I = 0.25$, $p = 0.00$) indicated that there are CBGs with both high and low density of GSI clustering within Portland (Fig. 2). Areas of high clustering appear throughout the city, most noticeably in outer Southeast Portland. Low-density clustering of GSI is present in Central Portland and inner Southwest Portland. Baltimore contrasts Portland in that it shows no distinct clustering of GSI facilities (Moran's $I = 0.01$, $p = 0.46$).

4.2. Factors associated with the spatial distribution of GSI

4.2.1. Baltimore and Portland

The GWLR model chosen for Baltimore (Table 5) indicated overall, a positive relationship between % green space, and % imperviousness, and a negative relationship with population density at the CBG scale. A percent deviance result of 0.22 indicated that a moderate amount of variability is explained by this model. At the tract level, a GWLR model indicated that overall, a positive relationship between mean elevation, % poverty, mean tax lot value, and a negative association with % English and average building size. This model has a percent deviance result of 0.12, which is notably smaller than the model performed at the CBG scale.

Spatial lag and error models, including Portland's GSI distribution at the CBG scale produced an R^2 value of 0.21 (Table 6). Median income, % A/B soil, and % White were significant and negatively associated with GSI density, while pipe density exhibited a significant positive

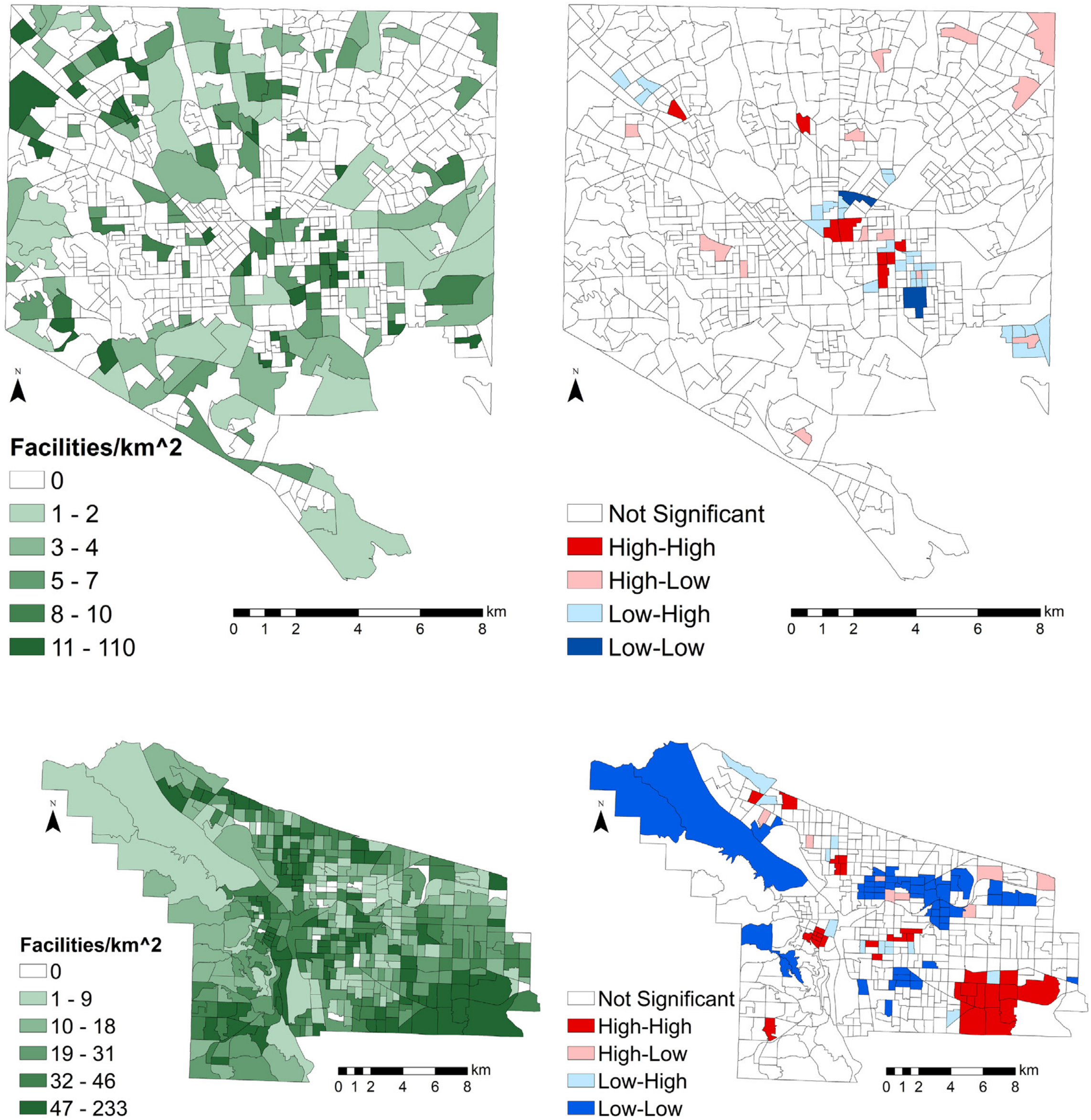

Fig. 2. GSI density (left) and clustering of census block groups by GSI density (right).

Table 5
Results of Geographically Weighted Logistic Regression Model for both census block group (n = 650) and census tract (n = 199) scale Baltimore study area.

	Coefficient					
	Census block group			Tract		
Variable	Mean	Min	Max	Mean	Min	Max
% Green space	5.06	0.47	12.15	–	–	–
% Impervious	0.04	−0.00	0.09	–	–	–
Mean elevation (m)	–	–	–	0.01	−0.01	0.02
% English	–	–	–	−4.05	−6.76	−1.68
% Poverty	–	–	–	1.50	−0.82	3.20
Population density+	−2.44	−5.18	0.02	–	–	–
Mean taxlot value+	–	–	–	0.09	0.04	0.13
Building area (ft^2)	–	–	–	−6.20	−9.44	−1.83
AIC	578.03			264.60		
R^2	0.22			0.12		

+ variable coefficient x 10,000. Unit references see Table 3. AIC = Akaike information criterion.

Table 6
Results of spatial lag and error models for Portland, at both the census block group (n = 442) and census tract (n = 142) scale.

	Census block group				Tract			
Variable	Lag		Error		Lag		Error	
% A/B soil	−0.45	***	−0.57	***	–		–	
Pipe density+	0.14	***	0.16	***	0.16	***	0.19	***
Median income+	−0.05	***	−0.05	***	−0.06	***	−0.07	***
% White	−0.88	**	−0.83	**	–		–	
Mean building age	–		–		−0.01	*	−0.01	*
ρ	0.43	***	–		0.39	***	–	
λ	–		0.44	***	->		0.44	***
Breusch-Pagan	15.72	**	16.48	***	1.64		1.38	
Log likelihood	−606.25		−607.39		−132.18		−131.04	
AIC	1224.5		1224.78		274.40		270.07	
R^2	0.21		0.21		0.25		0.27	

Significance value * = $p < 0.10$, ** = $p < 0.05$, *** = $p < 0.01$. + variable coefficient x 10,000. Unit references see Table 3. ρ = lag coefficient spatial lag model. λ = lag coefficient spatial error model. AIC = Akaike information criterion.

association. At the census tract level, the preferred spatial error model (as determined by model diagnostics including: AIC, R^2, Breusch-Pagan test, Log likelihood, and Lagrange Multiplier test) shows that GSI density was negatively associated with building age and median income, while positively associated with pipe density. Spatial error models also effectively removed spatial autocorrelation in residuals as shown in the Appendix Figure.

Comparing both Portland and Baltimore, no common significant variables were present for both cities at either scale. Variables that were present in both the CBG scale and census tract scale for Portland, such as median income and pipe density, consistently showed the same negative or positive relationship respectively, though the strength of the coefficients were different. In Baltimore, depending on the spatial location of the CBG or tract, certain coefficients of variables experienced a sign change (i.e., a variable may exhibit a positive relationship with GSI density in one part of the city while the same variable displays a negative relationship with GSI density elsewhere). Additionally, there was no duplicate presence of significant variables between the CBG and census tract scale in Baltimore, a contrast to the similar results between both scales witnessed in the spatial model results of Portland.

4.2.2. Spatial patterns of coefficients and explanatory variables

As shown in Fig. 3, there is a spatially varying relationship between the dependent and independent variables in Baltimore. The range of

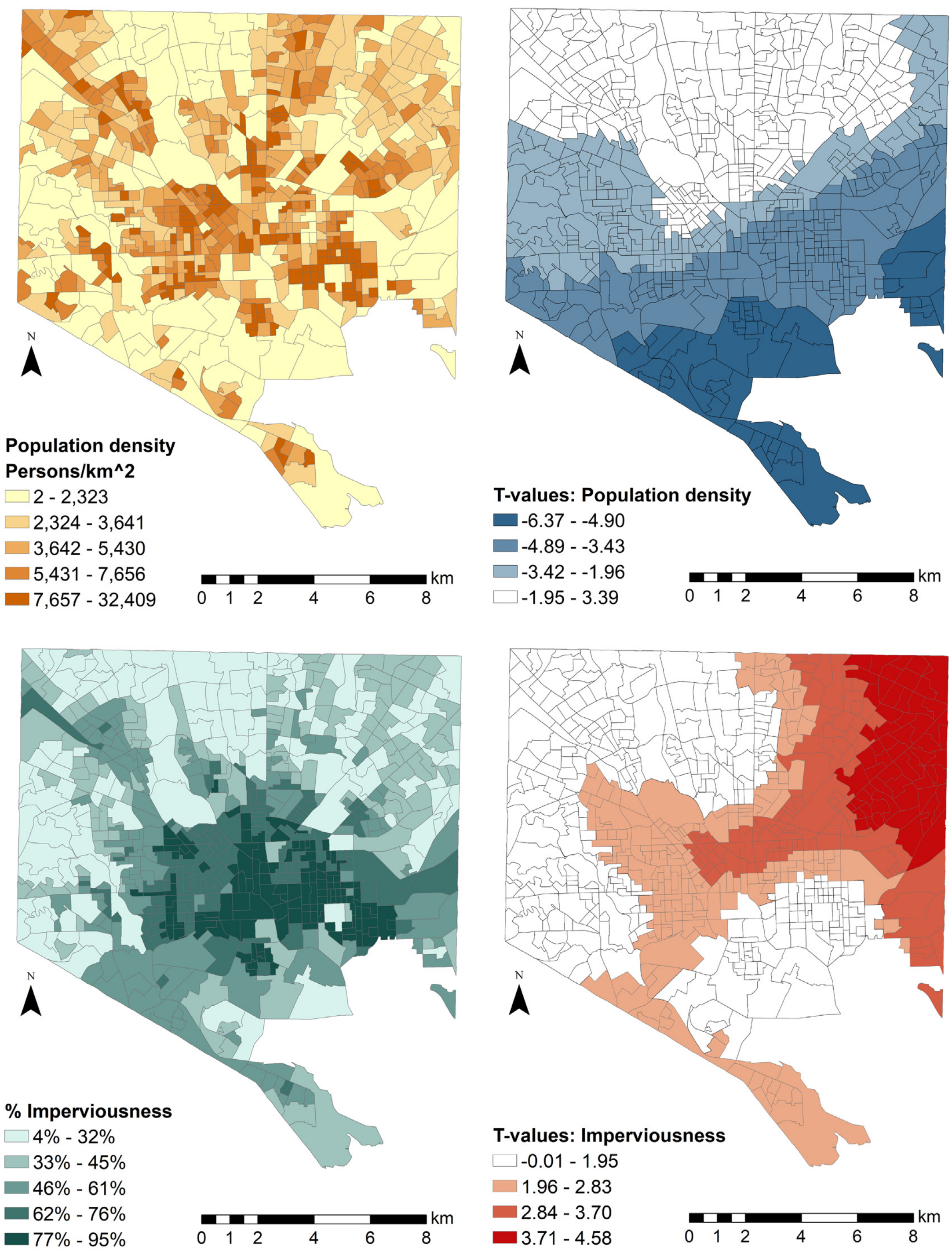

Fig. 3. Spatial characteristics of GWLR variables (left) and their corresponding areas of significance (−1.96 < t < 1.96) significant results (right) in Baltimore study area.

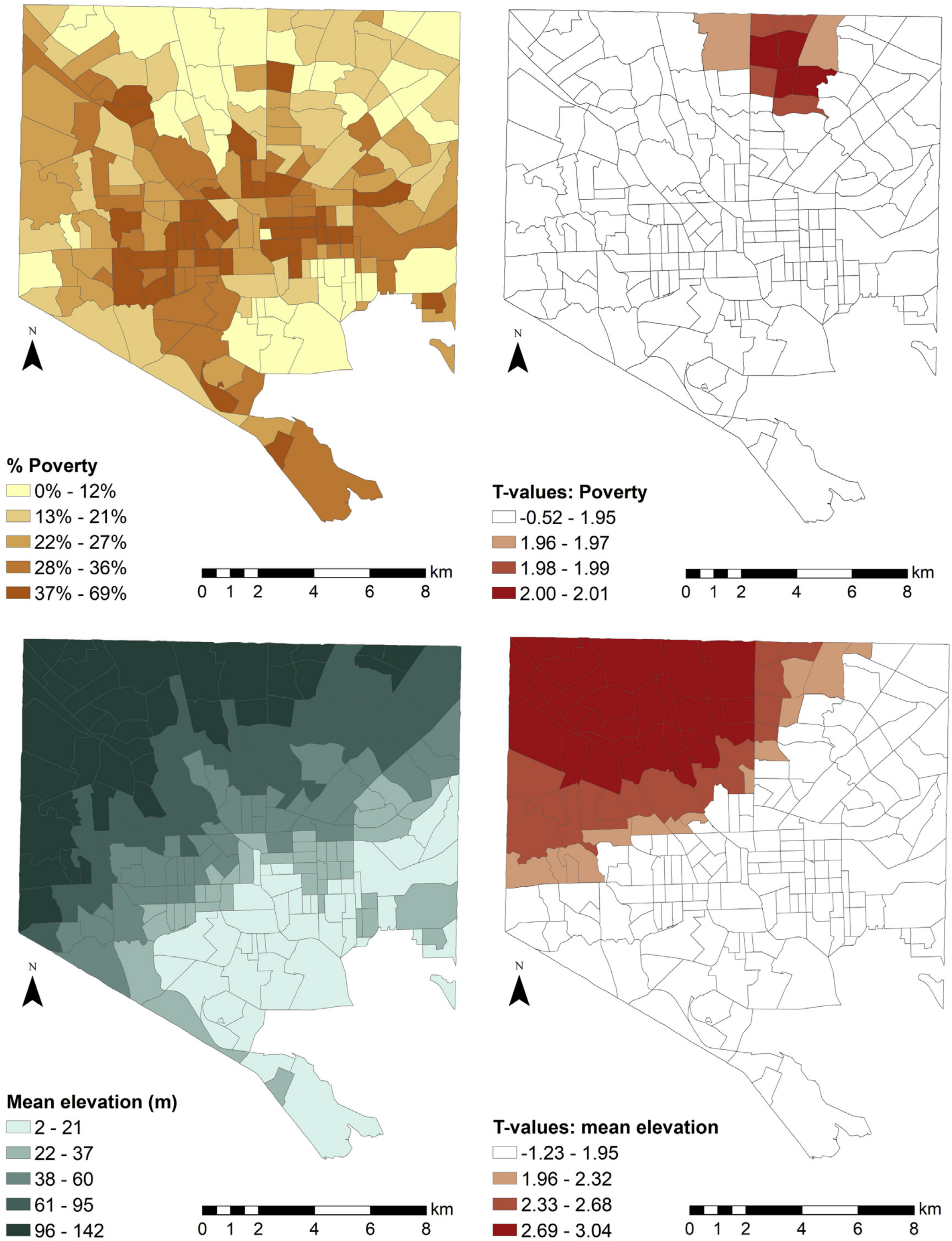

Fig. 3 (*continued*).

coefficients for each GWLR model was examined to identify spatial variation between negative and positive coefficients. Positive and negative relationships also exist in regards to population density at the CBG scale in Baltimore, while significant coefficients of impervious surface coverage, comprised entirely of positive values, were found on the east side of the city at the CBG. Significant positive coefficients of % poverty and mean elevation were found in far north and northeastern Baltimore, respectively. Fig. 4 shows spatial patterns of statistically significant independent variables for Portland, which also illustrates strong positive spatial autocorrelation in those explanatory variables.

4.3. Portland Hierarchical Spatial Autoregressive Model

Of all 16 variables included in the HSAR model, only pipe density, combined sewer (CS) pipe density, % impervious surface, and median income were statistically significant (Table 7). The magnitude of the covariate effects is described as direct, indirect and combined total impact. If pipe density increases by 1%, GSI density will increase by 0.214% from the direct effect, decrease by −0.017% from the indirect effect, thus producing a total effect of a 0.198% increase in GSI density. Interpreting the model results in this manner indicates that CS pipe density exhibits the greatest relationship with GSI density with both scales and all explanatory variables considered. The resultant ρ (−0.08) suggests that GSI density is expected to be lower when a CBG is surrounded by CBGs of higher GSI density, and λ (0.78) states that GSI density values are expected to be higher when an observation's tract is surrounded by tracts with higher GSI density values. However, the much larger λ value indicates the presence of a higher magnitude higher-level group dependence within the data.

5. Discussion

5.1. Spatial patterns and explanatory factors of GSI density in Baltimore and Portland

Distinct spatial patterns of GSI were found in both Baltimore and Portland at the resolutions examined in this study, though across the two cities there were no common variables that explained GSI density. Best-fit models were at different resolutions between the two cities, with the ideal model for Portland representing the census tract level while the best model for Baltimore represented the CBG scale. This range of results indicates that scale is of extreme importance when considering city-wide or regional GSI planning, both in statistical efficiency and in capturing multiscalar indicators. The shifts in influence identified within significant relationships, discussed in-depth below, represent

Table 7
Results of Hierarchical Spatial Autoregressive Model for Portland study area.

Variable	Mean coefficient		Direct	Indirect	Total
Intercept	4.166	***	4.171	−0.321	3.850
Mean elevation+	0.571		−0.572	0.044	−0.527
SD elevation	0.005		0.005	−0.000	0.004
Mean slope	0.067		0.066	−0.005	0.061
SD slope	−0.184		−0.184	0.014	−0.170
Pipe density+	0.214	***	0.214	−0.017	0.198
CS pipe density	−85.757	***	−85.848	6.617	−79.231
% A/B soil	−0.380		0.398	0.031	−0.368
% Green space	0.596		0.596	−0.045	0.550
% Impervious	1.491	**	1.492	−0.115	1.377
Population density+	−0.231		−0.231	0.018	−0.214
Median income+	−0.080	*	−0.080	0.006	−0.074
% White	−1.050		−1.050	0.081	−0.970
% Higher education	0.411		0.411	−0.031	0.379
% Poverty	0.029		0.029	−0.002	0.027
Mean building age	−0.002		−0.002	0.000	−0.002
Mean taxlot value+	−0.003		−0.003	0.000	−0.003
ρ	−0.082				
λ	0.781				
DIC	1411.335				
Pseudo R^2	0.250				

Significance value * = p < 0.10, ** = p < 0.05, *** = p < 0.01. + variable coefficient x 10,000. Unit references see Table 3. ρ = lower-level spatial autoregressive parameter. λ = higher level spatial autoregressive parameter. DIC = deviance information criterion. SD = standard deviation.

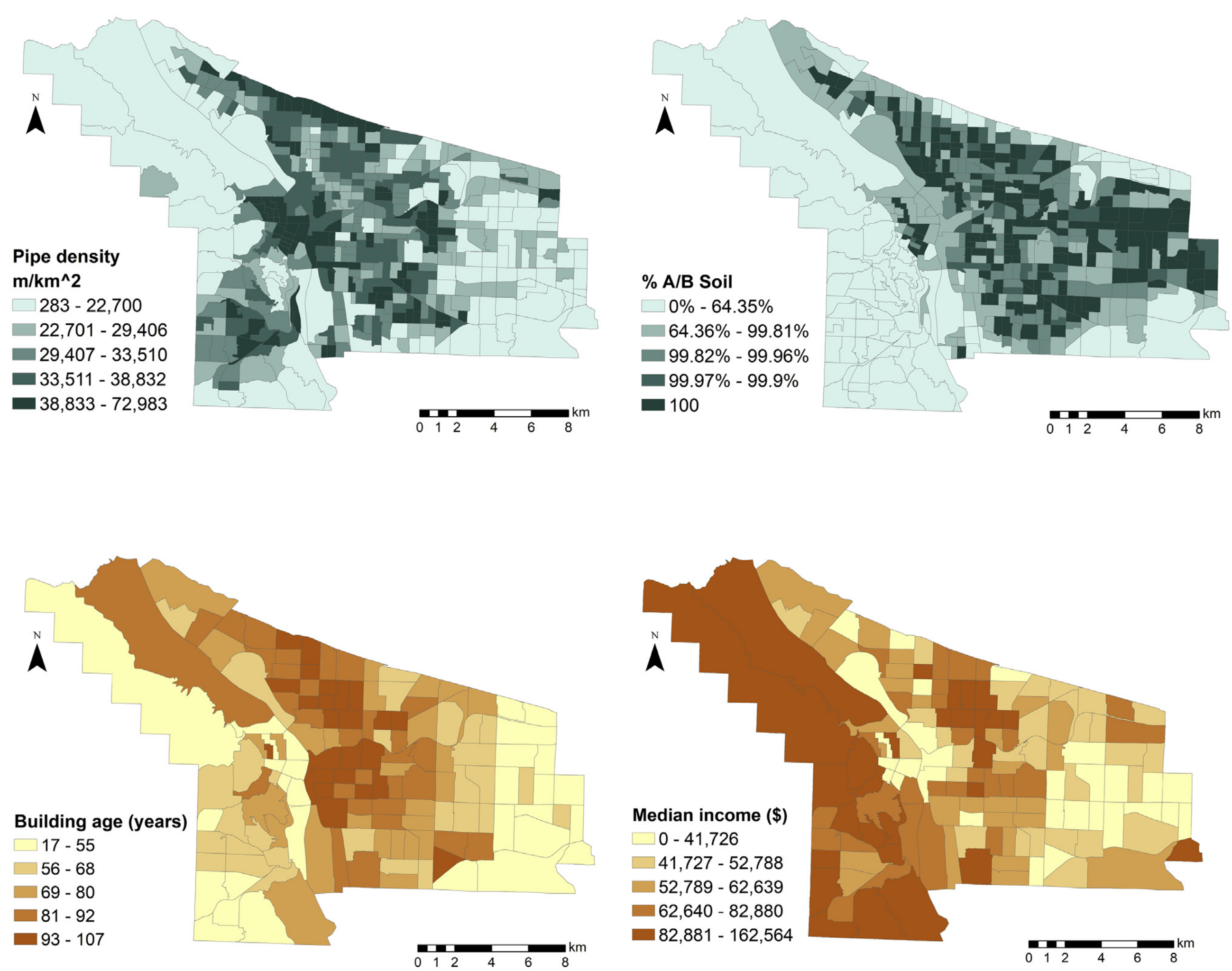

Fig. 4. Raw values of significant variables used in spatial model for GSI density distribution in Portland.

the spatial dependence of explanatory variables used to describe GSI density both within study areas and the dissimilarities between cities.

The spatially varying coefficients of impervious surface (higher T-values in east) at the CBG scale in Baltimore indicate that more GSI implementation has been occurring outside of the dense city center (East and Southeast Baltimore, Fig. 3), in neighborhoods that have room for GSI installation either as new construction or in areas of GSI retrofits or urban infill development (McPhillips and Matsler, 2018). Either way, newer development – whether greenfield or infill – is expected to be a strong indicator of GSI placement since new development code and design guidelines in both Portland and Baltimore (i.e. the Portland Stormwater Management Manual and the Maryland Stormwater Design Manual) encourage and sometimes require GSI. This spatial analysis affirms the influence of development code on GSI development in cities (as McPhillips and Matsler (2018) hypothesized).

Additionally, while the entire city of Baltimore is highly urbanized, GSI was found in CBGs with relatively lower population density. This is most likely because there is more space for GSI facilities in these areas even though the most densely populated areas of Baltimore would be particularly in need of the benefits of GSI due to the number of people served. This finding highlights the technical difficulties faced by potential ultra-urban sites for GSI. Conflicts with underground utilities and poor-draining, hydrologic soil group D soils throughout downtown Baltimore are major barriers to increased GSI implementation. This is clearly shown with much lower coefficient values (as shown in lower T-values in Fig. 3) toward coastal areas. This finding also supports other studies where population density was found to be negatively associated with public green space in the U.K. (Ferguson et al., 2018).

The spatially varying positive correlation between green space and GSI density in Baltimore (Table 5) displays the convoluted nature of combined landscape characteristics and development patterns (i.e., GSI retrofits versus new construction installation) captured at the smaller CBG scale. Toward the boundaries of the study area, with increasing distance from the highly impervious downtown, green spaces increase. In a future study, it might be advantageous to provide two distinct green space variables representing both undeveloped green space (e.g. intact forest) and intentionally greened land (e.g. parks) in to further highlight how shifts in design principles might impact GSI inclusion. In particular, this distinction is important to allow comparison of GSI across cities with a broader definition of green infrastructure/GSI that may include parklands, forest patches, and other more ecologically-based facility types (Matsler, 2017; Bell et al., 2018; McPhillips and Matsler, 2018).

Baltimore's % poverty and mean elevation coefficients at the tract scale (Fig. 3) also exhibit a spatially varying positive significance, but only in the North and Northeast sections of the city. This elevation relationship may indicate a growing trend toward distributed GSI being located closer to the area of runoff generation, which may be further up in the watershed, or may result again from there simply being more space available for GSI implementation in the outskirts of the city. The positive relationship between GSI and % poverty but negative relationship with tax lot value is counterintuitive, though it is possible that this may result from differences in renters versus homeowners within the data. These types of counterintuitive findings may result from the combined influence of different planning and regulatory drivers of GSI. For example, GSI implementation is occurring with new private development, which may represent these lots of higher tax lot value, while comprehensive planning strategies and retrofits of GSI into public land may favor areas with higher poverty. Similar patterns have been observed in Philadelphia, PA, where significant explanatory variables differed by whether you were considering publicly or privately implemented GSI (Mandarano and Meenar, 2017).

The negative relationship between GSI density and % White in the Portland spatial lag and error models was anticipated (Chan and Hopkins, 2017) but a relationship between race and GSI density was absent in Baltimore. This is consistent with counterintuitive findings in other research in Baltimore, which Grove et al. (2018) attributed to economic policies shifting racial patterns of home ownership through time. These findings suggest the importance of examining policy across time to better understand spatial relationships. For example, the negative relationship between % White and GSI density in Portland is likely influenced by the work the City of Portland has done to intentionally place GSI among CBGs with lower proportions of White residents in an attempt to provide inclusive benefits of these facilities to communities of color (Entrix, 2016). In particular, as part of the CSO mitigation plan in Portland, the city intentionally installed GSI in historically underserved neighborhoods (Shandas, 2015). In Baltimore, efforts to install GSI on vacant lots throughout the city (Green Pattern Book) has the potential to benefit communities of color, though a significant relationship with race was not seen in this analysis. This is likely influenced by the fact that Baltimore's public green infrastructure efforts are primarily in the planning stages and not yet implemented on-the- ground, even though non-profits, like BlueWater Baltimore, have begun to opportunistically build and encourage some facilities on private property in close cooperation with residents (Blue Water Baltimore, 2019).

The negative relationship between GSI density and less permeable soils in Portland could be attributed to the fact that many of the facilities located in downtown areas are not direct infiltration facilities. Thus, soil information may not have been critical when deciding the location of these facilities. Higher densities of GSI in the most southeast and northeast census blocks correspond well to hydrologic soil group A/B soil percentages in the range of 0–36%, while the rest of the city is nearly 100% A/B soil. Conversely, these similar clusters of GSI density in southeast Portland have much lower pipe densities compared to inner city census blocks with higher pipe densities. The CBGs with the highest GSI density are located near the city center, with very high corresponding pipe densities.

At the tract scale in Portland, similar relationships of model coefficients exist between median income and pipe density, with similar spatial patterns as well. In addition, a negative relationship between building age and GSI density indicates that the local requirements of GSI installation within areas of new construction could be impacting the GSI distribution throughout the city. That being said, the coefficient of −0.01 is quite small, and these relationships could change as retrofits of older areas continue. In Portland, the CSO pipeshed is located in the low elevation and relatively flat areas adjacent to the Willamette River, as water would obviously drain from outlying areas to these places; hence the overwhelmed sewershed.

5.2. Portland Hierarchical Spatial Autoregressive Model

While many possible factors can explain GSI density, we again see the importance of sewershed and median income when accounting for hierarchical controls on GSI density in Portland. Similar to the models for CBG and tract separately, the coefficients for median income and overall pipe density are negative and positive respectfully, indicating GSI density in less wealthy areas with high pipe density. These pipe dense and low-to-medium income areas correspond to the highly impervious census blocks in the city, which aligns with the positive relationship between imperviousness and GSI density that we see from the HSAR model. Interestingly, this is a relationship that was unidentified in the absence of this hierarchical approach. While pipe density coefficients are typically positive, the HSAR model indicates a significant inverse relationship with combined sewer pipe density. This is a bit counterintuitive, given that Portland's older and inner-city sewer system is largely combined sewer pipes, with newer parts of the city on the east and west side of the city. The absence of combined sewer pipes in nearly half of the CBGs may have led to this inverse relationship. The spatial coefficients, ρ and λ, indicate that both spatial dependence and group dependence are identified for our GSI density data, though group dependence appears stronger as indicated by a larger λ value.

5.3. Implications for urban sustainability and resilience

Urban green infrastructure has been introduced as a solution to urban hydrological and ecological issues that also provides social benefits that traditional grey infrastructure does not generally offer. This new effort is in line with green urbanism and urban sustainability or resilience initiatives in many cities (Andersson et al., 2014; Staddon et al., 2018). The integration of green infrastructure into a green urban design is an attempt to revitalize the city and improve stormwater management in a decentralized way (Wendel et al., 2011). GSI, in particular, has been presented as a cheaper and greener way to upgrade old and outdated grey stormwater infrastructure, which presents a risky and expensive challenge to most of the cities in the United States (ASCE, 2017). This decentralized stormwater management has also gained attention as a viable way to adapt to climate change (US EPA, 2016) when nuisance pluvial flooding is likely to occur more often than in the past (Rosenzweig et al., 2018).

Incorporating residents' perspectives into new GSI installation and design also empower them and could contribute local social and environmental resilience (Bendor et al., 2018). In both Portland's Climate Action Plan and Baltimore's Sustainability Plan, green infrastructure has been referred to many times to combat climate change mitigation (temperature regulation, carbon sequestration) and adaptation strategies (e.g. flood water control, improving water quality). Inclusion of resident voices has been strong in both cities due to their explicit commitment to use equity as a planning lens (City of Portland 2035 Comprehensive Plan, 2018; Baltimore Department of Planning, 2019 Baltimore Sustainability Plan); however, these visions have yet to manifest on the ground in many cases. Temporal and spatial analysis of green planning efforts will be essential to track as new green equity, and specifically GSI, planning efforts move forward. While these types of climate adaptation efforts using GSI are underway in many cities (Ambrey et al., 2017; Derkzen et al., 2017), our spatial analysis could be used in conjunction with community inclusion work. Community-oriented spatial analysis will further reveal where the city could focus or invest more considering the current distribution of GSI associated with the neighborhood sociodemographic characteristics to achieve urban environmental and social resilience.

5.4. Limitations and suggestions for future research

Several limitations and considerations exist in the current study. For example, there were limitations to data acquisition in Baltimore as sewer pipe data was restricted and therefore unavailable for use in this analysis. While pipe densities are an especially important consideration for stormwater management in Portland due to their combined sewer system and extensive CSO Plan, stormwater still contributes to Sanitary Sewer Overflows (SSO) in Baltimore (City of Baltimore Department of Public Works, 2018) even though the sewer system is completely separated. Including a method of analysis for Baltimore's aging pipeshed (Kaushal and Belt, 2012) would be ideal to fully understand the impact of GSI on this type of infrastructure.

Data for GSI was also limited by attributes, with some data displaying area of GSI facilities while others were only points. An analysis expanded to include facility area rather than the number of facilities normalized by city area could provide more specific information. It is also vital to further examine GSI by facility type, while considering that the classification of GSI across cities differ on a city by city basis (Bell et al., 2018). One other insightful attribute to consider in future analyses is the ownership of GSI features. There is a likely different spatial organization of GSI based on whether it is owned by the city or other governmental jurisdiction, versus being implemented on private property, due to the differing associated drivers and goals of implementation between these groups. There may also be non-regulatory GSI that is also providing environmental benefits, but that was not included in this dataset.

Spatial scales are also relevant. Examining these relationships aggregated up to a CBG scale or tract scale can inherently mask unique characteristics that may exist at a finer scale. This study confirmed the importance of considering scale when exploring the distribution of GSI, as some relationships only appear at certain scales while others remain consistent. To capture influential indicators, scale of analysis is clearly one of the most important considerations. While we have attempted to address this with multiple models at different scales, future work should consider how to better incorporate sewershed as a scale, given that sewershed characteristics strongly influence the hydrologic suitability and benefits of GSI implementation. Further analysis may want to examine temporal changes, evaluating relationships during different periods in Portland and Baltimore; currently, the smaller number of GSI in Baltimore severely limited this approach.

6. Conclusions

This research identified spatial patterns between landscape and sociodemographic variables and above ground GSI density in two U.S. cities. GSI exhibited a clustered distribution in Portland, whereas GSI density was random in Baltimore. Spatial models, including GWLR, spatial error, spatial lag, and Hierarchical Spatial Autoregressive Models were applied to account for spatial autocorrelation and derive spatially varying relationships between indicator variables and GSI. The results asserted that a variety of sociodemographic and landscape variables exhibit significant spatial relationships with GSI density, within both the local, global, and hierarchical models. Some of these variables align well with the factors mentioned in local stormwater planning and policy documents, while others appear to be more unintended or potentially confounded by multiple interacting planning and regulatory influences. There were no common explanatory factors between Baltimore and Portland. In Baltimore, significant factors varied by scale, with landscape factors like green space and impervious surface appearing at the CBG scale, while socioeconomic factors were significant at the tract scale. GSI density in Portland had positive relationships with pipe density and negative associations with median income, at both the CBG and tract scales. There was also significant spatial dependence and group dependence of GSI density.

While we did not explicitly quantify the benefits of GSI in this study, the landscape and sociodemographic variables that were considered have implications for manifestation and delivery of important hydrologic, ecological, and social benefits. The spatial approach employed in our study highlights how past policies and initiatives regarding GSI installation have manifested on-the-ground as an actual spatial distribution of GSI. Various planning strategies and stormwater regulations may have different goals (e.g., equity of environmental benefits, mitigation of runoff volumes from impervious surfaces) and mechanisms (private implementation with new development versus public retrofits), which may manifest in a mixed or unexpected manner. Across both cities, there was some evidence of increased GSI implementation in areas with historically underserved populations, but there were also indications on the contrary. Information such as this creates a pathway to better understand the placement of GSI and potential access to GSI-associated environmental and social benefits in urban environments; equitable access to these benefits is critical in the quest of enhancing overall urban resilience to climate change (Leichenko, 2011). We hope that this kind of analysis can reveal where on-the-ground trends align well with expectations, as well as patterns that are surprising, helping inform adjustments to future stormwater management planning efforts and create more resilient cities.

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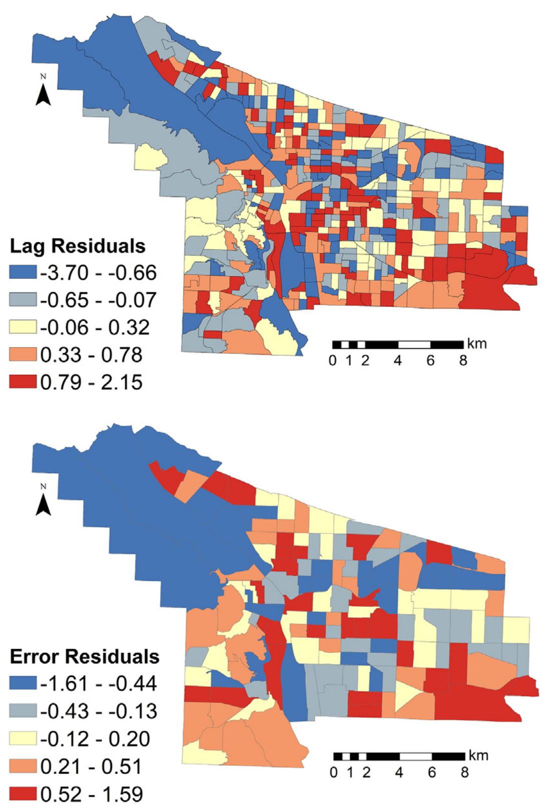
Author contributions

Ashley Baker and Emma Brenneman conceptualized the study, organized the data, conducted GIS and spatial analysis, and wrote the manuscript. Heejun Chang designed the study, supervised GIS and spatial analysis, wrote, reviewed and edited the manuscript. Lauren McPhillips and Marissa Matsler interpreted the results, reviewed and edited the manuscript.



Appendix Figure Mapped residuals from spatial lag model at census block group scale and residuals from spatial error model at tract scale in Portland.

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